# Inclusion-by-Design: Designing a Reference Architecture for Inclusive Lending Systems

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# Inclusion by Design

## Designing a Reference Architecture for Inclusive Lending Systems


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TU Delft

# Inclusion-by-Design:
## Designing a Reference Architecture for Inclusive Lending Systems

**Dissertation**

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*Key words:* Inclusive Lending, Reference Architecture, Inclusion-by-design, Financial Inclusion Metrics, Design Science Research, Value-Based Requirements, Design Principles, Machine Learning, Inclusive Scoring, Hybrid Feature Penalty Tuning, Borrower Reclassification

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## Summary

Despite the recent expansion of digital lending platforms in developing countries, marginalized segments still face challenges in accessing credit. Many borrowers are excluded due to the absence of formal financial histories or insufficient profiles. Existing research primarily focuses on improving model accuracy and ensuring profitability rather than addressing inclusion. Hence, more inclusive digital lending systems are needed. Inclusion in this study refers to "the equitable access, distribution, and utilization of financial resources, ensuring that all societal segments, particularly underserved populations, can participate meaningfully in lending systems." This definition emphasizes removing systemic challenges and fostering empowerment by enabling individuals to make informed decisions.

**Research Objective and Approach**

This research has three main goals. *First*, to design **a Reference Architecture (RA)** that supports financial inclusion by addressing the challenges faced by underserved groups, such as limited access to financial services, poor data availability, and inflexible credit products. *Second*, it seeks to establish *measurable inclusion indicators*, providing clear metrics to evaluate how well lending systems serve underserved populations. *Finally*, it addresses *socio-technical challenges* by incorporating design principles and architectural elements. The RA is designed and evaluated to address the inclusion challenges for marginalized borrowers in lending systems.

This study adopts the Design Science Research (DSR) methodology to design and evaluate the artifact. The research stages are structured into three interconnected spaces: *problem space, solution space, and evaluation space.* These spaces correspond to the rigor, relevance, and design cycles of DSR.

In **the Problem Space**, we identify challenges of inclusion and the measurement of inclusion in lending systems. This study conducted a Systematic Literature Review (SLR) and stakeholder interviews to answer Research Questions 1 (the challenges) and RQ2 (the inclusion metrics). We designed a reference architecture (RQ3) in the solution space by combining literature, interviews, and system analysis results. The reference architecture comprises Value-Based Requirements, Design Principles, and Architectural Components. In **the Evaluation Space**, we evaluate the RA by developing a prototype, followed by feature testing, sensitivity analysis with machine learning simulations, and survey-based behavioral analysis. This evaluation (RQ4) aims to examine the impact of RA in improving inclusion outcomes.

**Research Questions**

This study formulates four research questions (RQs) corresponding to the core stages of Design Science Research. ***RQ1: What are the socio-technical challenges to achieving inclusion in lending systems?*** aims to identify challenges in designing lending systems to improve inclusion for marginalized segments. We answer RQ 1 by conducting an SLR and interviews. ***RQ2: What indicators can measure inclusion within these systems?*** aims to develop a set of inclusion metrics to evaluate how lending systems respond to the needs of marginalized groups. RQ2 bridges the problem and solution spaces by transforming the inclusion concept into quantifiable evaluation metrics.

***RQ3: What elements make up a reference architecture for an inclusive lending system?*** is the main deliverable of this study, also a central design question in the solution space. The RA comprises three elements: Value-Based Requirements (VBRs), Design Principles (DPs), and Architectural Components. These elements were developed by conducting interviews and information flow analysis. We applied Value-Based Engineering (VBE) to elicit the requirements (VBRs). VBRs provide *what* functional

requirements should be included in the RA, whereas design principles provide the direction *(how)* of improving inclusion. ***RQ4: What is the impact of the proposed RA on inclusion?***, guides the evaluation space to examine whether the RA can address the inclusion challenges identified in RQ1.

**<u>Key Findings</u>**

**RQ1: Socio-technical challenges of inclusion**

Based on the literature and semi-structured interviews with eight types of stakeholders consists of fourteen respondents, we identify six categories of challenges: Technology and Data, Financial Lending, Organizational, Regulatory and Governance, Socio-Cultural, and Literacy. Participants were interviewed through purposive sampling to represent key perspectives in Indonesia's alternative lending ecosystem. The groups included regulators and policy-makers, central bank officials, ministry representatives, academics, P2P lending practitioners, microenterprise owners, senior banking professionals, and lenders.

In ***the technology and data category***, lending systems operate on fragmented infrastructures with a lack of flexibility in integrating alternative data sources. Moreover, marginalized segments tend to have incomplete, outdated, or unverifiable data, which results in their exclusion from credit recommendations. Another challenge is information asymmetry, in which lenders struggle to assess borrower profiles due to limited or low-quality data, and borrowers lack the ability to revise their personal information and understand how their information is used in credit decisions.

***The Financial Lending category*** addresses the trade-off between profitability, as the main interest of the lenders and fintech, and inclusion, as a main interest of borrowers and the government. Most loan products target low-risk borrowers with predictable incomes, such as salaried workers, rather than those with irregular cash flows, such as informal workers, farmers, and microenterprises. Moreover, rigid loan schemas with inflexible repayment terms may not align with the marginalized borrowers' capacity for payment. In ***the organizational category***, fintech companies face operational challenges in reaching marginalized segments due to missing or low-quality borrower information. This limitation forces lenders to rely on personal judgment rather than system-driven assessments.

***The Regulatory and Governance category*** addresses the challenges of legislation, policy, and coordination among institutions. The literature emphasizes the importance of data protection, while the interviews reveal practical challenges, such as overlapping regulatory mandates. ***Social and Cultural category*** challenges include gender discrimination and distrust of lending systems. ***Literacy category challenges*** are regarding borrowers and lenders. Borrowers often have low literacy in understanding loan terms or navigating digital systems; meanwhile, lenders may have difficulties understanding borrowers' profiles.

The categories show that inclusion challenges represent a broad and interconnected area of research, ranging from the technological to institutional and cultural aspects. Addressing inclusion requires understanding the broad view of challenges because the system-level issues alone may not fully capture the complex interplay among challenges. While this study acknowledges the broad spectrum of inclusion-related challenges, the reference architecture (RA) design focuses explicitly on challenges within the technical system, including its users, such as data handling and scoring configurations that can be addressed through technological and design interventions. Broader concerns remain outside the scope of this study. Within this boundary, this study concentrates on *two challenges*. First, *Technology and Data*, where challenges include poor data quality, integrating alternative data, and information asymmetry. Second is *financial Lending challenges*, where rigid scoring models and inflexible loan products fail to accommodate marginalized segments. These focused challenges define the problem space for the reference architecture.

**RQ2: Inclusion Metrics**

RQ2 aims to develop a set of metrics to measure inclusion in lending systems. The proposed metrics are developed based on literature review and conducting six interviews with respondents from the Financial Service Authority, the Ministry of Cooperative and SMEs, the Central Bank, fintech lending firms, and university lecturer, with professional experience ranging from three to six years in their respective fields. Inclusion metrices are presented in four categories: Penetration, Financial Access, Analytical Inclusion, and Literacy, which are classified based on the recurring themes during the analysis.

***Penetration metrics*** consist of physical and digital access indicators to monitor whether marginalized groups are excluded due to geographic or demographic structure. ***Financial Access metrics*** examine affordability issues to monitor whether marginalized segments can access it based on their payment capacity. ***Analytical Inclusion metrics*** address data representation, algorithmic design for the scoring system, and transparency and interpretability of the outcome. ***Literacy metrics*** capture whether borrowers and lenders can understand and navigate the system. Although the RA does not address literacy gaps, we keep providing literacy metrics for evaluation purposes. RA features such as contested decision-making and transparent scoring require a basic level of borrower understanding. The metric framework incorporates ***borrower*** and ***lender*** perspectives. Indicators such as *interest affordability* and *understanding loan terms* reflect *borrower* concerns, while metrics like *the Productive Loan Ratio* capture how *lenders* approve the loan for productive purposes vs. consumption loans.

Despite the range of metrics elaborated in RQ2, this study only tested a subset of the metrics due to the focus on evaluating the designed RA. Evaluations of RA in RQ4 focused on *borrower reclassification presented with inclusion ratio* (Chapter 8), *loan approval rates* (Chapter 7), and *system features impact on perceived inclusion* (Chapter 6). The evaluation of other metrics is proposed for future research and implementation.

**RQ3: Reference Architecture**

RQ 3 aims to design a reference architecture that improves inclusion in lending systems. This study designs and evaluates the RA based on the concept of ***inclusion by design***, which refers to *integrating inclusion goals throughout system development and evaluation*. The RA comprises three elements: Value-Based Requirements (VBRs), Design Principles (DPs), and Architectural Components.

*The elicitation of* ***VBRs*** was conducted through interviews with six groups of respondents (three respondents from the Financial Services Authority, three from the Central Bank, two from fintech companies, one from small-medium enterprises, one investor, and one academic) and information flow analysis. This study formulates seven VBRs: equal access, inclusive scoring, equitable credit distribution, tailored loan products, perceived social benefits, trust in data exchange, and transparent operations.

***The Design Principles (DP)*** provide direction on *how to* embed inclusion into the system's architecture. These principles were derived through a multi-stage process grounded in the VBRs, informed by literature on principle-based design in information systems, and refined through iterative mapping to system components and stakeholder interviews. The DP consists of five principles: (1) Formulate a comprehensive set of inclusion metrics to promote inclusive access and performance evaluation; (2) Leverage alternative data for enhanced borrower and lender participation to mitigate information asymmetry; (3) Enhance inclusion through transparency in loan terms, approval explanations, and borrower appeals; (4) Tailor credit solutions to empower underserved borrowers; and (5) Address long-term sustainability while balancing inclusion and risk.

***The architectural components*** implement VBRs and DPs in four blocks of architecture: (1) Loan Assessment block, which consists of an inclusive scoring component, borrower contestation component, and inclusive loan distribution component; (2) Data Collection block, which validates data inputs while preserving traceability and integrity; (3) Distributed Ledger block, consists of distributed ledger transaction and distributed ledger audit to ensures auditability through immutable records and consensus mechanisms; and (4) User Dashboards block, which provides access for borrowers, lenders, validators, regulators, and collaborators. The term “block” refers to a group of related components that together perform a core function in the architecture. These blocks were derived by clustering system components based on their functional roles in addressing inclusion challenges, following the translation of value-based requirements into architectural features.

By embedding inclusion into the architecture, the RA offers a technical model and a design philosophy to ensure that future lending systems can improve inclusion.

**RQ4: Testing the Reference Architecture**

RQ4 evaluates the impact of the reference architecture on improving inclusion. This study applied a three-phase evaluation method to assess the RA's impact, consisting of prototyping and feature testing, a behavioral survey, and a series of sensitivity analyses with machine learning simulation. Each method serves a distinct purpose. *The prototype* testing examines whether specific system features, i.e., Contested Decision-Making, Dual Rating Systems, and Collaborative Data Collection, can address data inaccuracy, limited borrower histories, and fragmented data availability. These three features were selected because they operationalize key Design Principles and directly address core inclusion challenges such as information asymmetry, fragmented data collection, and the lack of diverse, verifiable data sources. *The survey* evaluates how additional borrower information affects lenders' approval behavior. *The machine learning simulation* investigates how enriched data and scoring configurations influence the system's loan recommendation outcomes.

**A. Prototyping and feature testing**

This study developed a prototype of a lending system using Distributed Ledger Technology (DLT), which was implemented with Hyperledger Besu. In this study, DLT served as a distributed infrastructure to support inclusive system features, rather than a central solution. Besu was selected because it supports permissioned access that is suitable for regulated lending environments. Moreover, Hyperledger Besu can easily be integrated with other development tools and is cheaper than other software. The prototype included interactive dashboards, a loan assessment engine, data collection components, and a distributed ledger infrastructure.

The evaluation is focused on the impact of three core features of the RA on inclusion: *Contested Decision-Making, Dual Rating Systems,* and *Collaborative Data Collection*. The prototype provides dashboards for borrowers, lenders, validators, regulators, and data collaborators to allow them to evaluate the impact of these features on the perception of inclusion. This focus was chosen because the main goal of the RA is to improve inclusion, and these features were designed to directly support that goal. At this stage, the evaluation aims to explore whether the features are perceived to improve inclusion by relevant stakeholders, before moving to more technical or behavioral evaluations.

Prototype testing of the features was conducted in two stages. The first stage allowed participants to interact freely with the prototype to familiarize themselves with the system and features. The second stage consisted of Focus Group Discussions (FGDs) to capture their reflections on inclusion-related impacts. Participants included IT and credit risk professionals. The results of the FGDs are as follows:

***The Contested Decision-Making*** feature enables borrowers to revise their data and appeal for changes in approval decisions. This feature supports inclusion by giving borrowers more agency in shaping how they are represented in the system. The FGD results show the potential of this feature in increasing inclusion, with concerns regarding data manipulation and data validation governance. These concerns indicate the need for simplified dispute workflows and clear validation protocols.

***The Dual Rating System*** allows borrower evaluation through lender-based and community-driven inputs. It contributes to inclusion by enabling borrowers with limited formal histories to be assessed through alternative perspectives. This mechanism was especially valued for its ability to assess borrowers with limited formal histories. Feedback emphasized the importance of standardized criteria and mechanisms to resolve discrepancies between ratings to ensure trustworthiness and consistency.

***The Collaborative Data Collection*** feature brings together data from borrowers, external contributors, and institutional providers to improve the completeness of borrower profiles. This feature contributes to inclusion by expanding the range and diversity of data that can be used to evaluate underserved borrowers. The respondents identified several challenges, such as data obsolescence, unstructured formats, and representation gaps. They suggest that robust data governance must accompany the implementation.

In general, the prototype features demonstrated the feasibility of improving inclusion. IT stakeholders emphasized technical scalability and aspects of the technology configuration, while credit risk professionals focused on systemic risk, borrower comprehension, and institutional collaboration. Despite implementation challenges, the FGDs affirmed that the perceived inclusion benefits stemmed primarily from how the features improved data quality, borrower agency, and trust.

**B. Sensitivity analysis with machine learning simulations**

Current lending systems process borrower data using preconfigured algorithms that prioritize accuracy and risk avoidance, often at the cost of inclusion. The RA proposed in this study aims to improve inclusion by adjusting how data is processed and interpreted in borrower classification. This part of the evaluation investigates whether modifying borrower data and tuning model parameters can improve borrowers' risk classification. Such improvements in classification are expected to reflect better inclusion outcomes, particularly by enabling more underserved borrowers to qualify for lower-risk categories and access credit opportunities.

Two hypotheses were tested using machine learning simulations.

**Hypothesis A1: Adding additional data variables increases loan recommendations by shifting borrowers to lower-risk classification.**

Hypothesis A1 examined whether enriching borrower profiles with new attributes could improve borrower reclassification. Six new attributes were added to the base model to enrich borrower profiles, followed by a custom variable capturing repayment capacity. While the data additions improved borrowers' profiles, their effect on borrower reclassification was limited. The simulation results show only small reclassifications and movements of borrowers. Hypothesis A1 was not supported. We concluded that data enrichment alone, without adjusting model parameters, cannot improve inclusion outcomes.

**Hypothesis A2: Tuning model parameters increases loan recommendations by shifting borrowers to lower-risk classification.**

Hypothesis A2 tested whether parameter tuning could more effectively shift borrower classifications. Three different methods were evaluated: Feature Weight Adjustment, Penalty-Based Models, and Hybrid Feature Penalty Tuning (HFPT). The Penalty-Based Model approach is widely supported in the literature as an effective method for controlling classification bias and improving fairness in risk assessment. Meanwhile, Feature Weight Adjustment is a practical and straightforward technique for evaluating how different attributes influence borrower classification. HFPT, introduced in this study, combines both approaches to offer a more adaptive and inclusive reclassification mechanism.

***The feature weight adjustment*** approach reduces the influence of several features within the model. The results show that by decreasing the weight of OVER_TIME, which captures the number of days a borrower exceeds the repayment deadline, borrowers were more likely to move into lower-risk categories. This confirms OVER_TIME as a sensitive feature. In contrast, lowering the weight of OVER_INT (interest rate) results in minimal changes, indicating its limited role in classification. This method helps isolate which features drive movement. However, this approach cannot detect borrowers' redistribution patterns across risk classes, only their movement patterns, limiting its utility in evaluating inclusion outcomes at a systemic level.

***The penalty-based*** approach, in contrast, can identify the borrower distribution patterns as the impact of penalizing specific classes. This approach uses two parameters: *penalty type* (which class is penalized) and *penalty value* (the magnitude of the penalty). These models shape the structural distribution of risk classes, allowing inclusion effects to be observed at the macro level. A critical innovation in this study is the identification of ***penalty thresholds***, *minimum penalty values required to trigger substantial borrower reclassification*. The analysis of *penalty thresholds* reveals an insight into model explainability: the effort required to shift borrowers between risk classes is influenced by the class size in the training data. For example, Class 0 dominates the dataset with over 50% of borrowers; therefore, substantially higher penalty values (e.g., 9060) are required to trigger reclassification. In contrast, classes with small proportions in the training data show movement at lower thresholds (e.g., *penalty value* 700). This suggests that the more dominant a class, the more resistant it is to change. These patterns illustrate that borrower movements are not arbitrary but are shaped by the interaction between penalty configuration, model structure, and the training data size. It also highlights a broader machine learning concern: that model sensitivity may vary depending on how training data is distributed, underscoring the importance of understanding data dynamics.

In conclusion, the penalty-based approach offers *more explicit control over inclusion* and is *easier to interpret* than the feature weight approach.

***Hybrid Feature Penalty Tuning (HFPT)*** is a novel method introduced in this study to enhance borrower reclassification by combining the previous two approaches: feature weight reduction and penalty-based. The feature weight approach reduces the influence of selected variables, while the penalty-based approach redistributes borrowers into different risk categories based on predefined rules. The results show that HFPT is effective when *penalty values* are moderate. However, when *penalty values* are set at relatively high levels, HFPT no longer adds additional benefits, as the redistribution effect is already saturated; in these cases, HFPT results are similar to penalty-only outcomes, indicating that penalty intensity remains the primary driver of changes.

The value added of the HFPT approach lies in its ability to ***fine-tune borrower movement*** within scoring configurations that have not yet reached their redistribution threshold. This flexibility does not appear in the previous two approaches (feature weight and penalty-based). This approach contributes directly to the Inclusive Scoring component of the RA by offering a way to calibrate how borrower attributes affect classification outcomes under various penalty configurations. Therefore, we propose HFPT as *a diagnostic tool* that helps identify which borrower attributes are most influential in any particular dataset. *We recommend using HFPT* as a practical tool for policy-makers and practitioners to explore how penalty configurations influence borrower redistribution and identify which features most affect borrower classification, using *threshold values* as a reference.

Hypothesis A2 is supported by the simulation experiments. Tuning model parameters improves inclusion outcomes depending on *the reduction factors*, *the attributes*, *the penalty types,* and *values*.

**C. Survey Experiment**

This evaluation phase examines the impact of enriched borrower profiles and system recommendations on lender loan approval. These two mechanisms are part of the RA's design, operationalized through the Inclusive Scoring component and the Lender Dashboard. *The Inclusive Scoring component* provides borrowers' scoring that is linked to system recommendations, while *the Lender Dashboard* presents both enriched profiles and system-generated recommendations to guide decisions. The evaluation was conducted through an online survey using *Qualtrics web software*. The total number of survey participants was 210, higher than the initial target of 90 respondents to meet the requirements for a statistically significant number. Participants were presented with a series of borrower profiles that varied in the amount of contextual data and the presence of system-generated recommendations. For each profile, they were asked whether they would approve the loan, and to rate their perception of the borrower's creditworthiness and data reliability.

This study tests four hypotheses to understand lenders' behavior on loan approval.

**Hypothesis B1: Incorporating additional information increases loan acceptance rates for micro-enterprises.**

Statistical tests of hypothesis B1 confirmed that adding contextual information, such as repayment capacity, business type, and business duration, significantly increased loan approval rates. This implies that adding more information to borrowers' profiles helps lenders assess their profiles better. These results support the RA's emphasis on the importance of alternative data in improving inclusion.

**Hypothesis B2: Incorporating system recommendations increases loan acceptance rates for micro-enterprises.**

Statistical tests of hypothesis B2 show that system recommendations showed no significant impact on loan approval. This implies that the system recommendation alone (with the basic borrowers' data) did not influence the decisions made by the lenders. This highlights a potential trust gap in merely providing system recommendations without being supported by additional contextual data.

Hypothesis B3 evaluated the impact of combining enriched data and system recommendations.

**Hypothesis B3.1: Combining additional information and system recommendations increases acceptance more than additional information alone**, and **Hypothesis B3.2: Combining additional information and system recommendations increases acceptance more than system recommendations alone.**

The combination of additional information and system recommendations did not significantly increase lenders' approval rates in comparison with the profiles with enriched profiles alone (B3.1). However, those combinations outperformed system recommendations alone (B3.2). This suggests that system recommendations are more persuasive when presented alongside enriched borrower data, as the additional context helps lenders understand the rationale behind the recommendation and feel more confident in their decisions.

**Hypothesis B4.1: Providing more detailed and comprehensive information increases the perceived creditworthiness**, and Hypothesis **B4.2: Providing more detailed and comprehensive information enhances the perceived data reliability.**

The results show that providing more detailed data and system recommendations did not significantly alter the perception of the creditworthiness of the borrowers for lenders' analysis (B4.1). However, adding more data and providing system recommendations substantially improved data reliability perceptions (B4.2). This suggests that higher trust in data can positively influence lending decisions.

**Research contribution**

From *a scientific perspective*, this study makes several contributions. It introduces the concept of inclusion by design, which emphasizes that financial inclusion should be embedded in the system architecture, not treated as a separate or secondary outcome. This idea is operationalized through the ***development of a Reference Architecture*** that integrates inclusion into the system's structure using Value-Based Requirements, Design Principles, and Architectural Components.

The RA was also designed to ***respond to key challenges*** faced by underserved borrowers, including limited access to formal data, rigid classification models, and the lack of opportunities for borrowers to contest or enrich their profiles. These challenges are addressed through specific features such as contested decision-making, dual rating systems, and collaborative data collection, which aim to improve the accuracy and fairness of credit assessment.

In addition, the study develops ***a set of inclusion metrics*** to assess how lending systems serve different borrower groups. These metrics provide a structured way to evaluate inclusion outcomes and were used to guide system design and evaluation. The findings highlight that *adding more data alone is insufficient to increase access*. Instead, **careful model tuning**, such as adjusting feature sensitivity or introducing penalty-based reclassification, is necessary to shift borrowers into lower-risk categories. Finally, the study offers **insights into lender behavior**. Survey results show *that enriched borrower profiles improve perceived data reliability* and increase loan approval rates, especially when combined with transparent system recommendations. These findings emphasize the importance of transparency, interpretability, and trust in improving inclusion outcomes.

***From the practical perspective,*** the design of the RA provides a step-by-step approach to translating inclusion into system features. This study develops a prototype with core features to be examined in FGD sessions. The testing results show that borrowers can become active agents in improving their profiles. The study also offers evidence that *combining enriched data with system recommendations increases the impact of inclusion*. In addition, adaptive mechanisms such as penalty-based tuning and hybrid adjustments help balance access and risk, giving policy-makers and practitioners *concrete tools to improve inclusion*.

**Limitations and future directions**

This research acknowledges several limitations in conducting this study, for example, regarding the generalization of results. Focusing on Indonesia allowed for context-specific solutions but limited the generalizability of the findings. Regulatory aspects, cultural borrowing practices, and informal lending behaviors in Indonesia might differ from those in other countries; therefore, further study should address this. Moreover, one of the design principles, Tailored Credit Solutions, was not tested due to time constraints. Furthermore, although we have developed a wide range of inclusion metrics, their practical implementation faced challenges due to data limitations.

Future research should address these limitations, for example, by exploring the RA's adaptability across different countries with different institutional and social settings. Several untested components require empirical validation. Moreover, expanding sensitivity analysis and conducting longitudinal studies can reveal how model tuning influences borrower outcomes.

In the study, many different challenges were found, and the research focused on overcoming system-design challenges. Further studies also need to explore broader challenges in inclusive lending, which can be organized into four thematic areas: (1) algorithmic explainability, expanding sensitivity analysis to developing methods that explain not just *what* a model predicts but *how* and *why* outcomes change under different configurations; (2) regulatory integration, embedding inclusion tools into institutional processes; (3) borrower engagement, ensuring users can interact meaningfully with inclusion features; and (4) data interoperability, addressing data fragmentation and enabling the use of alternative data.

# Samenvatting

De uitbreiding van digitale kredietplatforms in ontwikkelingslanden heeft nieuwe mogelijkheden voor financiële toegang gecreëerd, maar gemarginaliseerde groepen ondervinden nog steeds aanzienlijke obstakels. Veel potentiële leners worden uitgesloten omdat zij geen formele financiële gegevens hebben of omdat hun profielen ontoereikend zijn. Bestaand onderzoek richt zich voornamelijk op nauwkeurigheid en winstgevendheid, terwijl inclusie grotendeels buiten beschouwing blijft. Dit proefschrift beoogt die leemte te vullen door te onderzoeken hoe digitale leensystemen kunnen worden ontworpen om inclusie te ondersteunen, hier gedefinieerd als gelijke toegang, verdeling en benutting van financiële middelen, waardoor achtergestelde bevolkingsgroepen zinvol kunnen deelnemen aan leensystemen.

Dit onderzoek heeft drie doelstellingen. Ten eerste, het ontwerpen van een Referentiearchitectuur (RA) die de uitdagingen van gemarginaliseerde leners aanpakt, zoals dataschaarste, inflexibele leenproducten en het ontbreken van mechanismen om profielen te betwisten of te verrijken. Ten tweede, het vaststellen van meetbare indicatoren waarmee inclusie in leensystemen kan worden geëvalueerd. Ten derde, het confronteren van de socio-technische uitdagingen van inclusieve kredietverlening door principes en architecturale elementen te introduceren die conceptuele waarden verbinden met technische implementatie.

Het onderzoek maakt gebruik van de Design Science Research (DSR)-methodologie, gestructureerd in probleem-, oplossing- en evaluatieruimtes. In de probleemruimte zijn de uitdagingen en indicatoren van inclusie geïdentificeerd via een systematische literatuurstudie en interviews met belanghebbenden. In de oplossingsruimte is de RA ontwikkeld door inzichten uit de literatuur, interviews en systeemanalyse te combineren. De architectuur bestaat uit drie geïntegreerde elementen: Value-Based Requirements (VBRs), Design Principles (DPs) en Architecturale Componenten. In de evaluatieruimte is de RA beoordeeld door middel van prototyping en functionaliteitstesten, sensitiviteitsanalyses met machine learning-modellen, en een gedragsenquête onder kredietverstrekkers. Deze evaluaties waren bedoeld om na te gaan of de voorgestelde RA de inclusie-uitdagingen kan aanpakken die in de probleemruimte zijn vastgesteld.

De bevindingen benadrukken dat de obstakels voor financiële inclusie systemisch van aard zijn. Uitdagingen zoals gefragmenteerde infrastructuren, beperkte of slechte datakwaliteit van leners, en starre leenschema's tonen aan dat uitsluiting niet toevallig is, maar ingebed in de manier waarop huidige systemen functioneren. Om dit te verhelpen introduceert de studie een raamwerk van inclusiemetingen, gegroepeerd in vier categorieën: penetratie, financiële toegang, analytische inclusie en geletterdheid. Deze metrics vertalen abstracte concepten van rechtvaardigheid en toegankelijkheid naar meetbare uitkomsten en vormen een basis om te beoordelen hoe goed leensystemen inspelen op achtergestelde leners.

De ontwikkelde Referentiearchitectuur laat zien hoe inclusie rechtstreeks in het systeemontwerp kan worden ingebouwd. De Value-Based Requirements formuleren de kernwaarden die systemen moeten ondersteunen, de Design Principles geven richting aan de manier waarop deze waarden worden geïmplementeerd, en de architecturale componenten operationaliseren ze. Modules zoals inclusieve scoring, betwiste besluitvorming en collaboratieve dataverzameling illustreren hoe transparantie, lenersautonomie en datadiversiteit structureel kunnen worden ondersteund in plaats van behandeld als optionele toevoegingen.

Evaluaties van de RA bevestigen dit potentieel. Prototypetesten tonen aan dat functies waarmee leners bezwaar kunnen maken, gegevens kunnen bijdragen of via alternatieve mechanismen kunnen

worden beoordeeld, de perceptie van eerlijkheid en participatie vergroten. Sensitiviteitsanalyses laten zien dat inclusie niet alleen een kwestie is van meer data toevoegen, maar ook van het aanpassen van algoritmes en classificatie. In het bijzonder blijkt dat parameterafstemming, zoals penalty-gebaseerde modellen en de in dit onderzoek geïntroduceerde Hybrid Feature Penalty Tuning (HFPT), systematische herclassificatie van leners naar gunstiger risicocategorieën mogelijk maakt. Enquêteresultaten bevestigen daarnaast dat verrijkte lenerprofielen en transparante systeemsuggesties leiden tot hogere acceptatiepercentages en meer vertrouwen in data. Gezamenlijk tonen deze evaluaties aan dat inclusie kan worden geoperationaliseerd via zowel technische architectuur als besluitvormingsprocessen.

De bijdragen van dit onderzoek zijn tweeledig. Vanuit wetenschappelijk perspectief introduceert het het concept van *inclusie by design*, waarbij inclusie vanaf het begin in de architectuur van leensystemen wordt ingebed. Methodologisch draagt het bij door waarden, ontwerpprincipes en technische componenten te verbinden tot een samenhangende RA. Vanuit praktisch perspectief biedt de RA beleidsmakers, toezichthouders en systeemontwikkelaars concrete modules en evaluatiemethoden om toegang en risico in balans te brengen, en daarmee stappenplannen om inclusiedoelstellingen om te zetten in operationele functies.

Dit onderzoek erkent tevens enkele beperkingen. Het empirische werk is contextspecifiek gericht op Indonesië, wat de generaliseerbaarheid naar andere institutionele en culturele contexten beperkt. Sommige architecturale elementen, zoals op maat gemaakte kredietoplossingen, konden binnen de looptijd van dit onderzoek niet worden getest. Bovendien werd slechts een deel van de ontwikkelde inclusiemetrics praktisch geëvalueerd. Toekomstig onderzoek zou zich daarom moeten richten op de toepasbaarheid van de RA in andere landen, de uitbreiding van sensitiviteitsanalyses, en longitudinale studies naar de langetermijneffecten van systeemontwerp op leneruitkomsten.

Samenvattend laat dit onderzoek zien dat financiële inclusie in kredietverlening niet kan worden bereikt door incrementele aanpassingen aan bestaande modellen, maar een herziening van de systeemarchitectuur vereist. Door inclusie rechtstreeks in het ontwerp in te bouwen, biedt de Referentiearchitectuur zowel een conceptuele als praktische bijdrage om ervoor te zorgen dat leensystemen niet alleen de winstgevende, maar ook de gemarginaliseerde segmenten van de samenleving bedienen.

# Acknowledgement

One quiet evening, when I returned to my hometown in a small corner of Sumatra, I found myself sitting at the roadside stall of my grandparents. For decades they had sold satay in the same place, with the same routines, the same struggles, and only small changes over the years. Their perseverance was undeniable, but so too was the reality that progress always seemed out of reach. As I watched the dim light of the stall flicker into the night, I could not help but wonder: what lies behind these enduring struggles? Why is it that despite hard work and persistence, opportunities for advancement remain limited?

That moment stayed with me. It became a question larger than their story alone, a question about the invisible structures that shape access to opportunities, about the systems that open doors for some while leaving others at the margins. This dissertation is, in part, a response to that reflection. It is my attempt to understand how lending systems can be redesigned to serve not only those who already fit neatly into existing systems, but also those who remain unseen and excluded. It is about an architecture where participation is not an afterthought, but the very foundation of the system itself.

It is no coincidence that the cover illustration (by Satria) echoes this memory: a simple sketch of a hand holding a phone with a small stall *"Bakso Aman"* on its screen symbolizing micro and informal borrowers gaining access to finance through technology. The hand-drawn sketch style reinforces a human-centered approach, suggesting that the system is not only about data and algorithms but also about real people's everyday lives. At the same time, the structural lines surrounding the stall symbolize the broader architectural design that frames and supports inclusive finance. This combination conveys both the grassroots realities of borrowers and the systemic design needed to sustain inclusion.

This journey, however, was never one I walked alone.

To **Prof. Marijn Janssen**, who was my supervisor already during my master's thesis in 2015–2016, I owe an especially deep gratitude. When I decided to return to the Netherlands to begin this PhD, some friends wondered why I chose to work with you again, knowing your reputation for very high standards and discipline. My answer was simple: precisely because of that. I believed that such qualities were the very foundation needed to complete a PhD with elegance and quality. Yet throughout this journey, there were countless moments when I felt close to giving up, when the gaps in my work seemed too wide, when the thought of failure felt heavier than the hope of finishing. In those moments, it was often not my own strength that carried me, but yours. Your determination to keep me going, your patience and persistence in reminding me that there was still a way forward often outweighed my own resolve. It felt as though you believed in this journey even more than I did. Furthermore, perhaps the most transformative lesson I learned from you was the importance of asking *why* before anything else. When I began, I was impatient and always rushing toward solutions. You showed me that research must first confront the deeper question of *why the problem matters*, and what it means if it remains unsolved. That shift took time, but it changed the way I approached this work.

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that a PhD is not about how complicated a project can be, but about *how clearly its contribution can be expressed*. From you I learned how to sharpen my thoughts and communicate them with precision, something that has shaped not only this dissertation, but also my confidence as a researcher. And perhaps most importantly, you reminded me that this research is not only about answering academic questions, but also about the contributions it can bring to practice when I return to Indonesia.

To **Jolien Ubacht**, whom I have also known since my MSc thesis in 2016 under the supervision of Prof. Marijn and yourself, I am deeply thankful. I was touched that you still remembered those years, and your encouragement has been a source of confidence and motivation throughout this journey. I am grateful as well to **Prof. Ibo van de Poel** and **Prof. Frances Brazier**, whose feedback during my proposal defense and subsequent reviews sharpened my thinking and pushed me to grow. My sincere thanks also go to the brilliant lecturers and staff at TPM, from whom I learned, sometimes quietly, about research and communication skills. Whether during colloquia, seminars, teaching workshops, or informal dinners. In particular, I thank **Mark de Reuver** (who was also one of my MSc lecturers and among the first to congratulate me after passing the proposal defense), **Nitesh Bharosa**, **Anneke Zuiderwijk**, **Ilse Onk**, **Fernando Kleiman**, **Roel Dobbe**, and **Boriana Rukanova**.

A very special word of gratitude goes to the secretarial staff at TPM, especially **Ellen Schwencke-Karlas**, who was always there to help with everything from academic matters to the many memorable events that made TPM such a vibrant place. During some of my most difficult months with accommodation issues, Ellen's support was invaluable. My sincere thanks also go to **Sabrina**, **Cherelle**, **Fanny**, and many other secretarial staff whose dedication and kindness I deeply appreciate. I also want to thank **Janet Wong**, whose MSc thesis I had the privilege to co-supervise. That experience not only enriched my journey as a researcher but also reminded me of the value of guiding and being guided in turn.

I extend my sincere gratitude to **Bank Indonesia, the Central Bank of Indonesia**, my professional home since 2006. The institution has fully supported this PhD journey and entrusted me with the opportunity to pursue it. For this, I am deeply grateful. I look forward to returning and continuing to serve at the Central Bank, bringing with me the insights gained here.

I am equally grateful to my fellow PhD colleagues, who made this long journey lighter. To **Ini Kong**, the very first PhD colleague I met in room A3.040 in September 2021, thank you for the instant connection, for sharing laughter and tears, for joining conferences together, and for the many inspiring conversations. To my officemates **Mohammed Reza Satouri**, **Arina Soboleva**, **Ruixan Zhang**, **Nicole Orchard**, and **Joslyn Sun**, thank you for the daily camaraderie and countless small but meaningful exchanges. Each of you brought unique warmth and perspective: Mohammed, ever polite and humorous, always nostalgic about the rain; Arina, graceful and wise beyond her years; Nic, always caring and thoughtful (and whose Spanish peanut cakes I secretly looked forward to); Rae, stylish and determined, with whom every rare but deep conversation was memorable; Joslyn, endlessly energetic, with whom I felt as if speaking to a daughter, or even a granddaughter.

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families also grew close, turning Delft into a true home far from home. A special thanks goes to **Alfan Presekal**, whose professional advice on machine learning opened one of the most important doors in my research. Thank you!

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My deepest gratitude belongs to my family. To my extended family in Padang and Jakarta: to my cousin **Septria Yusrina**, who tirelessly sent rendang, clothes, and countless tokens of home to us in the Netherlands despite her demanding career as a civil engineering project manager in Jakarta; to my mother, who has been ill since 2018 and speaks little now, but whose prayers I believe have opened doors of blessing throughout this journey; to tante dan om di Padang, and fourteen cousins, whose support I deeply cherish.

And finally, the most heartfelt gratitude goes to my two beloved sons, **Hafidz Raditya Arsyad** and **Hanif Raditya Pilinih**, *nak kanduang sibiran tulang buah hati limpo bakuruang*, who spent four of their precious teenage years in the Netherlands while their mother was buried in books, writing, and endless revisions. Words will never be enough. You were also with me in the Netherlands during my Master's in 2014–2016, when you were still in kindergarten. After five years in Indonesia, we returned in 2021 for my PhD, and by the time we left in 2025, you were already in high school. You truly accompanied me through both journeys with patience, love, and a resilience. *Terima kasih teko teko kecil.* This dissertation is as much yours as it is mine. *Makasih udah mau makan masakan bunda yang itu itu aja, selalu mengucapkan terima kasih bahkan untuk hal-hal kecil, selalu nunggu bunda makan malam (dah dibilang gak usah), colab reels IG, punya drive foto video 2 TB, belanja sembako di Polat, membahas sejarah dunia sampai psikologi!* I also hope that these years will remain with you as a reminder of how essential family is in our lives. Whatever challenges you may face in the future, in any place or situation, never forget that family will always be there to love you, to stand by you, and to give you the strength to begin again.

If these pages stand as proof of perseverance, they do so only because of the many hearts and hands that carried me here. *Terima kasih!*

# PART I: PROLOGUE

## Chapter 1: Introduction

### 1.1. Financial System Overview

Access to formal credit is vital for economic participation; however, marginalized groups often face significant challenges. A World Bank survey shows that credit in many developing countries is sourced from informal channels instead of formal financial systems, reflecting the challenges faced by underserved groups (Demirguc-Kunt et al., 2018).

This exclusion mainly affects underserved groups. These groups include low-income individuals, people in remote areas, people with disabilities, and small businesses lacking collateral. Financial exclusion arises from a lack of resources and structural barriers, inhibiting participation in formal financial systems (Demirguc-Kunt et al., 2018; Demirguc-Kunt et al., 2017). Rigid lending criteria, high collateral demands, and centralized financial structures restrict their opportunities for financial stability and growth (Azis, 2024; Tambunan, 2022; Tambunan, 2015).

In many cases, formal financial institutions reinforce this exclusion through credit rationing practices, often perceiving underserved populations as high-risk borrowers (Azis, 2024). This exclusion is more pronounced in regions with underdeveloped financial infrastructure, where informal economies dominate, leaving a significant financial gap. Structural limitations within the financial system, especially in emerging markets, are barriers that restrict access to credit for informal economic actors (Azis, 2024; Tambunan, 2022).

In Indonesia, informal sectors represent approximately 97% of the workforce and contribute 61% to the national GDP (Situmorang, 2022). Despite the critical contribution of that economic sector, their access to credit remains low, with a credit-to-GDP ratio of 7%, identified as one of the lowest in the world (Azis, 2024). As a result, many rely on informal channels (Pambudianti et al., 2020). These challenges limit the potential scaling of the informal sector in the economy (Azis, 2024). Moreover, even though the 1998 crisis has encouraged Indonesia to adopt a more inclusive economic model (Tambunan, 2015); however, regulatory challenges might create other barriers (Azis, 2024).

Due to these challenges, improving financial inclusion is identified as an urgent need. Financial inclusion, accessibility of financial services to all segments of society, is crucial for fostering economic participation, reducing poverty, and promoting social inclusion (Cámara & Tuesta, 2014; Khan, 2011). However, despite these benefits, integrating underserved groups into the financial system remains a formidable challenge. The challenges comprise the questions of how to improve inclusion and how to measure it.

Technological advancements have emerged as promising solutions in response to these challenges. For example, Peer-to-Peer (P2P) lending systems, crowdfunding, and other online lending systems. These models allow individuals to connect with lenders or funders through digital channels. By leveraging technology, these systems appear as an alternative to the banking credit channels. In Indonesia, for example, research shows the gap that has been filled by lending companies as alternatives for those struggling with the rigid requirements of traditional banking (Azis, 2024). The P2P lending systems, for example, can lower transaction costs and minimize collateral requirements (Tambunan et al., 2021; Suryanto et al., 2020).

The benefits of online lending systems extend beyond access; they also include financial impacts. For example, Rang De lending in India provides affordable microloans to low-income households by leveraging social media (Gupta, 2014). In Nigeria, fintech lending platforms successfully contribute to microenterprises with a 24.9% improvement in survival rates and a 30.8% increase in sales revenue (Agboola, Adelugba, & UchennaEze, 2023).

However, despite the potential of fintech lending systems, inclusion challenges remain. Often, these systems cannot accommodate informal economic actors who lack conventional financial records (Pambudianti et al., 2020). Digital technology access also remains a barrier, particularly in areas with low internet penetration and limited digital literacy, restricting the reach of lending solutions. Additionally, many lending systems cannot adapt to diverse user needs, as rigid credit assessment criteria and inflexible loan terms can prevent underserved groups from accessing tailored financial products. Overcoming these challenges requires reshaping financial services to meet the diverse needs of underserved communities (Collins, 2009; Beck et al., 2007). Regulatory frameworks, while essential for stability, sometimes add complexity and can impose constraints that limit adaptability, making it difficult for lending systems to serve varied socioeconomic backgrounds (Lilienthal, 2016).

The diagram below illustrates the conflicting interests among key actors in the lending ecosystem, highlighting the inclusion challenges. Policy-makers, lenders, and underserved populations each have different objectives. For example, policy-makers prioritize regulatory oversight and stability, lenders focus on minimizing risk and profitability, and underserved groups seek loan approval. These competing interests create challenges in ensuring lending systems include underserved communities.

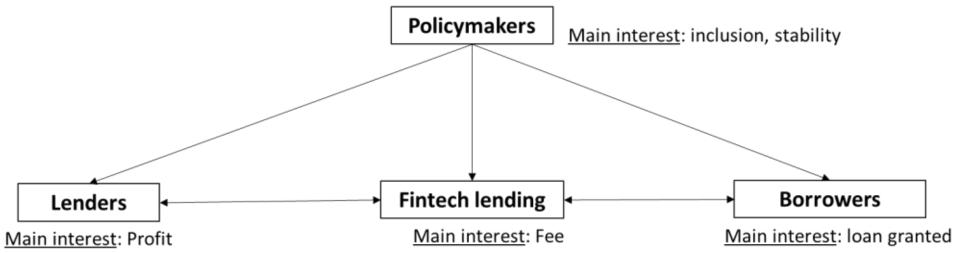


*Figure 1. Diverging interests of key stakeholders in lending systems*

The urgency for more inclusive lending systems is increasingly recognized, especially as financial inclusion becomes a global priority (Ozili, 2021; Queralt, 2016; Hannig & Jansen, 2010). Despite growing awareness, underserved populations face challenges in accessing formal financial services. Furthermore, as lending systems expand, their potential to bridge these financial gaps becomes evident; however, a structured approach is essential to ensure these systems address inclusion challenges. **The goal of this study** is to design *a Reference Architecture* to improve inclusion for underserved groups in lending systems. The RA provides a structured guideline that addresses the specific needs of underserved groups.

To establish the focus and direction of this thesis, Section 1.2 discusses technology developments that drive innovation in lending, laying the groundwork for understanding how these advancements impact inclusion. Section 1.3 further discusses the significance of inclusion in financial systems, while Section 1.4 lays out the research gaps and objectives that guide the study. The chapter concludes with Section 1.5, providing a roadmap for the thesis structure and a summary of each chapter's purpose.

### 1.2. Technology Development

As highlighted in Section 1.1, the limitations of conventional financial systems have spurred the growth of alternative, technology-driven solutions aimed at expanding financial inclusion. This section explores these technologies and discusses their roles and challenges in promoting financial inclusion through lending systems.

Access to credit is a persistent challenge for underserved populations, particularly in areas where traditional banking services are difficult to access (Agboola et al., 2023). P2P lending bypasses traditional banking intermediaries by directly connecting borrowers with lenders. P2P lending reduces operational costs and makes credit access more attainable for borrowers who might otherwise be excluded by conventional banks (Kohardinata-a et al., 2020; Lilienthal, 2016). The decentralized nature of P2P lending allows quicker loan processing, although data privacy concerns remain (Luo et al., 2011). Compared to banks' centralized processes, the flexibility and accessibility of P2P lending help reduce entry barriers for underserved segments (Lee & Shin, 2018). Figure 2 highlights this contrast, illustrating how lending models like P2P can reduce dependency on central intermediaries.

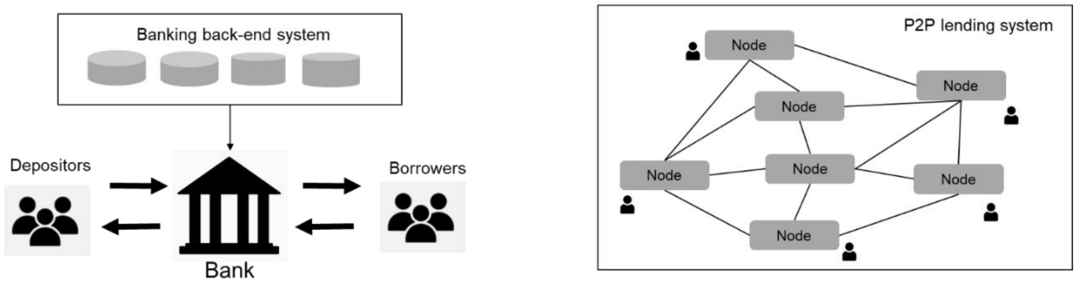


*Figure 2: Credit financing in the banking system (left) vs. decentralized lending models (right)*

Artificial intelligence (AI) and machine learning (ML) have brought transformative changes to the lending industry by enabling credit scoring models that extend beyond traditional financial data. Conventional credit scoring, heavily reliant on formal credit histories, often excludes underserved individuals who lack such records, restricting their access to loans (Hurley & Adebayo, 2016). AI-driven models, on the other hand, utilize alternative data sources, such as social media interactions, utility payments, and digital transaction histories, to provide a more inclusive view of creditworthiness (Jagtiani, 2017). This data-driven approach allows lenders to make informed decisions for borrowers with limited credit profiles (Khandani, Kim, & Lo, 2010).

The AI-based models do not have to be complex; they can be simple models with high interpretability, improving credit assessment (Baesens et al., 2003). Explainable machine learning models, such as those employing Shapley values, provide stakeholders with insights into the factors driving credit scores, thereby increasing transparency, trust, and regulatory compliance (Bussmann et al., 2021). The adaptability of ML algorithms also enables fairer lending practices by accounting for non-traditional financial behaviors, which helps mitigate biases often present in traditional data (Fuster et al., 2022). Together, these AI-driven advancements contribute to more inclusive and resilient credit models.

Distributed Ledger Technology (DLT) has been proposed as a means to improve data integrity and transparency in lending systems through decentralized, tamper-resistant storage (Pilkington, 2016). By recording transactions across multiple nodes, DLT can offer traceability and auditability that may help mitigate manipulation risks (Risius & Spohrer, 2017). Furthermore, DLT's decentralized structure supports accountable and verifiable data sharing, in which network participants can independently verify each transaction (Zavolokina, Dolata, & Schwabe, 2017). However, DLT's contribution to financial inclusion remains limited and context-dependent. Given these barriers, DLT should be viewed as one of many possible enablers, not a central solution for inclusive lending.

Mobile and digital banking platforms enhance inclusion by reducing physical and logistical barriers. In Indonesia, digital platforms are instrumental in reaching 97% of the workforce employed in informal sectors (Situmorang, 2022). Through user-friendly interfaces, lending systems are expected to provide user-friendly apps for users with limited digital literacy (Milne & Parboteeah, 2016).

Despite these advancements, significant challenges remain in ensuring these technologies achieve broad financial inclusion. Issues such as data unavailability, algorithmic biases, non-transparent processes, low digital literacy, and limited internet access continue to restrict the full potential of lending systems. For example, while these platforms have successfully broadened access to financing, their effectiveness often depends on the financial literacy of users (Pambudianti, Purwanto, & Maulana, 2020). Without careful guidance, technological innovations could reinforce the same barriers they aim to remove.

This research proposes a **Reference Architecture (RA)** to integrate inclusion into lending systems. The RA leverages the strengths of diverse technologies, such as AI and DLT, to address the specific needs of underserved populations. These groups include, but are not limited to, low-income individuals, people in remote areas with limited access to financial infrastructure, small businesses lacking collateral, and various groups, such as women, who may encounter unique social and economic obstacles to accessing formal financial services. For these groups, financial exclusion arises from a lack of resources and structural barriers, inhibiting their participation in formal financial systems (Demirguc-Kunt et al., 2018; Demirguc-Kunt et al., 2017).

### 1.3. Why Inclusion Matters

The term 'inclusion' has been used in many scientific and practical contexts and could lead to various interpretations. Therefore, it is important to explain how inclusion is defined in this study. This study draws from Capability Theory (Sen, 1990), which differentiates between *access to resources* and *the ability to use those resources* to achieve meaningful outcomes. Adopting this theory, financial inclusion is not simply about providing access to financial resources but enabling underserved groups to utilize them to improve their economic standing.

In financial inclusion, inclusion is explained as *"maximizing usage and access while minimizing involuntary financial exclusion"* (Cámara & Tuesta, 2014). This research builds on that definition by emphasizing the need for equitable distribution of resources, ensuring that financial empowerment is not disproportionately concentrated among privileged groups.

Technological advancements played a crucial role in reshaping financial inclusion by lowering the cost of reaching underserved populations (Hannig & Jansen, 2010). Innovations such as advanced credit-scoring algorithms have introduced *profit scoring* (Ye et al., 2018; Xia et al., 2017) and *poverty scoring* (Bumacov, Ashta, & Singh, 2017), enable lenders to assess creditworthiness beyond traditional methods. However, the transformative potential of these technologies depends on how they are integrated into systems that prioritize inclusion. Without intentional design for inclusion, these innovations risk reinforcing existing inequalities instead of reducing them.

In this study, we introduce the concept of *inclusion-by-design* as reflected in the dissertation title. This concept integrates inclusion into various aspects of system development since the early stages instead of perceiving inclusion as merely a goal. We adopt the reference architecture to explain system components and their interaction. This study was also inspired by Janssen et al. (2017), which integrated transparency into system design.

### 1.4. Research Gap and Research Objectives

Lending systems have emerged as an innovative response, providing financial opportunities to underserved segments through technology-driven channels such as Peer-to-Peer (P2P) lending.

However, despite these advances, significant research gaps remain, particularly in designing for inclusion within these systems. Three gaps have been identified through a review of the literature.

*First*, *the lack of focus on societal aspects* has resulted in systems emphasizing operational and technical efficiency, often at the expense of inclusion. For instance, much of the research on the P2P lending system centers around technical advancements aimed at enhancing the system's performance and financial profitability by utilizing big data and advanced statistical methods (Ariza-Garzon et al., 2021; Bachmann et al., 2011), with less attention to inclusion. Literature also suggests that lending systems should be able to address the specific needs of marginalized populations (Azis, 2024; Adriana, 2018). This gap leads to **Research Question 1 (RQ1)**, which explores the challenges in designing systems that improve inclusion.

*Second*, *there is insufficient literature explaining the indicators and measurement of inclusion* in lending. While "financial inclusion" is often cited as a goal, there is a lack of measurable indicators. Without clear benchmarks, assessing whether these systems are truly making an impact or simply replicating traditional barriers is difficult. Various studies emphasize the need for well-defined metrics to track inclusion and ensure that lending platforms meet their objectives (Tambunan, 2022; Reza-Gharehbagh et al., 2020; Pambudianti et al., 2020; Lilienthal, 2016). Quantifiable metrics are important in evaluating these systems' success and identifying areas for improvement. This research proposes **Research Question 2 (RQ2)** to address this gap, focusing on providing inclusion metrics.

*Third*, *there is an absence of structured guidelines* that prioritize inclusion in the design of lending systems. Current systems are largely driven by technological advancements and market demands, often neglecting the socio-technical complexities. Existing studies underscore the importance of integrating societal dimensions into the core of lending systems (Azis, 2024; Tambunan, 2022). Technology alone cannot solve these issues; a more holistic approach is needed, combining technological innovation with supportive policies and adaptable frameworks (Azis, 2024; Adriana, 2018; Böhmelt et al., 2016). Without such a guiding architecture, lending systems face limitations in scalability and adaptability, particularly in addressing barriers faced by underserved populations. This gap is addressed by **Research Question 3 (RQ3)**, which focuses on the elements that make up a reference architecture to navigate these complexities, and **Research Question 4 (RQ4)**, which examines the impact of such an architecture on inclusion. These identified gaps are summarized in Figure 3, highlighting the need for a structured reference architecture to enhance inclusion in lending.

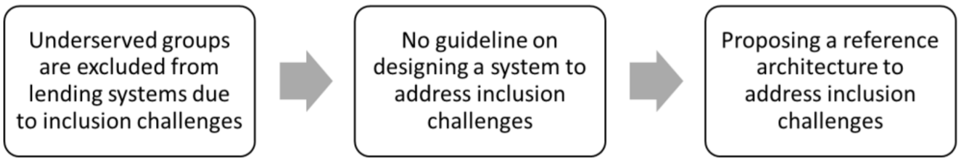


*Figure 3. Overview of Existing Inclusion Gaps*

In response to these gaps, this research has three main objectives. *First*, it aims to design **a Reference Architecture (RA)** that supports financial inclusion by addressing the challenges faced by underserved groups. *Second*, it seeks to establish *measurable inclusion indicators*, providing clear metrics to evaluate how well lending systems serve underserved populations. *Finally*, it *addresses socio-technical challenges* by incorporating design principles and architectural elements.

## 1.5. Structure of the Thesis

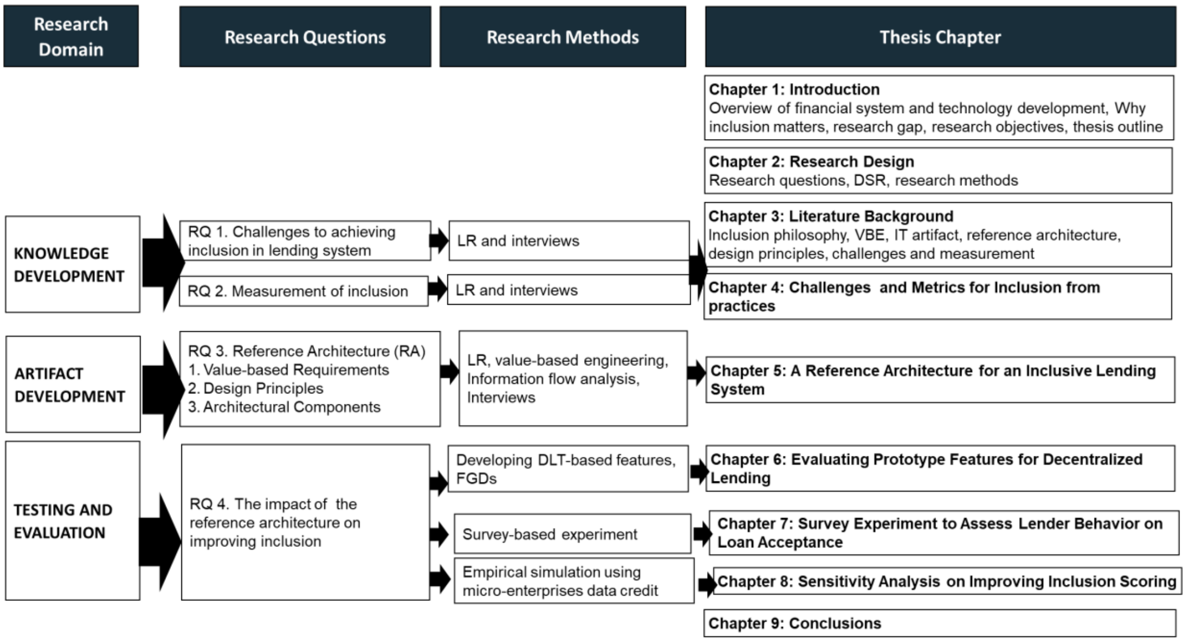


*Figure 4. Mapping of Research Domains, Research Questions, Methods, and Thesis Chapters*

This thesis is organized into nine chapters, systematically addressing the research questions and objectives through a phased approach. Figure 4 maps the relationships between the research domains, research questions, research methods, and thesis chapters, illustrating a phased approach to designing the reference architecture (RA). The research is divided into three key phases: **knowledge development**, **artifact development**, and **testing and evaluation**. Each phase corresponds to specific research questions and methodologies.

**Chapter 1** introduces the background and discusses the importance of financial inclusion. It outlines the study's research gaps, objectives, and the proposed Reference Architecture (RA) as a solution to improve inclusion.

**Chapter 2** outlines the research design, employing the Design Science Research (DSR) methodology to structure the development process. The chapter explains how iterative cycles are used to design the Reference Architecture, integrating inclusion metrics, socio-technical requirements, and practical evaluation through prototyping.

**Chapter 3** establishes the literature foundation for this research. Chapter 3 explores the concept of financial inclusion, examines *Sen's Capability Theory*, and introduces *Value-Based Engineering (VBE)* to align system objectives with inclusion goals. The chapter presents the concept of *design principles* to guide the development of the systems. It identifies preliminary challenges to inclusion and proposes initial metrics for measuring inclusion derived from a systematic literature review (SLR). These *challenges* (RQ1) and *metrics* (RQ2) will be refined in Chapter 4 through interviews.

**Chapter 4** builds on the theoretical insights from Chapter 3 by incorporating findings from the literature with interviews. The chapter finalizes the challenges (RQ1) and inclusion metrics (RQ2) by integrating practitioner insights.

**Chapter 5** addresses Research Question 3 (RQ3) by presenting the design and development of the Reference Architecture (RA). The RA comprises three elements: Value-based Requirements, Design Principles, and Architectural Components.

**Chapter 6** introduces the prototype development to answer RQ 4, explaining the technical features. This research leverages the distributed ledger for implementing the prototype. Chapter 6 also tests three core features of the prototype, followed by Focus Group Discussions (FGDs) to evaluate the impact of these features on the perception of inclusion.

**Chapter 7** expands the evaluation by incorporating behavioral insights from controlled surveys. This chapter analyzes four hypotheses (hypotheses B1-B4) to investigate how system-generated recommendations and borrower information influence *lender decision-making*.

**Chapter 8** evaluates the RA's impact on inclusion through sensitivity analysis with machine learning simulations. We examine two hypotheses in this chapter. Hypothesis A1 analyzes the impact of adding borrower information on loan recommendations, whereas hypothesis A2 evaluates the impact of parameter tuning. We develop various machine learning models and apply sensitivity analysis to analyze the results.

**Chapter 9** synthesizes the findings from all phases of the research, providing a comprehensive reflection on the Reference Architecture's contributions in improving inclusion. It presents answers to the research questions, highlights the study's theoretical and practical contributions, acknowledges its limitations, and outlines directions for future studies.

# Chapter 2: Research Approach

## 2.1. Introduction

This chapter explains the research design for designing a Reference Architecture (RA) to improve inclusion in lending systems. To achieve this, the study adopts Design Science Research (DSR), a structured and flexible methodology that integrates theoretical insights with real-world applicability, ensuring that the RA addresses conceptual rigor and operational relevance. The DSR framework combines literature reviews, empirical data collection, and iterative testing to provide a pathway for understanding, designing, and evaluating an RA that can respond to the complex socio-technical challenges in lending.

Following this introduction, Section 2.2 defines the research questions that guide the study, framing the scope and objectives of each stage in designing the RA. Section 2.3 elaborates on the DSR methodology and its philosophical grounding in constructivist and pragmatic paradigms, highlighting the iterative cycles that bridge theory and practice. Section 2.4 details the research stages (Problem Identification and Knowledge Development, Artifact Design and Development, and Testing and Evaluation) within the DSR framework, demonstrating how each stage contributes to the development of the RA.

## 2.2. Research Questions

The challenge of financial inclusion persists despite efforts to expand access. Underserved groups, such as low-income individuals, micro-entrepreneurs, and people in remote areas or informal economic sectors, remain marginalized due to various challenges. This research is guided by the following **Research Questions (RQs)**:

1. **RQ1: What are the challenges to achieving inclusion in lending systems?**
   This question identifies and *examines the challenges* in current lending systems that limit access for underserved groups. Understanding these challenges is essential for designing a reference architecture that addresses the socio-technical complexities and structural limitations.
2. **RQ2: What indicators can measure inclusion within these systems?**
   Although inclusion is often cited as a goal in lending, standardized metrics to define and monitor progress remain lacking. RQ2 focuses on *developing measurable indicators* that can assess how well these systems address the needs of underserved populations. These indicators will provide a foundation for evaluating the contribution of the RA in improving inclusion.
3. **RQ3: What elements make up a Reference Architecture for an inclusive lending system?**
   This question identifies *the elements of a Reference Architecture (RA)* designed to support inclusion. These elements will define how lending systems can be structured to address the challenges of underserved populations.
4. **RQ4: What is the impact of the proposed RA on inclusion?**
   This question evaluates how the proposed Reference Architecture addresses the inclusion challenges identified in RQ1. Through empirical evaluation, this question assesses whether the RA can improve inclusion for marginalized segments while demonstrating its technical feasibility in translating inclusion goals into system features.

## 2.3. Design Science Research

### 2.3.1. Philosophical Foundations of This Study

Research methodologies are shaped by their philosophical foundations, which guide how knowledge is explored and interpreted. In this study, the Design Science Research (DSR) approach is based on key considerations that address fundamental questions about the nature of knowledge (epistemology), the nature of reality (ontology), and the role of values in research (axiology)(Guba & Lincoln, 1994). As Guba and Lincoln (1994) state, *"The basic beliefs that define a paradigm are summarized by the responses given to three fundamental questions: the ontological, the epistemological, and the methodological."* (p. 108). Axiology, or the role of values in inquiry, is recognized as the fourth element. (Guba & Lincoln, 1994). Ontology addresses the nature of reality, epistemology concerns the relationship between the knower and what can be known, and axiology highlights the role of values (Guba & Lincoln, 1994).

The epistemology of DSR aligns with constructivist and pragmatic paradigms. *Constructivism* suggests that knowledge is constructed through interactions with the world (Avenier, 2010). In DSR, the artifacts created, such as the reference architecture for inclusive lending systems in this study, result from assessing systems designed to meet the needs of underserved groups. This constructivist stance shapes the iterative design cycles of DSR, where knowledge evolves through feedback from DSR's relevance cycle.

*Pragmatism* complements this approach by emphasizing that the value of knowledge lies in its practical application, with truth being determined by the outcomes it produces (Kaushik & Walsh, 2019). In DSR, this means focusing on creating artifacts that are theoretically sound and practically applicable. This pragmatic perspective ensures that the research outcomes are assessed based on their ability to address real-world challenges, which is examined in RQ4.

*Ontologically,* DSR adopts a constructivist perspective, recognizing that multiple realities exist depending on the viewpoints of different stakeholders. This perspective is essential for understanding the diverse needs of stakeholders, as their interactions with financial systems can vary based on socioeconomic and cultural factors (Chesky & Wolfmeyer, 2015). The constructivist view supports the idea that *contextual factors,* such as local market conditions and regulatory environments, play a significant role in shaping these interactions (Avenier, 2010). This ontological stance is reflected in the iterative nature of DSR, where artifacts are continuously refined through cycles of design and evaluation, incorporating feedback from a range of stakeholders.

*Axiology* in DSR emphasizes the role of values in guiding the research process. This study adopts a *value-sensitive design* approach, recognizing that creating financial systems inherent normative commitments to values such as inclusion (Mertens, 2007). Inclusion is central to this research, shaping the selection of design principles, the design of the reference architecture, and the evaluation criteria. Mertens (2007) highlights the importance of integrating social justice into research design, aligning with this study's goal of embedding inclusion at every stage. This value is crucial to ensuring that the research outputs are socially relevant and ethically sound, as Chesky & Wolfmeyer (2015) discussed in the context of educational practices. By prioritizing this value, the research aims to address the challenges faced by marginalized groups and contribute to the development of a more inclusive financial ecosystem.

**Integrating Philosophical Assumptions into DSR**

Integrating these philosophical assumptions into DSR provides a solid approach for the research. By acknowledging the constructed nature of knowledge (Avenier, 2010), the multiplicity of realities (Chesky & Wolfmeyer, 2015), and the centrality of values (Mertens, 2007), this study positions itself to create artifacts that are technically sound, socially relevant, and ethically grounded (Kaushik & Walsh, 2019). This philosophical foundation supports *the iterative, problem-solving nature of DSR*, ensuring that the research process is flexible, responsive, and deeply engaged with the practical challenges experienced by the underserved segments. It also highlights the importance of involving stakeholders, whose diverse perspectives are crucial to the research.

### 2.3.2. Methodological Framework of DSR

The methodology applied in this study is Design Science Research (DSR), introduced by Simon (1996). Simon differentiates between natural science, which explores *how things are*, and artificial design, which focuses on *how things should be*. In contrast to natural sciences, which aim to justify or develop theoretical knowledge, DSR is built around a problem-solving paradigm where artifacts are created to address practical, real-world issues. In this research, the primary artifact is a **Reference Architecture (RA)** that improves inclusion in lending systems.

The DSR framework for this study is grounded **in Sen's Capability Theory** as its kernel theory, followed by **Value-Based Engineering (VBE)** as a methodological approach. *Capability Theory* aligns with the study's objective by emphasizing empowering users with the resources and support they need to achieve meaningful financial outcomes. This theory is particularly relevant in shaping the RA's objectives, ensuring that the architecture does more than provide access but also actively enhances users' financial capabilities. *Value-Based Engineering (VBE)* supports the RA's commitment to inclusion by systematically integrating the core value of inclusion throughout the design process. This alignment ensures that the RA delivers socially relevant, ethically sound solutions that meet the unique needs of underserved groups.

DSR produces two outcomes: design artifacts and design theory (Baskerville et al., 2018). Viewing information systems as a design science implies focusing on IT artifact development (Iivari, 2005). Therefore, it is essential to define the type of artifact and the development process clearly. An artifact is not evaluated based on being *true* or *false* but rather on its effectiveness as a means to accomplish specific goals (Iivari, 2005). In this study, the RA serves as the primary design artifact and embodies principles that extend existing knowledge in financial inclusion and system design.

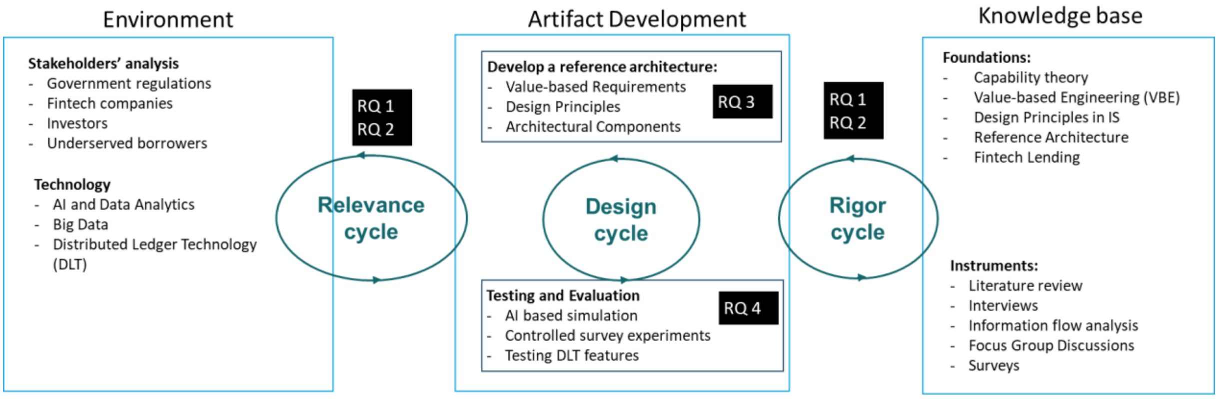


*Figure 5. The mapping of research methodology and research questions*

Figure 5 illustrates the DSR cycle adopted from Hevner and Chatterjee (2010) and its application to this research, explicitly showing how each component of DSR aligns with the research questions and study objectives.

*The relevance cycle* bridges the research to the real-world environment. These include insights from stakeholders, such as government regulators, fintech companies, investors, and underserved borrowers, and technology drivers like data analytics. Problems uncovered here serve as inputs for the **Design Cycle**, which focuses on building practical solutions. For instance, challenges to financial inclusion identified in this phase directly inform the design goals of the reference architecture (RA). Field testing ensures that the outcomes are evaluated and refined iteratively.

*The Design Cycle* drives the creation and continuous improvement of the RA. Grounded in principles derived from Capability Theory and Value-Based Engineering (VBE), the RA undergoes iterative development, testing, and evaluation. This iterative process ensures alignment with the study's goals of promoting inclusion in financial systems. Simulations, controlled experiments, and feature testing evaluate RA's impact. Feedback from each test phase drives necessary refinements.

*The rigor cycle* connects the research with the existing body of knowledge and is highly influenced by the researcher's skills and experience (Baskerville et al., 2018). The scientific contribution of DSR is closely related to the rigor cycle, distinguishing DSR from routine design. Knowledge contributions can include the development of new theories or the extension of existing knowledge (Hevner & Chatterjee, 2010). This cycle ensures the RA is innovative and theoretically grounded, relying on Capability Theory and VBE to inform its core principles.

**The DSR cycles** (relevance, design, and rigor) are highly interconnected in this study. Each cycle informs and enhances the others, ensuring a holistic RA design approach. Figure 5 maps the research methodology, research questions, and DSR cycles, showing the iterative process of designing and testing the RA. This process includes constructing Value-Based Requirements (VBR), Design Principles, and Architectural Components, followed by testing and evaluation.

**The Value-Based Requirements (VBRs)** are derived by applying Sen's Capability Theory as the kernel theory and incorporating Value-Based Engineering (VBE) as a methodological approach. These requirements are developed through interviews, literature review, and information flow analysis. Building on the VBRs, **the Design Principles** guide the RA's structural and functional design by embedding inclusion at its core. These principles are similarly refined through an iterative process involving interviews and literature study to address the inclusion challenges identified in the relevance cycle. Both the VBRs and Design Principles undergo continuous refinement through iterative cycles, with insights from each phase feeding into the other, shaping **the Architectural Components** of the RA.

Following the iterative development of these components, the study proceeds to testing and evaluation through a multi-faceted approach: simulations using quantitative data, survey-based assessments, and feature testing. These tests evaluate the RA's impact in addressing real-world inclusion challenges identified in the relevance cycle.

### 2.4. Research Methods

This section outlines a structured approach for designing a reference architecture (RA). The research is organized into three interconnected stages: **Problem Identification and Knowledge Development**, **Design and Development**, and **Testing and Evaluation**. Each stage is designed to ensure that the RA is theoretically grounded and applicable to the challenges of credit inclusion. Figure 6 summarizes the overall research process, showing the flow from knowledge development to artifact creation and testing.

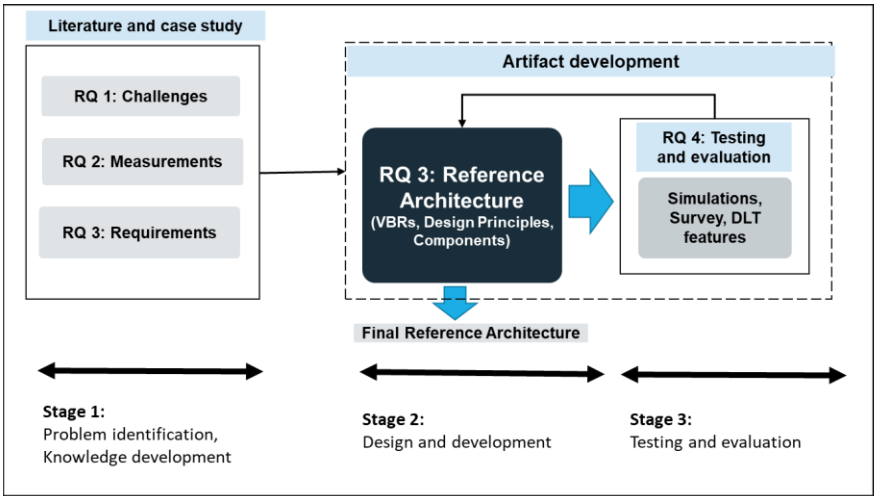


*Figure 6. Overview of Research Process and Stages*

The following table maps the design cycle, rigor cycle, and relevance cycle across each research stage, detailing how specific instruments help address each research question.

*Table 1. Interlinkage of the design cycle, rigor cycle, and relevance cycle in the research stages*

| RQ | Deliverables | DSR Cycle | | | Research Instruments*) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Design Cycle** | **Rigor Cycle** | **Relevance Cycle** | **LR** | **I** | **IFA** | **MLS** | **S** | **SA** | **FT** | **FGD** |
| **Stage 1: Problem identification and knowledge development** | | | | | | | | | | | | |
| RQ 1 | Challenges | Identifies inclusion challenges to inform artifact design. | The literature review provides a theoretical context for inclusion challenges. | Interviews explore challenges beyond literature findings. | V | V | - | - | - | - | - | - |
| RQ 2 | Measurements | Establishes inclusion metrics for artifact evaluation. | The literature review helps identify inclusion metrics. | Interviews expand on metrics. | V | V | - | - | - | - | - | - |
| **Stage 2: Design and development of artifact** | | | | | | | | | | | | |
| RQ 3 | Requirements | The elicitation of Value-Based Requirements (VBRs). | Identify the requirements of the lending system from the literature. | Interviews explore and elicit requirements. | V | V | V | - | - | - | - | - |
| | Design Principles | Formulates the design principles. | Principles are derived from theory to embed inclusion. | Stakeholder input refines principles to enhance real-world applicability. | V | V | - | - | - | - | - | - |
| **Stage 3: Testing and evaluation of artifact** | | | | | | | | | | | | |
| RQ 4 | Data-driven simulation | Simulations with Machine learning to evaluate how adjustments to data and parameters affect Loan Recommendation (LR). | Using insight from literature to structure simulations using real loan dataset. | N/A | - | - | - | V | - | - | - | - |
| | Controlled survey | A survey experiment to measure the impact of enriched information on lender loan approval (LA). | Survey questions and setup informed by literature and exploratory interviews. | Survey feedback provides practical insights, allowing RA adjustments. | - | V | - | - | V | V | - | - |
| | Features testing | Assesses the impact of specific features on perceptions of inclusion. | Literature-informed criteria guide feature design. | FGDs gather stakeholder feedback on inclusion perceptions. | - | - | - | - | - | - | V | V |

*) L: Literature review; I:Interview; IFA: Information Flow Analysis; MLS: Machine Learning Simulations; S: Survey; SA: Statistical Analysis; FT: Features testing; FGD: Focus Group Discussions

### 2.4.1. Stage 1: Problem Identification and Knowledge Development

As the first stage of design science research (DSR), problem identification focuses on investigating the problem and developing knowledge questions that will guide the subsequent stages of the research (Wieringa, 2014). Theoretical contributions are a critical issue in DSR, as insufficient theoretical contributions often lead to the rejection of DSR journal papers (Baskerville et al., 2018). One of the main distinctions between design science research and routine design is its contribution to the knowledge base and methodologies (Hevner et al., 2004).

The knowledge developed during this stage will undergo iterative refinement as new insights are gathered throughout the research process, ensuring that the foundation for the reference architecture remains robust and relevant. This stage addresses Research Questions 1 and 2 (RQ1 & RQ2). It combines theoretical and practical insights by employing a Systematic Literature Review (SLR) and interviews (I) as research instruments.

1) Challenges Identification (RQ1): This sub-stage explores challenges faced by underserved populations in lending systems. A Systematic Literature Review (SLR) forms the foundation for identifying theoretical gaps and existing barriers, providing a solid theoretical base (Rigor Cycle). The SLR helps identify broad themes of inclusion challenges and informs the design of subsequent artifacts (Hevner et al., 2004; Baskerville et al., 2018). Complementing this, Interviews with stakeholders, including regulatory bodies, practitioners, and underserved representatives, provide insights beyond the literature (Relevance Cycle).
2) Metrics Development (RQ2): The objective here is to establish measurable indicators of inclusion, which are essential for evaluating the RA's impact in later stages. Literature Review informs this process by offering theoretical perspectives on inclusion (Rigor Cycle). The review identifies commonly used inclusion metrics and indicators within the literature. Interviews further enrich this understanding by capturing stakeholder perspectives (Relevance Cycle). This dual approach ensures that the inclusion metrics are theoretically grounded and practically relevant.

The knowledge developed during this stage, through the rigor and relevance cycles, is essential for designing and developing the artifacts in the Design Cycle (Hevner et al., 2004). Operationalization is a crucial aspect of this stage, where each research question's elements are defined, and the measurement processes are detailed (Hale & Brown, 2014). By gathering primary and secondary data through interviews and SLR, this stage provides a comprehensive understanding of inclusion challenges and metrics that will guide artifact development.

### 2.4.2. Stage 2: Artifact Design and Development

Building on insights from the first stage, the second stage involves the iterative design and development of the Reference Architecture to address RQ3. This stage centers on defining the RA's requirements and formulating design principles. The research instruments include literature review (LR), interviews (I), and information flow analysis (IFA).

1. Value-Based Requirements (VBRs) are derived from Information Flow Analysis (IFA) to analyze information flow in existing systems, using Data Flow Diagrams (DFD) and Sequence Diagrams. After that, we conduct stakeholder interviews (Relevance Cycle) to capture context-specific needs and expectations, particularly within the P2P lending sector.

2. Iterative Process between Requirements and Design Principles: An iterative process between requirements elicitation and design principles formulation ensures that each informs and refines the other. Requirements are revisited and adjusted as design principles are formulated.
3. Design Principles and RA Development: With the requirements in place and iteratively refined, design principles are then formulated. These design principles are refined through interviews (Relevance Cycle).

#### 2.4.3. Stage 3: Testing and Evaluation

Testing and evaluating a Reference Architecture is challenging; the stakeholders might not be fully aware of future needs (Angelov, Trienekens, & Grefen, 2008). The stakeholders with a visionary mindset will be beneficial in testing and validation. The evaluation criteria are defined during the relevance cycle. *'IT artifacts can be evaluated in terms of functionality, completeness, consistency, accuracy, performance, reliability, usability, fit with the organization, and other quality attribute*' (Hevner, March, Park, & Ram, 2004, p. 279). There are five standard methodologies for testing and evaluation of artifacts; observational process, analytical process, experimental, testing, and descriptive analysis (Hevner, March, Park, & Ram, 2004). Testing and evaluation include continuous feedback loops that allow the RA to be iteratively refined until it meets the study's objectives.

This stage addresses Research Question 4 (RQ4). It includes various research instruments: Machine Learning Simulations (MLS), Survey (S), Statistical Analysis (SA), and Prototype testing, along with Focus Group Discussions (FGDs). These instruments provide quantitative and qualitative insights.

1. Prototype Development and Feature Testing: This testing phase examines how specific features of the RA impact perceptions of inclusion. Focus Group Discussions (FGDs) (Relevance Cycle) were used to gather stakeholder feedback on these features.
2. Machine Learning Simulations (MLS) with sensitivity analysis evaluate how data inputs and parameter adjustments impact Loan Recommendation (LR) outcomes. This simulation is a technical evaluation tool that assesses the RA's ability to recommend loans based on expanded data inputs and adjusted parameters (Design Cycle).
3. Controlled Survey: In response to enriched borrower information, this experiment evaluates the RA's impact on lender decision-making, particularly regarding Loan Approval (LA) rates. The survey is designed with guidance from literature interviews (Rigor Cycle) to ensure the questions are practically relevant. The Survey feedback (Relevance Cycle) provides insights into lender behavior, highlighting the RA's influence on inclusion perceptions and approval decisions. Statistical Analysis (SA) was then applied to derive quantitative insights.

#### 2.4.4. Stakeholder Interviews and FGDs

This study employed multiple rounds of semi-structured interviews and focus group discussions (FGDs) across different research stages to support the Design Science Research (DSR) cycles. Because interviews were used not only for initial problem identification (RQ1 and RQ2) but also for requirements elicitation (part of RQ3) and features evaluation (part of RQ4), methodological details for participant selection, interview protocols, and data processing are summarized here to ensure transparency and traceability.

Semi-structured interviews were particularly suitable for this research. As Elhami (2022) explains, they are informal, rely on open-ended questions and allow the conversation to flow in a way that helps participants speak openly and in detail about their experiences. This makes the interview feel more like a dialogue than a rigid *questionnaire*, and also gives space for follow-up questions when new insights appear. Ruslin (2022) emphasizes two main reasons for semi-structured interviews in qualitative study: first, it allows the researcher to obtain deeper information than *structured interviews*, and second, it is flexible and adaptable. In comparison, *unstructured or open interviews*, as described by Zhang and Wildemuth (2009), proceed without predetermined guiding questions. Unstructured interviews are most useful in early exploratory stages, when the aim is to let respondents generate broad narratives, but they are less appropriate for research like this, which requires consistency and traceability across multiple rounds of data collection.

Semi-structured interviews in this study contributed directly to several chapters:

- **Chapter 4** (RQ1 & RQ2): Semi-structured interviews were conducted with eight stakeholder groups for RQ 1 and with six respondents for RQ2, including regulators, fintech practitioners, academics with expertise in banking and inclusion, banking professionals, investors and borrower representatives to identify socio-technical challenges and develop inclusion metrics.
- **Chapter 5** (part of RQ3): Semi-structured interviews were conducted with eleven respondents from regulators, fintech companies, lenders, borrowers, banking practitioners, academics, and system architects to elicit Value-Based Requirements. Evaluation of Design Principles involves semi-structured interviews with seven respondents with expertise spans technology and infrastructure management, large-scale payment applications, information and technology architecture design, data management, and business analysis.
- **Chapter 6** (part of RQ4, Prototype & Feature Testing): feedback from FGDs with IT professionals and credit risk officers informed the evaluation of core features such as Contested Decision-Making, Dual Rating Systems, and Collaborative Data Collection.
- **Chapter 7** (part of RQ4, Survey Experiment): prior to designing the survey scenarios, exploratory interviews with lenders and borrowers helped survey development format.

All the interview protocols and the group discussion protocol for each chapter are compiled in **Appendix 14**. These include the *Interview Protocol on Challenges of Inclusive Lending in Indonesia* (Chapter 4), the *Interview Protocol on Metrics of Inclusion* (Chapter 4), the *Interview Protocol on VBR* (Chapter 5)*,* the *Interview Protocol on Design Principles* (Chapter 5), the *Focus Group Discussion Protocols* (Chapter 6), and the *Pre Survey Interview Protocol* to prepare the survey design (Chapter 7).

Participants were drawn from diverse professional groups, including regulators, fintech practitioners, system designers, academics, credit officers, and borrower representatives. Recruitment used purposive sampling, ensuring each group had direct involvement in lending systems or inclusion initiatives.

*Respondent selection* was aligned with the purpose of each research stage. In RQ1 and RQ2, diverse groups including regulators, industry practitioners, academics, investors, and borrower representatives were interviewed to identify socio-technical challenges and shape inclusion metrics. In RQ3, the elicitation of Value-Based Requirements drew on regulators, practitioners, academics, lenders and borrower voices to ensure that requirements reflected both systemic priorities and user needs. The subsequent evaluation of Design Principles, however, required a different profile: experts in technology management, payment infrastructures, and system architecture were involved because their technical and operational expertise was essential for evaluating whether the proposed principles could be realistically embedded in large-scale financial systems. For RQ4, IT professionals, credit officers, lenders, and borrowers were recruited to assess the prototype features in practice. This differentiation ensured that each RQ was addressed with respondents best positioned to contribute relevant insights.

The interviews were structured to ensure coverage of critical roles rather than statistical representativeness. Regulators, for instance, often chose to participate collectively and present a single consolidated position for their division, which was treated as one response. This *role-oriented approach* allowed saturation to be reached with the number of participants involved, as further recruitment no longer added substantially new perspectives. For the survey, statistical significance was addressed by targeting 20–30 independent assessments for each profile type, consistent with reliability guidelines (Macchi, 2023). In practice, the achieved sample size exceeded this threshold.

All interviews and FGDs followed the approved Human Research Ethics Committee (HREC) protocol. We can only conduct interviews and surveys following the approval of TU Delft HREC. For all interviewees, we informed them to sign an informed consent before conducting an interview, and they were also informed in advanced that they could stop the interview at any time. During the analysis, an anonymized label was assigned to each interviewees, therefore, we never refer to one particular name or initial. The question sets, tailored for each stage, are included in **Appendix 14**. For example, Chapter 4 focuses on inclusion challenges and metrics; Chapter 5 on requirements and design principles; Chapter 6 on evaluating prototype features; and Chapter 7 on designing the survey experiment. All interviews/FGDs were audio-recorded with consent, transcribed, and coded using thematic analysis. Themes were then linked to specific research questions in each chapter as described above. Informed consent was obtained and all data were anonymized in reporting.

Across all interview stages described in Chapters 4, 5, 6, and 7, the semi-structured question sets were developed through a two-step process. A core set of topics was first derived from the literature on financial inclusion, data governance, and reference architecture design, ensuring alignment with prior studies. These literature-based topics were then complemented with exploratory prompts informed by early field observations and informal practitioner discussions, so that context-specific issues in the Indonesian lending ecosystem could surface during the interviews. Each round of interviews adapted these questions to its specific focus (e.g., inclusion challenges in Chapter 4, value-based requirements in Chapter 5, feature evaluation in Chapter 6, and survey scenario in Chapter 7).

### 2.5. Overview of the Research Approach

This study adopts **Design Science Research (DSR)**, a structured approach that enables iterative design, refinement, and evaluation of the Reference Architecture. The RA is designed by aligning the DSR framework with the study's objectives to ensure it addresses theoretical and practical requirements for inclusion.

**Section 2.1** introduced the purpose of the research design and provided an initial context for the RA's development. **Section 2.2** outlined the research questions guiding this study. These questions explore theoretical and empirical dimensions of inclusion. **RQ1** identifies challenges to inclusion, **RQ2** develops measurable indicators, **RQ3** focuses on the design of RA's elements, and **RQ4** evaluates RA's impact on inclusion.

**Section 2.3** detailed the philosophical foundations and structure of DSR. It highlighted the constructivist and pragmatic perspectives that shape this approach. *Constructivism* frames knowledge as actively constructed through iterative design and evaluation cycles, while *pragmatism* emphasizes the practical value of creating artifacts that address real-world needs. These foundations ensure that the RA remains conceptually sound and operationally applicable. The section also explored *ontological* and *axiological* assumptions, recognizing the diverse realities of stakeholders and embedding inclusion as a core value in the design process. The iterative DSR cycles (the relevance cycle, the rigor cycle, and the design cycle) are interconnected throughout the study to refine the RA continuously.

**Section 2.4** describes the three stages of research within the DSR framework. *The first stage* addresses RQ1 and RQ2 by identifying challenges faced by underserved groups and defining measurable inclusion metrics through a Systematic Literature Review (SLR) and interviews. These findings provide the foundation for the RA's requirements and design principles. *The second stage* addresses RQ3 by constructing the RA based on insights from the first stage. Requirements are elicited through literature reviews, stakeholder interviews, and information flow analysis, ensuring alignment with inclusion principles derived from Capability Theory and Value-Based Engineering (VBE). Iterative refinement ensures that the RA remains adaptable to diverse needs. *The third stage* evaluates the RA's ability to improve inclusion, addressing RQ4. Testing involves machine learning simulations, surveys, statistical analysis, feature testing, and focus group discussions. These evaluations assess the RA across technical, behavioral, and perceptual dimensions, enabling iterative refinement.

In summary, the research design follows the DSR framework, addressing each RQ through targeted stages and research instruments. By integrating relevance, rigor, and design cycles, the study bridges theoretical insights with practical solutions.

# PART II: KNOWLEDGE DEVELOPMENT

# Chapter 3: Literature Background[1]

### 3.1. Introduction

This chapter establishes the literature foundation for addressing inclusion in lending systems. **Section 3.2** examines the ethical and theoretical foundation for inclusion in financial systems through *Sen's Capability Theory* and *Value-Based Engineering (VBE)*. **Sections 3.3** and **3.4** provide the literature-based foundations for Research Questions 1 (RQ1) and 2 (RQ2). Section 3.3 identifies *challenges of inclusion* in lending systems, while Section 3.4 explores *indicators for measuring inclusion*. Although these findings establish a conceptual basis for RQ1 and RQ2, the final conclusions of RQ1 and RQ2 will be presented in Chapter 4, integrating literature insights with interviews.

**Section 3.5** discusses the role of *reference architectures*, introducing their significance in addressing the socio-technical challenges of lending systems. **Section 3.6** focuses on *design principles*, discussing their role in guiding system development. Additionally, Sections 3.5 and 3.6 contribute to answering Research Question 3 (RQ3) by identifying elements of the Reference Architecture. However, a comprehensive exploration of RQ3 will be detailed in Chapter 5. Finally, **section 3.7** provides an overview of this chapter.

### 3.2. Theoretical Foundation for Inclusion in the Financial System

Understanding the philosophical foundations of inclusion is as important as understanding its practical considerations. These foundations provide the ethical basis for creating systems where inclusion is a core principle, guiding the development and evaluation of the reference architecture.

#### 3.2.1. The Concept of Inclusion

Inclusion extends beyond access, aiming to ensure that services equitably benefit all segments of society (Women's World Banking, 2023). This section explores how various views of inclusion can inform the design of lending systems. As a multifaceted concept, inclusion spans philosophy, social design, product design, gender equity, organizational systems, and education.

Ethical frameworks, such as John Rawls' theory of justice as fairness (Rawls, 1985), provide valuable insights into inclusion. Rawls argues that a just society is one where inequalities are structured to benefit *the least advantaged*. This aligns with financial inclusion goals, emphasizing not just access but equitable outcomes for marginalized groups. Applying Rawls' concept involves designing financial services that actively reduce existing disparities. This research prioritizes underserved populations, ensuring they gain access to the systems and derive sustainable benefits.

Different fields, such as philosophy, sociology, and finance, contribute varying perspectives. For instance, Buber & Kaufmann (1996) stated that *'Inclusion involves encounters in which the other is not an "It"—that I can also describe and manifest empathy with—but emerges as a "Thou" with whom I dialogue'* (Buber & Kaufmann, 1996, p. 115). They describe inclusion as a relational experience emphasizing mutual engagement, where individuals are treated as equals in meaningful dialogue rather than objects of concern. This *relational experience* is essential in financial contexts, as seen in microfinance models like Grameen Bank, which treat borrowers as *active participants*, emphasizing

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[1] Parts of this chapter are based on the following publications:
Sulastri, R., & Janssen, M. (2023, July). Challenges in designing an inclusive Peer-to-peer (P2P) lending system. In Proceedings of the 24th Annual International Conference on Digital Government Research (pp. 55-65).

mutual engagement (Yunus & Jolis, 1999). Such systems foster genuine interactions between end-users (lenders and borrowers) and the financial system, ensuring end-users are *not passive recipients*.

In the field of Socially Responsible Design, inclusion refers to the authentic involvement and the availability of the designers during the design and experiment process, not only as the facilitator but also as the participant (Cipolla & Bartholo, 2014). In the field of product and service design, the term *inclusive design* is perceived as the practice of ensuring that as many audiences as possible can use the products or services efficiently (Keates, 2014). This principle is central to creating products that are accessible and usable by diverse groups, minimizing exclusion. For instance, an experiment about gender inclusion and stereotyping using computer-based human-like objects found that the acceptance of people's capability is not affected by gender (Hill, et al., 2017). This finding reinforces the importance of designing systems that do not perpetuate biases or discrimination.

From an organizational perspective, Bennett (2015) and The Global Diversity and Inclusion Benchmarks (GDIB) issued by the Diversity Collegium (2014) define inclusion *as 'how diversity is leveraged to create a fair, equitable, healthy, and high-performing organization or community where all individuals are respected, feel engaged and motivated, and their contributions toward meeting organizational and societal goals are valued,'* as stated in the landing page of Austin Community College website (Austincc, n.d.). This definition aligns with this research's aim to create financial systems that actively *leverage diversity to achieve inclusive outcomes* and embed these standards into the architecture's design requirements.

From an educational perspective, the concept of *inclusive education* emphasizes the importance of ensuring access to educational services for all individuals, regardless of disabilities or severity (Special Education Degree, n.d.). They explain that inclusive education promotes an environment where *students with special needs* are integrated into regular classrooms with appropriate support and services, fostering collaboration and understanding. This approach contrasts with *exclusion* and *segregation*, which isolate special-needs students from their peers.

In summary, there is no general definition of inclusion. A common understanding is that inclusion aims to embrace the participation of as many audiences as possible and promote equal opportunity and access. It also includes the effort to remove barriers and deal with challenges. One question about inclusion is *who does and who does not belong to the demos* (Böhmelt, Böker, & Ward, 2016, p. 1276), which underscores the need to define the boundaries of inclusion.

These diverse perspectives on inclusion provide a foundation for designing a reference architecture that embeds inclusion into financial systems. The following sections expand on this foundation, starting with Sen's Capability Theory.

### 3.2.2. Defining Inclusion

Capability Theory, as articulated by Amartya Sen (1990), provides a concept that emphasizes *the empowerment of individuals* to utilize resources to achieve desired outcomes. This concept defines inclusion as more than access; it encompasses creating conditions that allow individuals to achieve their full potential and lead lives they value. Alkire (2005) expands on this by highlighting that the capability approach centers on what individuals are able to do and be, emphasizing *the importance of freedom* in achieving meaningful outcomes. This theory posits that inclusion extends beyond merely providing access to resources; it is about *empowering individuals* to utilize these resources to achieve their full potential.

In the context of financial inclusion, this means designing systems that provide financial services and enable users to utilize these services to improve their economic standing and quality of life. Sen's perspective and Alkire's interpretation shift the focus from a *resource-based approach* to a *capabilities-based approach*, where the ability to achieve desired outcomes is central. A capability-oriented financial system, for instance, would prioritize providing loans and literacy programs, support services, and tailored resources that empower users to make informed financial decisions. Sen's insights and Alkire's interpretation reinforce that financial systems should be designed to expand individuals' capacities for *meaningful engagement* with financial products, supporting sustainable financial empowerment.

Capability Theory also helps in *evaluating financial inclusion*. By examining whether financial services lead to real improvements in users' capabilities, such as increased loan approval rates, enhanced financial literacy, and sustained engagement, researchers can assess the effectiveness of these systems in fostering inclusion. Nussbaum (2011) adds that linking social justice to individual capabilities involves creating enabling conditions that allow individuals to achieve the outcomes they value. Within financial systems, this could translate into designing services beyond providing access, ensuring that users can exercise control and make choices that lead to economic well-being.

This research defines inclusion as: "*The equitable access, distribution, and utilization of financial resources, ensuring that all societal segments, particularly underserved populations, can participate meaningfully in lending systems."* This definition emphasizes not only the removal of systemic challenges, such as socio-economic disparities and information asymmetries, but also the creation of empowering conditions that enable individuals to make informed decisions.

**Inclusion-by-design**, as conceptualized here, extends beyond access, *embedding inclusion into the core structure and processes of lending systems*, creating opportunities for equitable participation and sustained engagement within financial ecosystems.

In summary, the ethical foundations of inclusion and the application of Sen's Capability Theory provide a multidimensional perspective on financial inclusion, emphasizing equity, social justice, and empowerment. Sen's Capability Theory reinforces the importance of designing systems that enable individuals to achieve meaningful outcomes. Section 3.2.3 builds on these principles by introducing Value-Based Engineering (VBE) as an operational framework to translate these ethical and empowerment-driven concepts into actionable design requirements.

### 3.2.3. Value-Based Engineering (VBE)

In system development, requirements define what the system should do and how it should behave. According to Sommerville (2005), requirements are classified into functional and non-functional requirements. *Functional requirements* specify the services, tasks, or behaviors a system must support, such as processing loan applications or generating credit scores. *Non-functional requirements* describe constraints or qualities the system must exhibit, such as security or usability. However, these technical requirements are insufficient for systems that aim to support broader social goals, such as inclusion. This is where value-oriented methodologies such as Value-Sensitive Design (VSD) and Value-Based Engineering (VBE) become relevant. VSD focuses on identifying core human values, while VBE goes further by *operationalizing these values into concrete system requirements*.

Instead of treating requirements engineering merely as a technical process, this study positions it as a reference point to highlight how value-based approaches extend beyond traditional specifications (Sommerville, 2005). While requirements engineering provides a systematic way to define goals, functions, and constraints of software systems (Zave, 1997), its emphasis remains on reconciling technical demands and stakeholder needs. Requirements engineering involves reconciling conflicting views among stakeholders during the negotiation, validation, and determining acceptance criteria (Baskerville et al., 2018).

While traditional requirements engineering focuses on technical specifications and stakeholder needs, VBE introduces a structured methodology that *integrates values into these requirements*, making ethical considerations a foundational element rather than an afterthought. VSD, introduced by Friedman (1996), prioritized human values in information systems. A systematic review by Winkler & Spiekermann (2021) showed that although VSD principles have been widely applied in 219 studies, however, only 17 studies consistently followed its full three-cycle methodology (conceptual, empirical, and technical) indicating a need for clearer guidance in applying value-sensitive methodologies.

In response to this challenge, VBE enhances the conceptual framework for translating values into design requirements. VBE employs a layered structure, as defined in IEEE 7000, organizes ethical values into three levels: core values, value qualities, and value dispositions (Spiekermann & Winkler, 2022). *Core values* represent intrinsic ethical priorities, such as privacy; *value qualities* provide specific interpretations, such as informed consent as a manifestation of privacy; and *functional requirements* translate these into technical elements, such as a layered privacy policy. By organizing values this way, VBE provides clarity and ensures that ethical values are systematically embedded into system design.

Effective value-based design also requires careful clarification of intended values and norms, as different interpretations can lead to divergent requirements (Veluwenkamp & Hoven, 2023). For example, a platform that prioritizes ‘voting’ as a core value will differ significantly in its design requirements from one focused on ‘contestation,’ with each value driving unique system functionalities. Furthermore, Keeney (1996) notes that distinguishing between objectives, constraints, and means is often challenging, which is why VBE’s structured approach provides crucial guidance. Spiekermann (2021) emphasizes that stakeholder involvement is essential for maintaining consistency in applying value, as stakeholders’ diverse interpretations must align.

To facilitate the translation of core values and value qualities into system requirements, Spiekermann & Winkler (2022) introduced the Ethical Value Requirements (EVRs), encompassing organizational and technical aspects. By grounding ethics in the system design process, this approach aligns directly with the study’s aim to create financial systems that respect stakeholder values and uphold inclusion.

In summary, VBE provides *a structured approach* to embedding ethical values within system requirements. By prioritizing inclusion as a core value, VBE facilitates the development of VBRs. The process of eliciting VBRs is elaborated in Chapter 5.

### 3.3. Literature on Socio-technical Challenges of Inclusion in Lending System (Part of RQ 1)

This section provides a literature-based exploration of Research Question 1 (RQ1): ***What are the challenges to inclusion in lending systems?*** By examining existing studies, this section aims to identify and categorize challenges in lending systems. The final answer to RQ 1 will be provided in Chapter 4, integrating the SLR findings from this section with interviews.

To systematically identify the challenges, a **Systematic Literature Review (SLR)** was conducted, supplemented by a flexible literature review that broadened the search criteria not covered by the SLR protocol. The search strategy involved defining keywords to cover general challenges specific to inclusion, such as financial inclusion, services for unbanked populations, prosocial lending, and fairness. Additional terms like ”trustworthiness” and ”equity” were also included to capture discussions on transparency and ethical considerations, often critical to inclusive finance.

As shown in Figure 7, the initial query retrieved 152 publications as of July 2022, spanning diverse themes and contexts. A multi-stage screening process was conducted to filter out irrelevant papers. The final dataset comprised 115 papers. Furthermore, to structure the identified challenges, we drew upon the socio-technical categories introduced in Sulastri & Janssen (2022), which outlines five core elements, Data and Processing, Business, Organizational, Policy and Governance, and Culture, within P2PLS. Later on, recognizing the broader scope of this study, we expanded this classification to six categories.

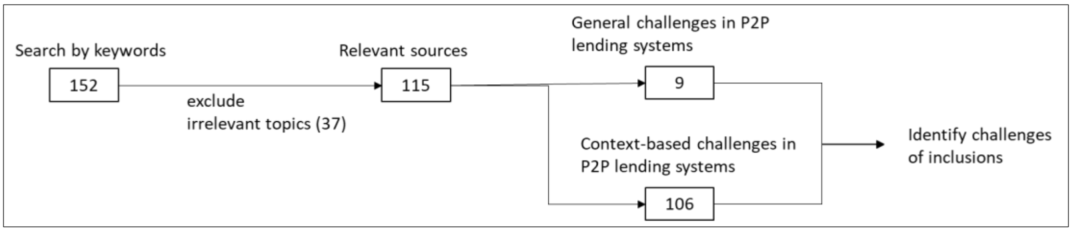



*Figure 7. SLR to identify challenges of inclusion*

**Technology and data challenges** are among the most frequently cited issues, appearing 50 times in the literature, with most (44 papers) addressing challenges in scoring formulation and default prediction. The topics include data quality (Zhang et al.,2016; Guo et al., 2016), data preparation (Li et al., 2018; Xia et al., 2018), searching cost (Li et al., 2020; Akanmu & Gilal, 2019), model development (Ariza-Garzon et al., 2021; Niu et al., 2020; Jiang et al., 2019; Wang et al., 2018), and class imbalance (Chen, Leu, Huang, Wang, & Takada, 2021); (Niu, Zhang, Liu, & Li, 2020); (Li, Ding, Wang, Chen, & Yang, 2020) (Li, Ding, Chen, & Yang, 2018). Traditional credit scoring models rely heavily on historical financial data and formal credit histories. While relevant for borrowers with well-documented financial profiles, these models make it challenging to assess individuals without such records, including low-income workers and those in informal economies. This reliance perpetuates financial exclusion by leaving significant portions of the population unserved as the systems struggle to adapt to non-standard borrower profiles (Suryono et al., 2019).

Scalability presents another challenge, especially as platforms expand into underserved regions. Lenz (2016) points out that scalable architecture is critical for extending services to broader populations. However, many existing systems lack the structural flexibility to meet these needs. Moreover, while decentralized technology solutions offer promising avenues to improve transparency and security, their scalability and cost remain challenging to widespread adoption (Shukla et al. 2021).

**Financial lending challenges** focus on the operational processes to evaluate borrowers and maximize profits. These challenges revolve around how the platforms structure their systems to determine loan approvals. Many platforms prioritize borrowers with documented financial histories, seeing them as low-risk and likely to repay. However, this approach often excludes those without formal credit records, such as informal workers or low-income individuals. Another issue is information asymmetry, where borrowers and lenders lack equal access to information (Yang & Lai, 2014). This gap can lead to misunderstandings about loan terms, particularly for borrowers with limited financial literacy (Yum, Lee, & Cha, 2012).

Profitability also plays a role, as platforms aim to scale their operations while minimizing costs (Ye, Dong, & Ma, 2018; Serrano-Cinca & Gutiérrez-Nieto, 2016; Xia et al., 2017). Cost-driven decision models often favor "low-risk" borrowers, leaving low-income individuals marginalized (Xia, Liu, & NanaLiu, 2017). Furthermore, the design of interest rate creates another affordability challenge for borrowers. Some systems let the borrower state the expected interest rate (Syamil et al., 2020; Zhao et al., 2017; Chen et al., 2016); however, the common practice is the rate is decided by the system based on a specific formula (Caldieraro, Zhang, Jr, & Shulman, 2018).

To address these challenges, fostering trust and improving transparency are critical. For example, building group networks can enhance social capital, enabling borrowers without formal credit histories to secure loans (Chen, Zhou, & Wana, 2016). Platforms can also adopt specific communication strategies to reduce information gaps, helping borrowers better understand lending terms and navigate the system (Suryono et al., 2019).

Unlike financial lending challenges, which deal with day-to-day operations, **organizational challenges** focus on structural decisions and institutional priorities. For instance, there is a cautious approach to lending where institutions limit exposure to informal or high-risk borrowers (Guo et al., 2016). Decision-making models often prioritize predictable financial outcomes and secure investments, as institutions focus on financial stability over inclusion. Lenz (2016) observes that conservative resource allocation leaves little room for initiatives targeting marginalized populations, highlighting the trade-off between stability and inclusion. The industry's emphasis on financial stability results in resource allocation toward low-risk portfolios, further limiting inclusion (Xia et al., 2017).

Hybrid operations have shown potential for bridging this gap. For instance, organizing in-person events to validate microenterprises' operations and introducing digital lending opportunities can help bridge the digital divide (Ravishankar, 2021). Such in-person interactions not only make lending more accessible but also support the creation of business networks (Tao, Dong, & Lin, 2017). By combining digital engagement with offline operations, institutions can create more equitable lending ecosystems without compromising operational stability. Lending platforms could also cooperate with banking institutions (Kohardinata et al., 2020), big data companies (Au & Sun, 2019), and non-government institutions (Ravishankar, 2021) for data exchange and risk assessment. Lending platforms can recommend borrowers with a solid repayment history to banks (Milne & Parboteeah, 2016).

Another challenge is a reputational issue. The rapid emergence of illegal lending platforms in countries like Indonesia and India has led to a negative perception of online lending. Predatory lending, unethical debt collection practices, and financial mismanagement raised questions about the credibility of this system (Ping, Yulin, Mengli, & Xuemei, 2019). The negative reputation of the platform and industry can discourage lenders and borrowers from using the system.

Another organizational concern is company default risk, driven by competitive pressures and inconsistent risk management practices. The collapse of numerous P2P platforms in China in 2015 due to issues like mismanagement, lack of regulatory oversight, and moral hazards is a stark reminder of the fragility of these systems (He, et al., 2020). Recent studies have developed deep learning models to predict platform default risks (Yoon, Li, & Feng, 2019), including utilizing investor feedback as a key indicator of stability (Fua, Ouyang, Chen, & Luo, 2020). However, high-risk environments and limited regulatory oversight exacerbate default risks, affecting borrowers and investors (He, et al., 2020).

**Policy and regulation challenges** include data protection, customer protection, supervision and monitoring, coordination, and collaboration. Data protection is a key issue, particularly in developing countries where personal data protection laws may be underdeveloped. In countries like Indonesia, personal data protection legislation is still being drafted as of 2022, leaving the systems in a regulatory gray area. Without clear guidelines, fintech companies lack the frameworks to manage data responsibly, creating risks for consumers and the industry. In regions where data privacy regulations are lacking, the risks of data breaches, misuse, and unauthorized access increase, jeopardizing user trust and safety (Au & Sun, 2019).

Supervision and monitoring present additional challenges, particularly for micro-entrepreneurs. Policy support for microenterprises, critical contributors to economic growth, remains underdeveloped.

Reza-Gharehbagh et al. (2020) note that limited frameworks are available to address financing for small businesses. Government oversight is necessary to help these entrepreneurs enhance their capabilities (Tambunan, 2015).

While governments encourage technological innovations to improve access to credit, such advancements bring risks, especially regarding consumer protection (Huang, 2018). Therefore, balancing innovation with consumer safety remains a significant challenge. Moreover, the change in the economic situation can influence repayment capacity (Zhou, Fujita, Ding, & Ma, 2021), which requires immediate adjustment in policy and regulation.

Regulatory inconsistencies also pose a challenge to the growth of lending platforms. In some regions, regulations may be overly restrictive, hindering innovation, while in others, they may be too loose, exposing systems to risks like fraud and instability (Huang, 2018). For instance, stringent regulations in some countries may limit platform flexibility and innovation, while more lenient environments may inadvertently permit unethical practices such as predatory lending.

The lack of regulatory frameworks leads to industrial collapse (Ariza-Garzon et al., 2021; Zhang & Wang, 2019). A case study from China by Reza-Gharehbagh et al. (2020) illustrates this dynamic further. Regulatory frameworks initially fueled the rapid growth of P2P lending by leveraging high internet penetration and market demand. However, subsequent stringent rules constrained platform adaptability, demonstrating the difficulty of balancing innovation and regulation. The European Banking Authority (EBA) also emphasizes that P2P platforms face distinct risks compared to traditional institutions, complicating oversight and creating challenges to inclusion (Lenz, 2016).

**Socio-cultural challenges**, cited five times, highlight the challenges of serving populations with varying backgrounds. Cultural and geographical similarities can also influence lending decisions (Burtch, Ghose, & Wattal, 2014).

Disparities in financial literacy and access are particularly evident in underserved regions, where issues like geographical distribution and user motivation create barriers (Chen, Li, & Lai, 2017). Limited awareness of financial products further exacerbates these challenges, as many borrowers lack the knowledge or confidence to navigate the system. This underscores the need for culturally sensitive approaches that address these disparities and improve accessibility (Chen, Lou, & Slyke, 2015).

Gender discrimination is another socio-cultural barrier in lending platforms. Despite being more likely to repay loans, research shows that women often face higher interest rates than men (Chen, Li, & Lai, 2017). This disparity reflects biases within lending models, driven by stereotypes about women's financial reliability, which perpetuate socioeconomic inequalities (Chen, Li, & Lai, 2017). Addressing these biases requires redesigning risk assessment models to ensure they are equitable and inclusive. In regions where cultural norms and gender biases prevail, as highlighted by Chen (2017) and Adbi & Natarajan (2021), additional efforts are needed to address these issues and foster inclusion. For example, women in certain regions may face systemic barriers to financial access, whether due to societal expectations, lower digital literacy, or limited financial autonomy.

Moral hazard presents an additional cultural challenge, particularly when borrower information is limited. Lenders may perceive certain groups as inherently higher risk based on sociocultural assumptions. Social capital, such as group networks, offers a potential solution by providing alternative indicators of borrower reliability (Suryono et al., 2019). The rise of unregulated or predatory lending operations can harm legitimate lending systems by damaging the sector's reputation, eroding trust, and creating a perception of risk within the community (Tambunan, 2022).

**Trust** is challenging in lending systems, where digital platforms replace traditional intermediaries. For lenders, trust depends on security, return rates, and regulatory compliance (Niu et al., 2020). Borrowers often experience a trust deficit due to historical issues such as predatory lending practices and a lack of transparency in platform operations. This dual-sided gap in trust limits participation. To address these challenges, decentralized technology solutions have been proposed to enhance transparency and security (Shukla, Nankani, Tanwar, Kumar, & Piran, 2021). While such solutions promise to resolve trust-related issues, challenges like scalability and implementation costs remain significant for widespread adoption (Shukla et al., 2021). However, this study excludes the aspects of trust evaluation in the proposed reference architecture.

The collective culture tends to create a positive impact on repayment behavior in comparison with the borrowers in a more individualist culture (Qiu, Xu, & Zhang, 2010), which might be associated with the investment behavior of the lenders in that community (Yang & Lee, 2016).

Transparency issues also contribute to the trust challenge. Borrowers often criticize platforms for unclear credit assessment processes, which can lead to disengagement and mistrust (Lenz, 2016). For lenders, the lack of visibility into borrowers complicates decision-making. While measures such as third-party guarantees have shown promise in reducing perceived risks (Huang, 2018), their broader impact on trust and participation remains underexplored.

This section has outlined key challenges to inclusion in lending systems, addressing RQ1 from a theoretical perspective. Chapter 4 will integrate this literature review with insights from interviews. The next section (3.4) transitions to RQ2, focusing on metrics to evaluate inclusion.

### 3.4. Literature on Measurement of Inclusion in Lending System (Part of RQ 2)

This section explores the literature to address RQ2: ”***What indicators measure inclusion in lending systems?"*** It provides an initial response by identifying inclusion indicators from the literature. The complete answer to RQ2 will be developed in Chapter 4, where these insights will be integrated with findings from interviews, as illustrated in Figure 8.

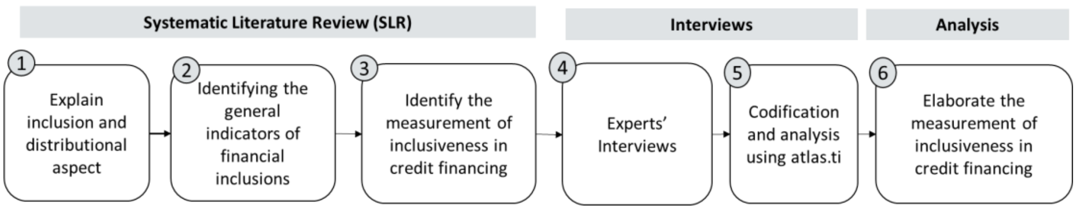



*Figure 8: Research steps for RQ2*

The goal of RQ2 is to identify inclusion metrics in lending systems. These metrics monitor inclusion while serving as feedback for improvement. By establishing these measures, the research bridges the gap between the theoretical ideals of inclusion and their practical application in lending systems.

Initially, a systematic literature review (SLR) was conducted to identify the general inclusion indicators. The review targeted publications from 2010 onwards, reflecting the heightened awareness of credit financing and micro-lending following the global financial crisis. Keywords such as ”Inclusion,” “Financial,” “Policy,” Indicators,” P2P lending,” Microfinance,” and related terms were used to search for relevant articles in the fields of economics and computer science.

However, the findings from the SLR revealed limitations. While general studies on financial inclusion are plentiful, few specifically address the intersection of inclusion, financial lending, and underserved segments. Following the abstract screening, we excluded 55 irrelevant papers. This process resulted in 283 sources (Figure 9), which are categorized into four groups: inclusion in general (n=18), financial inclusion (n=244), the role of micro and small enterprises in financial inclusion (n=10), and microfinance, non-bank institutions, and P2P lending systems (n=11).

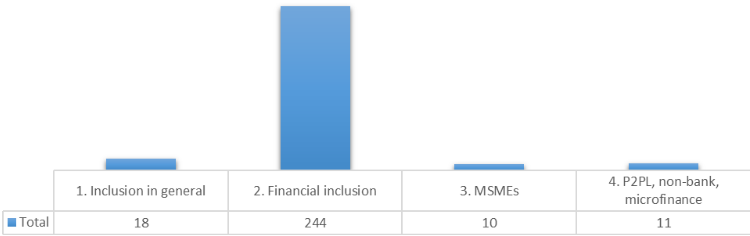



*Figure 9. Initial searching of literature of measurements*

Due to the limited overlap between the keywords ”inclusion,” “financial lending,” and ”microenterprises,” the strict SLR protocol was considered unsuitable. Relying solely on the SLR would have constrained the analysis. As a result, we transitioned to a more flexible literature review (LR). This allowed for forward and backward citation analyses and provided the flexibility to incorporate more relevant studies despite not strictly conforming to the SLR protocols. The literature review combined the findings from the SLR with additional papers categorized into **indicators**, **determinants**, **barriers**, and **impacts** of financial inclusion in general, not limited to lending/credit. See Figure .

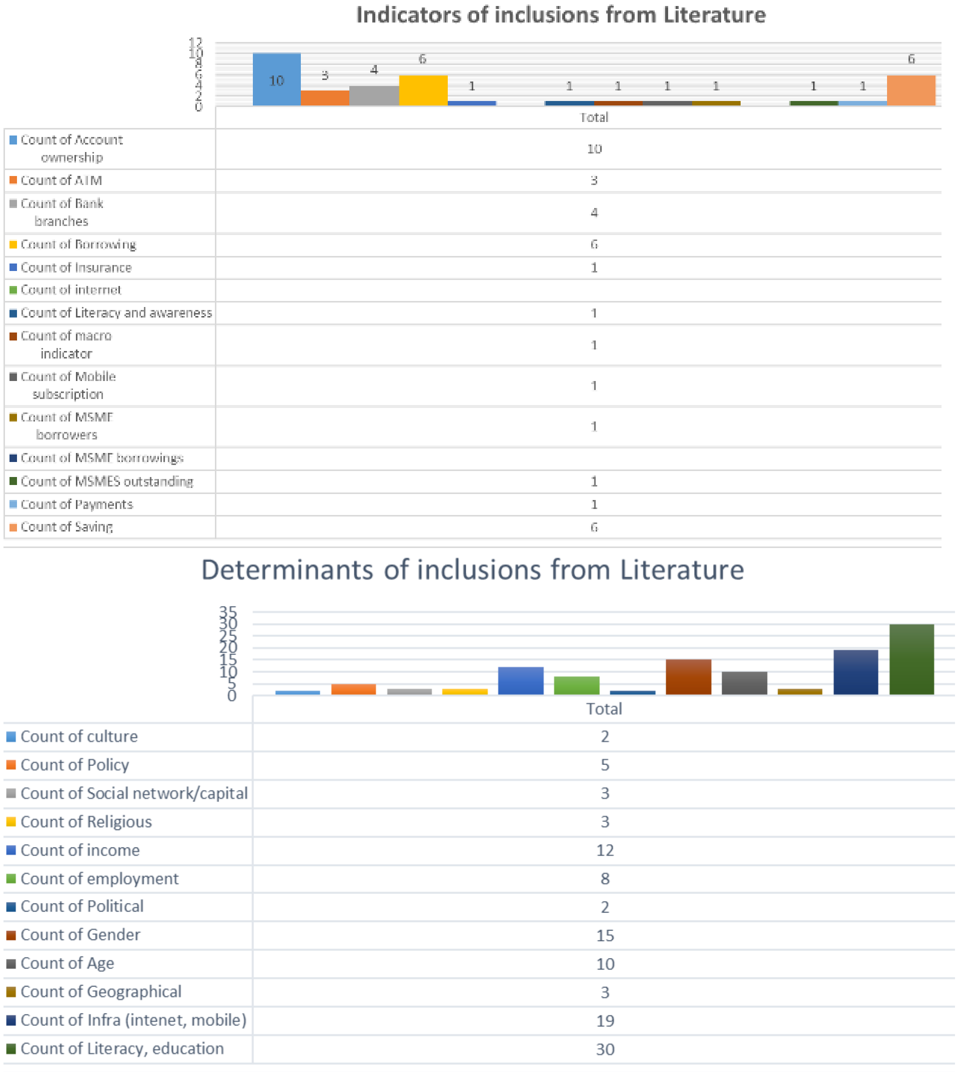
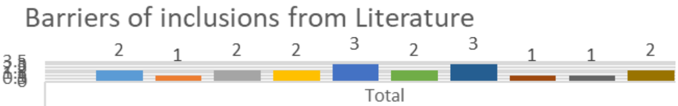
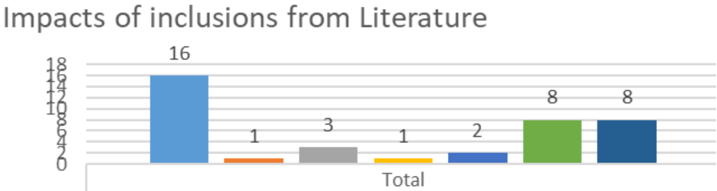



Figure 10. Indicators, determinants, barriers, and impacts of financial inclusion from literature




| | Total |
|---|---|
| Count of Trust | 2 |
| Count of Religious2 | 1 |
| Count of technology | 2 |
| Count of Distance | 2 |
| Count of cost | 3 |
| Count of money | 2 |
| Count of literacy | 3 |
| Count of sparse population | 1 |
| Count of infra | 1 |
| Count of Wealth and poverty | 2 |




| | Total |
|---|---|
| Count of economic growth | 16 |
| Count of monetary policy | 1 |
| Count of macro stability | 3 |
| Count of financial sector dev | 1 |
| Count of employment2 | 2 |
| Count of poverty and inequality | 8 |
| Count of bank performance | 8 |

Figure 10 (cont) Indicators, determinants, barriers, and impacts of financial inclusion from literature

The first focus area is **indicators**, where the literature identifies *account ownership*, *borrowing*, and *saving* as primary financial inclusion measures. *Account ownership*, cited in 10 sources, is the most discussed, emphasizing its foundational role in providing access to financial services. *Borrowing* and *saving*, cited in six sources each, represent key engagement indicators that reflect active participation in financial systems.

**The determinants** of financial inclusion are also well-documented in the literature, with *literacy and education*, *infrastructure*, *income*, and *gender* emerging as the most discussed. Literacy and education, cited in 30 sources, underline the role of financial literacy in empowering users to engage with financial services. Infrastructure, particularly internet and mobile access, is identified in 19 sources as essential for extending reach, especially in remote areas. Additionally, income and gender, mentioned in 12 and 15 sources, highlight socio-economic and demographic disparities. In examining **barriers to inclusion**, the literature points to *cost*, *literacy*, and *trust*. High costs and limited literacy are each highlighted in three sources.

Lastly, **the impacts** of inclusion in financial systems are closely tied to *economic growth*, *poverty reduction*, and *banking sector performance*. Economic growth is the most frequently cited impact, with 16 sources linking financial inclusion to broader economic benefits, such as increased economic activity and resilience in low-income communities. Poverty reduction, cited in eight sources, underscores the benefits of social equity, as financial inclusion provides tools for underserved groups to improve their financial well-being. These impacts collectively reinforce inclusion's societal and economic value in financial systems.

The four categories (Indicators, Determinants, Barriers, and Impacts) form the basis for understanding what to measure, why inclusion varies, the challenges faced, and the outcomes of inclusive practices. These insights inform the development of metrics that assess access and equity, which are further explored in the next section.

### 3.4.1. Inclusion and Distributional Aspects

This research applies Sen's capability theory. According to this theory, *capabilities* refer to the opportunities or freedoms individuals have to achieve specific outcomes (Nussbaum & Sen, 1993). Functioning refers to '*an achievement of a person, what a person manages to do or to be'* (Clark, 2005, p. 4). People value functioning through reasoning; capabilities, on the other hand, provide opportunities for people to act positively and to access a particular condition by preparing the necessary conditions and providing the required means. For example, promoting health capability means allowing people to choose or achieve a healthy lifestyle.

The following figure shows how Sen (1990) distinguishes between commodity, capability, functioning, and utility. This figure implies that (i) people could have the same commodity or resources but have no freedom or capability, and (ii) people could have the same commodity/resources and have the capability to function but choose not to do the action that leads to utility.

Commodity → Capability (to function) → Function(ing) → Utility (e.g. happiness)

*Figure 11: The logic in Sen's capability, as cited from (Clark, 2005, p. 3)*

In the context of lending, capability refers to *access*, enabling underserved populations to qualify for credit, while utility represents the actual utilization of these credit facilities. Capability is the availability of credit access to all, regardless of socioeconomic status or life circumstances. Figure 12 highlights the distinction between access and usage in credit financing, emphasizing that access represents the opportunity to use credit, whereas usage reflects the realization of that opportunity. This differentiation is critical: while reducing application barriers or simplifying eligibility criteria may expand access, actual uptake often remains low due to trust issues, user hesitancy, and hidden costs. Therefore, metrics must measure access and usage to capture financial inclusion fully (Dupas et al., 2011).

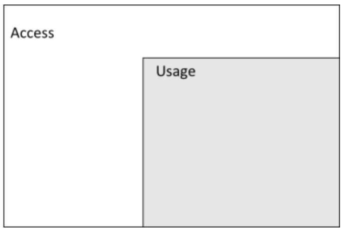



*Figure 12: Access vs usage*

Measuring usage is relatively straightforward, as it reflects the actual uptake of credit facilities. However, measuring access is more complex. Although credit facilities might technically be available to certain population segments, individuals may opt not to use them due to cultural norms, lack of awareness, or perceived barriers. This research emphasizes that credit access is broader than credit usage, as access represents the opportunity, whether or not it is utilized.

Inclusion, as defined in this study, goes beyond simply using credit. While informal credit systems can meet immediate needs, they often lack the institutional structure and long-term economic benefits provided by formal systems. Digital lending platforms should aim to replicate the transparency, reliability, and accessibility of formal institutions to support underserved populations more effectively (Giné & M. Townsend, 2004).

In refining the definition of inclusion, this study highlights the dual importance of *equal access* and *equitable distribution*. Inclusion is not merely about providing financial services but ensuring that access is equally distributed across all segments of society. Social status, geographical location, gender, race, and income should not become barriers to accessing credit. Inclusion ensures that everyone, regardless of their circumstances, has the same opportunity to access and utilize financial services.

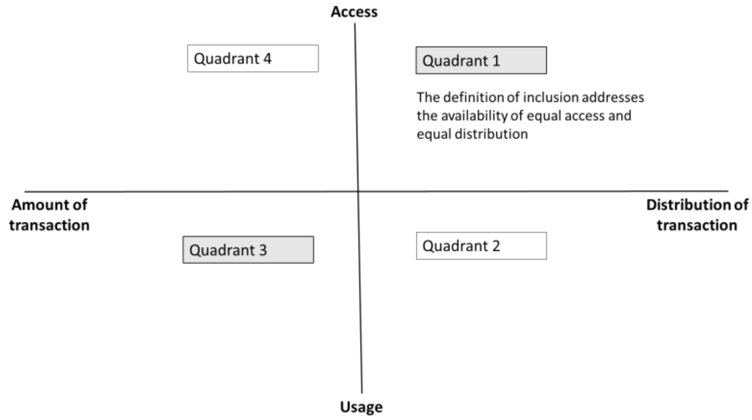



*Figure 13: Quadrant of access vs. usage and amount vs. distribution*

The relationship between access and usage (Y-axis) and the amount versus the distribution of lending (X-axis) is illustrated in Figure 13. The figure underscores that focusing solely on the total amount of credit distributed can lead to exclusionary practices if credit is not equitably allocated across societal segments. This research prioritizes *Quadrant 1* and *Quadrant 2*, which emphasize equitable access and usage, as opposed to Quadrant 3 and Quadrant 4, which focus on total credit volume without addressing how it is distributed.

Consequently, inclusion in lending systems is defined as *the availability of credit access that is equitably distributed across society*. This definition implies that measuring inclusion requires examining both the availability of credit and its distributional aspects, such as age, gender, income level, geographical location, and race. These two dimensions, *indicators* and *distributional aspects*, are essential for a comprehensive understanding of financial inclusion.

### 3.4.2. General Measurement of Financial Inclusion

To understand financial inclusion comprehensively, this study reviewed existing metrics in financial inclusion in general (not specific to lending). Table 2 summarizes several studies that contributed to financial inclusion measurement.

*Table 2: Research on the measurement of financial inclusion*

| | Literature | Dimensions | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Access/ availability | Quality | Usage | Impact | Barriers | Affordability | Financial literacy | Penetra tion |
| 1 | Sarma (2008) | √ | | √ | | | | | √ |
| 2 | Hannig & Jansen (2010) | √ | √ | √ | √ | | | | |
| 3 | Cámara & Tuesta (2014) | √ | | √ | | √ | | | |
| 4 | Shen, Hueng, & Hu (2021) | √ | | √ | | | √ | √ | |
| 5 | Tram, Lai, & Nguyen (2021) | √ | | √ | | | | | √ |

We classify four main categories of metrics (

Table 3) based on recurring themes, which consist of supply (infrastructure), demand (account penetration), demand (usage), and literacy. There is a difference between account ownership and the actual usage of an account. People having an account do not always use it, or people can borrow someone else's account for transactions.

*Table 3: Indicators of financial inclusion in general, retrieved from the literature*

| Type | Indicators | Explanation |
|---|---|---|
| Supply (infrastructure) | Bank branches | The number of bank branches per a specific population or geographical distance |
| | ATM | The number of ATMs per a specific population or geographical distance |
| | Telephone lines | The number of phone lines per a specific population |
| | Other infrastructure | Any infrastructure that improves access to financial services, including the Internet, transportation, power, and health |
| Demand (account) | Account penetration | Ownership of any account at formal or informal financial institutions. It includes credit and deposit accounts, post office accounts, and mobile money |
| | Mobile subscription | Mobile cellular subscription per a certain number of population |
| Demand (usage) | Saving | The share of adults saving money in any financial institution, or the total amount of saving. |
| | Borrowing | The share of adults borrowing money in any financial institution or the total amount borrowing |
| | Digital payment | The share of adults making or receiving payments or the total amount of transactions |
| | Macroeconomic indicators | The derivation of any macroeconomic indicators, such as the amount of credit to GDP ratio and the amount of deposit or credit per capita |
| Literacy | Literacy | Improvement of financial literacy and awareness in society |

The first indicator, supply, refers to the infrastructures provided by governments and technology providers to expand access to financial products and services, including physical and digital access. Demand (account) is reflected by the number of bank accounts and mobile subscriptions. Demand (usage) measures active participation, such as borrowing, saving, or payments. Literacy addresses the role of financial literacy in promoting inclusion.

The above metrics provide a general understanding of financial inclusion measurement but are not specific to lending systems. The following section provides the metrics focused on the lending systems.

### 3.4.3. Literature-based Inclusion Metrics

The literature-based metrics for lending systems are categorized into **four metric types**: *(1) Penetration Metrics, (2) Financial Access Metrics, (3) Analytical Inclusion Metrics,* and *(4) Literacy Metrics*. This categorization is based on recurring themes identified in the literature.

The following subsections detail each **metric type**, which is accompanied by **metric categories**. It is important to note that only a few studies explicitly identify metrics to measure inclusion in lending. Therefore, the metrics we propose in this study are *the direct interpretation* of insights drawn from literature rather than explicitly mentioned by the literature. For example, Giné & M.Townsend (2004) discuss transformative efforts for financial inclusion but do not explicitly mention how to measure inclusion; however, they address the importance of credit expansion to low-income individuals, which we translate as an example of penetration metrics. Doshi-Velez and Kim (2017) explore the importance of machine learning interpretability in credit scoring but do not mention the metrics; however, we interpret this need as part of the analytical metrics type with the category of Interpretability Metrics. Another example is Cull et al. (2009), which explores the impact of microloan credit with profit-oriented models vs. nonprofit models to improve inclusion. We translate this insight as part of financial metrics types, with the category of microloan access metrics.

### *A. Penetration Metrics*

Penetration metrics are inspired by the literature that addresses physical and digital barriers and disparities across regions or demographic groups to improve inclusion. Giné & M.Townsend (2004) explain that *financial liberalization* can be examined through the expansion of credit access and credit services to previously excluded populations (Giné & M. Townsend, 2004). For example, expanded credit helped low-income individuals become microenterprises (Giné & M. Townsend, 2004). In this study, we elaborate on **penetration metrics** in two categories: *physical access metrics* and *digital access metrics*.

**Physical Access Metrics** assess the availability of infrastructure in underserved regions. Based on the study of Dupas et al. (2011) in Kenya, long distances to financial services incur travel costs that discourage individuals from joining the system. Therefore, we introduce metrics like *Lending Service Point Density* to evaluate the number of service locations per 1,000 residents in a given area, such as microfinance branches. We can also measure the number of new loan accounts opened in remote areas. Literature shows that reducing account creation costs in rural areas has increased opening rates by 62% (Dupas et al., 2011). Another example is *Regional Disparities Metrics*, which explores access distribution between urban and rural areas. Urban areas typically have a higher density of financial service points in comparison with rural and remote areas (Demirguc-Kunt & Klapper, 2012). The literature also discusses the analysis of women in the repayment system, which inspired gender-related disparities metrics in loan approvals (D'Espallier, Guérin, & Mersland, 2011). Literature shows that female borrowers provide a better repayment outcome in microfinance lending (D'Espallier, Guérin, & Mersland, 2011).

**Digital Access Metrics** assess the availability of digital services. Literature shows that mobile and internet access have a positive relation with inclusion in developing regions (Mushtaq & Bruneau, 2019). However, digital platforms cannot fully replace physical services in areas with low literacy levels (Klapper, El-Zoghbi, & Hess, 2016). Moreover, mistrust of financial institutions and reluctance to digital adoption discourage engagement, even when costs are reduced (Dupas, Green, Keats, & Robinson, 2011). Therefore, digital access metrics have a strong relationship with other measurement metrics.

Penetration metrics help evaluate inclusion and identify opportunities for improvement. For instance, literature shows that rural farmers in Zambia who gained access to seasonal loans resulted in a 10% increase in agricultural output and revenue (Klapper, El-Zoghbi, & Hess, 2016), showing the impact of specific policy interventions on inclusion.

### *B. Financial Access Metrics*

Financial Access Metrics examines whether loans are affordable for marginalized segments. This study elaborates on **financial access metrics,** including *microloan access, loan affordability, and loan approval metrics.*

**Microloan Access Metrics** assesses how microfinance credit reaches underserved groups, including small-scale entrepreneurs and low-income borrowers. Microfinance institutions (MFIs) are vital in developing economies by serving those excluded from traditional banking systems (Cull, Demirguc-Kunt, & Morduch, 2009). However, high interest rates from commercial MFIs can undermine affordability. The literature shows that low interest rates do not guarantee improvement in borrowing due to the fear of losing collateral (Dupas et al., 2011). Moreover, the literature shows that women and younger entrepreneurs often face specific challenges to access microloan credit (Aterido, Beck, & Iacovone, 2013) (D'Espallier, Guérin, & Mersland, 2011).

**Loan Affordability Metrics** examine how lending products impact repayment ability. Beyond loan volumes, it is crucial to evaluate whether loans are affordable and tailored to the borrowers' needs (Banerjee, Karlan, & Zinman, 2015). High interest rates and short repayment periods do not meet the capacity of low-income borrowers and lead to payment defaults (Karlan & Zinman, 2010)(Armendáriz & Morduch, 2010).

**Loan Approval and Rejection Metrics** focus on disparities in loan approvals across different demographic groups. Lower approval rates for rural applicants or informal workers often due to strict collateral requirements or the absence of credit histories (Janvry, McIntosh, & Sadoulet, 2010). Furthermore, rejections due to lack of collateral may indicate the need for alternative models, such as income-based repayment (Beck & Torre, 2007).

### *C. Analytical Inclusion Metrics*

Analytical Inclusion Metrics address *data representation, algorithm design,* and *transparency*. **Data Representativeness metric** is critical for fair credit assessments; Aggarwal (2015) stresses that datasets should reflect varied demographics, such as income, location, and social background. Binns (2018) highlights the need for data diversity, while Banerjee et al., (2015) underscore the importance of capturing borrower heterogeneity.

**The Algorithm Design metric** assesses whether credit scoring models fairly evaluate individuals across demographic groups. Kleinberg et al., (2018) highlight the need for predictive parity, ensuring borrowers with similar creditworthiness have equal chances of approval. The literature shows that traditional scoring systems often rely on limited datasets, excluding borrowers with limited credit history (Hurley & Adebayo, 2016). The literature introduces the term *"thin-file borrowers"* to refer to individuals with limited credit history, while *"no-file borrowers"* refers to individuals with a lack of any formal credit record; both groups are often excluded from credit systems (Hurley & Adebayo, 2016).

**Transparency and Interpretability Metrics** evaluate how the systems promote understanding and trust. Doshi-Velez and Kim (2017) highlight borrowers' understanding of approval or rejection decisions can increase trust in the systems. Moreover, Hurley and Adebayo (2016) warn that big-data-driven models often lack transparency, preventing borrowers from contesting decisions. Therefore, utilizing various alternative data needs to be balanced with the explainability of the models and the outcome. Furthermore, according to Kleinberg et al. (2018), examining default rates across demographic groups is essential to monitoring fairness in algorithm outcomes.

### *D. Literacy Metrics*

Low awareness of financial products remains a challenge in inclusive lending; therefore, specific approaches are required to address this issue. For example, the literature shows that text message reminders in Bolivia, Peru, and the Philippines increased savings rates by 6%, illustrating the impact of literacy (Klapper, El-Zoghbi, & Hess, 2016). Literacy metrics should capture financial knowledge and the contextual factors influencing financial behaviors. Due to cultural familiarity, many underserved populations rely on informal savings systems, highlighting the importance of considering local values in designing inclusive lending products (Dupas et al., 2011). Financial literacy metrics should be able to monitor how credit access translates into productive outcomes (Giné & M. Townsend, 2004).

Borrowers with limited financial knowledge may not fully understand complex repayment structures (Dupas et al., 2011; Karlan & Zinman, 2010; Cull et al., 2009). Moreover, research highlights that women, particularly in developing economies, tend to have lower financial literacy levels than men (Aterido, Beck, & Iacovone, 2013). Targeted financial education programs can empower women to make informed decisions.

The following table summarizes Metrics Types, Categories, and several examples of inclusion metrics.

*Table 4. Literature-based Inclusion Metrics*

| Metrics Types | Metric Category | Metrics Example |
|---|---|---|
| **Penetration Metrics** | Physical Access Metrics | Lending service point density; New loan opening rate (remote); Regional disparities |
| | Digital Access Metrics | |
| **Financial Access Metrics** | Microloan Access Metrics | Microloan Outreach Rate; Interest Affordability Ratio; Loan Approval Rates |
| | Loan Affordability Metrics | |
| | Loan Approval and Rejection Metrics | |
| **Analytical Inclusion Metrics** | Data Representativeness Metrics | Data Diversity Index; Predictive Parity Index; Credit Dispute Resolution Rate; Inclusion Bias Detection Score |
| | Algorithm Design Metrics | |
| | Transparency and Interpretability Metrics | |
| **Literacy Metrics** | Financial Awareness Metrics | Borrower Financial Literacy Index; Financial Literacy Impact Index |
| | Financial Education Impact | |

This section has reviewed the literature on metrics for evaluating inclusion within lending systems as an initial response to RQ2. Chapter 4 integrates these findings with the interviews' results.

### 3.5. IT Artifacts and The Role of Reference Architecture

#### 3.5.1. What is an IT artifact?

IT artifacts are central to Design Science Research (DSR), serving as the constructs, models, methods, and implementations developed to solve problems or achieve specific goals within information systems. These artifacts provide the foundation for creating, evaluating, and guiding system development across various contexts.

March & Smith (1995) introduced a foundational classification of IT artifacts into constructs, models, methods, and instantiations. They also identified associated research activities such as building, evaluation, theorizing, and justification. *Constructs* represent domain-specific terms or concepts (e.g., definitions in data modeling); *models* illustrate connections among constructs to depict system requirements; *methods* specify processes for task completion based on constructs and models; and *instantiations* are prototype or implemented systems. This classification emphasizes the *building* and *evaluation* of artifacts in DSR, in contrast to the theory-driven focus (*theorizing* and *justification*) of natural sciences.

Hevner et al (2004) further consolidate the understanding of IT artifacts, summarizing them as *'constructs (vocabulary and symbols), models (abstractions and representations), methods (algorithms and practices), and instantiations (implemented and prototype systems')* (Hevner, March, Park, & Ram, 2004, p. 271). This holistic view collectively addresses system design's technical and socio-technical dimensions and their role in DSR.

Offermann et al. (2010) refined artifact categorization by identifying eight artifact types: System Design, Requirements, Method, Algorithm, Pattern, Guideline, Language/Notation, and Metric. These encompass system specifications and operational components. *System design* and *requirements* refer to the description and specification of the system. Methods and Algorithms are similar in defining tasks in a specific order; *algorithms* focus on computer activities, whereas *methods* are sequences of functions executed by human beings in various roles and responsibilities. *Patterns and guidelines* help generalize system design (pattern) and system development (guidelines), improving system adaptability and user accessibility. *Language/notation* is the interconnection between a concept in notation and rules. *Metrics* are used for system evaluation quantitatively and qualitatively. Offermann et al. (2010) explain that the *model* was initially considered one of the artifact's types; however, it was removed as they believe its characteristic can be found in another type such as *System Design*, *Language/Notation*, and *Metrics*.

Weigand et al. (2021) distinguish four types of IS artifacts: *Primary Artifacts* consist of Algorithms, Programs, and Applications; *Secondary Artifacts* consist of Languages, Constructs, and Methods; *Instantiations*; and *Models*. They explain four types of models in DSR: analysis models of socio-technical systems, design models of technical artifacts, analysis models, and scientific models of DSR artifacts. They argue that the definition of models in the DSR context could be different from the context of models for scientific understanding and mathematical tradition.

Drawing on these diverse perspectives, this research defines its deliverables through multiple lenses: as a Method (March & Smith, 1995), as Guidelines (Offermann et al., 2010), as Analysis Models of Socio-Technical Systems (Weigand et al., 2021), or as Methods that guide how to solve a particular problem (Hevner et al., 2004). Specifically, this study focuses on designing a reference architecture for an inclusive lending system. Table 5 outlines the key artifacts developed in this research. The primary deliverable is a reference architecture comprising value-based requirements, design principles, and architecture components.

*Table 5: Elements making up a reference architecture*

| | Element | Explanation |
|---|---|---|
| 1 | Value-based Requirements | Eliciting core requirements that align system functionality with inclusion value and value qualities |
| 2 | Design principles | Guiding the design philosophy for the reference architecture |
| 3 | Architecture components | Reflecting business feasibility and technological implementation |

### 3.5.2. Reference Architecture and Inclusion

A reference architecture provides a high-level guideline for information systems and is particularly useful in complex domains such as lending systems. By abstracting the guidelines, RA enables adaptability across diverse contexts and applications. Cloutier et al. (2010, p. 17) describe reference architecture as *"capture the essence of existing architectures and the vision of future needs and evolution to provide guidance to assist in developing new system architectures."* Angelov et al. (2012) refine this concept by emphasizing the importance of aligning architectural goals, design, and context.

Reference architecture generally falls into two types: research-driven and practice-driven (Angelov, Trienekens, & Grefen, 2008). *Research-driven architectures* address novel areas where established knowledge is lacking, creating frameworks to guide new system concepts developed from scratch without relying on any available architectures or systems (Galster & Avgeriou, 2011). They are often speculative, laying the groundwork for future systems. *Practice-driven architectures*, by contrast, build on existing knowledge and best practices, providing frameworks grounded in current needs but adaptable for future demands. The reference architecture developed in this study adopts a practice-driven approach, as it leverages established knowledge in fintech and lending to meet inclusion needs while allowing for future adjustments.

Cloutier et al. (2010) highlight that reference architectures address multiple objectives, including technology deployment, infrastructure design, and business alignment. In the fintech sector, these architectures address system interoperability, scalability, and user accessibility, all critical for inclusive lending systems. Creating a reference architecture helps manage system complexity, respond to industry changes, and enhance product effectiveness (Cloutier, et al., 2010).

Interoperability and streamlined development are additional benefits of a well-defined reference architecture, serving as a guideline to improve system components, reduce costs, and enhance communication (Weyrich & Ebert, 2016). Angelov et al. (2012) emphasize that multi-dimensional analysis is crucial for aligning stakeholder goals and technical requirements within the design of reference architectures.

Stakeholder concerns are central to the design of reference architectures, encompassing functionality, feasibility, and system performance. Each architectural component should be grounded in a clear rationale that considers trade-offs, available options, and possible alternatives to achieve this.(Maier et al., 2001). As shown in Figure 14, a holistic approach integrates customer, technical, and business contexts (Cloutier, et al., 2010). *The customer context* emphasizes user needs and inclusion, *the technical context* addresses functional and performance requirements, and *the business context* focuses on economic feasibility. Together, these dimensions ensure that the reference architecture aligns with stakeholder priorities, while remaining adaptable to the evolving needs of lending systems.

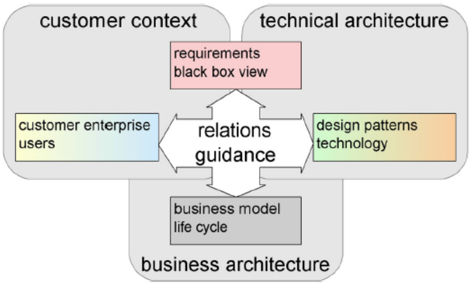



*Figure 14: Components of a reference architecture (Cloutier, et al., 2010)*

## 3.6. Design Principles for Inclusive Lending System

### 3.6.1. What are Design Principles?

Design principles serve as foundational guidelines that shape the development of systems, ensuring the systems meet technical and ethical requirements. In this study, design principles guide the development of lending systems that promote inclusion for marginalized segments.

Gregor and Jones (2007) emphasize that *design principles* are essential to Information Systems Design Theory (ISDT), providing a structured approach to solving complex *design challenges*. Their framework differentiates *design theories* from natural science methodologies, highlighting the unique complexities of designing systems tailored to user needs. Yang et al. (2012) further expand on this by arguing that design principles should align system features with user requirements. In this study, design principles play a critical role in ensuring that the proposed reference architecture supports inclusion while addressing the challenges faced by marginalized groups.

While Gregor and Jones (2007) emphasize the theoretical foundation of design principles, Möller et al. (2020) highlight their dual role as both *static guidelines* and *dynamic processes*. Design principles may describe static elements, such as rules or functionalities (nouns), and dynamic aspects, such as iterative processes (verbs), offering structured guidance for achieving practical solutions. Fu et al. (2015) differentiate principles, guidelines, and heuristics: *Principles* are evidence-based rules, *guidelines* are context-dependent recommendations, and *heuristics* rely on intuition and tacit knowledge.

In this research, design principles serve as essential rules that guide the development of RA. These principles ensure the challenges are addressed by offering structured yet adaptable guidance. The table below presents definitions and interpretations of design principles from the literature.

*Table 6. Definitions of principles from the literature on design principles in design science and information system*

| Category | Explanation |
|---|---|
| Definition | "Normative, reusable, and directive guidelines, formulated towards taking action by the information system architects" (Bharosa & Janssen, 2015, p. 4). |
| Description | "Following the duality of the term design, as both a verb and a noun, design principles may both address the process of designing an artifact (i.e., the development process), as well as its functionalities (i.e., the system features)" (Möller, Guggenberger, & Otto, 2020, p. 210) |
| Description | "…the formulation design principles that follow a nomothetic approach about how to design a class of things and their idiosyncratic use in highly contextual design practice" (Kruse, Seidel, & Purao, 2016, p. 39) |
| Description | "…principles in online course design and in a well-conceived way can significantly contribute to the solution of problems, such as low learning performance, attendance, motivation, engagement, social presence, etc., that can be experienced in online courses" (Sezgin & Yüzer, 2022, p. 486) |
| Description | We base these principles on our experience in developing the IBM System S middleware, a stream processing runtime system; Spade, its accompanying distributed application composition language; as well as our hands-on work in building several real-world applications from diverse domains using this computational infrastructure (Turaga, et al., 2010, p. 1074) |
| Template | Provide the system with [material properties such as specific features] to afford users [activity of user/group of users], given that [boundary conditions] (Seidel, Kruse, Székely, Gau, & Stieger, 2018) |
| Description | "…design principles as common ground for implementing corresponding solutions" (Nadj, Knaeble, Li, & Maedche, 2020, p. 140) |
| Description | "A set of design principles can assist her in traversing this problem space and in identifying feasible solutions efficiently and effectively" (Schneider, Seidel, Basalla, & Brocke, 2023, p. 66) |

Table 6 highlights diverse definitions and descriptions of design principles from the domain of design science and information systems. These definitions illustrate the multi-faceted role of design principles as *normative guidelines* and *actionable directives* in the design process. For instance, some definitions emphasize their dual function in guiding the development process and the system's functionalities, while others focus on their capacity to address specific challenges or serve as common ground for implementing solutions. Including a practical template further demonstrates how design principles can provide structured guidance in real-world applications. This study defines design principles as *distilled insights from literature and practice, serving as essential guidelines for the design process*.

### 3.6.2. Literature Review of Design Principles in Information System

Understanding current trends in IS design principles is essential for designing a reference architecture that supports inclusion. Inspired by Gregor and Jones (2007), this study conducted a systematic literature review, starting with 1687 articles containing "design principles" and related keywords. After narrowing the focus to computer science and information systems, 349 articles were identified. Further refinement through keyword analysis, abstract reviews, and citation tracking reduced the pool to 165 relevant documents. From these, 23 papers were selected for their significant contributions to IS design principles (Figure 15). Topics unrelated to this intersection, such as "Design principles in medical contexts" or "GDPR compliance," were excluded to maintain relevance.

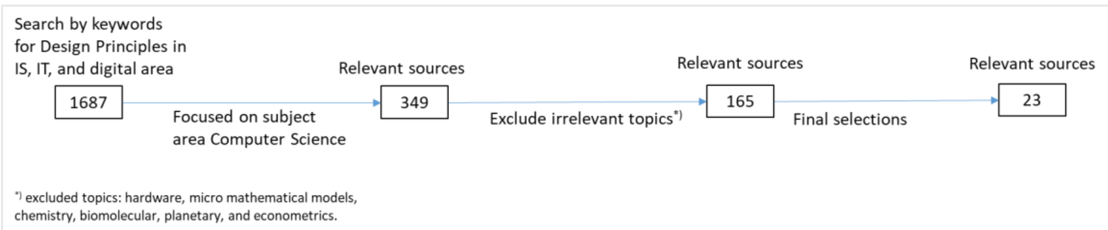



*Figure 15. Literature review about Design Principles in Information system*

One of the key references in this review is the taxonomy developed by Möller et al. (2020), which categorizes design principles across multiple dimensions, including perspective, research design, meta-requirement source, and evaluation iterations (Figure 16). Their work highlights the multifaceted nature of design principles in IS, offering valuable insights for guiding this study.

| Dimension ($D_n$) | Characteristics ($C_{nm}$) | | | | | EX |
|---|---|---|---|---|---|---|
| Perspective | Supportive | Reflective | | | | NE |
| Research Design | DSR | A(D)R | Qualitative | Case Study | | NE |
| MR Source | Literature | Theory | Interviews | Workshops/ Focus groups | None | NE |
| DP Design | Derived | Extracted | Responsive | | | NE |
| Iterations | Single | Multiple | | | | ME |
| Evaluation | Expert/User Feedback | Instantiation/ Field Testing | Argumentation | | | NE |
| Formulation | Free | Based on Template | | | | ME |

*Figure 16. Dimension of design principles research by Möller, Guggenberger, & Otto (2020)*

Differing from Möller et al. (2020), who categorize design principles across seven dimensions; this study emphasizes two key dimensions, **perspective** and **research design**, with the addition of a new dimension, **methodology**. Perspective refers to when design principles are developed, either *supportive* (before an artifact exists) or *reflective* (during development or availability). Research design encompasses methods such as Design Science Research (DSR), Action Design Research, qualitative studies, and case studies. Methodology, the new dimension we propose, highlights systematic frameworks and procedures for crafting design principles.

Building on this foundation, we analyzed various scholarly works. For example, Matheus et al. (2021) adopt a deductive approach within the DSR framework, aligning challenges systematically with design principles. Lindgren et al. (2004) use prototyping to test their proposed principles, while Nadj et al. (2020) conduct a qualitative literature review without incorporating interviews or prototyping. The table below summarizes these differing approaches to formulating design principles in information systems, illustrating the diversity of methodologies.

*Table 7. Highlighted literature about Design Principles in the domain of Information Systems*

| Perspectives | Methodology | Literature | Topics |
|---|---|---|---|
| **SUPPORTIVE** | | | |
| Qualitative study | Comparative study of existing technologies | (Belcastro, Cantini, Marozzo, Orsino, & Talia, 2022) | Design principles for programming big data analysis systems. |
| Qualitative study | Delphi panel methodology | (Sezgin & Yüzer, 2022) | Design principles for adaptive gamification in online courses. |
| Qualitative study | Literature | (Nadj, Knaeble, Li, & Maedche, 2020) | Design Principles for Interactive Labeling Systems in Machine Learning. |
| Qualitative study | Mapping from risk/challenges/threat | (Matheus, Janssen, & Maheshwari, 2020) | Design principles for data-driven dashboards in smart cities. |
| Qualitative study | Qualitative, experiment | (Johnson-Glenberg, 2018) | Design principles for best practices in educational virtual reality. |
| Qualitative study | Mapping from risk/challenges/threat | (Kömmerling & Kuhn, 1999) | Design principles for tamper-resistant smartcard processors. |
| Qualitative study | Available design framework | (Kim, Kim, Khera, & Getman, 2014) | Design principles for flipped classroom experiences in urban universities. |
| DSR | deductive approach | (Matheus, Janssen, & Janowski, 2021) | Design principles for digital transparency in government. |
| DSR | Literature | (Schneider, Seidel, Basalla, & Brocke, 2023) | Design Principles for Green Data Mining. |
| ADR | Literature, interviews | (Zuiderwijk, Janssen, Choenni, & Meijer, 2014) | Design principles for improving the process of publishing open data. |
| ADR | Prototyping | (Pan, Li, Pee, & Sandeep, 2021) | Design principles for wildlife management. |
| Case study | Prototyping | (Lindgren, Henfridsson, & Schultze, 2004) | Design principles for competence management systems. |
| Case study | Requirements followed by DP | (Chaturvedi, Dolk, & Drnevich, 2011) | Design principles for virtual worlds. |
| Case study | DP with simulations | (Nobre, et al., 2019) | Design principles for the integration of VSDN and fog computing. |

| Perspectives | Methodology | Literature | Topics |
|---|---|---|---|
| Case study | Challenges - design principles - architecture | (Salmon & Ray, 2017) | Design principles for developing a stream-based framework used in the analysis of mobility data. |
| Principle-based design | deductive approach | (Bharosa & Janssen, 2015) | Design methodology and principles for information quality assurance. |
| **REFLECTIVE** | | | |
| Case study | Lesson learned | (Bardram, 2004) | Design principles for context-aware computing in hospital environments |
| Qualitative | Issue mapping and literature review | (Darejeh & Singh, 2013) | Design principles for user interfaces for individuals with limited computer literacy |
| Case study | ontology-based framework | (Bruno, et al., 2019) | Design principles for culturally competent personal robots |
| Qualitative | Case study | (Turaga, et al., 2010) | Design principles for stream processing applications |
| **SUPPORTIVE AND REFLECTIVE** | | | |
| DSR | Action research, participatory design, situation awareness | (Yang, Su, & Yuan, 2012) | Design principles for emergency response information platforms |
| Case study | Literature research, performance analysis, and database design | (Deperlioglu & Arslan, 2010) | Design principles for web-based distance education systems |
| DSR | Prototyping | (Seidel, Kruse, Székely, Gau, & Stieger, 2018) | Design principles for sensemaking support systems |

Table 7 presents a range of methodologies employed in developing design principles within Information Systems. These methodologies include qualitative studies, deductive approaches, and case studies, often combined to ensure a thorough evaluation. For instance, some studies focus on prototyping to test principles in real-world scenarios, while others use mapping techniques to address challenges or risks. While the number of references may seem limited, they provide valuable insights into how researchers adapt methodologies to fit their objectives and the specific context of their work.

In summary, the methodologies in Table 7 highlight the importance of context-aware design principles in creating systems that improve inclusion. This research builds on these foundations to develop an inclusive reference architecture for lending systems, as will be explored in subsequent chapters.

### 3.7. Conclusion

This chapter provides a structured review of key concepts, challenges, and metrics from the literature. **Section 3.2** established ***the theoretical foundations of inclusion*** in financial systems. Drawing on the philosophical perspectives of Sen's Capability Theory, this study highlights the need to go beyond mere access by fostering equitable opportunities and empowering underserved populations. Frameworks like Value-Based Engineering operationalize these ethical principles, translating values such as inclusion into system requirements.

**Section 3.3** addressed Research Question 1 (RQ1) by categorizing ***the challenges of inclusion*** into six categories. *Technology challenges*, including reliance on traditional credit scoring models and limited scalability, exclude individuals without convincing financial histories. *Financial lending* challenges reflect structural biases in loan approval processes, emphasizing low-risk borrowers while sidelining marginalized groups. *Organizational challenges* address stability over inclusion, with rigid risk management frameworks and resource allocation reinforcing exclusion. *Policy and regulatory* constraints further complicate inclusion, as inflexible frameworks often fail to address the needs of diverse borrower segments. *Socio-cultural factors*, such as gender discrimination and limited financial literacy, deepen disparities, while *trust deficits* undermine borrower and lender confidence. These theoretical insights provide a structured understanding for addressing RQ1. Chapter 4 expands on these findings by integrating insights with interviews.

**Section 3.4** addresses RQ2 from the literature by developing ***inclusion metrics***. The metrics are clustered in four categories: penetration, financial access, analytical inclusion, and literacy. *Penetration Metrics* focus on how underserved populations are reached, addressing physical infrastructure and digital access. *Financial Access Metrics* examine whether credit services are fairly distributed, affordable, and accessible. *Analytical Inclusion Metrics* assess fairness and transparency in data-driven systems, highlighting the importance of balanced datasets and inclusive scoring models. *Literacy Metrics* measure how well the users understand financial products, emphasizing the importance of financial education for better decision-making. Chapter 4 will further refine these metrics with the interview's results.

**Section 3.5** examines IT artifacts and their role in Design Science Research (DSR), focusing on designing RA as a key artifact to promote inclusion in lending systems. IT artifacts, including constructs, models, methods, and instantiations, are foundational tools for designing, evaluating, and guiding systems in diverse contexts. This research identifies a reference architecture as its primary deliverable, structured around three core elements: value-based requirements, design principles, and architecture components.

**Section 3.6** explains the importance of ***design principles*** in this study. These principles serve as structured guidelines that align socio-technical requirements with the needs of underserved populations. By examining existing studies, the section highlights varied approaches to developing design principles, such as prototyping, literature reviews, and structured methodologies. Insights from this section inform how to develop the design principles that align with the goal.

**General requirements** for lending systems that promote inclusion have been identified in this chapter, focusing on the need for non-traditional data for credit assessment, flexibility in loan terms, transparency in decision-making processes, and mechanisms to foster trust. These requirements provide a high-level understanding of what lending systems must achieve to overcome systemic exclusion. The detailed exploration of requirements will be addressed in Chapter 5.

The next chapter will expand on the insights from this chapter by integrating interview results, offering a more comprehensive understanding of inclusion challenges, and refining the proposed metrics. The challenges, requirements, and metrics will be a foundation for developing Value-Based Requirements (VBRs) and Design Principles in Chapter 5.

## Chapter 4: Socio-technical Challenges[2] and Metrics for Inclusion from Practice

### 4.1. Introduction

Building on the theoretical foundation in Chapter 3, this chapter integrates literature insights with interviews to identify the inclusion challenges and the inclusion metrics in lending systems. This chapter addresses two research questions: *What are the challenges to inclusion in lending systems* **(RQ1)?** and *What indicators can measure inclusion in lending systems* **(RQ2)?** The challenges in Section 3.3 and the metrics in Section 3.4 are revisited and expanded with interview results.

The subsequent sections of this chapter are structured as follows: Section 4.2 integrates the literature-based challenges with the results of the interviews, and Section 4.3 integrates literature-based metrics with the insights from the interviews. Section 4.4 provides an overview of challenges and metrics. The findings in this chapter establish the foundation for the Reference Architecture (RA) in Chapter 5 by aligning *challenges* and *metrics* with actionable design principles and system requirements.

### 4.2. Socio-technical challenges to Inclusion in Lending Systems (RQ1)

This section addresses RQ1: *What are the challenges to inclusion in lending systems?* While the literature outlined foundational challenges (Section 3.3), the interview insights broadened this understanding, identifying challenges that existing studies may not have fully addressed.

The interviews aimed to capture practical perspectives on inclusion challenges from stakeholders in the lending ecosystem. Indonesia was selected as the geographic context for this study due to its rapid development in digital lending, particularly in P2PLS, and its diverse financial inclusion landscape. The interview protocol is provided in **Appendix 14**. We interviewed respondents representing *eight key stakeholder groups* within the lending landscape.

A total of *fourteen participants* were recruited through purposive sampling to ensure that each had direct involvement in lending systems or financial inclusion initiatives. Participants represented regulators and policy-makers, ministry representatives, academics with expertise in banking and inclusion, P2P lending practitioners, microenterprise owners, senior banking professionals, and private investors. Within this group there were eleven males and three females, covering roles such as division heads, directors, operational managers, and founders. The participants' age brackets ranged from early thirties to late fifties, reflecting seniority and experience in their fields.

Each participant was assigned an anonymized label based on stakeholder group and order of interview (e.g., R1–R7 for regulators, F1–F3 for fintech practitioners, B1 for bank directors, A1 for academics, M1 for MSME representatives, I1 for investors). These labels are used when referring to specific statements throughout this chapter.

The interviews followed a semi-structured format, allowing flexibility to explore themes in depth while maintaining consistency across topics. All sessions were conducted with prior ethics approval, audio-recorded with informed consent, and transcribed for analysis. The data collected from the interviews were analyzed in two stages. Initially, *open coding* was applied to identify emergent themes and patterns. This coding highlighted distinct categories of challenges, enabling a deeper exploration of how stakeholders perceive inclusion issues in lending. Following this, we conducted *a thematic analysis* using Atlas.ti software for further interpretation.

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[2] Parts of this chapter are based on the following publications:
Sulastri, R., & Janssen, M. (2023, July). Challenges in designing an inclusive Peer-to-peer (P2P) lending system. In Proceedings of the 24th Annual International Conference on Digital Government Research (pp. 55-65).

To structure the identified challenges, we drew upon the socio-technical elements introduced in Sulastri & Janssen (2022), which outlines five core elements (Data and Processing, Business, Organizational, Policy and Governance, and Culture) within P2PLS. Recognizing the broader scope of this study, we expanded this classification to include a sixth category: literacy and education.

#### 4.2.1. Integrating Inclusion challenges from literature and interviews

Through stakeholder interviews combined with the results from the literature in Section 3.3, we identified challenges as in Figure 17. This figure illustrates the challenges network, displaying how each challenge interrelates within the lending ecosystem. In this network:

- Nodes represent individual challenges.
- Node Size (G) reflects the frequency of a specific challenge mentioned in the interviews, even though higher frequency does not reflect the greater importance.
- Edges (D) illustrates the *association* between challenges.

The connections noted here indicate *the presence of relationships* rather than quantifying the magnitude (strength) or direction of these connections. For instance, trust in the system is associated with ten other challenges, including information asymmetry, company reputation, data protection regulation, customer protection regulation, the presence of illegal lending companies, perceived benefit, transparency, and moral hazard.

Notably, several challenges identified in the literature were *less prominent* in interview discussions (G=0, indicated by white blocks, such as scalable architecture and gender discrimination), possibly due to differing practical priorities of stakeholders, which did not necessarily align with the researcher's focus. Conversely, the interviews highlighted previously underexplored areas, including privacy and security, underscoring practical concerns that may lack visibility in the literature. Furthermore, the interviews indicated the need for an additional category on *Literacy and Awareness* while we merged the cultural challenges and trust. This was necessary to capture challenges related to low financial literacy, gaps in awareness, and education deficits, which were frequently highlighted by interviewees (based on the value of G=13). The following explains each of the challenges presented in Figure 17.

***A. Technology and Data***

**Technology**

Technology-related challenges are widely discussed in the literature. Traditional scoring systems heavily depend on historical financial data and credit histories, which work well for borrowers with documented financial profiles but exclude individuals without such records, like low-income workers or those in informal economies (Suryono et al., 2019). This reliance exacerbates financial exclusion, highlighting the need for innovative scoring systems to accommodate non-standard borrower profiles. Issues such as data quality (Zhang et al., 2016; Guo et al., 2016), data preparation (Li, Ding, Chen, & Yang, 2018), and addressing class imbalances (Chen et al., 2021; Niu et al., 2020; Li et al., 2020) are critical in improving credit scoring models.

As emphasized by Lenz (2016), scalability remains an important theoretical concern for extending lending services to underserved regions. Scalable architecture can support broader geographical outreach and adapt to diverse user needs. However, scalability issues (G=0, D=0) did not resonate with stakeholders during interviews. Instead, stakeholders emphasized the challenges of system availability (G=3, D=1), reliability (G=1, D=2), and user interface (G=1, D=1).

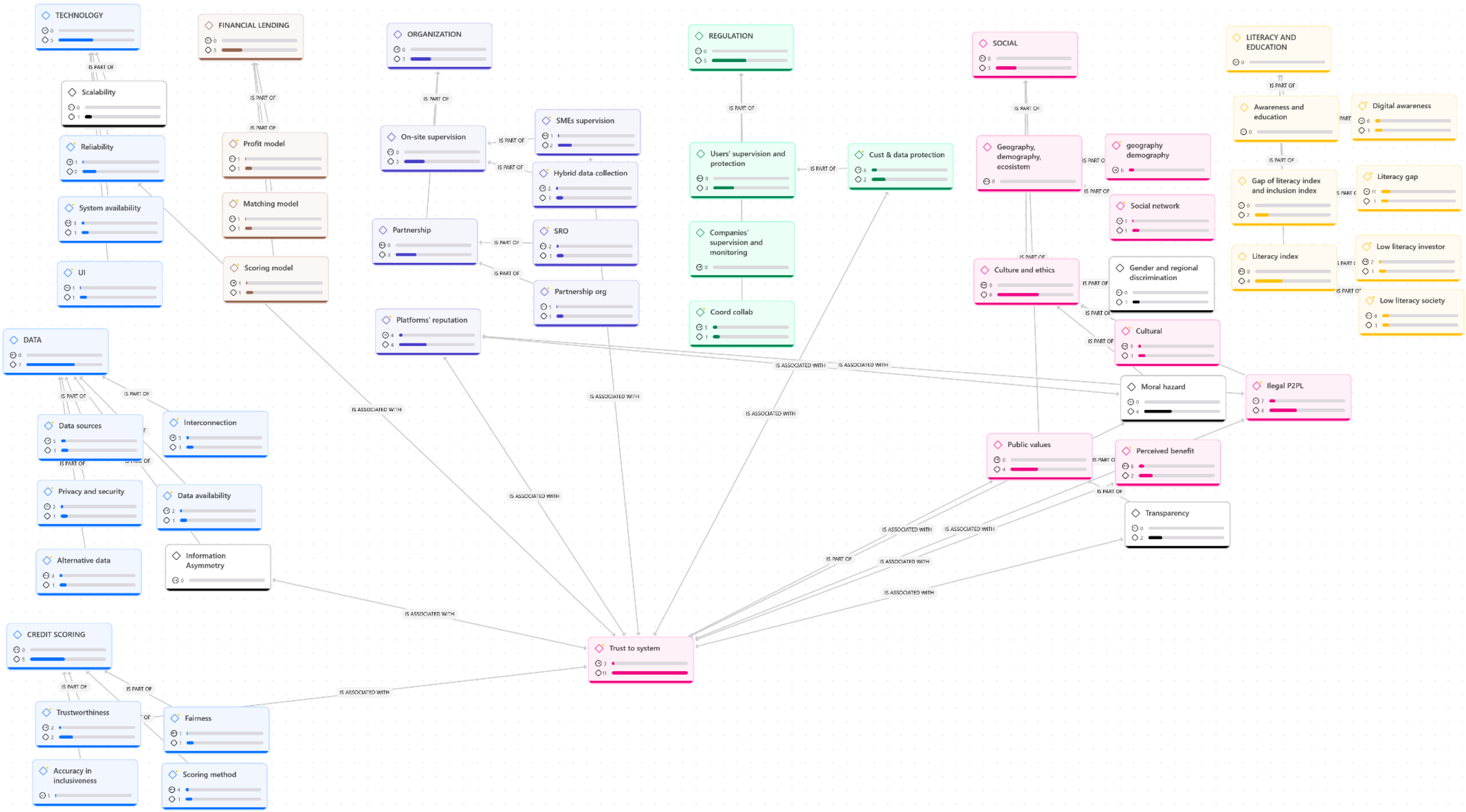



*Figure 17. Network of challenges: Initial identification from SLR and interviews (Sulastri & Janssen, 2023)*

**Data**

Data management challenges dominate discussions in literature and interviews, although stakeholder priorities differ. The literature frequently addresses data quality, preparation, and integration issues for improving credit scoring and default prediction models (Li et al., 2020; Akanmu & Gilal, 2019; Zhang et al.,2016; Guo et al., 2016). Meanwhile, stakeholders focused on trust in data sources (G=5, D=1), data interconnection (G=3, D=1), privacy and security (G=3, D=1), data availability (G=2, D=1), and alternative data (G=3, D=1) as challenges to inclusion. The lack of data interconnection mechanisms prevents platforms from validating borrower information across multiple systems.

Privacy and security concerns (G=3, D=1) are also featured in stakeholder discussions. While the literature often discusses these concerns in the context of model development (Ariza-Garzon et al., 2021; Niu et al., 2020), stakeholders stressed the need for frameworks to protect sensitive borrower data, particularly in regions with underdeveloped data protection regulations. Addressing these issues is crucial to building trust in lending systems. Moreover, information asymmetry (G=0, D=2) is a significant theme in the literature but was not explicitly mentioned by stakeholders.

**Modeling**

Credit scoring and default prediction modeling challenges are a critical focus of the literature, appearing in discussions of class imbalance, model development, and algorithmic fairness (Chen et al., 2021; Niu et al., 2020; Li et al., 2020; Li et al., 2018; Wang, et al., 2018). A well-designed credit scoring system can increase profits while minimizing bad debts (Bellotti & Crook, 2009). Interviews emphasize the following challenges: trust in scoring algorithms (G=2, D=2), fairness (G=1, D=1), accuracy and inclusiveness (G=1, D=1), and scoring methods (G=4, D=1).

**Integrating Literature and Stakeholder Insights**

While the literature provides a broad theoretical foundation, stakeholders *reflect a more immediate focus* on data reliability, system availability, data availability, data interconnection, and data privacy.

***B. Financial lending Challenges***

The literature underscores the importance of innovative risk assessment techniques to address scoring model limitations. For instance, incorporating non-traditional data sources can better capture the realities of underserved borrowers. However, these methods require significant investment in algorithmic development and data integration (Ariza-Garzon et al., 2021). Meanwhile, interviews emphasized the *scoring model in general* (G = 1, D = 1), *profit models* (G = 1, D = 1), and *matching models* (G = 1, D = 1) as challenges. Interviews also highlight the difficulty of balancing inclusion with profitability under strict policies, such as maintaining low non-performing loan (NPL) rates.

*The interviews mentioned the profit model*, with stakeholders pointing out the challenge of setting interest rates that remain affordable for borrowers yet profitable for platforms. Borrower-defined interest rates (Syamil et al., 2020; Zhao et al., 2017; Chen et al., 2016) offer flexibility to borrowers but limit platforms' sustainability. Meanwhile, system-defined rates, though efficient, can marginalize borrowers unable to meet rigid financial terms (Caldieraro et al., 2018). Stakeholders noted that these trade-offs necessitate transparency and trust-building mechanisms, such as group networks as discussed in Chen et al. (2016). Group networks, as part of social capital, are shown to improve the repayment performance of individuals (Chen, Zhou, & Wana, 2016).

**Integrating Literature and Stakeholder Insights**
The literature and interviews identify scoring and profit models as critical challenges. Issues such as managing *non-performing loan* rates and setting interest rates that are affordable and profitable are crucial in addressing inclusion challenges.

### *C. Organizational Network Challenges*

Lending systems face organizational challenges in three main areas: on-site supervision for data collection, partnerships, and reputational issues.

**On-site supervision challenges for data collection**
According to the literature, hybrid operational models integrating digital and offline strategies are crucial to improving accessibility and trust, especially in underserved segments (Ravishankar, 2021). Offline events, such as financial education workshops or in-person loan verification, are emphasized as complements to digital systems to reach rural and low-literacy populations. Stakeholder interviews reinforced the importance of *hybrid offline approval* (G = 2, D = 1) and *SME* supervision (G = 1, D = 2) to improve data availability. One of the most pressing challenges in serving marginal borrowers in Indonesia is not merely the issue of incomplete data but the absence of data. Fintech providers have begun partnering with local agents to collect borrower information actively.

**Partnership**
The literature stresses the role of partnerships between lending institutions, such as banks, big data companies, and non-government organizations, to expand credit access. Stakeholder interviews highlighted two subcategories under partnerships: standard partnership (G = 1, D = 1) and self-regulated organizations (SROs) (G = 2, D = 1), industry associations that facilitate data sharing and promote responsible lending standards among fintech companies.

**Reputation**
Reputation emerged as an important challenge in stakeholder interviews (G = 4, D = 5). The literature discusses this challenge, identifying regulatory compliance as the influencing factor (Ping et al., 2019). Stakeholders reemphasize these findings, highlighting public concerns about unethical lending practices, data breaches, and predatory lending.

**Integrating Literature and Stakeholder Insights**
The literature and stakeholder interviews consistently highlight the difficulties in on-site data collection, the need for effective partnerships, and concerns over reputation and public trust.

### *D. Regulatory and Governance Challenges*

Regulatory challenges are categorized into User Supervision and Protection, Company Supervision and Monitoring, and Coordination and Collaboration**.**

**User Supervision and Protection**. The literature emphasizes the importance of customer and data protection, especially in regions where regulatory frameworks for data privacy remain underdeveloped (Au & Sun, 2019). Stakeholders strongly echoed this concern, as indicated by *Cust & Data Protection* (G = 6, D = 2), with G=6 making it the most frequently discussed issue.

**Companies' Supervision and Monitoring.** The literature highlights gaps in regulatory frameworks, such as policy support for underserved segments (Reza-Gharehbagh et al., 2020; Tambunan, 2015). This aligns with the results of the interviews with G=5 and D=3.

**Coordination and Collaboration.** Both literature and interviews point to coordination as a major challenge. Interview findings (G = 5, D = 1) stress its significance, noting that regulatory misalignment across institutions can create barriers for borrowers. Literature echoes this, showing that inconsistent regional regulations hinder innovation and cause inefficiencies (Huang, 2018).

**Integrating Literature and Stakeholder Insights**

The literature and interviews highlight similar concerns around data protection and coordination. These themes appeared frequently in interviews, with data protection (G = 6) and coordination (G = 5). While company supervision is discussed in both sources, the literature emphasizes regulatory support for credit risk and underserved groups. Stakeholders tend to frame these issues as operational.

***E. Social and Cultural Challenges***

Social challenges are grouped into three areas: geographical, demographic, and ecosystem; culture and ethics; and public values.

**Geography, Demography, Ecosystem.** *Geography and demography* (G = 6) are frequently mentioned in the interviews, with stakeholders emphasizing the operational complexities of delivering financial services to remote and underserved regions. This aligns with the literature, which highlights that geographical disparities in access create systemic barriers for borrowers in rural areas, who often lack the infrastructure and digital tools (Chen, Li, & Lai, 2017). While less prominent, *social network (G = 1, D = 1)* was noted as a challenge in interviews. Align with the literature emphasizes the potential of social networks to improve creditworthiness and foster lender confidence (Qiu, Xu, & Zhang, 2010).

**Culture and Ethics.** *Gender and Regional Discrimination* (G = 0, D = 1) were minimally discussed in interviews, suggesting that stakeholders paid limited attention to gender-specific challenges despite their extensive documentation in the literature. Research shows that women often face systemic disadvantages in accessing credit, including higher interest rates and biases in risk assessments (Chen, Li, & Lai, 2017). *Cultural challenges* (G = 3, D = 1) were moderately emphasized, with interviews pointing to the need for culturally sensitive financial systems. Literature supports this by highlighting the importance of addressing socio-cultural norms and collective behaviors, which can influence repayment (Qiu, Xu, & Zhang, 2010). Stakeholders stressed the necessity of aligning system designs with local values to enhance borrower trust and engagement. *Moral Hazard* (G = 0, D = 4), while not explicitly prioritized by stakeholders, remains a critical issue in the literature. Borrowers with limited financial knowledge often misuse funds (Suryono et al., 2019).

**Public Values.** *Illegal P2PL* (G = 7, D = 4) was a dominant concern in interviews. Stakeholders described how unregulated or predatory lending operations damage the reputation and create a negative perception. Literature aligns with this, emphasizing that such practices result in trust issues and discourage borrower participation (Tambunan, 2022). *Perceived Benefit* (G = 6, D = 2) also emerged as a key theme. Literature suggests that clear communication about loan benefits and repayment terms can enhance borrower trust, reducing disengagement and improving overall inclusion (Yang & Lee, 2016). *Transparency* (G = 0, D = 2) was noted in the literature as a trust-building mechanism, yet stakeholders gave it limited attention. Borrowers often criticize platforms for opaque credit assessment processes, which contribute to mistrust and disengagement (Lenz, 2016).

**Integrating Literature and Stakeholder Insights**

Both literature and interviews highlight geographic and demographic barriers (G = 6) as major challenges, especially in rural areas. Cultural and ethical concerns received less focus. Stakeholders mentioned cultural fit (G = 3) but gave little attention to gender bias or moral hazard despite their importance in the literature. Public values were a top concern in interviews. Illegal P2PL (G = 7) and perceived benefit (G = 6) were important challenges. Transparency was noted in the literature but rarely discussed by stakeholders.

### F. *Literacy and Awareness*

Both the literature and stakeholder interviews underscore literacy and awareness challenges. The category encompasses digital awareness and literacy levels.

*Digital Awareness* (G = 6, D = 1) emerged as a key issue, highlighting the limited ability of borrowers to navigate the system. Users often struggle with understanding online processes, safeguarding their data, or evaluating financial products, leading to misuse, fraud, or poor financial decisions. Both the literature and interviews called for targeted education initiatives to address this gap, focusing on teaching users how to access, compare, and use digital financial services securely (Kohardinata, Soewarno, & Tjahjadi, 2020).

*Literacy gaps, in general,* were the most frequently mentioned concern (G = 11). This gap limits borrowers' ability to leverage lending opportunities. The literature emphasizes that low financial literacy leads to higher default rates (Suryanto, Tahir, & Dai, 2020). Moreover, we differentiate *borrower literacy* (G = 8, D = 1) and *lender literacy* (G = 2, D = 1). Borrowers often lack basic financial skills like understanding interest rates or cash flow management. Additionally, low literacy among lenders creates hesitancy in funding high-risk borrowers. Literature underscores this concern, noting that financial literacy programs are essential to enhance the utility of financial services among low-income groups (Chen, Li, & Lai, 2017). Lenders with low financial literacy may hesitate to fund high-risk borrowers due to their limited understanding of risk mitigation (Yang & Lee, 2016).

**Integrating Literature and Stakeholder Insights**

Literacy and awareness challenges were strongly emphasized in literature and interviews. Literacy gaps (G = 11) were the most frequently mentioned, especially among borrowers (G = 8). Low financial skills limit their ability to manage loans and increase default risks. Lender literacy (G = 2) was also noted, as a limited understanding of risk reduces their willingness to fund high-risk borrowers. Digital awareness (G = 6) emerged as another key issue. Many users struggle to use digital platforms.

### 4.2.2. Conclusions of RQ 1

This study combines a systematic literature review and stakeholder interviews to categorize the challenges to inclusion in lending systems into six categories: *technological and data*, *financial lending, organization*, *regulatory and governance, social and cultural*, and *literacy*.

The table below highlights the key differences between insights from the literature and interviews. Challenges identified in the literature tend to emphasize systemic and long-term issues, whereas stakeholders prioritize more practical and immediate concerns.

*Table 8. The differences between insights from literature and stakeholder interviews*

| Category | Literature Focus | Interview Focus |
|---|---|---|
| **Technology** | Emphasizes long-term challenges like scalable infrastructure, data quality, and modeling techniques to enhance inclusion. | - Prioritizes trust in data sources (G=5), UX usability issues (G=3), and system availability (G=3).<br>- Scalability (G=0) and information asymmetry (G=0) were not emphasized in interviews. |
| **Financial lending** | Focuses on challenges related to innovative risk assessment, profit models, and balancing inclusion with sustainability. | Stresses balancing affordability and profitability in profit models (G=1). Scoring issues were acknowledged but with less depth (G=1). |
| **Organization** | Highlights challenges in building partnerships with external institutions (banks, NGOs) and developing hybrid operational models for system flexibility. | Emphasizes on-site supervision to improve data quality (G=3) and reputation (G =4), with less emphasis on broader partnerships. |

| | | |
|---|---|---|
| **Regulation** | Discusses challenges in creating consistent regulatory frameworks, ensuring consumer protection, and balancing innovation with operational stability. | - Focuses on coordination among institutions (G=5), addressing fragmented regulatory environments, and adapting policies for economic changes.<br>- Technical regulations (G=1) were less emphasized. |
| **Social & Cultural** | Explores challenges related to gender discrimination, moral hazard, and transparency. | - Highlights illegal lending challenges (G=7) and perceived borrower benefits (G=6).<br>- Gender discrimination (G=0) received no mention from stakeholders. |
| **Literacy** | It focuses on systemic educational challenges and literacy issues. | Focuses on literacy gaps (G=11) and digital awareness (G=6). |

Furthermore, this research focuses on the challenges directly related to system-level intervention. While critical to long-term inclusion, certain areas, such as broader social dynamics, cultural biases, and literacy gaps, extend beyond the RA's scope. The challenges addressed in this study are in the following table.

*Table 9. Inclusion challenges addressed in this study*

| Category | Scope of the Reference Architecture in this study |
|---|---|
| **Technology and Data** | - Fragmented and siloed data collection<br>- Limited integration of alternative data<br>- Incomplete or unverifiable borrower profiles<br>- Exclusionary scoring due to reliance on conventional credit data |
| **Financial lending** | - Rigid loan structures incompatible with informal or seasonal income flows<br>- Scoring models prioritizing low-risk borrowers<br>- Lack of adaptive loan products (e.g., flexible loan terms, seasonal repayment). |

### 4.3. Metrics of Inclusion for Lending System (RQ2)

This section addresses RQ2: "**What indicators measure inclusion in lending systems?"** by integrating literature-based metrics from Section 3.4 with insights from interviews. Six semi-structured interviews were conducted in Indonesia, a country experiencing significant growth in lending, especially within the fintech sector. Respondents were selected for their professional experience in financial inclusion, fintech, and financial literacy, representing policy-makers, fintech practitioners, and academics. The data was analyzed using Atlas.ti, qualitative analysis software, to identify recurring themes and classify relevant inclusion indicators for lending.

#### 4.3.1. Inclusion Metrics from Interview Findings

The interviews highlighted a blend of empirical observations and practical recommendations aligned with the respondents' experience. We did not share the literature-based identification of metrics with the respondents to avoid confirmation bias. However, this approach also had its challenges. It took significant time to explain the concept of metrics in this study and why they are important. This difficulty in obtaining insights on metrics was not surprising, as even in the literature, identifying specific metrics was a challenge. As discussed in Section 3.4, most metrics developed are interpretations from the literature rather than explicitly mentioned.

*Six respondents* were involved in this stage, drawn from the Financial Service Authority, the Ministry of Cooperative and SMEs, the Central Bank, two fintech lending firms, and a university lecturer, with professional experience ranging from three to six years in their respective fields. Each interview followed a semi-structured format, was recorded with consent, transcribed, and analyzed through open coding followed by thematic coding in Atlas.ti.

*Table 10. Respondents of RQ2*

| Stakeholder Type | Institution | Years of Experience |
|---|---|---|
| Expert 1 | Financial System Authority | 6 |

| | | |
|---|---|---|
| Expert 2 | Ministry of Cooperative and SMEs | 3 |
| Expert 3 | Central Bank | 6 |
| Expert 4 | Fintech Lending | 6 |
| Expert 5 | Fintech Lending | 4 |
| Expert 6 | University Lecturer | 4 |

Fintech practitioners (Experts 4 and 5) emphasized the most basic and operational metric as total disbursement, covering both productive and consumptive loans. They noted that while 80 % of P2PL loans are currently consumptive, a shift toward productive loans would better support SMEs growth. They also highlighted qualitative assessments, such as evaluating how credit directly impacts micro-enterprise development. Additional indicators proposed included dispute resolution statistics, monitoring of illegal fintech activities, the number of borrowers and accounts, and ethical compliance, underlining that inclusion without ethical practices could be harmful.

Regulators and policy-makers (Experts 1 and 3) underlined that inclusion should capture how many individuals who were previously excluded can now access financial products, segmented by region, sector, income level, and education. They distinguished access metrics (e.g., account ownership, mobile wallet use) from usage metrics (e.g., transaction volume, frequency of electronic payments), pointing out that mobile transactions rose sharply post-Covid. They also stressed that primary survey data is more accurate than secondary records, which often omit informal inclusion activities like cooperatives or arisan. The ministry representative (Expert 2) added that limited budget allocations for SMEs programs affect the feasibility of measuring and expanding inclusion, since regulatory mandates (such as those in UU 23/2014) often outpace available resources. The academic respondent (Expert 6) supported the need for a mixed approach, combining hard indicators like disbursement data with soft indicators that capture borrower well-being and ethical treatment.

These interview insights complement the literature by providing operational metrics (disbursement levels, borrower counts, dispute resolution) and highlighting gaps (ethical safeguards, survey-based validation, and definitional issues around mobile accounts) that were not fully addressed in prior studies. The interviews added the following highlights.

**1. Total Disbursement Metrics**

Respondent highlighted total disbursement as a key metric for measuring inclusion, including productive and consumptive loans. They pointed out that while total disbursement is an important measure, it is essential to differentiate between productive loans and consumptive loans. One respondent explained, ”*The total disbursement metric is important. However, we should focus on productive loans that contribute to economic growth, especially for SMEs, rather than just looking at the overall amount disbursed.”* These insights emphasize the importance of tracking how credit is used and its potential to lead to productive outcomes.

**2. Dispute Resolution Metrics**

Respondents emphasized that ethical lending practices ensure financial inclusion does not lead to exploitation. One of the respondents explained, ”*Inclusion is not just about increasing access to credit; it is about ensuring that the credit provided is fair and that unethical practices or inappropriate financial products do not mislead borrowers*.” Respondents proposed dispute resolution metrics to track disputes between lenders and borrowers. Moreover, interviewees suggested monitoring illegal fintech operations as part of this framework, ”*Monitoring illegal fintech platforms is crucial because they often operate without proper oversight*.”

### 3. Equity of Access Metrics

Respondents highlighted that geographical disparities in access to lending services remain a significant challenge. Regional access metrics were suggested to evaluate whether lending services are equitably distributed across urban and rural areas. One respondent remarked, "*While urban areas have good access to digital lending, rural areas remain underserved. We must ensure lending services reach all regions, not just cities*." Moreover, digital engagement metrics were emphasized. Mobile payments and wallets were important tools in increasing financial access. However, respondents cautioned that the growth of mobile payments needs to be complemented by an analysis of actual engagement. "*Owning a mobile wallet account does not automatically mean financial inclusion. We need to measure how actively people are using these services*," said one respondent.

### 4. Digital Payments Metrics

Interviews pointed to the rise of digital payments and mobile wallets as inclusion indicators. Digital payment adoption in rural and underserved areas was mentioned as a key metric. As one respondent explained, "*Mobile wallets have become a lifeline for many individuals without access to traditional banking, and their usage rates are crucial for measuring financial inclusion*." The increased usage of digital payments is expected to improve access for groups that might otherwise be excluded.

### 5. Financial Literacy Metrics

Financial literacy was repeatedly identified as a critical challenge to inclusion. Respondents noted that without a solid understanding of financial products, even those with access to financial services might not use them effectively. One respondent stated, "*Inclusion does not work unless people know what they are getting into. You can access credit, but it does not lead to good outcomes if people do not understand the terms or the risks*." Awareness of financial products and the ability to make informed credit decisions were cited as essential for sustainable financial inclusion.

### 4.3.2. Integrating Literature Insights with Interviews to Develop the Metrics.

As explained in Section 3.2, the key concept in understanding financial inclusion is the continuum from access to usage. *Access* refers to engaging with financial products or services, such as having a mobile wallet or bank account, applying for loans, or conducting other transactions. *Usage* goes further, measuring whether individuals actively engage with these services over time and apply for loans and other transactions. This continuum highlights that financial inclusion is not solely about providing access but ensuring individuals *can use and benefit* from services effectively. It aligns with Amartya Sen's Capability Theory, which emphasizes access to resources and the ability to use them to improve one's capabilities.

The following section proposes metrics integrating literature and interview findings, focusing on access and usage, and summarized in Table 11. Each metric is tagged based on its relevance to different actors: borrowers, lenders, or the system.

*Table 11. Inclusion Metrics (RQ2)*

| Metrics Types | Metric Category | Relevant to | Metrics Example (not limited to this list)[*)] |
|---|---|---|---|
| **Penetration Metrics** | Physical Access Metrics | Borrower | Lending service point density; New loan opening rate (remote); Regional disparities; *Mobile Wallet Usage Index* |
| | Digital Access Metrics | Borrower | |
| **Financial Access Metrics** | Microloan Access Metrics | Borrower | Microloan Outreach Rate; Interest Affordability Ratio; Loan Approval Rates; *Productive Loan Ratio* |
| | Loan Affordability Metrics | Borrower | |
| | Loan Approval and Rejection | Lender | |
| | Algorithm Design Metrics | System | |
| | Equitable Scoring Metrics | System | |

| | | | |
|---|---|---|---|
| **Analytical Inclusion Metrics** | Transparency and Interpretability Metrics | Borrower, Lender, System | Data Diversity Index; Predictive Parity Index; Credit Dispute Resolution Rate; Inclusion Bias Detection Score; *Data inclusion ratio* |
| **Literacy Metrics** | Financial Awareness Metrics | Borrower | Borrower Financial Literacy Index; Financial Literacy Impact Index |
| | Financial Education Impact | Borrower | |

*) Metrics written in *italics* represent additional insights from the interviews.

### *A. Penetration Metrics*

Penetration metrics assess how effectively lending systems reach underserved populations. These metrics encompass physical presence and digital reach, addressing disparities across regions and demographics. This approach aligns with the continuum from access to usage, emphasizing that true inclusion requires the availability of financial services and active participation. The metrics are categorized into *Physical Access* and *Digital Access*. **Physical Access Indicators** assess the accessibility of financial services across geographic and demographic boundaries. **Digital Access Indicators** address the role of digital platforms in overcoming physical infrastructure limitations. Inspired by the interviews, we added the *Mobile Wallet Usage Index* to complement the indicators from the literature.

### *B. Financial Access Metrics*

Financial Access Metrics examines the affordability of credit for underserved populations. These metrics go beyond physical and digital availability, aiming to measure how well credit services meet the needs of marginalized groups. The metrics are categorized into *Microloan Access Metrics, Loan Affordability Metrics,* and *Loan Approval Metrics*.

**Microloan Access Metrics** assess the proportion of micro-loans issued to underserved groups like low-income borrowers or SMEs. A new metric example from the interviews is the *Productive Loan Ratio*, which evaluates the proportion of loans for productive purposes (e.g., entrepreneurship) versus credit for daily consumption. **Loan Affordability Metrics** focuses on the capability of borrowers in making repayments. Even when credit is available, the repayment terms might not be affordable for low-income borrowers. **Approval Loan Metrics** evaluates disparities in loan approval rates across demographic and socioeconomic lines, such as examining the reasons for loan rejections.

### *C. Analytical Inclusion Metrics*

Analytical Inclusion Metrics focuses on the data, algorithms, and transparency. **Data Representativeness Metrics** address how well the datasets represent data diversity. **Equitable Scoring Metrics** examine algorithmic outcomes, such as whether individuals with similar repayment capacities have equal probabilities of loan approval across demographic groups. **Transparency and Interpretability Metrics** examine the ability to interpret credit decisions. One interviewee proposed *the Algorithmic Transparency Awareness Index* to this category to capture borrower understanding on how credit scoring algorithms work.

### *D. Literacy Metrics*

Literacy metrics examine the ability of borrowers and lenders to understand, engage with, and benefit from financial services. **Financial Awareness Metrics** assess understanding of financial products and services, such as *the Borrower Financial Literacy Index*, which measures borrowers' understanding of key financial concepts such as loan terms, interest rates, and repayment schedules. Furthermore, financial education is important in enhancing borrowers' ability to navigate complex financial systems; therefore, we need to provide metrics to examine changes in borrower behavior after participating in educational programs.

### 4.3.3. Conclusions of RQ 2

The literature in Chapter 3 proposes inclusion metrics categorized into four categories: Penetration, Financial Access, Analytical Inclusion, and Literacy. This framework transforms inclusion from an abstract concept into a *measurable and actionable* objective. Integrating interview insights refines the inclusion metrics framework by adding examples in several metrics categories. For instance, the *Productive Loan Ratio* assesses the proportion of loans allocated to entrepreneurial activities (productive loans) compared to consumptive loans. Analytical inclusion is expanded with the *Data Inclusion Ratio*, which measures the proportion of borrowers assessed using alternative data sources relative to those evaluated using traditional credit histories.

By integrating these insights, the proposed metrics offer practical tools for stakeholders to assess inclusion and identify future opportunities for improvement. *Policy-makers* can evaluate inclusion efforts at national or regional levels; practitioners can refine lending products to meet the needs of marginalized populations; and *researchers* can adapt and expand these metrics to address underexplored categories.

## 4.4. Conclusions of Socio-technical Challenges and Inclusion Metrics

This chapter identifies the challenges to inclusion in lending systems (RQ1) and develops metrics to evaluate inclusion (RQ2) by combining insights from literature and interviews.

**Inclusion challenges** were categorized into six categories: *technological and data*, *financial lending, organization*, *regulatory and governance, social and cultural*, and *literacy*. While some challenges, such as data integration or algorithmic design, can be addressed through technical solutions, broader societal and structural issues, such as cultural biases, gender inequities, and low financial literacy, *fall outside the immediate scope of this study*. This study's reference architecture focuses on two challenges: technology and data (e.g., data diversity, information asymmetry, incomplete and unverifiable borrower profiles) and financial lending (e.g., loan structures and non-inclusive scoring).

**Inclusion metrics** span four categories (*Penetration, Financial Access, Analytical Inclusion, and Literacy*) reflecting the complexity of financial inclusion beyond simple access. These metrics emphasize financial services' availability and active usage, aligning with the access-to-engagement continuum, as inspired by Amartya Sen's Capability Theory. *Penetration* focuses on who is reached; *Financial Access* examines the terms under which borrowers receive credit; *Analytical Inclusion* considers how borrowers are assessed by scoring mechanisms; and *Literacy* relates to whether users can understand and engage with the system.

The **dynamic and evolving nature of inclusion** requires that metrics remain adaptable. As financial technologies advance, such as the increasing use of machine learning in credit scoring or the expansion of lending platforms, the risks and opportunities within lending systems also change. Several metrics must be periodically reviewed and updated to remain relevant. For instance, as algorithms become more complex, new biases may emerge. Without periodic updates, these metrics risk becoming outdated and may fail to capture the dynamic nature of inclusion challenges.

The insights from RQ1 and RQ2 establish the groundwork for the Reference Architecture (RA) to be developed in Chapter 5. **Challenges (RQ1)** inform the functional and non-functional requirements of the RA; while **Metrics (RQ2)** serve as benchmarks for evaluating the RA's impact on inclusion.

# PART III: ARTIFACT DEVELOPMENT

# Chapter 5: A Reference Architecture for Inclusive Lending Systems[3]

The literature and interviews from previous chapters highlight the challenges of inclusion (RQ 1) in lending systems, which stem from technical and societal challenges. These challenges include *information asymmetry, limited access to reliable and diverse data sources, fragmented and siloed data collection, non-inclusive scoring, scalability issues, and prioritizing profit over financial inclusion and long-term sustainability*. This research focuses on system-level intervention. Furthermore, the metrics proposed in RQ2 (Penetration, Financial Access, Analytical Inclusion, and Literacy) represent a set of indicators to measure inclusion in lending systems, highlighting the importance of access and engagement. RQ3 builds on the findings from RQ1 to design a Reference Architecture (RA) that addresses the key challenges.

This chapter addresses **RQ3**: *What elements make up a Reference Architecture (RA) for an inclusive lending system?* The RA comprises three interconnected elements: value-based requirements (VBRs), design principles (DPs), and architectural components. The VBRs outline the system's objectives, derived from literature reviews, flow analysis, and stakeholder interviews. The DPs guide the design to address technical and societal needs. The architectural components implement these elements, adding specific functionalities to existing systems to promote inclusion.

Figure 18 outlines the structured development of the **Reference Architecture (RA)** to address **RQ3**. The process begins with identifying *value-based requirements* through flow analysis and interviews (Step 1), followed by defining *system requirements* (Step 2). *Design principles* (DPs) are then formulated (Step 3) and later refined based on feedback (Step 4-6) to ensure alignment with the objectives. Finally, Step 7 identifies system components to operationalize these principles, ensuring practical implementation in lending systems.

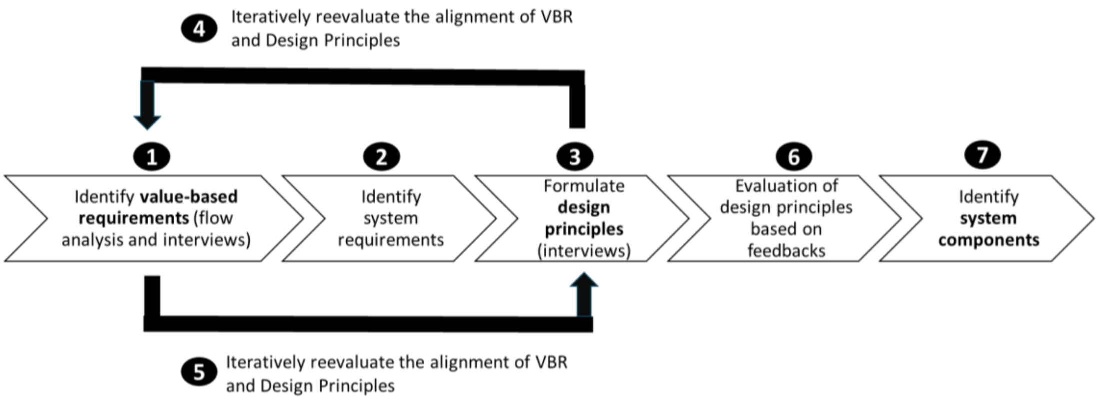



*Figure 18. Stages of the development of the Reference Architecture*

[3] *Parts of this chapter are based on the following publications: Sulastri, Ding, Janssen, & poel, (2024). Towards Inclusion-by-Design: Information System Design Principles Shaping Financial Inclusion. Government Information Quarterly 41 (2024) 101979*

This chapter is organized into four sections. Section 5.1 elaborates on value-based requirements, detailing their derivation through a value-based approach. Section 5.2 introduces the design principles that guide the system's design and ensure alignment with inclusion objectives. Section 5.3 explains the architectural components, focusing on their functionality and integration into existing systems, while Section 5.4 presents an overview of the RA.

## 5.1. Value-based Requirements

### 5.1.1. Approach to Deriving Value-Based Requirements

We apply value-based engineering to derive the Value-Based Requirements. As explained in Section 3.2.3, VBR is a structured approach to deriving system requirements from core values. It builds upon Value-Based Engineering (VBE), which provides a methodological framework for translating abstract values into concrete system features. VBR follows a systematic process: (1) identifying *core values*, (2) defining *value qualities*, and (3) mapping them to *functional requirements*. In designing an inclusive lending system, VBR provides a structured method to translate inclusion values into architectural requirements. The requirement elicitation process follows an *inductive approach*, beginning with *information flow analysis*, followed by *stakeholder interviews*, to identify the requirements for designing an inclusive lending system.

This research uses *Use Case Diagrams* and *Sequence Diagrams* to identify points where exclusion may occur and the system requirements needed to mitigate such issues. P2P lending systems are selected as representative lending models, as they are widely implemented in Indonesia. The information flow analysis examines the most common online lending processes based on consultation with fintech lending companies and stakeholders supervising lending operations. The findings from this analysis and the challenges from RQ1 serve as the foundation for designing the interview questions.

Interviews were conducted to identify value and requirements. Interviews were used because requirements in this study are rooted in values, and these cannot be captured well through surveys or documents alone. Talking directly with stakeholders made it possible to uncover priorities, concerns, and trade-offs that are often implicit. The interviews were conducted in Indonesia, with the following considerations: *First*, before the global financial crisis of 1997, Indonesia was considered one of the countries that successfully implemented nationwide microfinance credit programs, providing an example of how financial inclusion can be extended to marginalized segments (Tambunan, 2015). *Second*, there has been a remarkable growth of Fintech Lending companies in Indonesia since 2016. Based on data from the Indonesian Financial Services of Authority (OJK), as of December 2022, there are 102 registered fintech lending companies in Indonesia, with a total lending of 225.55 trillion rupiahs. This amount increased compared with 155.97 trillion rupiahs in 2021, 81.5 trillion rupiahs in 2019, and 22.7 trillion rupiahs in 2018 (OJK, 2023).

To ensure coverage from different groups in the public and private sectors, we interviewed respondents from six stakeholder groups, as summarized in Table 12: three respondents from the Financial Services Authority, three from the Central Bank, two from fintech companies, one from a small-medium enterprise, one investor, and one academic. By engaging with stakeholders in Indonesia's financial ecosystem, including policy-makers, fintech companies, lenders, and borrowers, we sought insights into system improvements for enhancing financial inclusion. We treat respondents from the same division or work group as a single source, as they have stated that the interview results represent the team's views, not individual opinions. Both public and private perspectives were needed: regulators to bring in compliance and consumer protection issues, and private actors such as fintech, investors, and SMEs to highlight operational realities and innovation opportunities.

*Table 12. Respondents of VBR (RQ4)*

| Stakeholders type | Institution | Number of respondents | Years of experience |
|---|---|---|---|
| Policy-maker | Financial service authority | 3 | 4-6 |
| Policy-maker | Central bank | 3 | 4-6 |
| Industry | Fintech companies | 2 | 4-6 |
| Industry | Small-medium enterprises | 1 | 4 |
| Industry | Investor | 1 | 4 |
| Academics | Academics | 1 | 4 |

The eleven interviews were sufficient as they covered six key stakeholder groups and reached thematic saturation, where further interviews were unlikely to add new insights. Other institutions were not included because these groups already represent the core actors shaping and implementing inclusive lending in Indonesia. The interviews took an *exploratory* approach to thoroughly understand the situation, especially since assumptions and theories from existing literature may not fully apply in real-world contexts (Yin, 2009). We applied open-ended questions to allow for deeper exploration, which we expected to uncover valuable insights.

The respondents were selected based on their direct involvement in key regulatory and operational aspects of fintech lending. Specifically, we chose institutions responsible for *regulating fintech lending innovation, lending supervision, payment systems, and microenterprises,* ensuring that perspectives from policy development, oversight, and financial inclusion were well represented. The interviews were conducted with three government institutions, the Financial Services Authority, the Central Bank, and the Ministry of MSMEs. We also interviewed fintech lending companies, lenders, borrowers, and academics. Discussions within government institutions involved various divisions with different areas of authority, including *Fintech Supervision and Licensing, Digital Financial Innovation, Financial Literacy, Payment System Policy, and Macroprudential Policy*. Academics contributed practical perspectives from their experience in fintech and inclusion initiatives. By incorporating voices from regulators and market participants, we aimed to capture a wide perspective on the requirements.

The interview questions were designed based on the respondent's role in Indonesia's online lending ecosystem. The interview themes were organized around stakeholders' perceptions of inclusion, the requirements they considered most important for designing an inclusive lending system, and their views on data, technical, and non-technical conditions. Respondents were also asked about the alignment of their institution's role with broader financial inclusion agendas, as well as collaboration and coordination mechanisms across regulators, banks, fintechs, SMEs, borrowers, and investors. To avoid confirmation bias, findings from the literature were not disclosed. Instead, the focus was on exploring requirements based on respondents' experiences. The interviews were coded using Atlas.ti through open coding to identify the initial topics and axial coding to make connection among topics (Mohajan & Mohajan, 2022). Once the coding process was completed, the results were transferred to Microsoft Excel to facilitate analysis. The interviews resulting in eight categories of requirements, each of them having one or more two sub-categories as in Table 14.

This section presents the findings from stakeholder interviews, beginning with an information flow analysis, which utilizes available documents supplemented by informal interviews, followed by stakeholder interviews to identify key challenges and requirements.

### *1. Information Flow-Based Analysis*

This stage examines information flow in lending systems, focusing on P2P lending as a representative case. By understanding how information moves within the system, we identify potential issues that might impede financial inclusion. The analysis uses two types of diagrams, Use Case Diagram (Figure

19) and Sequence Diagram (Figure 20), to illustrate system interactions, behavior, and information flow. *The Use Case Diagram* highlights actors' interactions and functional requirements, while *the Sequence Diagram* details the sequential flow of information between system components. The diagram was derived from the typical pattern of the P2P lending system.

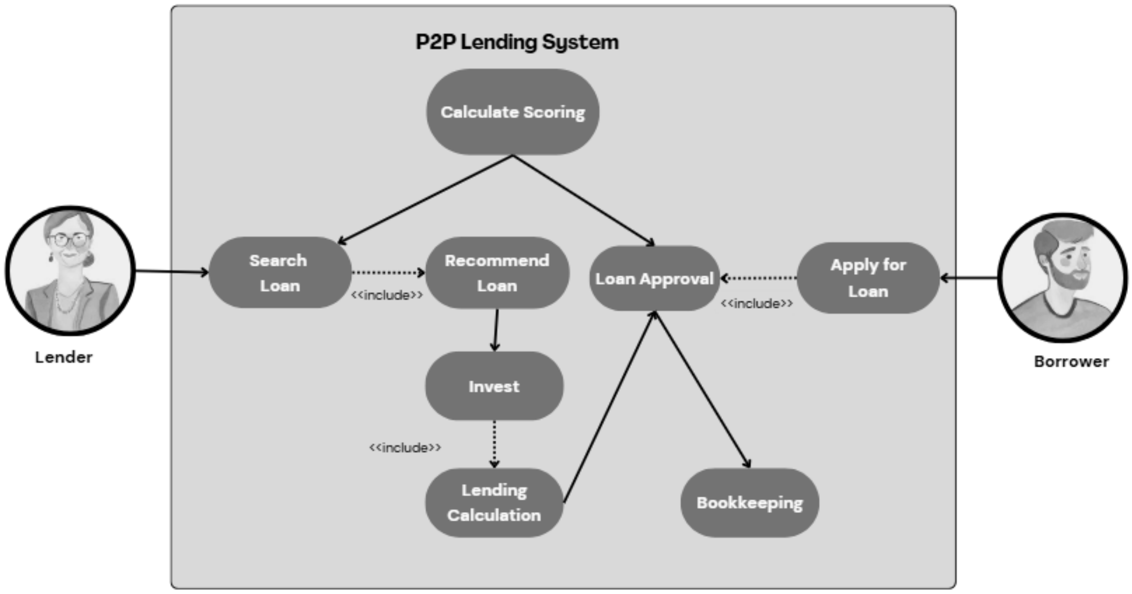



*Figure 19. Overview of the Typical Use Case Diagram in a P2P lending system*

Use Case Diagram (Figure 19) emphasizes circles that influence inclusion issues, including *calculating scoring, recommending loans, lending calculation,* and *bookkeeping*. *Calculate Scoring* assesses borrower creditworthiness, expanding access to loans for individuals with limited credit history. However, if the scoring model relies heavily on traditional financial data, it may unintentionally exclude borrowers with informal income sources. *Recommend Loan* offers personalized credit options based on borrowers' needs. Borrowers from underserved segments may be excluded from the lending pool without an adaptive recommendation mechanism. *Lending Calculation* sets favorable loan terms for borrowers and attractive profit opportunities for lenders. However, rigid risk models may still impose high interest rates on lower-income borrowers, limiting their financial sustainability. Finally, *Bookkeeping* ensures transaction transparency, fostering trust and credibility in the system. However, if transaction records lack visibility or auditable tracking, borrowers and lenders may struggle to contest unfair lending decisions, reducing trust in the system.

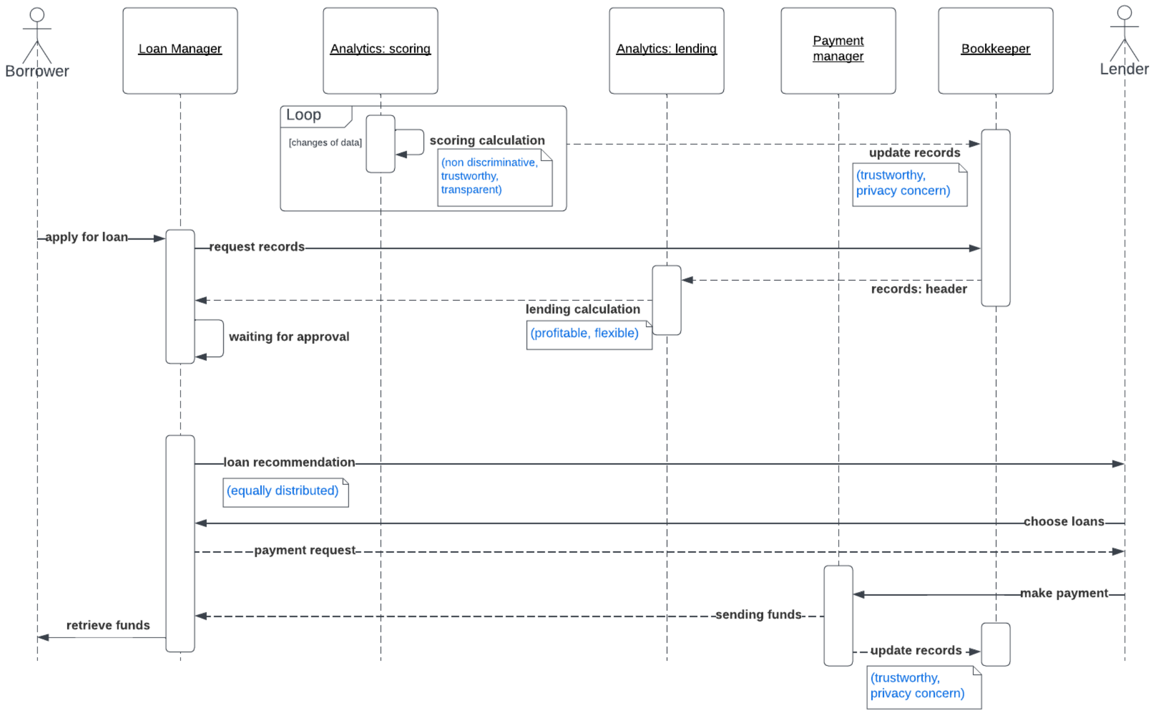



*Figure 20. Overview of the Sequence Diagram in a P2P lending system*

*The Sequence Diagram* (Figure 20) provides a more detailed view of how information flows between key components in a P2P lending system. Unlike the Use Case Diagram, which outlines system functionalities and actor interactions, the Sequence Diagram highlights sequential dependencies and data exchanges, revealing points where inclusion issues might emerge. It traces the borrower's journey from loan application to getting a loan, showing how scoring is assessed, recommendations are generated, and financial records are updated.

The Sequence Diagram shows that *scoring calculations* are initiated when borrowers apply for loans, pulling data from multiple sources to assess eligibility. If the system lacks robust integration of alternative financial data, applicants with informal earnings may be misclassified as high risk due to underrepresented data points. *Loan recommendations* follow this assessment, generating personalized options, but biases in historical lending patterns may influence the distribution of credit offers, limiting opportunities for certain borrower groups. *Lending calculations* define the structure of loan terms and repayment schedules. Without adaptive mechanisms, borrowers with irregular cash flows may be penalized with unfavorable terms. The final phase, *updating borrower records*, ensures that past repayments and financial behaviors influence future lending decisions. However, delays or inconsistencies in record updates could unfairly impact a borrower's ability to access credit.

Table 13 summarizes inclusion requirements across system components, data, and end-user (lenders and borrowers) perspectives. These requirements highlight *systemic* and *data aspects*. In the next section, we identify the requirements based on the results of the interviews.

*Table 13. Requirement of inclusion in P2PLS from the perspective of system, data, and end-users*

| System Component | Perspective | Challenges | Requirements to address the issue |
|---|---|---|---|
| Scoring Calculation | System | Non-inclusive or discriminatory scoring processes. | Inclusive scoring systems for underserved groups **(Usr1)**. |
| Lending Calculation | System | High interest rates or inflexible terms disadvantage certain groups. | Flexible lending schemas address profitability and affordability **(Usr2)**. |

| | | | |
|---|---|---|---|
| Loan Recommendation | System | Non-inclusive or discriminatory loan recommendation algorithms. | Algorithms to personalize loan options for diverse borrowers **(Usr3)**. |
| Bookkeeping | System | Vulnerable bookkeeping processes prone to fraud or errors. | Secure, transparent bookkeeping with tamper-resistant data protocols **(Usr4)**. |
| Scoring Models | Data | Label bias favoring specific outcomes or demographics. | Data collection protocols with bias mitigation techniques **(Usr5)**. |
| Data Collection | Data | Selection bias results in unrepresentative datasets. | Representative datasets **(Usr6)**. |
| Data Inputs | Data | Poor data quality (imbalance, non-uniformity, lack of diversity) | Validation mechanism to ensure data quality and diversity **(Usr7)**. |
| Investment Decision | End-user | Bias in investment decisions made by lenders, limiting inclusion. | Transparent loan rating with diverse recommendations **(Usr8)**. |
| Borrower Input | End-user | The inability to provide reliable data limits fair assessments. | Alternative data sources **(Usr9)**. |

### *2. Interviews*

The identification of value-based requirements (VBRs) in this study builds on the exploration of challenges in inclusive lending systems (RQ1 of this research). While the earlier analysis focused on obstacles that hinder inclusive lending, this section was designed to capture *forward-looking insights*, that is, what values and qualities stakeholders believe should guide the design of a more inclusive lending system.

The codification and reclassification of keywords from the interviews resulted in eight categories of requirements, as shown in Table 14, including technology, data, analytics, operations, regulation, coordination and collaboration, literacy and education, and ecosystem.

*Table 14. Requirements for inclusive lending system (interview results)*

| Category | Subcategory | Respondent code | List of requirements |
|---|---|---|---|
| 1. Technology | Seamless infrastructure | Exp7 | Ensuring infrastructure readiness to facilitate access to underserved segments. |
| | Anti-fraud technology | Exp7 | Adopt fraud prevention technology. |
| 2. Data | Alternative data source | Exp1, Exp5 | Utilizes alternative data sources, such as social media and social networks. |
| | Reliable data source | Exp1, Exp6, Exp8, Exp10 | Develop reliable microenterprises databases. |
| | Data interconnection | Exp1, Exp8 | Establishing a mechanism to integrate industry data with government data; Improving access to reliable data sources. |
| 3. Analytics | Improved scoring system | Exp1, Exp8, Exp9, Exp11 | Develop scoring algorithms that consider payment capacity inadequately represented in traditional data sources. |
| | Matchmaking algorithm | Exp9 | Technology to connect borrowers and lenders. |
| 4. Operation | On-site supervision | Exp2, Exp8, Exp11 | On-site supervision is needed to improve MSE networking and monitor the impact of financing. It may involve collaborating with regional agencies. |
| 5. Regulation | Credit regulation for productive sectors | Exp1 | Credit regulations for the productive sector. |
| | Law enforcement | Exp1, Exp8 | Regulations to address and mitigate illegal lending practices. |
| | Consumer and data protection | Exp2, Exp5 | (1) Regulation of consumer protection and risk management, (2) Regulation on data privacy and protection. |
| 6. Coordination and collaboration | Government coordination | Exp1, Exp2 | Coordination and collaboration among policy-makers. |
| | Shared vision | Exp4 | Shared visions among regulators and industry stakeholders. |
| 7. Literacy and education | Financial literacy | Exp5, Exp7, Exp10 | Education and literacy for end-users and regulators; Government programs to improve microenterprise financial, business management, and legal knowledge. |

| Category | Subcategory | Respondent code | List of requirements |
|---|---|---|---|
| | Digital literacy | Exp2, Exp11 | (1) Literacy programs for borrowers and investors, focusing on digital literacy and security. (2) Ensuring participants meet minimum literacy standards for informed decision-making. |
| 8. Ecosystem | Agent banking | Exp4 | Agent banking's role in enhancing outreach and system adoption. |
| | Financial-lending-savvy ecosystem | Exp5 | Understanding of the benefits of online lending. |

The following section discusses the elicitation of VBRs based on the results of information flow analysis and interviews.

### 5.1.2. Formulation of VBRs

The elicitation of VBRs follows a Value-Based Engineering (VBE) approach, which structures value into three levels: *core values*, *value qualities*, and *value dispositions* (Spiekermann & Winkler, 2022). *Core values* represent intrinsic general value, such as privacy; *value qualities* provide specific interpretations of value, such as informed consent as a manifestation of privacy; and *value dispositions* refer to the translation of value qualities into technical elements, such as a layered privacy policy (Spiekermann & Winkler, 2022).

This study integrates findings from *information flow analysis* and *stakeholder interviews* to establish *the value qualities* relevant to improving inclusion in lending. Information flow analysis provides a systemic view of technical requirements, while stakeholder insights offer practical and contextual challenges. However, as established in Chapter 4 (RQ1), this research focuses on system-level interventions. Broader aspects such as regulatory policies, financial literacy, and inter-organizational coordination are beyond the primary technical scope of the Reference Architecture (RA) but provide valuable context in shaping system design choices.

To facilitate the discussion of value qualities, the analysis is organized into three perspectives: *data-related requirements*, *technology-related requirements*, and *analytics-related requirements*.

#### A. <u>Data-Related Requirements</u>

Information flow analysis highlights several data issues in the lending system: label bias (Usr5), selection bias (Usr6), and poor data quality (Usr7). *Label bias* happens when many labels in the training data are wrong or inconsistent; therefore, the trained model produces biased results. *Selection bias* occurs when the training data does not represent the whole population (Zewe, 2022). *Poor data quality* (Usr7), is characterized by imbalances, non-uniformity, and a lack of diversity.

Interviews highlight the following issues. The lack of alternative data sources (Exp1, Exp5) limits the ability to assess borrowers with limited formal credit histories, excluding microenterprises and informal workers. The absence of reliable data sources (Exp1, Exp6, Exp8, Exp10), such as verified transaction histories for microenterprises, reduces the accuracy of credit assessments. Insufficient data interconnection (Exp1, Exp8) between government and private-sector databases results in fragmented borrower profiles, increasing redundancy and limiting lenders' visibility into borrowers' financial behaviors.

These data issues hinder inclusion because by distorting the evaluation of borrowers' creditworthiness, restrict access to credit for underserved segments, and perpetuate lending inequalities. Selection and label biases prevent fair credit allocation, particularly for marginalized communities. The lack of alternative and reliable data sources excludes borrowers with non-traditional financial histories, and weak data interconnection results in incomplete borrower profiles that further reduce their eligibility.

From these findings, **we derive three *value qualities*** (hereafter referred to as 'requirements') for designing inclusive lending systems: *equal access*, *equal distribution,* and *transparency*. ***Equal access*** requires that borrowers are assessed using a broader set of financial indicators, reducing exclusion due to insufficient formal financial history. The requirement to leverage alternative data sources (Usr9, Exp1, Exp5) allows microenterprise owners, informal workers, and underserved segments to be evaluated beyond traditional credit scoring models. This aligns with stakeholder concerns (Exp1, Exp5) about enforcing policies for integrating non-traditional data into credit evaluations.

***Equal distribution*** addresses disparities in credit allocation, ensuring that loans are distributed fairly across borrower segments, regardless of income levels, geographic location, or industry type. This requirement emerges from selection bias due to an unrepresentative dataset (Usr6) and bias in lender investment decisions (Usr8), which disproportionately exclude certain borrower groups.

***Transparency*** ensures that data integrity and accessibility are maintained throughout the system, enabling stakeholders to trace data origins, identify consistencies, and assess data diversity. Robust data management practices are necessary to mitigate data imbalances, inconsistencies, and low diversity (Usr7). Additionally, stakeholders (Exp1, Exp6, Exp8, Exp10) emphasize the importance of interconnecting private-sector and government-held data (Exp1, Exp8) to create comprehensive borrower profiles and reduce redundancy.

### B. Technology-Related Requirements

The information flow analysis reveals key issues in system operations related to technological shortcomings. Scoring models often rely on rigid, standardized assessments, failing to capture borrowers' financial capacity with irregular income patterns, such as microenterprise owners or gig workers (Usr1). Additionally, loan recommendation systems are often non-personalized, offering generic lending products that might exclude underserved borrowers whose financial behaviors do not fit standard requirements (Usr3). The bookkeeping processes (Usr4), while critical for tracking borrower records, are vulnerable to errors and fraud, undermining trust in the lending process.

Stakeholder interviews reinforce these technological concerns and emphasize the need for adaptive, scalable, and secure infrastructures (Exp7). Stakeholders highlight the necessity of hybrid operational models (Exp2, Exp8, Exp11), which blend digital and offline approaches, particularly for underserved rural borrowers.

The identified technological issues hinder inclusion by perpetuating non-adaptive scoring, limiting outreach to marginalized borrowers, and undermining trust through insecure bookkeeping practices. From these findings, **we derive two requirements**: *Inclusive Scoring* and *Credit Schema for Marginalized Segments*.

***Inclusive Scoring*** ensures that the lending system adapts to diverse borrower profiles rather than relying on standardized credit models that exclude non-traditional borrowers. It responds to the issues identified in scoring models (Usr1) and loan recommendation systems (Usr3). Achieving inclusive scoring requires modular, rule-based scoring engines that integrate alternative data sources and dynamically adjust risk assessments based on behavioral indicators. Stakeholders (Exp2, Exp3, Exp4) emphasize that human-centered design principles must guide these adaptive mechanisms to ensure alignment with user needs.

***Credit Schema for Marginalized Segments*** ensures that loan products are tailored to meet the unique needs of marginalized borrowers, such as microenterprise owners or seasonal workers. It addresses the limitations in loan recommendation systems (Usr3), which might fail to customize lending offers, and aligns with the stakeholder emphasis on hybrid operational models (Exp2, Exp8, Exp11) to reach underserved borrowers.

*Inclusive Scoring* and *Custom Schema* require technological advancements at system architecture and operational levels. The system architecture must be modular and scalable, integrating diverse data sources and adjusting lending decisions in real-time. Additionally, technological frameworks must support personalized loan recommendation engines, enabling dynamic, profile-based credit offerings. From an operational perspective, hybrid models, which combine digital platforms with local outreach networks, are essential to extend the system's reach to underserved communities (Exp8, Exp11). Further, secure and auditable bookkeeping mechanisms (Usr4, Exp7) must be integrated to maintain trust and transparency in financial transactions.

**C. <u>Analytics-Related Requirements</u>**

Unlike technology-related requirements focusing on the system infrastructure, analytics-related requirements pertain to the logic and models driving credit evaluations. Analytics-related requirements address how borrower data is processed, modeled, and analyzed to produce credit recommendations and risk assessments.

Findings from the information flow analysis and interviews highlight several analytical issues. Scoring models frequently fail to accommodate borrowers with irregular income patterns, resulting in non-inclusive assessments (Usr1, Usr5). Additionally, selection and label biases within lending algorithms disproportionately favor specific borrower segments (Usr5, Usr6). Stakeholder interviews reinforce these findings, emphasizing the need for improved scoring models (Exp1, Exp8, Exp9, Exp11) and reliable matchmaking algorithms (Exp9) to connect borrowers and lenders better. Transparency concerns emerge from discussions on consumer protection (Exp2, Exp5).

**We derive five requirements** that address analytical issues: *Inclusive Scoring, Equal Distribution, Perceived Societal Benefits, Transparency,* and *Information Exchange Trust*. ***Inclusive Scoring*** ensures that borrower evaluations are not limited to conventional credit histories but integrate diverse data sources to create more representative assessments. This requirement is derived from Usr1 (discriminatory scoring models) and Usr5 (label bias in scoring). Interviews (Exp1, Exp8, Exp 9, Exp11) stress the importance of developing inclusive scoring that considers the capacity of microenterprises, often inadequately represented in traditional data sources. ***Equal Distribution*** addresses the systemic biases that influence loan allocation. Findings from Usr6 (selection bias in data collection) and Usr8 (investment decision biases) highlight that lending patterns often reinforce financial exclusion without targeted interventions. However, the issue and requirement of equal distribution are not discussed in the interviews.

***Perceived Societal Benefits*** emerge from issues identified in information flow analysis, reflecting the importance of inclusive lending practices that provide value for borrowers and lenders. The analysis highlights three key issues impacting inclusion: First, high interest rates and inflexible terms disproportionately disadvantage certain borrower groups, prompting the requirement for *flexible lending schemas* to balance profitability with affordability (Usr2). Second, non-inclusive or discriminatory loan recommendation algorithms limit opportunities for diverse borrowers, necessitating *personalized loan recommendation algorithms* (Usr3). Third, biases in lenders' investment decisions restrict inclusion, driving the need for *transparent loan rating systems with* *diverse recommendations* (Usr8). Additionally, stakeholder interviews emphasize that a *financial-lending-savvy ecosystem* (Exp5) is crucial to fostering a shared understanding of lending benefits across all participants.

***Transparency*** emerges from challenges in bookkeeping (Usr4), investment decisions (Usr8), and borrower input (Usr9), highlighting issues of visibility and fairness. Usr4 reveals bookkeeping vulnerabilities, requiring tamper-resistant protocols to ensure transaction clarity and traceability. Usr8 identifies biases in investment decisions, calling for transparent loan rating systems to expose how borrower eligibility is determined. Usr9 addresses the inability of borrowers to provide accurate information. Together, these issues underscore the necessity of transparency to promote trust, clarity, and accountability in inclusive lending systems.

The next value quality is ***Information Exchange Trust***. From the information flow analysis, challenges include vulnerable bookkeeping processes prone to fraud (Usr4) and biased investment decisions by lenders that limit inclusion (Usr8). These issues highlight the need for secure, transparent bookkeeping with tamper-resistant protocols and transparent loan ratings with diverse recommendations. From stakeholder interviews, concerns about unreliable data sources (Exp1, Exp6, Exp8, Exp10) and fragmented data interconnection between institutions (Exp1, Exp8) further emphasize that trust depends on consistent, high-quality data sharing and reliable infrastructure.

The discussion above shows the elicitation of seven requirements (Table 15). Notably, technological-related and analytical-related requirements often overlap due to their interconnected nature. While technological requirements focus on building the system infrastructure and enabling data integration, analytical requirements center on how the system processes and utilizes data for scoring models and credit recommendations. As a result, some requirements emerge across both perspectives, reflecting how technological capabilities support analytical outcomes and how analytical needs technological innovations within the system.

*Table 15. Value-Based Requirements Derived from Information Flow and Interviews*

| **Requirement types** | **Sources** | | **Elicitation of requirements** |
|---|---|---|---|
| | **Information flow analysis** | **Interviews** | |
| Data-Related Requirements | Data collection protocols with bias mitigation techniques **(Usr5)**. Representative datasets **(Usr6)**. Validation mechanism to ensure data quality and diversity **(Usr7)**. Alternative data sources **(Usr9)**. | Alternative data sources **(Exp1, Exp5)**. Reliable data sources **(Exp1, Exp6, Exp8, Exp10)**. Data interconnection **(Exp1, Exp8)**. | - Equality of access<br>- Equality of distribution<br>- Transparency |
| Technology-Related Requirements | Inclusive scoring systems for underserved groups **(Usr1)**. Flexible lending schemas address profitability and affordability **(Usr2)**. Algorithms to personalize loan options for diverse borrowers **(Usr3)**. Secure, transparent bookkeeping with tamper-resistant data protocols **(Usr4)**. | Seamless infrastructure **(Exp7)**. User-centric and contextual-based design approach **(Exp2, Exp3, Exp4)**. Hybrid operational **(Exp2, Exp8, Exp11)**. | - Inclusive scoring<br>- Credit schema for marginalized segments |
| Analytics-Related Requirements | Inclusive scoring systems for underserved groups **(Usr1)**. Flexible lending schemas address profitability and affordability **(Usr2)**. Algorithms to personalize loan options for diverse borrowers **(Usr3)**. Secure, transparent bookkeeping with tamper-resistant data protocols **(Usr4)**. Data collection protocols with bias mitigation techniques **(Usr5)**. Representative datasets **(Usr6)**. Transparent loan rating with diverse recommendations **(Usr8)**. Alternative data sources **(Usr9)**. | Inclusive scoring system **(Exp1, Exp8, Exp9, Exp11)**. Reliable matchmaking algorithm **(Exp9)**. Consumer protection and data protection **(Exp2, Exp5)**. Financial-lending-savvy ecosystem **(Exp5)**.<br>Reliable data source **(Exp1, Exp6, Exp8, Exp10)**.<br>Data interconnection **(Exp1, Exp8)**. | - Inclusive scoring<br>- Equal distribution<br>- Perceived societal benefit<br>- Transparency<br>- Information Exchange Trust |

The following section explains each requirement.

### *1. Equality of access*

The first requirement, **equality of access**, underscores the need for financial services to be available to all, regardless of banking history or demographic constraints. Inclusion improves when previously excluded groups, such as low-income workers or rural communities, gain access to loans. Conversely, the system is exclusive if specific segments continue to be excluded. These disparities highlight the dual challenges of *regional discrimination* and *social discrimination*. Such biases often originate from systemic flaws in data quality and credit scoring algorithms (Tsai et al., 2014; Crook et al., 2007).

Several studies highlight the role of alternative credit assessment models in expanding access for borrowers without formal financial records. Björkegren & Grissen (2020) demonstrate that mobile phone usage data can serve as an effective proxy providing financial access to unbanked individuals who would otherwise remain excluded. Similarly, Wang et al. (2019) argue that AI-based credit scoring increases loan approval rates for underserved populations, ensuring that more borrowers can access credit without increasing lender risk. Óskarsdóttir et al. (2018) further illustrate that smartphone-based microlending platforms can enhance financial inclusion, provided they maintain fairness and transparency in their assessment models. Despite these innovations, concerns persist regarding the potential for biased segmentation, where algorithmic decision-making may inadvertently reinforce exclusionary patterns (Aitken, 2017). This underscores the need for regulatory oversight in alternative scoring models to ensure that increased access does not result in new forms of systemic exclusion.

Biases in data and analytics, such as *label bias* and *selection bias*, significantly hinder inclusion. For instance, MIT research (Zewe, 2022) revealed race-based discrimination in mortgage lending, while other studies showed disparities in city-level lending success rates, with developed cities achieving higher approval rates than underdeveloped areas (Shi & Zhang, 2016). Additionally, *taste-based bias* favors higher-income borrowers, increasing their likelihood of receiving funding at the expense of underserved groups (Tao, Dong, & Lin, 2017). These examples emphasize the need for fair data representation and bias mitigation in analytics to ensure equal access. These findings underscore the need to examine how model parameters influence borrower classifications. Biases may not only stem from the data but also from the algorithm in risk assessment models, where small variations in certain parameters could disproportionately impact different borrower groups. **Sensitivity analysis** is essential to assess how these factors shape inclusion outcomes and to determine whether adjustments could lead to a more equitable distribution of credit.

Aitken (2017) introduces the concept of *calculative infrastructure* to make underserved groups visible by integrating financial and non-financial data. This approach involves three key steps: (1) identifying unbanked and excluded populations, (2) creating calculative infrastructures through psychometric and behavioral analysis, and (3) segmenting individuals into potential borrowers (manageable risk) and non-potential borrowers (unmanageable risk). While effective for expanding loan pools, this concept does not sufficiently address regional or social discrimination.

Equal access to credit is critical for individuals and microenterprises, as it *enhances productivity* and unlocks business potential. For instance, rural farmers have been shown to benefit significantly from equitable credit systems (Aisaiti, Liu, Xie, & Yang, 2019). Moreover, studies highlight the potential of alternative data in improving financial inclusion by targeting low-income individuals and underserved youth (Roa, et al., 2021). Additionally, mobile phone data has been shown to outperform conventional credit scoring models that rely on credit bureau information (Björkegren & Grissen, 2020). The trust further plays a central role in achieving equal access to P2P lending. The trust between lenders and borrowers not only increases access opportunities but also encourages lenders to invest in overlooked individuals and microenterprises (Chen & Xie, 2020 ).

This study defines the requirement **equality of access** as *the capacity to provide access based on an individual's creditworthiness, which is linked to their payment capacity, despite demographic profiles*.

### *2. Inclusive scoring*

The second requirement is **inclusive scoring**, which discusses the specific scoring system required for particular segments, such as credit for low-income and young borrower (Roa, et al., 2021), financing for ultra-poor and moderate-poor individuals (Shaikh, 2017), credit for smallholder farmers (Simumba, Okami, Kodaka, & Kohtake, 2018), credit for low-income (Ntwiga, Ogutu, & Kirumbu, 2018), and reduce the false rejection rate for marginalized groups (Wang, Li, Gu, & Min, 2019).

Recent research emphasizes the transformative potential of alternative scoring models in improving access and equity. For example, Fu et al. (2021) show that machine recommendations for borrowers with low credit scores significantly enhance investment opportunities and return predictions compared to human-based approaches. Similarly, Kumar et al. (2022) explored machine learning (ML) models using non-traditional data, demonstrating their effectiveness in developing equitable and inclusive credit assessment algorithms. Ntwiga et al. (2018) employed Hidden Markov Models (HMM) to support underserved borrowers by analyzing their daily financial activity patterns.

Wang et al. (2019) emphasized the superiority of AI-enhanced features in improving approval rates, reducing default rates, and identifying creditworthy. These models utilize diverse non-financial data sources, such as behavioral and transactional data, to expand credit opportunities for previously excluded individuals. Moreover, Simumba et al. (2018) proposed alternative scoring tailored to smallholder farmers, reflecting their specific repayment capacities and financial behaviors. Such models underline the importance of context-specific approaches.

Incomplete or missing credit data remains a challenge to equitable scoring. Zhang et al. (2022) introduced a matrix decomposition technique to address missing data, enabling more accurate and fair credit evaluations for low-income borrowers and microenterprises. Additionally, Rebecca and Karen (2021) examined alternative data sources, including utility bills, social media activity, geolocation, and psychometric assessments, highlighting their potential to improve creditworthiness assessments for excluded individuals.

The state diagram analysis identifies scoring calculations as a key event requiring algorithmic inclusion (Usr1). Bias mitigation and data preprocessing are essential to ensure fair outcomes during this process. Interviews corroborate these findings, emphasizing the need for reliable matchmaking algorithms that facilitate equitable borrower-lender connections (Exp9). These algorithms should integrate advanced scoring methods to cater to underserved segments effectively.

This study defines the requirement of **an inclusive scoring system** as having *the ability to implement adaptive scoring algorithms that account for heterogeneous financial behaviors, particularly for marginalized segments.*

### *3. Equality of distribution*

Beyond expanding financial reach, the third requirement, **equality of distribution**, ensures that credit allocation is not disproportionately concentrated among specific segments while others remain underserved. This concept extends beyond access, addressing how resources and credit are distributed across diverse borrower demographics. Kozodoi et al. (2022) emphasize the importance of fairness criteria in credit financing, ensuring marginalized markets receive equitable treatment. Although their study focuses on fairness rather than inclusion per se, its insights contribute to promoting financial inclusion by addressing systemic inequities. Lee and Floridi (2021) propose a relational and contextual fairness framework in mortgage lending, suggesting that fairness should account for trade-offs between competing interests. In the context of P2P lending, Katsamakas and Sánchez-Cartas (2022) highlight how increased platform scale and expanded agent reach contribute to more balanced credit distribution for MSEs, enabling marginalized groups to participate more. Similarly, Meshram and Venkatraman (2022) reveal how caste-based discrimination and biased algorithms in India exclude marginalized communities from financial systems. Kumar et al. (2022) explore the intersection of fairness, discrimination, and credit-scoring algorithms, recommending that policy-makers and developers prioritize fairness to prevent systemic exclusion.

The literature highlights that even when access increases, disparities in loan distribution can persist due to biases embedded within algorithmic decision-making. Meshram & Venkatraman (2022) illustrate how caste-based discrimination in microcredit lending in India continues to restrict financial opportunities for marginalized groups despite broader lending expansions. Fu et al. (2021) argue that machine learning-driven credit models, although improving predictive accuracy, can unintentionally amplify gender biases.

In use case and sequence diagrams analysis, equitable distribution requirements were highlighted in events concerning default prediction and loan recommendation, emphasizing the importance of designing a component for diverse borrower segments and implementing fair data collection protocols. This study defines the requirement for **equality of distribution** as *providing equality in credit allocation across diverse segments of society, avoiding the concentration of credit access in specific segments.*

#### ***4. Credit schema for marginalized segments***

The fourth requirement, **lending schema**, covers the studies that address credit structures that accommodate diverse borrower needs. Shankar (2022) and Katsamakas & Sánchez-Cartas (2022) demonstrate that non-traditional lending models, such as P2P lending, agricultural value-chain financing, and micro-equity investments, offer more adaptable financial solutions that move beyond salary-based risk assessments. Gupta (2014) illustrates how low-cost P2P microfinance models expand credit availability while mitigating cost barriers for underserved borrowers. By rethinking eligibility criteria and lending conditions, these alternative models help create a more inclusive financial landscape that does not rely solely on traditional banking structures.

Marginalized segments often face challenges to formal credit due to unconvincing financial profiles or limited collateral (Situmorang, 2022; Tambunan et al., 2021; Milne & Parboteeah, 2016). Lending models provide a promising avenue for addressing these gaps through flexible credit schemes that align with the needs of marginalized borrowers. Such schemes might include low-interest loans, daily repayment structures, or rapid disbursement processes to accommodate urgent liquidity needs.

The concept of equitable distribution, as highlighted by (Shaikh, 2017) while citing Sen (1983), emphasizes that poverty and hunger are not primarily caused by scarcity but rather by the unequal distribution of resources. In the context of Islamic economics, (Shaikh, 2017) argued that *mudarabah* (a profit-sharing partnership) is more suitable for the ultra-poor and moderate-poor segments of the economy compared to *musyarakah* (a joint venture), as it eliminates the need to provide capital. In this regard, equity-based financing is considered more appropriate than debt-based financing.

According to (Gupta, 2014), RangDe, an Indian P2P platform offering low-interest microloans, excels in three key areas: targeting underserved communities, employing innovative marketing strategies, and partnering with field agents in remote regions. These efforts collectively advance its mission to alleviate poverty. In the agricultural sector, Simumba et al. (2018) highlight the importance of non-financial data collected via a mobile application, which captures farmers' behavioral interactions with the app. Implementing an alternative credit assessment system to support financial inclusion for small farmers, as highlighted by Shankar (2022), underscores several key requirements. The system must collect and analyze diverse data sources, provide flexible financing options while managing associated risks, and maintain transparency.

In the information flow analysis, specific credit schema for individuals was an integral part of the lending recommendation state. This study defines the requirement for **credit schema for marginalized segments** as the ability *to develop flexible loan products with repayment structures that accommodate diverse borrower needs.*

### *5. Perceived Societal benefits*

**Perceived societal benefit** refers to whether financial services deliver meaningful benefits to users. Borrowers are more likely to engage with lending systems when they perceive tangible advantages, such as reduced transaction costs, lower interest rates, and improved credit accessibility (Aisaiti et al., 2019; Li et al., 2017). Studies indicate that profit-driven scoring increases lender participation by optimizing loan selection for maximum returns and balancing financial risk with potential gains (Serrano-Cinca & Gutiérrez-Nieto, 2016; Ye et al., 2018). However, Wang et al. (2019) caution that profit-focused lending must be aligned with ethical financial practices, ensuring that incentives for lenders do not result in exploitative credit for borrowers

Literature highlights that inclusion and profitability can coexist and reinforce each other when supported by well-designed approaches tailored to these challenges. Research by Kozodoi et al., (2022) highlights how credit-scoring algorithms can balance fairness and profitability. By integrating fairness processors into machine learning models, these systems reduce discrimination while maintaining profit margins. Similarly, Fu et al. (2021) emphasize the borrower-centric benefits of machine-driven credit scoring. Their study shows that automated models enhance access for high-risk borrowers, stabilize interest rates, and provide opportunities for individuals with limited credit histories.

Advancements in credit-scoring technologies also play a pivotal role in enhancing societal benefits. For example, algorithms that optimize lending formulations and individual borrower ratings improve profitability and foster a more equitable financial ecosystem. Verstraeten & Poel (2005) emphasize that addressing sample bias in these models can improve performance and inclusion, ensuring that underrepresented groups are fairly assessed and included.

Stakeholder interviews emphasized the need for financial literacy in low-income and low-education communities to enhance understanding of lending mechanisms and risks, fostering trust and informed participation. This confidence is expected to increase borrower engagement and lender investment. This study defines the requirement for **perceived societal benefit** as *the ability to provide sustainable benefits for all parties involved.*

### *6. Information Exchange Trust*

Trust is essential in lending systems, as it influences users' confidence in participation. Chen, Lai, & Lin (2014) emphasize accountability as a cornerstone of trust, where borrowers and lenders must responsibly fulfill their roles. Meanwhile, Chen, Lou, & Slyke (2015) identify social capital and perceived information quality as critical determinants, demonstrating that trust extends beyond system reliability to include subjective perceptions. Yan, Lv, & Hu (2018) explores how financial parameters like cash flow and interest rates affect trust levels. These findings highlight that low trust can deter participation, hindering access to credit for underserved groups and compromising the overall inclusion of the system.

Qian & Lin (2020) argue that trust enables underserved individuals, often excluded from traditional banking systems, to access financial resources. By fostering confidence in the system, trust ensures that investors are more willing to support projects that traditional institutions might overlook, while borrowers feel empowered to engage without fear of unfair treatment. From the borrower's perspective, Li et al. (2017) show that trust is influenced by subjective norms, perceived authority, and clear communication.

Interviews emphasized trust in lending systems hinges on reliable data sources and seamless interconnectivity. Respondents highlighted that integrating data across stakeholders enables more accurate borrower assessments while tamper-proof management systems prevent fraud and preserve data integrity. This study defines the requirement for **information exchange trust** as *implementing secure, tamper-proof audit mechanisms to reinforce trust in financial transactions.*

***7. Transparency***

Although transparency was not a primary focus in interview discussions, it emerged as a significant factor in the sequence diagram analysis. Key operational requirements include a trustworthy bookkeeping system with reliable and tamper-proof data management (Usr4) and a transparent review and rating system to ensure diverse and inclusive loan recommendations (Usr6).

Several studies emphasize that opaque AI-driven lending models undermine trust, as users struggle to interpret why individuals are approved while others are denied (Seng Ah Lee & Floridi, 2020; Stevens et al., 2020). In response, researchers advocate for explainable AI in credit scoring, ensuring that algorithmic lending decisions remain interpretable and accountable (Kumar, Hines, & Dickerson, 2022). Transparency is also crucial in financial platform governance. Qian & Lin (2020) illustrate that transparent disclosure of operational policies and risk management strategies enhances investor confidence in P2P lending platforms, reinforcing participation. Similarly, Roa et al. (2021) emphasize that alternative data-based credit models must meet regulatory transparency standards to prevent discriminatory lending outcomes.

Li et al. (2020) emphasize the need for transparency in using social features in credit assessment. Their research shows that clearly explaining how social features influence credit decisions reduces risks of bias and discrimination. Granting users control over their data and implementing transparent policies for social data usage further enhance user trust (Li, Ning, Liu, Wu, & Wang, 2020).

The study by Stevens et al. (2020) highlights the critical role of explainability in loan recommendation systems. First, it clarifies loan determination by explaining the factors influencing decisions, helping borrowers understand outcomes. Second, it aids bias prevention by regularly monitoring algorithms to ensure impartial recommendations. Third, it promotes user education by enhancing financial awareness and literacy, particularly for underserved groups. Finally, it reduces uncertainty by offering clear, transparent processes that build acceptance among previously excluded societal segments. This study defines the requirement for **transparency** as *the ability to ensure that lending decisions are explainable and clearly communicated to borrowers and lenders.*

### 5.1.3. Overview of VBRs

The Value-Based Requirements (VBRs) provide a foundational approach to embedding inclusion in system design. The requirements apply inclusion-by-design, positioning inclusion as a deliberate and central focus in system architecture.

Seven requirements have been identified. *Equality of Access* ensures equitable opportunities for all demographics, addressing exclusion across income, gender, or geographic divides. *Inclusive Scoring* leverages advanced algorithms and diverse data sources to reduce biases in credit assessments. *Equitable Distribution* promotes balanced credit allocation across societal segments to prevent concentration or exclusion in underserved groups. *Tailored Credit Schemes for Marginalized Segments* address the unique needs of underserved groups, such as low-income individuals and microenterprises. *Perceived Societal Benefits* balances profitability with inclusion goals, ensuring mutual advantages for borrowers and lenders. *Information Exchange Trust* requires reliable data sources and seamless interconnectivity, creating a level playing field where everybody can access all information. Finally, *Transparency* enhances clarity and accessibility in decision-making processes, empowering users with greater understanding and trust in the system. These requirements provide a structured pathway for embedding inclusion into system design, addressing challenges to financial inclusion while setting a roadmap for developing design principles.

## 5.2. Design Principles

While value-based requirements (VBRs) define the ”what” of inclusion (the qualities a system must embody), design principles focus on the ”how,” guiding the realization of those values. This distinction highlights their role in embedding inclusion into system design, moving from aspirational goals to measurable outcomes. The principles presented in this section were iteratively developed based on the previously identified VBRs. The subsequent subsections detail the methodologies to formulate these principles, their alignment with VBRs, and their role in shaping the Reference Architecture.

### 5.2.1. Approach to Deriving Design Principles

As shown in Figure 18, having established the Value-Based Requirements (VBRs), we use these as the foundation for formulating design principles. The second stage is translating VBR into system requirements, setting the groundwork for Stage 3, where the initial Design Principles are developed.

Stage 3 includes a review of relevant methodologies in the literature, examining approaches implemented by literature in developing design principles in IS domain. For example, Bharosa & Janssen (2015) emphasize principle-based design as normative guidelines for system architects, aligning with our approach to inclusive lending systems. Dolk and Drnevich (2011) highlight the importance of aligning principles with clearly defined requirements, while Nobre et al. (2019) propose simulations to validate principles in the absence of pre-existing reference architectures. Similarly, Salmon and Ray (2017) emphasize deriving principles directly from identified challenges, and Pan et al. (2021) use Action Design Research (ADR) to create principles rooted in product requirements and system features. These insights inform the structured development of principles in this research.

In Stages 4 and 5, iterative evaluations are conducted to ensure alignment between principles and requirements. In Stage 6, the conceptual principles were assessed through targeted interviews with IS domain architects, as detailed in Table 16. This team was deliberately composed of seven respondents with extensive expertise in shaping information and technology landscapes. Their expertise spans technology and infrastructure management, large-scale payment applications, information and technology architecture design, data management, and business analysis.

*Table 16. Respondents of Design Principles (RQ4)*

| Stakeholders type | Years of experience | Code |
|---|---|---|
| Application Architect | 15 | R1 |
| Application Architect | 8 | R2 |
| Information Architect | 15 | R3 |
| Technology Architect | 8 | R4 |
| Data Specialist | 15 | R5 |
| Information system analyst | 15 | R6 |
| Business analyst | 8 | R7 |

The interview protocol is provided in Appendix 14. The interview respondents represent a diverse cross-section of expertise. The decision to involve seven individuals from diverse fields was a deliberate response to the challenge of expertise scarcity in this domain, as there are no identified specialized experts in Indonesia. As a result, this study draws insights from professionals with relevant experience across multiple domains. Their collective experience includes technology architecture, infrastructure management, data analytics, and business analysis, focusing on systems for marginalized groups, such as microenterprises. The group comprises six male professionals and one female professional, bringing together various perspectives. The limited presence of female respondents aligns with the broader gender disparity observed in fintech and technology roles. Despite this imbalance, including diverse professional backgrounds ensures that the principles are evaluated through multiple lenses.

### 5.2.2. Formulation of Design Principles

The formulation of Design Principles posed significant challenges, as the landscape of methodologies within Information Systems and Information Governance often lacks transparency in connecting conceptual frameworks with actionable outcomes. The literature review revealed diverse approaches to formulation of design principles. For instance, some studies, such as Salmon & Ray (2017), directly translated identified challenges into principles; Schneider et al. (2023) employed data mining frameworks to organize principles systematically. Deductive methods, such as those used by Matheus et al. (2021), aligned principles with challenges identified in the literature, while other works, like Matheus et al. (2020), mapped principles to risks, challenges, or threats. Notably, Nobre et al. (2019) categorized design principles into clusters (system, network, and service) establishing actionable groupings from the outset. Despite these varied methodologies, a recurring challenge lies in bridging the gap between abstract formulations and the operational needs of system development.

In response, our methodology adopts an inductive approach inspired by Fu et al., (2015) and Turaga et al. (2010), emphasizing empirical evidence and practical industry experience. This process starts by systematically translating each VBR into high-level system requirements and further deconstructing these into specific system components, as shown in Table 17. For instance, the VBR ”equal access” is operationalized through *collaborative and distributed data-capturing*, *a distributed architecture, and an Inclusive rule engine*.

*Table 17. Mapping of value quality, high-level system requirements, and system components*

| **Requirements (VBRs)** | **High-level system requirements** | **System components** |
|---|---|---|
| 1. Equal access | Leveraging alternative data sources to attain a more comprehensive individual profile that reflects creditworthiness | Collaborative and distributed data-capturing |
| | | Distributed architecture |
| | Assessment of creditworthiness using predefined inclusion criteria | Inclusive rule engine |
| 2. Equal distribution | Ensuring credit distribution does not disproportionately favor specific segments | Inclusive distribution mechanism |
| 3. Inclusive scoring | Developing an individualized credit scoring system | Inclusive scoring algorithm |

| Requirements (VBRs) | High-level system requirements | System components |
|---|---|---|
| 4. Credit schema for marginalized segments | Developing loan products tailored for marginalized segments, addressing their unique needs | Custom schema |
| 5. Perceived societal benefits | Allowing borrowers to contest credit decisions and to propose data revision | Contestation component |
| 6. Transparency | Ensuring transparency in decision-making and credit formulation | Auditable logging |
| 7. Information exchange trust | Ensuring transactional integrity, preventing manipulation, and fostering confidence in financial interactions | Distributed Ledger |

Based on the table above, we formulate *the candidate design principles* by systematically linking high-level requirements with the conditions that will serve as future guidelines (Sulastri, Janssen, Poel, & Ding, 2024).

Furthermore, we interviewed professionals from diverse fields to ensure the design principles align with practical and technical realities. While not all participants had direct experience with system inclusion, their expertise in addressing marginalized groups was invaluable. We avoided validating *the candidate of design principles* to mitigate confirmation bias. Instead, the interviews were designed to elicit insights through open-ended questions. This process resulted in excluding certain candidates and formulating one principle solely based on interview findings (principle P5). Interviewees feedback referenced in this section is denoted by respondent codes (e.g., R1, R3). Table 18 presents the list of *Design Principles* with their rationale and implications.

*Table 18. Design Principles Description*

| Principle Statement | Rationale | Implications |
|---|---|---|
| P1. Define a comprehensive set of *inclusion metrics* to promote inclusive access | Providing inclusion metrics provides a set of measurable criteria to assess the improvement of inclusion in system design and system outcome | Define and adapt inclusion metrics in all system domains to assess the outcome. |
| P2. Leverage *alternative data* for enhanced borrower and lender participation to mitigate information asymmetry | Incorporating alternative data is expected to reduce information asymmetry and encourage greater participation. | Identify reliable alternative data sources, utilize advanced technology for data analysis, and apply data protection and privacy compliance. |
| P3. Enhancing inclusion through *transparency* in loan terms, approval explanations, and borrower appeals | Personalized insights, audits, and dispute resolution boost trust and user loyalty. These are necessary to improve trust and engagement. | Provide personalized simulation tools. Enable lender-borrower communication, including the ability to contest decisions. |
| P4. *Tailor credit solutions* to empower underserved borrowers | Lack of customized credit schema can sustain financial inequality due to the inability of borrowers to be involved in lending systems. | Recognize the unique needs of underserved borrowers, create customized products, and provide financial education. |
| P5. Addressing *long-term sustainability* while balancing inclusion and risk. | This principle prevents prioritizing short-term inclusion over long-term stability, avoiding heightened risks and instability. | Establish a comprehensive risk management, adapt to regulatory changes, and implement data-driven decision-making. |

*Principle 1: Formulate a comprehensive set of inclusion metrics to promote inclusive access and performance evaluation.*

Our understanding of inclusion metrics in lending involves combining quantitative and qualitative measures to evaluate access and usage. Principle 1 emphasizes enforcing a comprehensive set of inclusion metrics within lending systems to foster inclusion and improve performance evaluation. By actively monitoring and adapting these metrics, decision-makers can ensure their policies remain responsive. For instance, R1 emphasized that ”metrics must be dynamic, adjusting to rapidly changing societal and technological contexts, especially in underserved regions.” For example, if inclusion metrics reveal disparities in loan allocation to marginalized groups, approaches like targeted outreach, enhanced financial literacy programs, or algorithmic adjustments can be implemented proactively.

How are inclusion metrics defined? Despite lacking comprehensive literature, the interviews suggest a dual approach to inclusion metrics (R7). At the *macro level*, these metrics involve quantitative data that capture statistical representations of inclusion, such as increased credit recommendations and improved payment capacity for microenterprises across diverse income segments. At the *micro level*, inclusion metrics delve into philosophical and mathematical aspects, focusing on algorithms designed to enhance inclusion by reducing potential biases in evaluating individual creditworthiness. *Macro-level inclusion metrics* are relatively prevalent, especially in research that utilizes World Bank surveys on financial inclusion, despite a need for more analysis on distribution aspects. However, *micro-level inclusion metrics* tied to algorithms and mathematics formulations are not readily available, unlike extensively researched and established fairness metrics in machine learning, such as Binns (2018), Hardt et al. (2016), and Koumeri et al. (2023). Another example is a study by Kozodoi et al. (2022) revisiting fairness research in machine learning and categorizing it into various intervention methods and criteria evaluation perspectives.

Given the limited exploration of *micro-level inclusion metrics*, one suggestion is to adopt fairness measures considering the relational and contextual nature of the measurement. This is also in recognition that, in defining inclusion metrics, the emphasis should not solely be on mathematical or statistical interpretations but on addressing existing inequalities and issues with exclusions. Lee and Floridi (2021) underscore the importance of a relational and contextual approach to measurement, allowing decision-makers flexibility. Their framework evaluates the equilibrium between enhancing financial access and its effects on minority groups, aiding decision-makers in choosing algorithms that match their ethical standards and risk capacity. The concept of trade-offs can also be extended to inclusion metrics, adaptable to the risk appetite of the decision-makers.

In this study, inclusion metrics refer to structured indicators to assess how effectively lending systems achieve financial inclusion. This definition emphasizes quantitative and qualitative measures, reflecting the availability of financial services (access) and the extent to which they are meaningfully utilized (*usage*). Unlike traditional financial indicators, inclusion metrics focus on reducing barriers for underserved groups, encompassing geographic reach, affordability, representativeness, and transparency. This research introduces a context-specific **definition of inclusion metrics**:

*"Inclusion metrics are structured indicators designed to operationalize the continuum from access to usage, measuring how lending systems reach, engage, and empower underserved populations while addressing systemic challenges."*

This definition situates inclusion metrics within the broader concept of *capability expansion*, inspired by Amartya Sen's Capability Theory, ensuring that inclusion is practically actionable and socially impactful. The formulation of inclusion metrics is underpinned by the continuum of access to usage, a conceptual framework introduced in Chapter 4. *Access* refers to the availability of financial products or services, such as eligibility for loans or digital wallets, providing the potential for engagement. *Usage* evaluates how these services are actively utilized, measuring frequency, depth, and meaningful impact over time. For example, access can be represented by metrics like *Lending Service Point Density*, while *Mobile Wallet Usage Index* can capture usage.

The development of inclusion metrics in this research reflects an iterative process integrating literature and interview results. Metrics like the *Data Diversity Index* stem from the literature on algorithmic inclusion, addressing biases in traditional credit systems. Stakeholder interviews highlighted practical challenges, such as the opacity of credit scoring, which informed the creation of the *Loan Transparency Score*.

As elaborated in Chapter 4 (RQ2), the inclusion metrics proposed in this principle are grouped into four categories, each addressing specific challenges identified in RQ1. *Penetration Metrics* measure the extent of financial inclusion by evaluating physical access and digital access; *Financial Access Metrics* address affordability and equitable credit distribution; *Analytical Inclusion Metrics* assess fairness and transparency in data-driven systems; and *Literacy Metrics* focus on borrower understanding and engagement, emphasizing the role of financial literacy.

This principle establishes the foundation for embedding inclusion as a measurable, actionable, adaptable objective, bridging theoretical frameworks with practical realities.

*Principle 2: Leverage alternative data for enhanced borrower and lender participation to mitigate information asymmetry.*

Inclusion in lending cannot be achieved without addressing the core issue of information asymmetry, which disproportionately impacts marginalized populations. Traditional credit assessments, reliant on narrow datasets like formal credit histories or collateral, often exclude individuals and microenterprises operating in informal economies. Principle 2 elevates the role of alternative data as a transformative force in bridging this gap, enabling systems to provide equitable opportunities for borrowers and lenders. Without leveraging alternative data, the foundation of inclusion would remain compromised as traditional approaches fail to account for the complexities of underserved populations.

Alternative data represents not just an enhancement but a fundamental shift in how creditworthiness is evaluated. Alternative data, including digital transaction histories, utility payments, and behavioral patterns, offers a pathway to address inclusion by providing a more comprehensive view of financial behaviors (Roa, et al., 2021; Aitken, 2017). These datasets illuminate the financial activities of individuals often overlooked by traditional systems, offering insights into payment capacity, financial stability, and long-term creditworthiness. For instance, **RQ2** underscores the importance of adopting metrics that evaluate access and usage, which alternative data sources can support.

This principle moves beyond functionality to embody the concept of inclusion-by-design, ensuring that credit systems are designed to serve the excluded and *empower* them as legitimate participants in the financial ecosystem. Interviews highlight the complexities of relying solely on primary data, particularly when serving marginalized populations (R1, R8), noting *that "without alternative data, the scope of inclusion is fundamentally limited; many borrowers are invisible to traditional models."* By integrating alternative data, lending systems challenge systemic biases inherent in conventional credit evaluations. R8 emphasized that "*alternative data opens doors for marginalized groups to participate in the financial system, not as exceptions but as legitimate participants with measurable financial behavior."* This shift from exclusion to empowerment aligns closely with Amartya Sen's Capability Theory, which emphasizes expanding capabilities and opportunities for underserved populations.

While alternative data holds immense potential, its integration is not without challenges. For instance, the interviews revealed that primary data for microenterprises and informal workers is often unavailable or fragmented (R1, R3). This limitation necessitates the creation of collaborative and sustainable data collection systems. Countries like Indonesia, where reliable microenterprise data is scarce, require innovative approaches such as partnerships with local governments or leveraging fintech ecosystems to collect and validate data. This aligns with findings in Chapter 4, where collaboration was identified as a critical enabler of systemic inclusion.

Moreover, real-time monitoring facilitated by alternative data supports proactive risk management, addressing issues identified in **RQ1** regarding trust and transparency. However, as noted in Chapter 3.5, balancing privacy with data utility remains a persistent challenge. R2 highlighted the importance of ensuring that *"data-driven transparency does not compromise borrower trust."*

Alternative data should not be seen as *merely a supplementary addition* but as a critical element requiring an iterative and tailored approach to meet the specific needs of inclusive lending systems.

*Principle 3: Enhancing Inclusion through Transparency in Loan Terms, Approval Explanations, and Borrower Appeals*

Inclusion in lending extends beyond providing access; it requires building systems prioritizing trust and transparency. Principle 3 emphasizes the critical role of transparent insights and contestable decision-making in fostering financial inclusion.

Transparency is essential for addressing information asymmetry and fostering trust. Traditional lending systems often obscure critical details about loan terms, fees, and eligibility, which disproportionately disadvantages borrowers in underserved communities. Principle 3 asserts that transparent insights, such as clear explanations of loan eligibility, terms, and conditions, are vital for reducing these challenges.

Interview findings also highlight the importance of transparency in addressing predatory lending practices. R1 noted that *"borrowers in underserved segments often prioritize loan approval over data privacy."* This observation underscores the need for systems that foster trust by ensuring transparency, thereby empowering borrowers to make informed decisions. This aligns with Matheus et al. (2021), who argue that transparency strengthens trust in complex systems, fostering broader stakeholder participation. By ensuring clarity in financial communications, systems can empower borrowers to make informed decisions, mitigating risks and enhancing their confidence in engaging with formal credit channels. This principle aligns with Nadj et al. (2020) emphasizing the importance of user engagement in the lending system.

Moreover, while transparency ensures that borrowers can access clear and understandable information about lending processes, **contestability** enhances inclusion by empowering borrowers to engage in decision-making actively. Contestability enables borrowers to challenge or request clarification on credit denials, creating opportunities for feedback and redress. Borrowers denied credit can use contestation mechanisms to understand the reasons behind the decision and present additional context or evidence. For example, R3 emphasized that *"contestation options make the system feel less transactional and more collaborative, reinforcing the borrower's trust and long-term attachment to the platform."* Contestability also serves as an educational tool, enhancing borrower literacy by providing clear explanations for decisions and highlighting areas for improvement in their credit profiles.

This principle aligns with Amartya Sen's Capability Theory, which emphasizes empowering individuals to participate in systems that impact their opportunities and choices actively. Transparency and contestability do not guarantee loan approval; they ensure that borrowers can take proactive steps to enhance their financial standing. For example, feedback mechanisms help borrowers better understand inclusion metrics, fostering a sense of agency and long-term engagement with the system.

Principle 3 broadens the concept of inclusion, extending beyond mere access to emphasize awareness, financial literacy, and meaningful engagement. An inclusive system is not measured solely by the volume of loans disbursed but by the quality of interactions and the empowerment it offers borrowers. This principle ensures that financial inclusion supports active participation and borrower empowerment by integrating transparency and contestability into its design.

In conclusion, Principle 3 positions transparency and contestability as transformative elements of inclusive lending systems. These mechanisms address key challenges in trust and borrower engagement, reinforcing the concept of inclusion by design. By equipping borrowers with clear information and opportunities for collaborative decision-making, Principle 3 ensures that lending systems are not only accessible but also empowering.

*Principle 4: Tailor credit solutions to empower underserved borrowers*

Financial inclusion demands more than generic credit options. Principle 4 highlights the need to design credit solutions that address the distinct challenges faced by marginalized borrowers, such as micro-enterprises, informal workers, and women entrepreneurs. Traditional credit systems, bound by rigid eligibility criteria and standardized products, often exclude these groups due to their limited formal credit histories or collateral. By aligning credit products with borrowers' specific needs, this principle makes tailored credit solutions a cornerstone of inclusive system design.

Beck and Torre (2007) identify information asymmetries and collateral requirements as important challenges in the lending system perpetuating financial inequality for underserved populations. Interviews with stakeholders (R1) reinforced this perspective, emphasizing the importance of adapting credit products to borrowers' unique circumstances. For instance, street vendors may require microloans with shorter repayment cycles, while agricultural workers need credit schemes aligned with seasonal cash flows (R8). Similarly, gender-sensitive credit products are essential for women entrepreneurs, as noted by the United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP, n.d.).

Tailored credit solutions address these challenges by leveraging alternative data sources and implementing flexible eligibility criteria. Stakeholder interviews (R1, R8) emphasized the importance of perceived benefits, including profitability and sustainability, as key drivers in designing such solutions. For example, respondents noted that differentiating credit schemes by sector-specific risks enables lending systems to serve micro-enterprises better while maintaining financial stability.

Principle 4 aligns with inclusion-by-design by embedding borrower-centricity into the lending system architecture. This approach is consistent with Amartya Sen's Capability Theory, which advocates for expanding individuals' abilities to achieve their goals. Tailored credit solutions empower borrowers by aligning financial products with their realities, ensuring access to credit translates into sustained economic growth and participation.

Interviews further highlighted the importance of categorizing borrowers to refine credit solutions (R8). Respondents noted that effective segmentation, such as distinguishing between street food vendors and agricultural workers, helps align credit products with borrowers' unique needs, fostering accessibility and sustainability. This operational approach expects that tailored solutions promote financial inclusion without compromising the system's long-term viability.

In summary, Principle 4 emphasizes the necessity of designing tailored credit solutions to empower underserved borrowers. Lending systems can foster meaningful participation and long-term growth by addressing their specific challenges and leveraging alternative data sources. This principle bridges the gap between access and engagement, ensuring that inclusion becomes an actionable and measurable objective within financial ecosystems.

*Principle 5: Addressing the long-term sustainability while balancing inclusion and risk*

Achieving financial inclusion in lending systems requires more than expanding access; it demands careful integration of inclusion with risk management to ensure the system's long-term viability. Principle 5 addresses the challenge of expanding access for underserved groups while maintaining the financial stability of lenders and the overall ecosystem. Unlike generalized discussions on sustainability, this principle highlights the trade-offs inherent in inclusion-by-design to balance inclusion with long-term resilience.

Challenges such as high default rates and limited repayment capacities among marginalized borrowers, as identified in RQ1, underscore the importance of this principle. These issues, if unaddressed, can destabilize inclusive systems and erode stakeholder trust. Stakeholder interviews (R1, R3, R8) emphasized the necessity of embedding risk-aware mechanisms into inclusive lending practices. For example, R3 noted that *"inclusion lending without robust risk strategies might create systemic vulnerabilities that undermine the objectives of financial inclusion."*

This principle frames risk management as a tool for empowerment rather than a limitation. Drawing from Amartya Sen's Capability Theory, the principles stress that systems should expand access while safeguarding long-term opportunities for borrowers and lenders. Adaptive strategies, like cross-subsidization, help serve high-risk borrowers by balancing risks with more stable, low-risk portfolios. For example, real-time monitoring of repayments supports proactive risk management and builds trust and transparency. As R1 stated, "Inclusion must come with stability mechanisms to ensure lasting impact, not just a temporary fix."

Principle 5 reframes sustainability as a central consideration in system design, ensuring the system remains resilient while expanding access to marginalized groups. This principle bridges short-term inclusion goals with long-term systemic stability by integrating risk management. Together, these five design principles form the conceptual foundation for the architectural components described in the next section, where they are operationalized into system-level functionalities.

## 5.3. Architectural Components

As we transition into the architectural discussion, we recall the system components outlined in Table 17 and expand on them by introducing an additional classification: Block of Architecture. This grouping structures the architecture into higher-level functional groups. While individual components may differ depending on the system context, the blocks provide a consistent foundation that supports alignment with value-based requirements. Table 19 illustrates how these blocks map VBRs to corresponding components, helping clarify each block's role in fulfilling inclusion goals. The block categorization is not based on a formal methodological framework, but is a pragmatic approach to structure the discussion.

*Table 19. Mapping High-Level Requirements to Architectural Components*

| **Requirements (VBRs)** | **System components** | **Block of architecture** (not including all from RA) |
|---|---|---|
| 1. Equal access | Distributed nodes | Data Collection |
| | Distributed data capturing | Data Collection |
| | Inclusive rule engine | Loan Assessment System |
| 2. Equal distribution | Inclusive distribution mechanism | Loan Assessment System |
| 3. Inclusive scoring | Inclusive scoring algorithm | Loan Assessment System |
| 4. Credit schema for marginalized segments | Custom schema | Loan Assessment System |

| Requirements (VBRs) | System components | Block of architecture<br>(not including all from RA) |
|---|---|---|
| 5. Perceived societal benefits | Contest decision – interface | Borrower Dashboard |
| | Contestation component | Loan Assessment System |
| 6. Transparency | Auditable logging | Data Collection |
| 7. Information Exchange Trust | Distributed ledger (or equivalent traceability system) | Distributed Ledger |

For instance, *Distributed Nodes* and *Distributed Data Capturing* are grouped under the Data Collection block to reflect their shared role in integrating diverse data sources to improve borrower profiling. Similarly, *the inclusive distribution mechanism* and *inclusive scoring algorithm* are categorized under the Loan Assessment System, reinforcing its role as the core analytics engine. Transparency mechanisms like auditable logging fall within the Data Collection System. The Distributed Ledger block supports Information Exchange Trust by offering verifiable, tamper-resistant storage. This implementation is illustrative, not prescriptive; other secure data governance methods could fulfill the same role depending on system context and capacity.

Figure 21 illustrates the building blocks of the RA. The diagram was created using ArchiMate 3.2, a standardized language for enterprise architecture modeling, in the Archi tool (version 5.6.0). Each block group contains components that serve a common functional goal, with ***the block*** providing structural context and ***the components*** delivering specific functionalities. It assumes that organizations already operate standard components in financial lending such as bookkeeping, payment processing, and data storage, which are therefore excluded from this discussion. Instead, the focus is on the additional components exclusively introduced by the Reference Architecture in this study to address inclusion challenges.

The RA consists of four blocks, each addressing specific challenges in inclusive lending. The User Interface Block (Block D) provides dashboards for borrowers, lenders, validators, regulators, and external collaborators, ensuring accessibility and visibility across user groups. The Loan Assessment System Block (Block A) is the core decision-making component, supporting the contestation component, inclusive credit scoring, and equitable loan distribution. The Data Collection Block (Block B) facilitates the use of alternative borrower data, allowing external agents and financial institutions to contribute validated financial information beyond conventional credit scores. The Distributed Ledger Infrastructure Block (Block C) is a secure record-keeping layer that supports traceability and auditability, helping prevent data tampering. While not central to inclusion logic, block C provides verifiable storage for finalized credit decisions. The explanation of each block is as follows:

### A. Loan Assessment Block (Block A)

The Loan Assessment Block evaluates borrower eligibility and manages loan distribution based on validated data submitted by borrowers, lender ratings, and other trusted sources. It acts as the core decision-making layer, interfacing with the Data Collection Block (Block B) to receive verified inputs and with the Distributed Ledger Block (Block C) to record finalized decisions, ensuring transparency and auditability.

*The Contestation Component* allows borrowers to challenge loan assessments by submitting corrections or additional supporting data. Data corrections submitted by borrowers must first be validated through the Data Collection Layer before being incorporated into reassessments. Once a contested decision is updated, the revised assessment is recorded in the Distributed Ledger, ensuring that changes remain transparent and immutable.

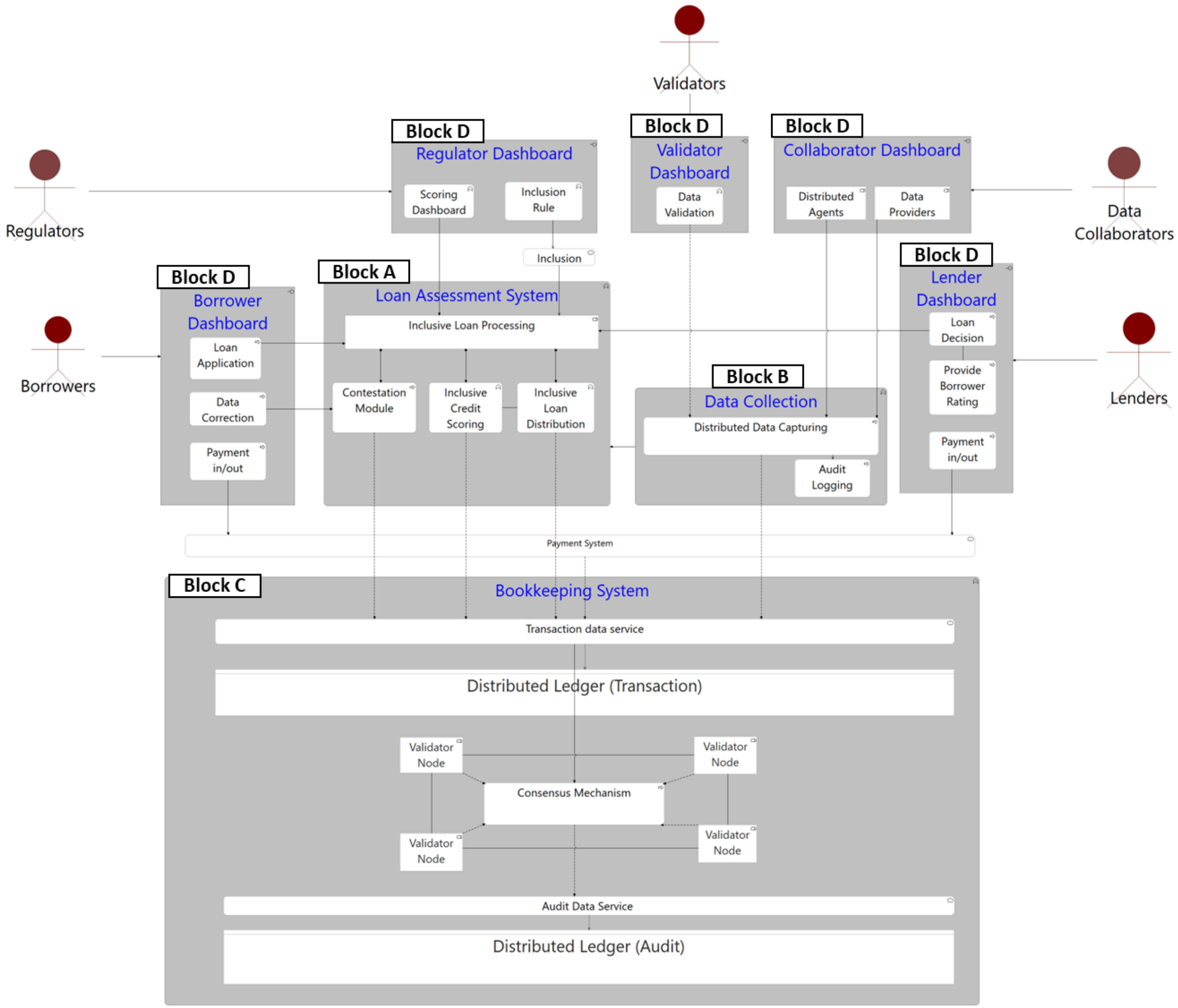



*Figure 21. Components of the Reference Architecture*

*The Inclusive Credit Scoring component* integrates multiple validated data sources, such as, payment records, utility bill payments, and behavioral patterns, to construct a broader borrower risk profile. It moves beyond conventional credit histories by incorporating alternative financial transactions. The scoring model can incorporate advanced machine learning techniques to process complex datasets and detect repayment potential patterns, even among borrowers with limited formal credit history. Since borrower-provided data and external inputs come from the Data Collection Layer, this component only processes information that has been verified. Finalized scoring results, once assessed, are stored in the Distributed Ledger to maintain consistency and prevent manipulation.

*The Inclusive Loan Distribution component* monitors and adjusts credit allocation to prevent systemic exclusion of specific borrower groups. By actively tracking and balancing allocation patterns, this subcomponent ensures equitable distribution among various borrower demographics, such as urban versus rural applicants or gender-based lending disparities. If imbalances are detected, the system recalibrates distribution parameters to align with inclusion objectives. This component interacts with the Data Collection Layer to incorporate validated borrower characteristics and stores allocation outcomes in the Distributed Ledger to maintain accountability.

*The Custom Schema component* is integrated into the Loan Distribution Component, enabling tailored loan structures based on borrower needs. For example, seasonal income trends for farmers can inform repayment schedules aligned with harvest cycles, while daily wage earners can access micro-loans with shorter repayment terms. Since these adjustments depend on borrower profiles, they rely on verified data from the Data Collection Layer before structuring tailored repayment plans.

*The Inclusive Loan Processing component* manages borrower submissions, eligibility assessments, and approvals before transactions are recorded in the Distributed Ledger. This ensures that only validated borrower data from the Data Collection Layer is used in credit evaluations. Once a loan decision is finalized, the outcome is permanently logged in the ledger, providing a transparent and immutable record of lending activities.

**B. Data Collection Block (Block B)**

The Data Collection Block gathers, validates, and updates borrower information before integrating it into the loan assessment process. This layer ensures that alternative data sources, borrower corrections, and third-party financial inputs are incorporated while maintaining accuracy and preventing misinformation.

*The Distributed Data Capturing* component collects inputs from three main sources: borrowers submitting corrections, data collaborators (distributed agents) contributing external financial data, and data providers supplying institutional financial data. However, these updates do not directly modify borrower records and must first be verified to prevent inaccuracies. The Validator Dashboard facilitates this process by enabling Validators to review and approve all submitted data. Validators verify borrower-submitted corrections, assess the reliability of external data contributions, and ensure that data provider inputs meet integrity standards. *The Audit Logging component* maintains a verifiable history of all data modifications and assessment changes.

By establishing a structured validation process, the Data Collection Layer ensures that only verified information informs lending decisions. This enhances data integrity, transparency, and accountability.

**C. Distributed Ledger Block (Block C)**

The Distributed Ledger Infrastructure serves as a secure record-keeping layer that captures finalized lending activities to support transparency, auditability, and data integrity. It maintains a verifiable history of loan decisions, borrower ratings, and credit scoring outcomes, reducing the risk of unauthorized modifications through a distributed consensus mechanism. While this layer supports compliance and traceability, its role complements the core processes of borrower assessment and inclusion tracking.

The Distributed Ledger (Transaction) records approved loan transactions, borrower ratings, and finalized credit scoring outputs. These records are submitted by the Loan Assessment System and lenders, then validated through a consensus mechanism involving Validator Nodes before being committed. This validation process helps prevent tampering and maintains consistency, though it relies on appropriate infrastructure and digital readiness.

The Distributed Ledger (Audit) stores long-term historical records, including prior assessments. Separating audit data from the transaction ledger improves system efficiency. The consensus mechanism ensures that only verified transactions are added to both ledgers. This infrastructure enhances system accountability by enabling traceable and tamper-resistant records, but should not be seen as the primary driver of financial inclusion.

#### D. User Dashboard Block (Block D)

The Dashboard Block provides interfaces that reduce information asymmetry by giving each user group access to verified, relevant data.

*The Borrower Dashboard* enables loan applications, borrower data corrections, and repayment tracking. *The Data Correction Component* allows borrowers to submit updates to their personal and financial information, ensuring that loan assessments are based on the most accurate data. Any corrections submitted through this dashboard require validation before being used in decision-making. *The Payment Component* allows borrowers to track loan disbursements and manage repayments. *The Lender Dashboard* supports loan approval decisions and borrower ratings. Lenders review applications, assess borrower risk, and assign ratings contributing to *the dual-rating system feature*.

*The Validator Dashboard* is responsible for data validation. It ensures that submitted borrower data and external financial records are verified before entering the system. This component does not influence credit scoring or financial inclusion tracking; it maintains data integrity. *The Regulator Dashboard* provides oversight on financial inclusion policies. It includes *the Scoring Dashboard*, which allows regulators to monitor different credit scoring models. *The Inclusion Rule* Component enables regulators to define eligibility criteria, ensuring lending decisions align with inclusion principles.

*The Collaborator Dashboard* serves as an interface for *Distributed Agents* and *Data Providers*, who supply borrower-related data such as financial histories, behavioral insights, and alternative credit indicators. These inputs are processed within Data Collection, validated by the Validator Dashboard, and used in the Loan Assessment System.

### 5.4. Overview of Reference Architecture

The Reference Architecture (RA) proposed in this chapter is structured to improve inclusion in lending systems by building upon existing infrastructure rather than replacing it. It integrates VBRs, Design Principles, and Architectural Components to address challenges in inclusion.

**The VBRs** consist of requirements that define the fundamental conditions an inclusive lending system must fulfill. *Equal Access* ensures that all borrowers, particularly those from marginalized groups, have the opportunity to apply for credit without being excluded due to traditional eligibility constraints. *Equal Distribution* prevents excessive concentration of credit in specific segments, ensuring that lending is not disproportionately directed toward specific groups. *Inclusive Scoring* requires that borrower assessments reflect actual repayment ability, incorporating diverse financial behaviors rather than rigid traditional metrics. *Credit Schema for Marginalized Segments* mandates loan products that accommodate borrowers with varying financial conditions, such as seasonal income fluctuations or informal earnings. *Perceived Societal Benefits* ensures that the system remains financially viable for lenders while offering meaningful advantages for borrowers. Inclusive lending should not compromise sustainability; borrowers gain fair access to credit, while lenders maintain confidence in returns. *Transparency* ensures that all stakeholders, including borrowers, lenders, and regulators, can understand and verify credit decisions, preventing exclusionary or arbitrary practices. *Information Exchange Trust* guarantees transaction integrity through auditable records and decentralized validation, ensuring that financial interactions remain transparent and resistant to manipulation.

The **Design Principles (DP)** translate these VBRs into actionable design strategies that guide system implementation. The RA is structured around five principles: (1) Inclusion Metrics, (2) Leverage Alternative Data, (3) Transparent Insights and Contestable Decision-Making, (4) Tailored Credit Solutions, and (5) Sustainability and Inclusion Balance. These principles ensure that inclusion is not treated as a mere outcome but is actively embedded in the system's decision-making processes. They promote measurable inclusion, expand data sources beyond traditional financial indicators, enhance system transparency, ensure that credit models address diverse borrower needs, and maintain a sustainable approach to inclusion.

The Reference Architecture (RA) **components** operationalize the Value-Based Requirements (VBRs) and Design Principles (DPs) by embedding inclusion mechanisms at every stage of the lending process. **The Loan Assessment Block** ensures that credit evaluations move beyond traditional metrics by integrating *Inclusive Credit Scoring*, which leverages alternative financial indicators, and a *Contestation Mechanism*, allowing borrowers to challenge decisions and provide additional supporting data. To promote equitable access, the *Inclusive Loan Distribution* component actively monitors and adjusts loan allocations, preventing systemic exclusion of specific borrower groups, while the *Custom Schema* component enables tailored credit solutions, such as flexible repayment schedules for seasonal or low-income earners. **The Data Collection Block** facilitates financial inclusion by incorporating *Distributed Data Capturing*, enabling data from external agents and institutional providers to be validated before influencing loan assessments, while *Audit Logging* ensures transparency in borrower histories. **The Distributed Ledger Block** serves as a tamper-resistant storage layer that helps preserve transparency and traceability in finalized credit decisions. While not essential to inclusion logic, it supports accountability by ensuring that recorded outcomes remain verifiable and resistant to manipulation. **The User Dashboard Block** provides targeted access for borrowers to correct their financial records, lenders to integrate dual-rating mechanisms, regulators to define and monitor inclusion metrics that guide eligibility criteria, validators and data collaborators for data enrichment and assessment. Rather than replacing existing systems, these components are designed to extend and enhance them, embedding inclusion mechanisms into credit assessments, eligibility criteria, and data governance processes.

The following chapters will evaluate the RA by assessing the feasibility and impact of selected components through prototype development, testing key features, conducting a sensitivity analysis, and performing a controlled survey. These evaluations will offer empirical evidence of the proposed RA in addressing inclusion challenges within lending systems.

# PART IV: TESTING AND EVALUATION

# Chapter 6: Evaluating Prototype Features for Decentralized Lending

## 6.1. Introduction

The previous chapter introduced a Reference Architecture (RA) designed to improve inclusion in lending systems by embedding Design Principles (DPs) and Value-Based Requirements (VBRs). Building on this foundation, the next step is to evaluate the RA's impact through a series of tests to answer **Research Question 4 (RQ4)**: *What is the impact of the proposed Reference Architecture on inclusion?*

The testing is conducted in three stages, each with distinct objectives:

1. **Developing a prototype for technical feasibility and feature testing (Chapter 6)**. This stage evaluates whether the proposed architecture can be implemented technically. It assesses three key features: *Contested Decision-Making*, *Dual Rating System*, and *Collaborative Data Collection*. These features are tested using the prototype through focus group discussions to examine *how these features affect the perceptions of inclusion*. The three tested features were implemented because they address information asymmetry, fragmented data collection, and limited access to diverse data sources.
2. **Controlled Surveys (Chapter 7)**. This stage investigates how different types of borrower information affect *lender decisions* in approving or rejecting loan applications
3. **Sensitivity analysis with machine learning simulations (Chapter 8)**. This stage measures how the *Inclusive Scoring Feature* improves loan recommendation outcomes. The experiment evaluates the impact of *adding borrower data* and *tuning model parameters*.

Table 20 shows the testing roadmap to answer RQ 4 and the mapping with design principles (DPs).

*Table 20. Prototype components and testing approach*

| Testing Method | Objective | Hypotheses | Design Principle |
|---|---|---|---|
| Prototype feature testing | Assess how these features affect the perceptions of inclusion | The three features (contested decision-making, dual rating system, and collaborative data collection) improve the perceptions of inclusion | DP2; DP3; DP5 |
| Empirical simulations | Assess the impact of adding more data variables and models' tuning on the system's ***Loan Recommendation (LR)*** | A1: Additional data variables increase the system's loan recommendations (LR).<br>A2: Tuning models' parameters increases the system's loan recommendations (LR). | DP1; DP2 |
| Controlled surveys | Assess how additional information and system recommendations affect the lender's ***Loan Acceptance (LA)***. | B1: Additional information increases loan acceptance rates.<br>B2: System recommendations increase loan acceptance rates.<br>B3: Combining additional information and system recommendations increases loan acceptance rates.<br>B4: Incorporating additional information and system recommendations impacts lenders' perceptions of (i) creditworthiness and (ii) reliability of the information. | DP2; DP3 |

The table above summarizes the three-stage evaluation strategy and the design principles addressed in each. The first stage, covered in this chapter, focuses on three specific prototype components, Contested Decision-Making, Dual Rating System, and Collaborative Data Collection, to test their feasibility and perceived inclusion impact. These components are linked to DP2 (Alternative Data), DP3 (Transparency and Contested Decision-Making), and DP5 (Sustainability). Chapters 7 and 8 also build on components of the same prototype. Chapter 7 analyzes lender decisions using controlled surveys, focusing on DP2 and DP3. Chapter 8 uses simulation to evaluate how inclusive scoring improves loan recommendations, addressing DP1 and DP2. Chapter 8 uses simulation to evaluate how inclusive scoring improves loan recommendations, addressing DP1 and DP2. DP4 (Tailored Credit Solutions) is not included in testing due to implementation constraints during prototyping and is therefore proposed as a direction for future research.

This chapter begins by providing an overview of the prototype's components in Section 6.2, followed by an explanation of the configuration and user Interfaces in Section 6.3. The prototype is then evaluated through focus group discussions to evaluate the feasibility of its key features: *Contested Decision-Making, Dual Rating System,* and *Collaborative Data Collection* (Sections 6.4 and 6.5).

## 6.2. Prototype Design and Implementation

### 6.2.1. Purpose of Prototyping

The prototype in this study was developed as a testbed to explore the technical feasibility of selected RA components and to simulate how users interact with core inclusion features. It serves as an experimental tool to implement and refine key functionalities in a controlled setting, allowing focused evaluation before full-scale deployment.

Prototypes fulfill *several roles*, including demonstrating system functionality, simulating user interactions, and assessing technical feasibility (Houde & Hill, 1997). According to Jensen et al. (2016) prototypes serve dual roles: as *evaluative tools* to test system components and as *adaptive tools* that allow adjustments throughout the design phases. Prototyping must consider fidelity, embodiment, and cost constraints at each stage to align with project goals (Houde & Hill, 1997; Jensen et al., 2016). By selecting the appropriate fidelity level, low fidelity in early ideation phases and high fidelity in later stages, prototyping facilitates exploration while minimizing design fixation (Jensen et al., 2016). A structured approach with clear objectives and controlled iterations ensures the alignment of prototypes with user requirements while maintaining design consistency (Shoval & Pliskin, 1988).

There are several prototyping approaches, each addressing different design needs and stages. *Exploratory Prototyping* enables early experimentation to refine system requirements and address core challenges (Houde & Hill, 1997). *Iterative Prototyping* involves design and testing cycles, incorporating feedback at each stage to balance ideation and evaluation throughout the process (Jensen et al., 2016; Hardgrave et al., 1999). *Evolutionary Prototyping* incrementally builds toward the final product, allowing key features to develop while preserving essential functionalities. *Experimental Prototyping*, on the other hand, is designed to test specific features or hypotheses; experimental prototypes offer detailed insights into critical functionalities. Jensen et al. (2016) note that specialized prototypes can yield targeted insights, especially in controlled environments.

The prototyping process in this research was *iterative and experimental*, focusing on specific RA features tested in controlled environments and refined based on participant feedback. In this research, prototypes were designed as structured testbeds to evaluate the RA's core functionalities and assess their alignment with inclusion goals. Each testing phase involved designing and implementing specific features of the RA and gathering feedback to refine these features further.

Moreover, the approach in this research was designed to accommodate dynamic environments by integrating stakeholder feedback (Hardgrave et al., 1999). Feedback loops played a critical role in guiding the refinement process, ensuring that adjustments were informed by hands-on interaction and practical insights (Naumann & Jenkins, 1982). With this rationale established, the following section details the prototype's architecture.

### 6.2.2. Prototype Components

The RA prototype is developed by leveraging Distributed Ledger Technology (DLT). In this study, DLT was employed as a demonstrative implementation to support inclusive system features, without being positioned as a central solution to the inclusion challenge. DLT provides a decentralized platform that ensures data security, transparency, and tamper-proof records (Hoque, Kummer, & Yigitbasioglu, 2024), critical elements in fostering trust and inclusion in lending practices. This empirical testing employs a cloud-based DLT application on *the Hyperledger Besu platform*, deployed within a controlled environment simulating a P2P lending system. Participants interact directly with these features and provide feedback.

#### A. Prototype Blocks

Figure 22 illustrates the prototype developed in this chapter, which implements selected components from the RA. It is based on the same RA structure as Figure 21, with black-boxed components indicating elements *that are **not implemented** in the prototype*. This prototype focuses only on features that can be directly tested (white boxes) through user interaction and data processing, prioritizing those most relevant for evaluating inclusion. Several RA components were excluded from the prototype as their implementation would require extensive rule-based automation, long-term historical tracking, and integration with the payment system, which go beyond the immediate scope of this evaluation.

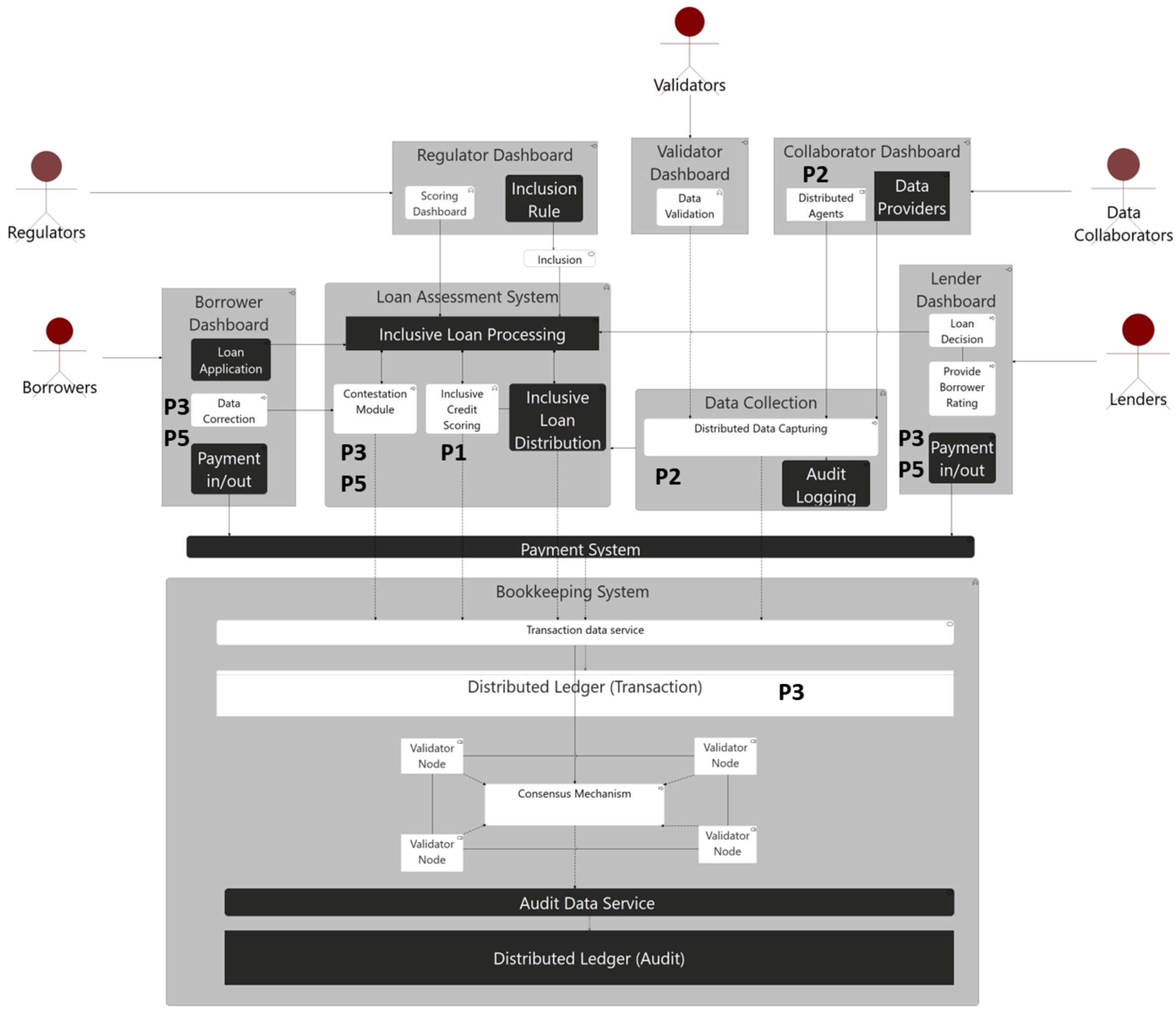



*Figure 22. Prototype components*

The prototype ensures that key inclusion mechanisms can be tested in a controlled setting before scaling to a fully deployed system. The prototype consists of **four blocks**: User Interface, Processing Layer (Loan Assessment System), Data Collection, and Distributed Ledger Infrastructure mapped to the Design Principles (P1 to P5).

**The User Interface Block** provides role-based dashboards for borrowers, lenders, validators, data collaborators, and regulators. *The Borrower Dashboard* allows users to submit data corrections before loan processing, ensuring data accuracy and dispute resolution (DP3, DP5). *The Lender Dashboard* supports loan approval decisions and borrower ratings, facilitating dual rating transparency (DP3, DP5). *The Validator Dashboard* enables approval of data corrections submitted by borrowers and collaborators, ensuring data validation before inclusion in loan assessments. *The Regulator Dashboard* is used for monitoring the impact of different scoring models on inclusion outcomes, supporting further evaluation in Chapter 8. Unlike the RA, this prototype does not include *Inclusion Rule Management*, as automated rule-based decision-making and fund allocation are beyond the prototype's scope. *The Collaborator Dashboard* allows external agents to contribute borrower data through Distributed Agents (DP2), enhancing the system's ability to integrate alternative data sources.

**The Processing Block** is centered around the Loan Assessment System, which integrates *the Contestation Component* (DP3, DP5) to allow borrowers to challenge credit evaluations. *The Inclusive Credit Scoring component* (DP1) aggregates borrower and lender-provided ratings, improving assessment accuracy. The Inclusive Credit Scoring feature will be further tested in Chapter 8 through sensitivity analysis, evaluating its impact on loan recommendations based on alternative data and model tuning. However, *Inclusive Loan Processing* is not implemented, as the prototype does not handle loan applications. Similarly, *the Inclusive Loan Distribution component* is omitted, as automated fund allocation is beyond the prototype's scope.

**The Data Collection Block** includes *Distributed Data Capturing* (DP2), enabling borrower data updates from validators and external collaborators. Data Collaborators enable distributed agents to submit borrower data allowing evaluation of how alternative data sources can contribute to borrower assessments. *Audit Logging*, which was included in the RA for tracking decision histories is not implemented as long-term compliance monitoring is beyond the scope.

In the **Distributed Ledger Infrastructure Block**, the prototype features *a Distributed Ledger* (Transaction), ensuring secure, tamper-proof loan transaction records. *The Consensus Mechanism* (DP3) validates transaction integrity through Validator Nodes, reinforcing transparency and reliability. However, *the Audit Ledger* from the RA has not been implemented, as long-term verification and scalability are not the focus of this prototype.

In this prototype, each transaction recorded in the Distributed Ledger (Transaction) includes *(1) loan approval records*, which store loan decisions (approved/rejected), loan amounts, interest rates, and repayment terms; *(2) contestation records*, which capture borrower-contested data, validation status (approved/rejected by a validator), and timestamps of changes; *(3) validated borrower data updates*, which reflect approved corrections to borrower profiles, including financial details such as income or repayment history; *(4) credit scoring results*, which represent the final borrower risk assessment after processing verified data; *(5) lender ratings*, which lenders assign based on borrower risk assessments or repayment history; and *(6) Data Collection component updates*, which store verified inputs from distributed data capturing, such as alternative financial indicators submitted by data collaborators.

### B. Prototype Implementation and Technology Stack

The prototype is implemented with a multi-tier architecture comprising *front-end, back-end,* and *distributed ledger technology (DLT),* as illustrated in Figure 23. The prototype follows a permissioned blockchain model, where only authorized participants can validate and store transactions to ensure privacy, security, and scalability. The source code for the smart contract layer, middleware DLT service layer, and backend API layer are provided in **Appendix 1, 2, and 3** of this document.

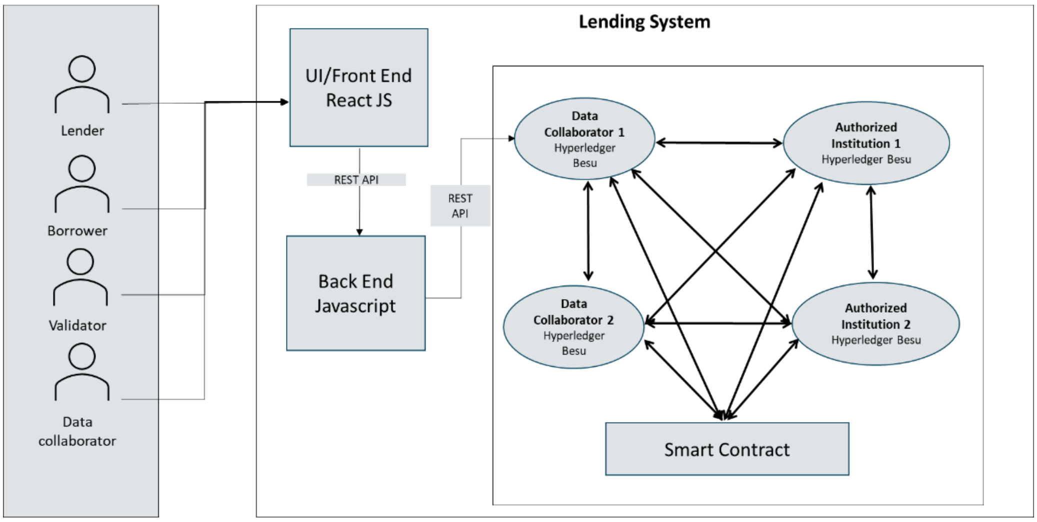



*Figure 23. Prototype Implementation – architecture*

**The front-end UI**, built using *React JS*, provides an interface for borrowers, lenders, validators, and data collaborators, facilitating seamless user interactions. It connects with the back-end through REST APIs, enabling real-time submission, retrieval, and validation of borrower data, loan applications, and contested decisions.

**The back-end**, developed in *JavaScript*, manages business logic, smart contract execution, and database operations. It acts as an intermediary between the front end and the blockchain, ensuring only verified transactions are committed to the ledger. Instead of storing sensitive borrower information on-chain, the back-end processes apply business rules and send hashed references (pointers) to the DLT for security and compliance.

**The DLT layer**, implemented using *Hyperledger Besu*, addresses transparency and tamper-proof record-keeping. The system operates on a private, permissioned blockchain network, where nodes represent financial institutions, data collaborators, and validators. These nodes communicate through a peer-to-peer (P2P) network, verifying transactions while restricting access to sensitive financial data. Unlike public blockchains, this setup ensures that only authorized entities participate, preventing unauthorized modifications while maintaining an auditable transaction history.

The prototype implements key features tested in Chapter 6, including the dual rating system, contested decision-making, and alternative data collection. **The dual rating system** consists of *lender ratings* and *community ratings*, allowing different stakeholders to evaluate borrowers. **Contested decision-making** allows borrowers to challenge credit assessments by submitting correction requests via the borrower dashboard. These requests are processed by the back-end, verified by validators or data collaborators, and, once approved, permanently recorded on the DLT.

A smart contract is a self-executing program deployed on a distributed ledger to automate transaction recording and enforce predefined rules (Buterin, 2014). In this prototype, the smart contract is assumed to be created and deployed by financial institutions to manage the lending ledger, storing borrower data, lending history, and contestation records. It ensures that all authorized parties access the same verifiable records while maintaining data integrity and security. The smart contract allows borrowers to submit and track data corrections using their *public key*. For lenders, it provides real-time access to verified borrower data for loan decisions. For validators, it maintains an immutable record of lending transactions and contested data, ensuring compliance and preventing unauthorized modifications.

The entire system is containerized using **Docker**, allowing for flexible cloud-based deployment. Simulations are conducted to test the system under varying transaction loads, ensuring the network can handle contested decisions, loan processing, and credit scoring without performance degradation.

## 6.3. Prototype Configurations and User Interface

This section describes the cloud-based configuration of DLT and the user interface. Participants accessed the prototype directly through a provided site link, enabling them to simulate interactions on personal devices.

### 6.3.1. Prototype Configuration

The configuration in this prototype (Figure 24) utilizes Hyperledger Besu, a permissioned blockchain platform chosen for its ability to provide better network control and data security while keeping operational costs lower.

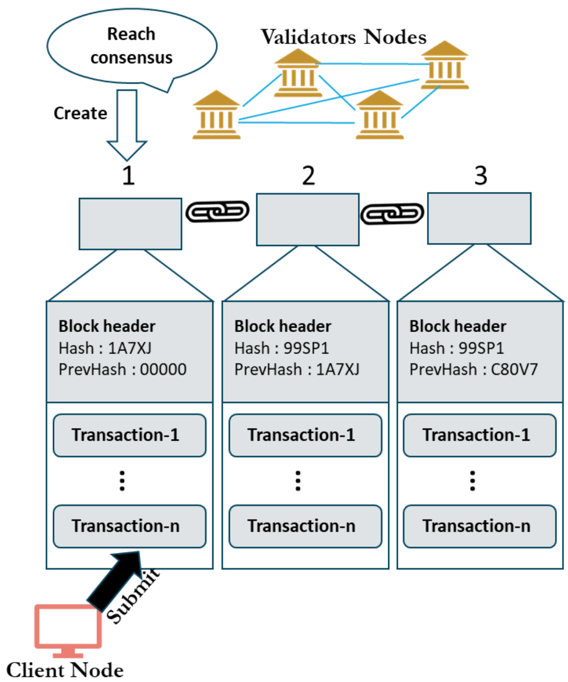



*Figure 24. DLT configuration with Hyperledger Besu*

Hyperledger Besu supports *Proof of Authority (PoA)*, which enables faster transaction validation, lower computational costs, and controlled validator participation, making it well-suited for a regulated lending system (Shahrukh & Mansoor, 2023 ). Compared to other permissioned blockchains like *Corda* and *Hyperledger Fabric*, Besu offers greater flexibility by avoiding reliance on a central validating entity (as in Corda) or additional complexity in transaction flow (as in Fabric) (Derecha, n.d.) (Chamria, 2022). Moreover, as an Ethereum-based blockchain, Besu allows seamless integration with existing Ethereum tools and smart contracts, reducing development overhead while ensuring scalability and efficient governance (Shahrukh & Mansoor, 2023 ).

Figure 24 illustrates how the system operates within a decentralized network. **Validator nodes**, represented at the top, are responsible for achieving consensus and ensuring transaction integrity by verifying and securing data across the network. These validator nodes are held by the regulators, with each regulator overseeing specific approval functions based on their authority. For example, regulator X acts as a validator for approving the classification of marginalized borrower segments, as it holds macroprudential authority, while regulator Y validates borrower information to ensure alignment with small business policies. The validator nodes can create interconnected blocks (for example, labeled 1, 2, and 3) responsible for recording transactions. Each block contains a *header* (including a current hash and previous hash) and a series of transactions (Transaction-1 to Transaction-n), where *hashes* ensure the integrity and linkage of blocks in the chain.

At the bottom of the diagram, **Client Nodes** represent *borrowers*, *lenders*, and *data collaborators* interacting with the system. Unlike validator nodes, which hold regulatory authority, client nodes do not participate in consensus or transaction validation. Instead, they access the network to submit transactions using public keys, such as applying for loans or contesting decisions. This distinction ensures that regulators maintain oversight and enforce compliance via validator nodes, while borrowers and lenders interact with the system as client nodes.

Beyond ensuring data integrity and transparency, the DLT network integrates credit scoring models to support decentralized workflows. Figure 25 illustrates the workflow for managing and updating credit scoring models within a decentralized lending system powered by Distributed Ledger Technology (DLT). This process involves stakeholders, including regulators (User A and User B), machine learning models, and the DLT network, all interacting through web-based user interfaces. Credit scoring is updated within the DLT network to ensure transparency, accuracy, and trust. Further details on scoring are provided in Chapter 8.

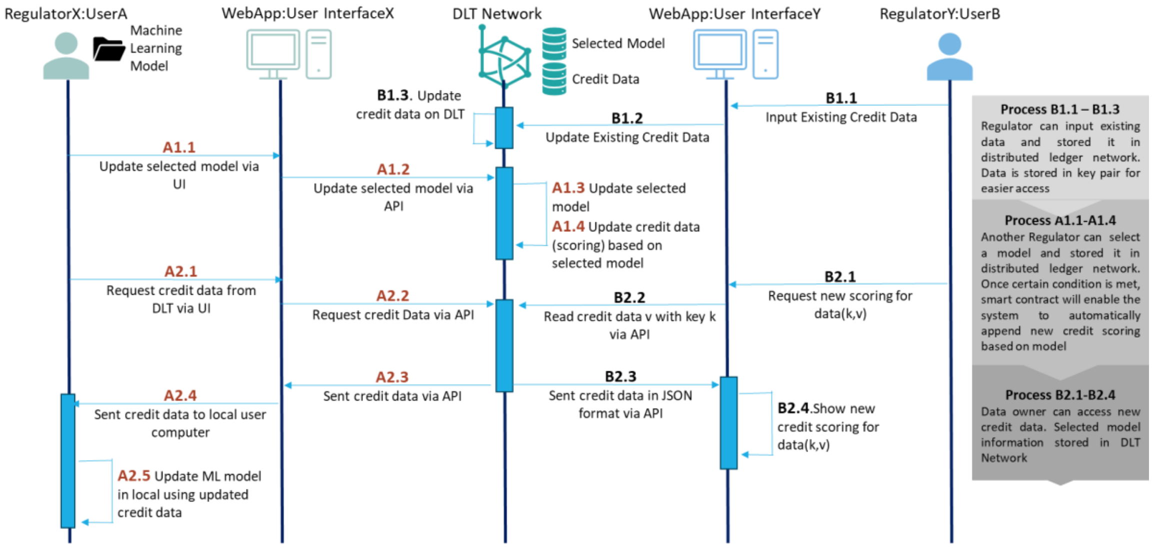



*Figure 25. Sequence diagram for Data Updates and Credit Scoring Monitoring in DLT*

The workflow begins with **User B** (on the right side of the figure) inputting existing credit data via a web application (User Interface Y). This data is securely stored in the DLT network using a unique key pair, ensuring accessibility and traceability. Once stored, the data becomes available for further processing, including updating credit scoring models. **User A** selects a scoring model via the interface and updates it with new parameters or data. The updated model is sent to the DLT network through an API, where it is validated and stored. The DLT network then uses smart contract functionality to automatically update the credit data based on the selected model, ensuring consistent and accurate scoring. **User B** requests specific data points using unique keys and values through the web interface when a new credit score is required. The DLT network retrieves the requested data, processes the scoring request, and sends the updated score back in JSON format via the API. The new credit score is then displayed on the **User B** web page.

Additionally, **User A** can request the updated credit data from the DLT network. The data is retrieved, processed, and sent back in JSON format through the API, allowing **User A** to download the updated data locally. This data can then be used to refine the machine learning model. This system ensures that all data updates and scoring processes are securely logged and tamper-proof, leveraging the DLT network's transparency and integrity. APIs enable seamless communication between user interfaces and the DLT network, while smart contracts automate re-scoring based on selected models. By facilitating secure and collaborative workflows, the system supports transparency across stakeholders while maintaining data integrity.

#### 6.3.2. Testing Scenario for Microenterprises

While the broader scope of this research targets underserved segments, this testing framework focuses on microenterprises as a representative case. This focus is justified for several reasons:

1. Intersectionality of Challenges
   Microenterprises frequently embody the multidimensional challenges faced by underserved groups. These include a lack of formal financial records, low digital literacy, and limited access to formal credit systems due to stringent collateral requirements and extensive documentation processes (Azis, 2024; Tambunan et al., 2021). Addressing these intersecting challenges provides a starting point for developing scalable solutions that can be applied to other underserved groups.
2. Economic and Social Importance
   While often operating at a small scale, microenterprises form a critical backbone of many economies, particularly in developing nations. In Indonesia, they account for the majority of small business activity and are essential drivers of local economic growth (Situmorang, 2022). Enhancing credit access for microenterprises has the potential to generate substantial economic impact.
3. Availability of Real Loan Data
   The focus on microenterprises is supported by the availability of data provided by financial institutions in Indonesia. These datasets, anonymized and shared under strict non-disclosure agreements (NDAs), offer detailed insights into borrower profiles and lending history.
4. Relevance to Lending Systems
   Microenterprises often rely on lending systems, such as P2P lending, to overcome exclusion from formal financial institutions. These systems leverage digital technology to provide credit access, bypassing traditional challenges such as high collateral requirements (Tambunan et al., 2021).

Furthermore, DLT holds significant potential for improving microcredit activities by creating transparent, tamper-proof financial records, which build trust between lenders and borrowers and reduce intermediary costs (Hoque et al., 2024). Integrating DLT with microfinance enhances operational efficiency and governance, mainly by reducing human intervention and operational costs (Hoque et al., 2024). Moreover, DLT's decentralized nature ensures that data updates and transactions are securely propagated across distributed nodes, minimizing risks of tampering or data silos, critical challenges in conventional lending systems.

### 6.3.3. User Interface

We provide *five dashboards* for simulation purposes: the borrower, the lender, the data validator, the regulator, and the data collaborator. Participants use the borrower dashboard to review and update their profile data, the lender dashboard to assess borrowers and make loan decisions, the validator dashboard to approve or reject data updates, the regulator dashboard to manage inclusion rules, and the data collaborator dashboard to upload external borrower data.

#### ***1. The borrower's dashboard***

The borrower dashboard (Figure 26 and Figure 27) allows borrowers to access and manage their profiles with information on business type, income, customer demographics, and loan status.

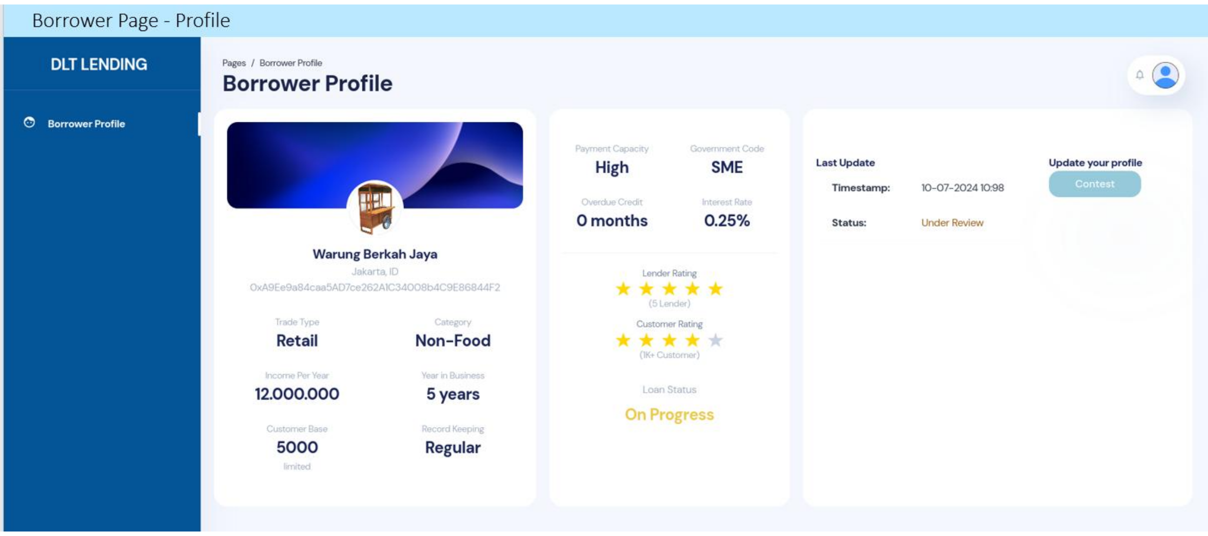



*Figure 26. Borrower dashboard - Landing Page*

Figure 26 presents the Borrower Dashboard, the primary interface for borrowers to access and manage their profile information. *The profile section on the left* displays key borrower details, including the registered business name and location, the borrower's unique blockchain address, and the trade type and category to indicate the business sector. Financial data such as annual income (Rp 12,000,000), years in business (5 years), and customer base (5000 customers) provide insights into the borrower's financial capacity and operational scale. The record-keeping status (Regular) also reflects the borrower's bookkeeping practices, which may influence credit assessment.

*The middle section of the dashboard* contains indicators related to creditworthiness and loan assessment, including payment capacity (High), classification as an SME based on the government code, and overdue credit status (0 months), which signifies that the borrower has no outstanding payments. The interest rate (0.25%) assigned to the borrower is also displayed. This section integrates the Dual Rating System, consisting of a lender rating (5-star rating from five lenders) and a customer rating (4-star rating from over a thousand customers), which provide a combined assessment of the borrower's creditworthiness. The loan status (On Progress) indicates that the borrower's application is still being evaluated.

*The right section* of Figure 26 focuses on profile updates and contestation features. It displays the last profile update timestamp (10-07-2024 10:98), the current review status (Under Review), and the Contest button, which enables borrowers to dispute financial data inaccuracies or submit updated information. This feature ensures that borrowers can actively participate in maintaining accurate financial records within the system.

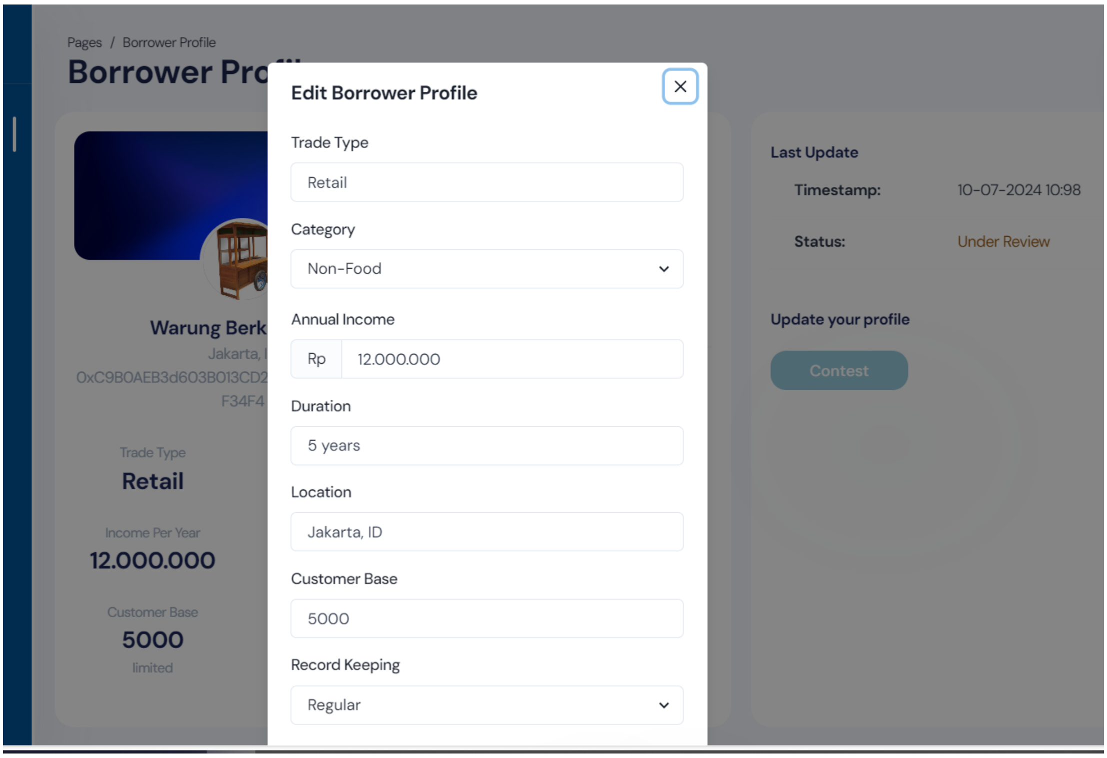



*Figure 27. Borrower dashboard - Update information page*

Figure 27 illustrates the Edit Borrower Profile interface, which appears when a borrower selects the *contestation feature*. This pop-up form lets borrowers update details such as trade type, category, annual income, business duration, location, customer base, and record-keeping practices. Once submitted, these modifications undergo validation before being reflected in the borrower's profile. The ability to request updates reinforces borrower engagement and transparency in credit assessments.

### 2. *The lender dashboard*

Figure 28 presents the Lender Dashboard that provides key borrower information to support loan approval decisions. The interface displays the borrower's business name and location, helping lenders identify potential borrowers. Financial details such as trade type (Retail), category (Food), annual income (Rp 24,000,000), years in business (2 years), customer base (8,500 customers), and record-keeping status (Irregular) provide a snapshot of the borrower's financial stability. A system-generated rating (Low) assesses the borrower's creditworthiness based on available data.

At the bottom of the interface, lenders are presented with two action buttons: "Grant Loan" (green) and "Reject Loan" (red). These options allow lenders to make immediate lending decisions based on the borrower's profile and system rating. This decision-making mechanism aligns with the RA's objective of streamlining loan approvals while incorporating automated and manual assessments.

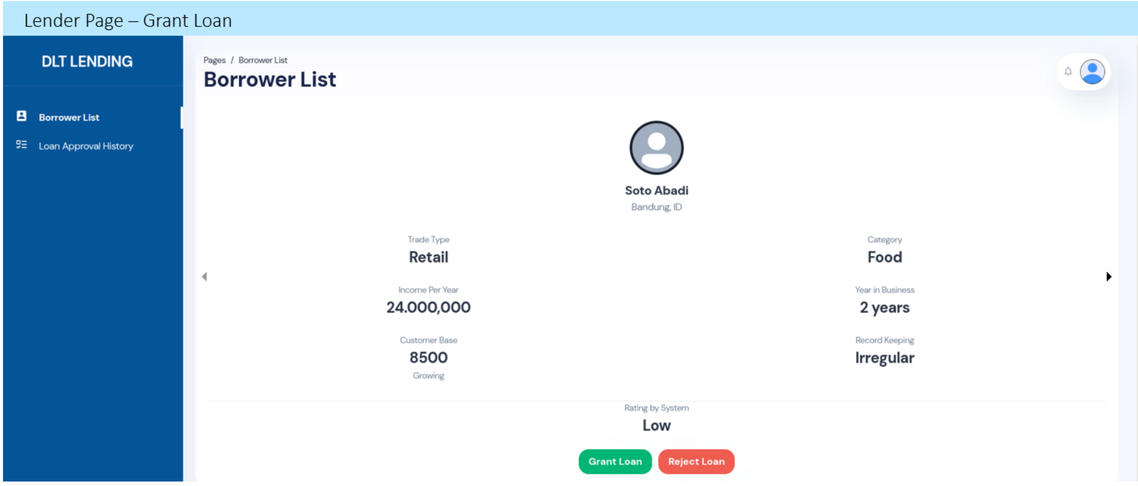



*Figure 28. Lender dashboard - Loan Approval/Rejection*

Figure 29 illustrates *the Loan Approval History* and *Borrower Rating Interface*, which enables lenders to review past interactions with borrowers and provide ratings based on their lending experience. The "Give Rating" button next to each borrower entry allows lenders to submit their ratings. This cumulative rating system builds an evolving borrower profile, reflecting multiple lenders' assessments.

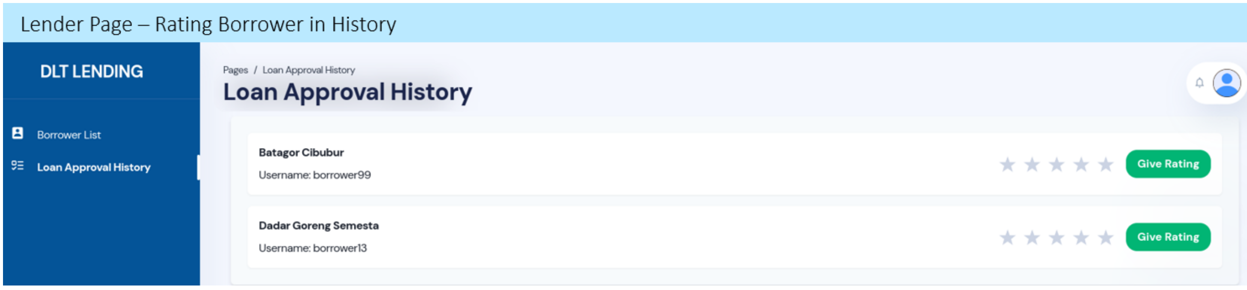



*Figure 29. Lender page - rating borrower's performance*

### *3. The Validator dashboard*

Figure 30 presents *the Validator Dashboard*, which is designed to manage and verify borrower data modifications. The main interface displays a list of pending Data Modification Requests, where each entry consists of the borrower's username and the request status (on progress or under review). Each row contains two action buttons: "Accept" (green) and "Reject" (red), enabling validators to either approve or deny the requested modifications.

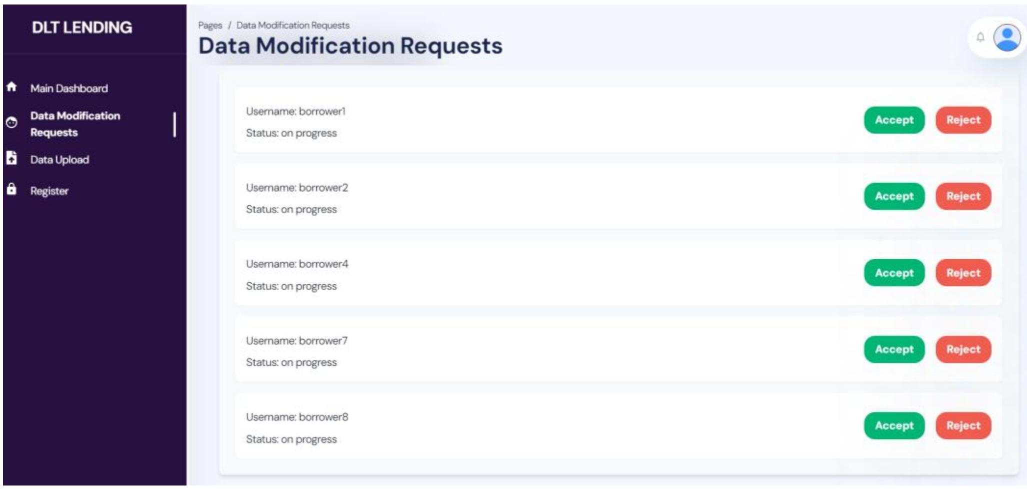



*Figure 30. Validator Page - Data Modification Request*

Figure 31 illustrates the *Data Modification Request Detail Page*, which provides a detailed view of a borrower's profile before the validator makes a decision. When a validator selects a pending request, a pop-up window displays the borrower's trade type, category, annual income, business duration, location, customer base, and record-keeping status. This interface allows validators to carefully examine the updated information before deciding whether to accept or reject the modification. The "Accept" and "Reject" buttons at the bottom of the pop-up enable immediate action. While the approval process follows a specific data governance framework, its details are beyond the scope of this research. However, this dashboard plays a crucial role in ensuring transparency and trust in borrower data management.

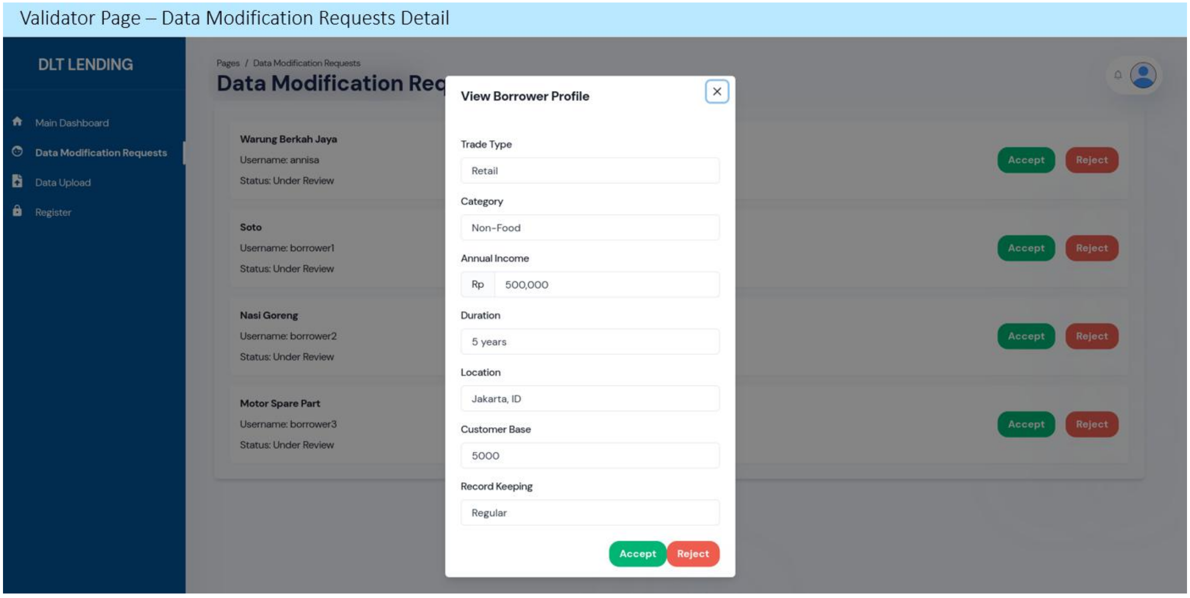



*Figure 31. Validator Page - Data Modification Request Detail*

### *4. Regulators' dashboard*

The Regulator Dashboard visually represents various scoring models and statistical evaluations, assisting regulators in analyzing credit scoring methodologies and their impact on borrower inclusion. This dashboard reflects the four methodologies tested under hypotheses A1 and A2 in Chapter 8: *additional data* (Figure 32), *feature weight* (Figure 33), *penalty-based* (Figure 34), and *hybrid feature penalty-based tuning* (HFPT) (Figure 35). These four methodologies encompass 63 models for additional data, 15 for feature weight, 56 for penalty-based, and 629 for HFPT. For simplicity, model statistics are grouped into summary visuals: one for additional data, one for feature weight, eight for penalty-based, and 18 for HFPT. Detailed explanations of the scoring model are provided in **Chapter 8**.

Figure 32 presents *the Additional Data Modeling interface*, which evaluates how incorporating alternative data sources affects borrower classifications. The chart visualizes movements between risk classes and the resulting inclusion ratios, providing insights into whether additional data improves or worsens accessibility. *The Data Sample Comparison* table on the right lists individual borrowers alongside their scores under the base model and the additional data model, allowing regulators to track the direct effects of incorporating new data.

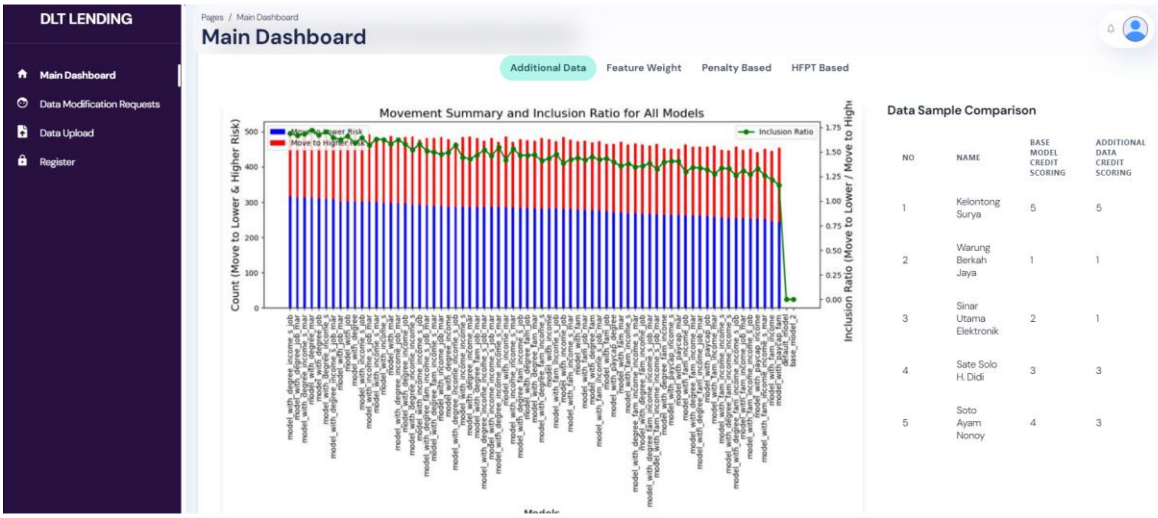



*Figure 32. Data collaborator – additional data modeling*

Figure 33 illustrates *Feature Weight Modeling*, where different model configurations adjust the importance of specific borrower attributes in credit scoring. The visualization highlights how altering feature weights influences the distribution of borrowers across risk classes. The green inclusion ratio line represents changes in movement, and *the comparison table* on the right tracks scoring differences between the base model and the feature-weighted model for sample borrowers.


*Figure 33. Data collaborator – feature weight modeling*

Figure 34 shows *Penalty-Based Modeling*, which evaluates the impact of introducing penalties to borrowers' classification. The bar chart represents shifts in borrower classifications, distinguishing between those who move to lower or higher risk classes, while the inclusion ratio trend assesses the comparison of lower movement vs higher movement. The model selection dropdown at the top allows regulators to choose specific penalty configurations for deeper analysis.

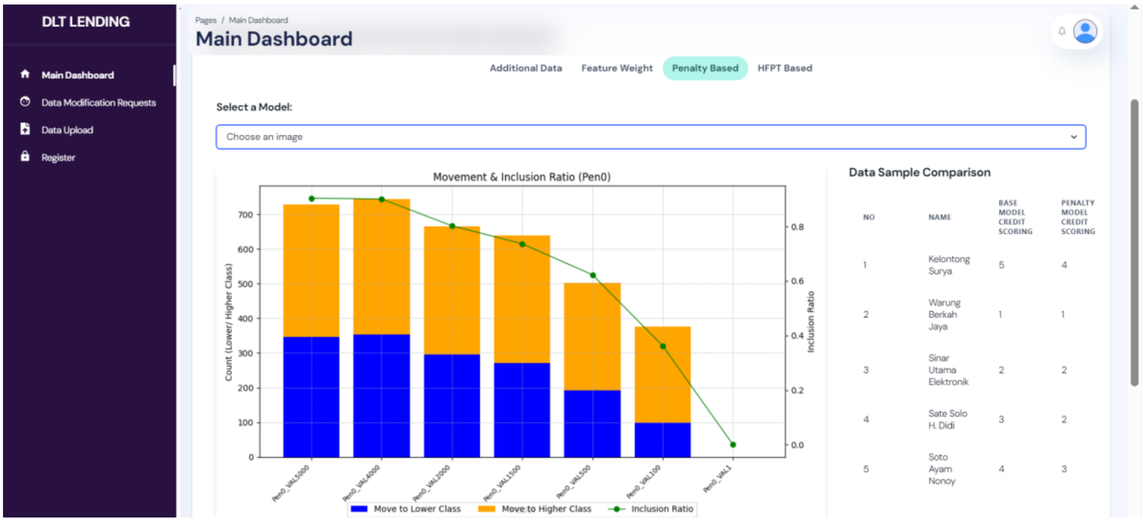



*Figure 34. Data collaborator – penalty based modeling*

Figure 35 presents an example of a snapshot from *Hybrid Feature Penalty-Based Tuning (HFPT) Modeling*, a novel approach introduced in this study, combining feature weight adjustments and penalty mechanisms to refine inclusive credit scoring. The visualization follows a similar structure to Figure 34 but reflects HFPT-specific configurations.


*Figure 35.Data collaborator – HFPT*

### *5. The Data Collaborators' dashboard*

Figure 36 presents the Data Upload Page, which allows data collaborators, such as field agents, regional providers, and microfinance partners, to contribute borrower data. The interface supports uploading borrower information, including credit schema, usage, city, total debt, instalment terms, interest rate, and delay time. The borrower data table displays uploaded records, enabling users to review and verify details before submission.

This decentralized input system supports localized data collection, extending financial inclusion efforts across geographically dispersed regions. However, submitted borrower data is not immediately integrated into the system; it must first undergo a review process by validators. This process follows specific data management procedures that are beyond the scope of this research but are essential for maintaining data integrity and compliance.


*Figure 36. Data Collaborator Page - Data upload*

Figure 37 provides the Network Configuration Page, which offers a real-time overview of the Hyperledger Besu blockchain network. This interface ensures that all uploaded borrower data is securely recorded and synchronized across multiple nodes. At the top, key blockchain metrics are displayed, including the current status of the node (Running), number of recorded blocks (11), active peers (7), and queued transactions (0). The “Node ID” and “Node Name” identify the current blockchain client instance, confirming that it is operating under Hyperledger Besu v23.4.1. The “Enode URL” and “IP Address” enable secure communication between network participants, ensuring that borrower data remains accessible while maintaining decentralized system integrity. The RPC URL allows external applications to interact with the network for loan processing and borrower verification.

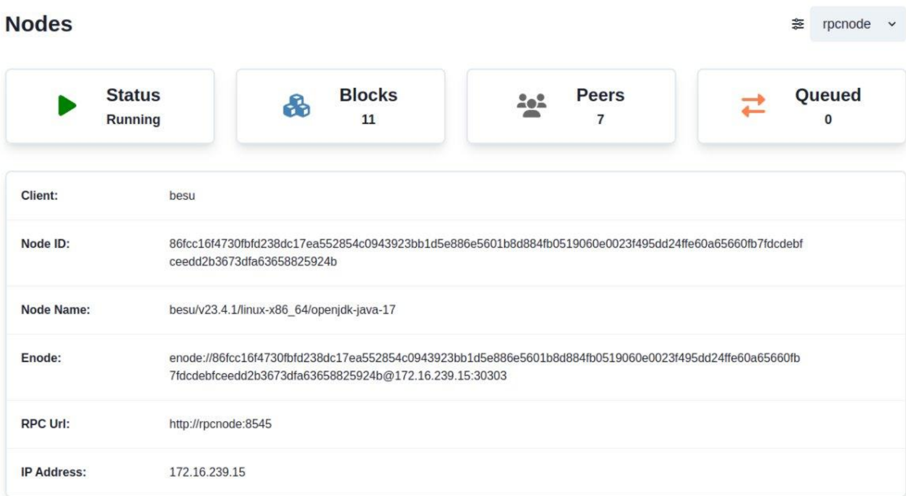



*Figure 37. Hyperledger Besu Network Status Overview*

During the focus group discussions (FGDs), participants interacted with the Data Collaborator Dashboard to simulate real-world borrower data submission. They uploaded borrower records containing trade type, income, loan history, and repayment behavior using a pre-formatted CSV template. After submission, participants reviewed the borrower data in the system and finalized the upload through the “Publish Now” step, simulating how financial agents or regional providers contribute data in a decentralized system. The submitted data was then reviewed by validators, following predefined governance rules. Although the validation process itself is beyond the scope of this research, participants examined how data integrity is maintained through the decentralized network structure using the Network Configuration Page (Figure 37).

## 6.4. Experimental Set-up for FGDs

This section describes the experimental setup used to assess the impact of three core features in the first stage of RQ4 testing (chapter 6). The experiment is structured in two stages: **feature simulation** and **focus group discussions (FGDs)**.

**Stage 1: Feature Simulation**
The first stage of the experiment involves an interactive simulation where FGD participants, who will be referred to as *participants*, engage directly with the three features deployed on a cloud-based DLT. This controlled environment simulates a P2P lending system, enabling participants to experience how each feature contributes to transparency and inclusion. Participants are assigned specific roles with the use case diagram in Figure 38 illustrates the interactions within the P2P lending system. Core system functionalities, i.e., contesting decisions, approving loans, and updating data rules, are mapped to relevant stakeholders

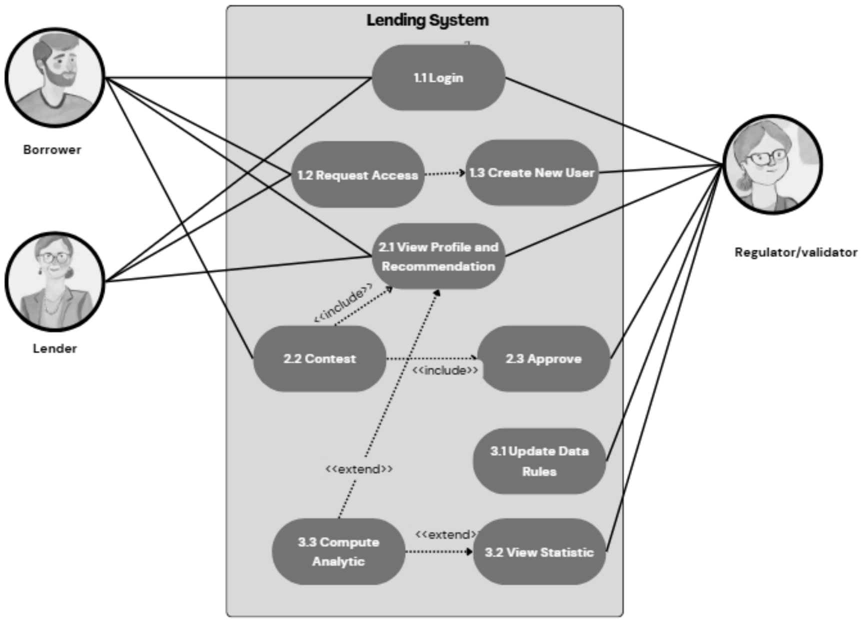



*Figure 38. Use case diagram for feature testing and FGDs*

The features evaluated are: **(i) Contested Decision Making (CDM)**, which allows borrowers to dispute recorded financial data to take corrective actions. Participants experience the dispute process firsthand while validators assess the validity of these updates; **(ii) Dual Rating System (DRS)** allows lenders and community members to contribute feedback on borrower (microenterprises) profiles, providing a multi-source evaluation. The testing scenario allows participants to observe how aggregated ratings from diverse perspectives influence lending decisions, and **(iii) Data Collaborator Features (DC)**: This feature enables data collaborators to update borrower profiles with supplementary information from diverse sources.

**Stage 2: Focus Group Discussions (FGDs)**
The second stage is Focus Group Discussions (FGDs). All participants received an informed consent form outlining the study's purpose, confidentiality protocols, and the voluntary nature of their involvement, which they reviewed and signed before participation.

Participants were recruited through purposive sampling, drawing on institutional contacts established in earlier research phases. Selection criteria required a minimum of five years of relevant professional experience. For the IT group, participants needed direct experience in system architecture, operational management, or analytics in lending or payment ecosystems. For the Macroprudential group, participants were drawn from credit-risk, supervisory, or regulatory roles with oversight of microenterprise lending. Participation was voluntary, and all respondents provided informed consent.

A total of *12 participants* joined the FGDs. *The IT group* included seven professionals (5 males and 2 females) aged between 28 and 47 years, covering roles such as technology architects, application architects, IT operational experts, and information system analysts. *The Macroprudential group* included five professionals (3 males and 2 females) aged between 33 and 52 years, including credit analysts, macroprudential experts, credit-risk experts, and microenterprise specialists. Each participant was assigned an anonymized code (IT1–IT7 for the IT group and MP1–MP5 for the Macroprudential group) to maintain confidentiality while enabling traceability in the analysis.

*Table 21. Respondents of FGDs*

| Group | Code | Role | Years of Experience | Gender | Age Bracket |
|---|---|---|---|---|---|
| IT | IT1 | Technology Architect | >15 | F | 40–45 |
| | IT2 | IT Operational Expert | >15 | M | 45–50 |
| | IT3 | Application Architect | 5–8 | F | 30–35 |
| | IT4 | Technology Architect | 5–8 | M | 30–35 |
| | IT5 | Information System Analyst | >15 | M | 40–45 |
| | IT6 | Application Architect | 5–8 | M | 28–33 |
| | IT7 | IT Operational Expert | 5–8 | M | 30–35 |
| Macroprudential and credit risk analysts | MP1 | Credit Analyst Expert | >15 | M | 45–50 |
| | MP2 | Macroprudential Expert | >10 | M | 40–45 |
| | MP3 | Credit Risk Expert | >10 | F | 35–40 |
| | MP4 | Microenterprise Specialist | >10 | F | 33–38 |
| | MP5 | Credit Risk Expert | >10 | M | 40–45 |

Given recruitment challenges, borrowers and lenders were not included in the FGDs. Instead, two specialized groups were selected to ensure the depth of feedback as summarized above. Group 1 (IT professionals) offers insights into the technical feasibility, data integration challenges, and potential scalability of the DLT-based RA features. Group 2 (Macroprudential and Credit Risk professionals) provide perspectives on the implications of RA features for regulatory compliance, risk management, and macroprudential oversight.

The FGDs are structured around a predefined protocol as attached in **Appendix 14**, beginning with an introduction to the RA features and objectives, followed by sessions facilitated through the Miro platform. *Miro,* a web-based discussion platform, supports real-time discussion and asynchronous feedback through virtual sticky notes, which remain accessible for several days post-discussion, allowing participants to add further insights. The FGDs consist of three sessions:

1. Session 1 (strengths and challenges): Participants examine each feature's overall strengths and challenges, focusing on their technical and functional performance.
2. Session 2 (exploration of ambiguity): This session explores unclear or uncertain aspects of the features, such as potential misinterpretations, procedural gaps, or design elements that may confuse users, distinguishing these from general challenges.
3. Session 3 (conditions for success): Participants discuss the technical and usability factors necessary for each feature to succeed.

## 6.5. Focus Group Results

This section presents an analysis of the findings from FGDs. Two distinct FGD sessions were organized, one with IT professionals and another with macroprudential and credit risk professionals, offering complementary technical and regulatory perspectives. Table 22 summarizes the key findings from both FGDs, providing an overview of technical and regulatory perspectives on each tested feature. This comparative summary helps to highlight the main insights before diving into the detailed analysis in the following sections.

*Table 22. Comparison of FGD Findings*

| Feature | IT Professionals' Perspective | Macroprudential & Credit Risk Professionals' Perspective | Key Takeaways |
|---|---|---|---|
| Contested Decision Making (CDM) | - Improves data accuracy by enabling borrower corrections.<br>- Requires a structured validation process to ensure legitimacy.<br>- Raises performance concerns due to system-wide validation.<br>- Scalability risks if financial institutions hesitate to validate data. | - Enhances borrower engagement by allowing them to refine financial profiles<br>- Risks of borrowers manipulating data to secure better loan conditions.<br>- Borrowers lack awareness of the importance of regular updates.<br>- Fintech collaboration could increase adoption. | - IT professionals emphasize scalability and system performance, while credit risk professionals focus on borrower behavior and compliance risks.<br>- Tiered validation, borrower education, and standardized governance are critical for success. |
| Dual Rating System (DRS) | - Enhances borrower assessment through lender and community perspectives.<br>- Requires mechanisms to handle conflicting ratings.<br>- AI/ML integration could improve real-time risk assessment.<br>- Increases verification workload for lenders. | - Balances objective and subjective factors, giving a more holistic borrower profile.<br>- Risks ambiguity in rating criteria, reducing lender confidence.<br>- Customer feedback may not align with actual creditworthiness.<br>- Needs external validation from rating agencies. | - IT professionals focus on AI-driven automation, while credit risk professionals emphasize credibility and regulatory alignment.<br>- Standardized rating models, proportional weight mechanisms, and verified data sources are necessary. |
| Data Collaboration (DC) | - Strengthens borrower profiling through multi-source validation.<br>- Challenges in ensuring consistency across multiple data sources.<br>- Collaboration disputes could affect reliability.<br>- Requires robust governance for sustainable operations. | - Expands borrower data access, particularly for unbanked borrowers.<br>- Risks data quality issues (outdated, unstructured, or irrelevant inputs).<br>- User-friendly interfaces and borrower education are critical. | - IT professionals focus on data validation workflows and scalability, while credit risk professionals emphasize representation gaps and borrower engagement.<br>- Success depends on strong governance, real-time validation, and borrower participation. |

The following sections provide a detailed breakdown of these findings, elaborating on the strengths, challenges, and conditions for success discussed in each FGD session.

### 6.5.1. IT Professional - FGD Results

The first FGD session involves *seven IT professionals*. The group included two technology architects (one with over 15 years of experience and another with 5–8 years), two IT operation professionals (one with more than 15 years and another with 5–8 years), two application architects (both with 5–8 years of experience), and an information system analyst (with over 15 years of experience). Their insights provided a technical perspective on data integration, system scalability, and the feasibility of implementing decentralized lending features.

**A. Contested Decision Making (CDM) Feature**

**Strengths.** Respondents E1, E4, and E5 emphasized CDM's role in *ensuring data accuracy and fairness*, enabling borrowers to correct data that might otherwise disadvantage them. E4 highlighted that *validated corrections enhance the reliability* of borrower ratings. CDM also *provides flexibility for borrowers*, as noted by E2, allowing them to update or amend their data with validation from trusted entities. This ensures only verified and up-to-date information is used, fostering transparency and maintaining the system's credibility. Lastly, *the feature empowers borrowers*, as emphasized by E4, by enabling borrowers to contest inaccurate records.

**Challenges.** *Institutional willingness and objectivity* were highlighted by respondents E1 and E4, with doubts about whether institutions would consistently perform data validation tasks. Ensuring the objectivity of authorized entities and avoiding potential biases in the validation process is also a challenge. Infrastructure performance was also flagged by E4, noting that DLT requires all nodes to maintain consistent performance, an expectation that may strain system resources. Moreover, E2 emphasized the need for an upload feature that enables borrowers to provide supporting documents for validation.

**Ambiguity and Complexity.** Technological accessibility was a primary concern raised by E1, who noted that not all borrowers possess the technological skills necessary to update their records, potentially excluding less tech-savvy users. Additionally, undefined resolution mechanisms could create significant obstacles, as highlighted by E4. If the processes for resolving disputed data are poorly defined or unclear, borrowers and lenders may find the system less effective and user-friendly.

**Conditions for Success.** Respondents E1 and E2 recommended a *tiered validation approach*, where non-critical updates are auto-approved to reduce system load, while critical updates require manual validation with supporting documents for accuracy. *User-friendly templates and guidance*, as suggested by E1, would simplify the data correction process and enhance accessibility for borrowers. Periodic *data updates and a visible history of changes* were highlighted by E2 as essential for maintaining accuracy and lender trust. Borrowers should be required to update their records regularly, especially before loan applications. E4 emphasized the need for *standardized infrastructure* to ensure consistent performance.

**B. Dual Rating System (DRS)**

**Strengths.** Respondents, such as E1, highlighted DRS's role in mitigating biased evaluations by incorporating diverse perspectives, including input from lenders and customers (E4). This 360-degree approach *fosters transparency* and enhances inclusion, offering lenders a more comprehensive understanding of borrower profiles. E2 emphasized that DRS gives more information to lenders, particularly benefiting borrowers with limited formal financial histories. Moreover, DRS delivers *additional contextual insights* by incorporating non-financial feedback, such as customer experiences, to evaluate borrower performance (E5). While not directly tied to repayment capacity, these insights enrich borrower profiles and offer lenders a broader view of the borrower's reliability and character.

**Challenges.** Respondents, such as E1 and E2, pointed out the *complexity* of managing two separate ratings. E4 emphasized that the feature "increases verification efforts," raising concerns about scalability and resource demands. Another challenge is the *ambiguity in rating interpretation*, as the dual nature of ratings can confuse lenders. E4 noted that *"conflicting ratings may lead to questions about which rating is reliable."* Additionally, *data integrity* emerged as a concern. E2 highlighted that "ratings are not validated," posing risks of irrelevant contributions. For instance, customer experience ratings, while helpful in understanding service quality, may fail to reflect financial capability.

**Ambiguity and Complexity.** Participants (E1, E4) identified *conflicting ratings* as a key issue, emphasizing the need for mechanisms to weigh and prioritize the ratings to avoid confusion for lenders. Moreover, E4 stressed the importance of incorporating advanced technologies, such as AI and machine learning, to enable real-time processing and ensure the system can handle dynamic and large-scale data efficiently.

**Conditions for Success.** The system must implement *clear mechanisms for resolving rating discrepancies*, as E1 suggested, by providing recommendations on which rating to prioritize. This would reduce lender confusion. Moreover, *trusted and relevant data sources* are important. Ratings should come from credible entities, such as banks or independent appraisers (E2). Next, *proportional and verified ratings* are critical to avoid bias or manipulation. E4 highlighted the importance of assigning proportional weights to different inputs.

### C. Data Collaborators (DC)

**Strengths.** Respondents (E2, E4) emphasized that *DC improves borrower profiles* by validating data through multiple sources, ensuring a more *comprehensive and reliable assessment*. This capability is critical in cases where traditional credit data is unavailable (E5). Moreover, DC *fosters validation and trustworthiness* by involving trusted parties in the data verification (E2). This ensures that only credible and consistent information is utilized. By enabling multi-source validation, DC enhances the reliability of decision-making processes and reduces the likelihood of errors or biases in borrower evaluations.

**Challenges.** *The complexity of implementation* was highlighted by E1, who raised concerns about the intricacy of the input process and the workload required to maintain consistency and validate data from multiple sources. *Disputes between collaborators* present another challenge. E2 and E4 pointed out that disagreements among collaborators over data validity may arise, underscoring the need for hierarchical approval systems or dispute resolution mechanisms. Lastly, the *operational scalability* of DC systems was noted by E4. The distributed nature of the framework demands robust infrastructure to manage data distribution and validation.

**Ambiguity and Complexity.** *Representativeness of data* emerged as a key concern, with E4 noting that data obtained through collaboration might not accurately reflect borrowers' actual conditions. Moreover, E1 highlighted that input mechanisms can be labor-intensive, reducing practicality for large-scale use cases. To address this, E1 suggested alternative methods, such as incorporating user reviews from platforms like Google Maps, which may expedite data collection but with trade-offs in data accuracy.

**Conditions for Success.** *Hierarchical dispute resolution mechanisms* are crucial to manage approvals and resolve discrepancies, as suggested by E2 and E4. This would streamline conflict resolution and enhance trust. Moreover, E2 and E4 stressed the need to track changes and ensure data consistency of historical records.

### D. Thematic analysis

The features demonstrate **a strong potential** to foster inclusion by addressing critical barriers in decentralized lending systems. *Contested Decision-Making (CDM)* empowers borrowers through transparent mechanisms for correcting inaccuracies, ensuring data fairness and reliability. *A dual rating system (DRS)* enhances borrower evaluations by integrating diverse perspectives and creating more inclusive profiles. Meanwhile, *Data Collaboration (DC)* improves data completeness and accuracy by leveraging multiple sources and offering holistic borrower profiles.

While promising, these features introduce distinct **challenges**. CDM faces concerns regarding scalability and institutional willingness to validate data, particularly in environments with high user volumes. DRS's complexity and dual-source structure risk causing lender confusion and trust issues, especially when ratings conflict. Similarly, DC's reliance on distributed systems raises questions about operational scalability, data consistency across nodes, and collaboration dispute resolution.

**The success of these features** depends on several factors. CDM requires scalable and efficient validation protocols and user-friendly templates to accommodate borrowers with varying levels of digital literacy. DRS needs standardized mechanisms for resolving rating discrepancies and proportional weighting to maintain data integrity. DC depends on technology implementation to ensure data consistency, supported by multi-channel updates, validation metadata, and dispute resolution. Some IT professionals also reflected on the DLT-based implementation, particularly in relation to system scalability and validation mechanisms.

### 6.5.2. Macroprudential and Credit Risk Professionals - FGD Results

This FGD involved five professionals with extensive experience in macroprudential regulation, credit risk management, and microenterprise policy. The group consisted of a credit analyst professional with over 15 years of experience, a macroprudential professional with more than 10 years of expertise, two credit risk professionals with over 10 years of experience each, and a microenterprise specialist with more than 10 years of experience. Their insights provide a regulatory and risk-based perspective, complementing the technical feedback gathered in the first FGD session.

### A. *Contested Decision Making (CDM)*

**<u>Strengths</u>.** The CDM feature offers several strengths. Firstly, *it ensures data accuracy* by involving borrowers in the data verification process, a point emphasized by respondent M2, who highlighted that borrower participation leads to more precise borrower profiles. Additionally, CDM *enables comprehensive borrower profiling*, as noted by M3, who explained that this feature allows borrowers to present a more accurate picture of their business, thereby improving lender understanding. Furthermore, M4 underscored its *utility for non-bank financial institutions*, noting that the output from CDM can be shared with other lending institutions, facilitating better engagement with microenterprises. Finally, M5 observed that CDM *enriches the information for lenders*, thereby enhancing their ability to make informed decisions.

**<u>Challenges</u>.** A significant concern is *the risk of data manipulation*, where borrowers may intentionally provide inaccurate information to secure better ratings. This issue, highlighted by M2 and M3, complicates the verification process. Additionally, M4 emphasized *the challenge of maintaining dynamic microenterprise* databases, as many borrowers lack awareness of the importance of regularly updating their data, leading to outdated profiles. Lastly, *borrowers' reluctance to disclose accurate information* presents another hurdle. As noted by M5, some borrowers may fear that providing truthful details could negatively impact their chances of obtaining funding.

**Ambiguity and Complexity.** No specific ambiguities were explicitly identified.

**Conditions for Success**. *Robust data validation processes* are critical, as emphasized by M2, to ensure accuracy. Additionally, *collaboration with fintech associations*, as suggested by M4, can make the CDM feature more appealing and accessible by leveraging industry-wide support and resources. Simplified data update mechanisms are also essential; M4 recommended *designing user-friendly forms* to encourage microenterprises to maintain up-to-date records. Lastly, A5 highlighted that educating borrowers on the importance of accurate data improves the system's reliability.

**B. *Dual Rating System (DRS)***

**Strengths.** M2 highlighted DRS *introduces additional evaluation criteria* beyond payment history, boosting lender confidence and enabling more informed decisions. M3 emphasized DRS ability *to balance objective and subjective perspectives*, fostering a nuanced understanding of profiles. M4 noted that DRS supports comprehensive assessments, *empowering lenders to make better-informed credit decisions*. Additionally, M5 stressed its *role in verifying borrower-provided data*, which enhances transparency.

**Challenges.** *Ambiguity in rating criteria*, as flagged by M2, underscores the need for objective metrics to align borrower profiles with standard credit evaluations. M3 raised concerns about *the relevance of certain ratings*, like customer feedback, which may not accurately reflect borrowers financial quality. *Outdated data*, noted by M4, poses a risk to the credibility of borrower data. Additionally, M5 highlighted fairness concerns pointing out untrustworthy ratings.

**Ambiguity and Complexity**. This section was marked as not applicable in the provided responses.

**Conditions for Success**. *Regular validation of credit scoring models*, as recommended by M2, is essential to maintain the models' accuracy. Iterative reviews and updates to these models are required to ensure they are aligned with current data. Additionally, *collaboration with rating agencies*, as suggested by M4, can enhance the depth and breadth of borrower data, filling gaps in existing datasets. Furthermore, M4 also emphasized *the importance of timely data updates* to address concerns about outdated or irrelevant data.

**C. *Data Collaboration (DC)***

**Strengths.** According to M2, *the ability of DC to incorporate diverse data variables* improves the comprehensiveness of borrower profiles, enabling more accurate assessments. M3 further emphasized that *richer borrower information* equips lenders with the insights needed to make informed decisions. Additionally, M5 highlighted the efficiency of the DC feature in gathering borrower data, *reducing operational barriers, and streamlining the process* of assessing creditworthiness.

**Challenges.** M2 raised concerns about *maintaining data quality*. M3 flagged issues related to data *representation*, noting that collected data might not accurately reflect borrower characteristics, potentially leading to misinformed decisions. Additionally, M3 pointed out *the prevalence of unstructured and invalid data* in Indonesia, emphasizing the need for data governance frameworks. M4 highlighted *the risk of data obsolescence*, as many SMEs borrowers are unaware of the importance of updating their information.

**<u>Ambiguity and Complexity.</u>** This section was marked as not applicable.

**<u>Conditions for Success.</u>** M2 recommended designing *user-friendly applications* for less tech-savvy users. Additionally, M2 emphasized the need for *validation mechanisms* to address data quality. M4 highlighted the importance of *education* in maintaining and updating data.

**D. *Thematic analysis***

*Contested Decision Making (CDM)* empowers borrowers by enabling them to update their data and addressing inaccuracies. However, challenges such as data variability and manipulation risks remain significant. Respondents emphasized the importance of data validation mechanisms, borrower education, and streamlined processes for data updates. *The Dual Rating System (DRS)* enriches borrower evaluations by integrating diverse rating perspectives. Nevertheless, DRS faces challenges, including ambiguity in rating criteria and the impact of subjective inputs, such as customer feedback. Respondents suggested regular validation of rating models and collaboration with rating agencies. *Data Collaboration (DC)* enhances borrower profiles by aggregating data from multiple sources. However, data variability, unstructured inputs, and system disruptions were identified as barriers. Addressing these requires user-friendly designs, robust validation protocols, and education. While the prototype employed a DLT-based infrastructure, participants' feedback in this group did not directly attribute inclusion outcomes to the underlying technology, but rather to the design and function of the tested features.

### 6.5.3. Summary of FGD Findings

The two FGDs offered complementary perspectives on the feasibility of the tested features. IT professionals focused on technical scalability, system performance, and validation workflows, while macroprudential and credit risk professionals emphasized regulatory compliance, financial risks, and borrower behavior. Their insights highlight both operational challenges and systemic considerations for integrating these features into inclusive lending environments.

The results show that each feature contributes to financial inclusion, but implementation challenges differ across technical and regulatory domains. IT professionals stress scalability, validation efficiency, and automation, while macroprudential and credit risk professionals focus on borrower engagement, compliance, and policy alignment. The findings emphasize the need for *tiered validation for CDM*, *structured DRS weighting mechanisms*, and *robust DC governance*.

## 6.6. Conclusion

This chapter connects the conceptual foundation of the Reference Architecture (RA) with its practical application through prototyping and testing. To answer RQ 4, this study developed a prototype and conducted three stages of testing in Chapters 6, 7, and 8. Chapter 6 explains the prototype, followed by testing three core RA features: Contested Decision Making (CDM), Dual Rating System (DRS), and Data Collaboration (DC). Chapter 7 addresses behavioral surveys, while Chapter 8 focuses on sensitivity analysis with machine learning simulation.

The prototype architecture consists of four functional blocks: user interface, loan processing, data collection, and a supporting ledger layer. The analysis in Section 6.5 evaluates the operational feasibility and perceived inclusion impact of three key features through a combination of simulated interactions and FGDs. Two FGDs provided complementary perspectives: IT professionals offered technical and architectural insights, while macroprudential and credit risk professionals emphasized regulatory, financial, and systemic implications.

*The Contested Decision Making (CDM)* feature demonstrated its potential to enhance inclusion by empowering borrowers to challenge and update inaccurate data. Both FGDs confirmed that this feature fosters inclusion and transparency. However, scalability, data variability, and manipulation risks were critical challenges requiring robust validation protocols and borrower education.

*The Dual Rating System (DRS)* was evaluated as an important tool for enhancing inclusion and transparency by integrating lender and community feedback to create multidimensional borrower profiles. This feature is valuable for borrowers with limited credit histories. However, concerns about ambiguous rating criteria, relevance of subjective inputs, and potential conflicts between ratings highlighted the need for clear rating mechanisms , and collaboration with rating agencies.

*The Data Collaboration (DC)* feature was confirmed as an important enabler of inclusion by aggregating data from diverse sources to build richer borrower profiles. Both FGDs acknowledged its ability to provide lenders with more comprehensive borrower insights. Nonetheless, the challenges of unstructured data, representation gaps, and data obsolescence underscore the need for user-friendly designs, strong data governance, and borrower education.

Furthermore, the two FGDs provided complementary analyses. The IT professionals focused on technical feasibility, system scalability, and the operational challenges of implementing the features. The macroprudential and credit risk professionals addressed broader systemic considerations, including regulatory compliance, risk management, and the operational implications of integrating RA features into existing financial ecosystems.

Chapter 6 established the initial evaluation of RA features through prototyping and FGDs, offering key insights into their inclusion potential. Chapter 7 builds on this by examining behavioral responses in controlled surveys to assess how the RA influences lender approval. Chapter 8 extends the analysis through empirical simulations, evaluating how enriched data and model tuning affect loan recommendations.

# Chapter 7: Survey Experiment to Assess Lender Behavior on Loan Acceptance

The previous chapter (Chapter 6) evaluated key prototype features such as contested decision-making, dual rating systems, and collaborative data collection using focus group discussions and feature tests. The goal was to explore stakeholders' perceptions of whether and how these prototype features could support inclusion within lending systems, particularly by identifying their perceived strengths, weaknesses, and success factors.

Building upon the broader theme of enhancing inclusion, this chapter complements the qualitative evaluations from Chapter 6 by quantitatively examining lender behaviors related to loan acceptance. Understanding how lenders respond to enriched borrower profiles and system recommendations helps assess whether these features can improve access to credit for borrowers who are often underserved in conventional systems. Specifically, this survey experiment investigates how providing lenders with enriched borrower profiles, including additional borrower data attributes and system-generated loan recommendations, affects their lending decisions.

The experiment follows a structured timeline, as shown in Figure 39. The preparation phase included pre-survey interviews and piloting to refine the survey design. Ethics approval was sought in parallel to ensure compliance with research standards. The main survey was conducted with participants from various professional backgrounds. The final phase focused on data analysis and interpretation.


*Figure 39. Survey Experiment Milestones*

The rest of the chapter is organized as follows. Section 7.1 explains hypothesis derivation, and Section 7.2 describes the setup for the controlled survey experiment, including survey preparation, protocols, and piloting. Section 7.3 presents the survey results, analyzing them against the hypotheses. Section 7.4 concludes with key findings and their implications

## 7.1. Hypothesis Derivation

The expansion of financial inclusion through lending systems is shaped by credit availability and how lenders assess borrower risk and make loan decisions. Traditional credit scoring models rely heavily on historical financial data and formal credit histories, which inherently exclude borrowers in informal economies and low-income sectors (Suryono et al., 2019). This exclusion results in significant financial gaps, as many underserved populations lack the documentation required by conventional lending systems (Demirguc-Kunt et al., 2018). Lending systems attempt to address these challenges by leveraging non-traditional data sources, yet the extent to which these innovations influence lender behavior remains unclear.

This study examines how enriched borrower profiles affect lenders' loan acceptance rates. The hypotheses in this chapter are based on previous discussions on related challenges, as outlined in Chapters 1 and 3, such as the lack of verifiable financial records, the exclusion of informal-sector borrowers, and the limited transparency in borrower assessments.

**Hypothesis B1** examines whether providing additional borrower information increases loan acceptance rates for micro-enterprises. Conventional financial systems classify borrowers based on rigid credit criteria, excluding those without formal financial records (Azis, 2024). However, lending models show that expanding borrower profiles to include utility payments or other contextual attributes can expand access to the underserved population (Berg & Kuiper, 2020). Studies on inclusive lending highlight that alternative data offers a path to inclusion by providing a more comprehensive view of individual behavior (Roa et al., 2021; Aitken, 2017). Given that traditional scoring approaches often perpetuate financial exclusion (Suryono et al., 2019), this hypothesis investigates whether enriched data mitigates such biases and leads to more positive loan acceptance.

**Hypothesis B2** investigates whether system-generated recommendations influence lenders' loan approval decisions. Decision-support tools in credit evaluation are increasingly used to standardize risk assessment and minimize subjectivity in lending decisions (Doshi-Velez & Kim, 2017). While these systems have been shown to improve efficiency, their impact on lender behavior is unclear, particularly in cases involving micro-enterprises with limited credit histories (Demirguc-Kunt et al., 2017). Automated recommendations can increase trust in the lending process by reducing uncertainty, yet prior studies suggest that unclear credit assessment could lead to disengagement (Lenz, 2016). This hypothesis tests whether system recommendations have a positive effect on loan acceptance rates.

**Hypothesis B3** examines whether combining additional borrower information and system-generated recommendations results in higher loan acceptance rates than using either factor independently. Hypothesis B1 tests whether additional borrower information increases approval rates, while Hypothesis B2 investigates whether system-generated recommendations influence lender decisions. However, it remains unclear whether these two factors reinforce each other or function independently in the lending process. Lenders may be hesitant to rely solely on system recommendations unless supported by richer borrower data, while additional borrower information alone may not fully address inconsistencies in decision-making. This hypothesis (B3) tests whether integrating both elements leads to more inclusive lending outcomes.

**Hypothesis B4** examines whether different types of borrower information influence lenders' perceptions of creditworthiness and data reliability. Transparency is essential in lending systems, as it affects lender confidence in P2P lending (Qian & Lin, 2020). When borrower data lacks clarity or transparency, lenders may hesitate to engage, limiting financial access for underserved groups (Stevens et al., 2020). Furthermore, Chen, Lou, & Slyke (2015) identify perceived information quality as an important factor in improving trust. Since additional borrower data offers more contextual information, and system-generated recommendations provide standardized suggestions based on predefined calculations; this hypothesis tests whether these factors positively affect how lenders perceive creditworthiness and data reliability.

This study conducts a controlled online survey experiment where respondents evaluate borrower profiles with varying levels of information types. Multiple statistical methods are applied to analyze the results. T-tests and Z-test compare mean differences in loan acceptance rates across conditions, while ANOVA assesses variations across multiple experimental groups. Tukey's HSD test provides post hoc comparisons to identify significant differences between conditions. The following section discusses the experiment setting, including survey design, evaluation metrics, and piloting results.

## 7.2. Experiment Setting

Experimental research is designed to assess causal relationships by systematically manipulating independent variables and observing their effects on dependent variables (Shadish, Cook, & Campbell, 2002). A well-structured experiment ensures that observed changes in the dependent variable result from controlled variations in the independent variables rather than external influences (Rogers & Révész, 2019). The *independent variables* in this study are the availability of additional borrower information and system-generated recommendations, and the *dependent variable* is the loan acceptance rate, which reflects lender decision-making.

The experiment was conducted in two stages: *pre-survey interviews and piloting*, followed by *the main survey experiment*. Before conducting the survey, as required by protocols for research involving human participants, we submitted an application to the Human Research Ethics Committee (HREC) at TU Delft. The submission included a Data Management Plan (DMP), an Ethics Review Checklist for Human Research, a consent form for respondents to review and approve, and the survey protocol. Only after undergoing revisions and receiving official approval were we able to proceed with the survey. The following sections describe each stage in detail.

### 7.2.1. Pre-survey Interviews

**Interview Preparation and Respondent Selection**

The pre-survey interviews aimed to refine the survey design by understanding how lenders assess borrower risk and how borrowers perceive loan approval factors. Respondents were selected based on direct involvement in the digital lending ecosystem. Lenders were required to have *at least two years of experience* in any registered P2P lending platform in Indonesia. Borrowers were selected based on their experience applying for and receiving at least one digital loan in the past two years.

Initially, nine participants (four lenders and five borrowers) agreed to participate in the interviews. However, *five withdrew* before the interviews were conducted. The reasons for withdrawal were concerns about professional reputation and the stigma of online lending in Indonesia. Some respondents feared that being associated with digital borrowing could harm their future employment. Others were reluctant because digital lending is often seen as a last-resort financial option, and they did not want to be associated with it. We explained that all interviews would be anonymous and followed ethical standards, and no personal details would be shared and the approach was approved by TU Delft ethical committe. However, these assurances were not enough to change their decision. After these withdrawals, *two lenders* and *two borrowers* participated. The two lenders are professionals with more than five years of experience in online lending, whereas the borrowers are relatively new to the online lending system and have 1-2 years of experience. One of the borrowers has faced several credit repayment difficulties. The two lenders were both male, and among the two borrowers, one was male and one was female. All respondents were assigned anonymized labels (L1–L2 for lenders, B1–B2 for borrowers) in the transcript and analysis to preserve confidentiality. Although precise age brackets were not recorded, all participants were working-age adults with active involvement in lending activities.

Each interview lasted between 30 and 45 minutes and followed a semi structured format, as explained in the interview protocol in Appendix 14. Participants were recruited through purposive sampling by contacting registered P2P lending platforms and borrower communities to identify individuals meeting the criteria. The questions were designed to examine two key aspects: the types of information lenders prioritize in loan decisions and the factors borrowers perceive as most critical for loan approval. The interviews also explored the role of system-generated recommendations and additional data attributes in shaping lending behavior. Ethical approval was obtained prior to conducting the interviews, and all interviews were recorded with consent and analyzed through open coding and thematic analysis. Table 23 mapped to the hypotheses explored during the pre-survey interviews.

*Table 23. Pre-survey Interview Questions and Hypothesis Mapping*

| Hypothesis | Related Interview Questions |
|---|---|
| **H1:** Lenders consider borrower financial and personal data more critical for loan approval than system-generated recommendations. | 1. What types of information do you consider most important when evaluating loan applications? 2. How important is historical financial data in your decision-making process? 3. Would you consider lending to borrowers with limited financial history if other strong indicators (e.g., system recommendations) are present? |
| **H2:** Borrowers perceive financial and personal data as more critical for loan approval than system-generated recommendations. | 1. What information is crucial to include in your loan application to improve your chances of acceptance? 2. What are the biggest barriers to getting a loan approved? 3. How comfortable would you be if a system provided recommendations or decisions on your loan application? |

### Interview Results

In the interview phase, discussions with lenders and borrowers provided insights into the factors influencing loan decisions in the peer-to-peer lending ecosystem. The table below presents the summarized findings from the interviews.

*Table 24. Summary of Pre-survey Interview Findings*

| Key Aspects | Lender L1 (5 years experience) | Lender L2 (5 years experience) | Borrower B1 (2 years experience) | Borrower B2 (First-time borrower) |
|---|---|---|---|---|
| **The most important factors for loan approval** | Loan history, business stability, and borrower demographics. Prefers a thorough assessment of borrower financial behavior. | Interest rates are the primary factor. Other borrower attributes are secondary. | Credit history and salary slips are essential. Missing documents result in higher interest rates. | Credit history and official documentation are critical. Lacks confidence in non-traditional assessments. |
| **Use of additional data** | Uses external data for high-risk borrowers. It helps compensate for a lack of formal credit history. | Not interested in additional borrower data unless it directly affects interest rate calculation. | Providing more financial details improves approval chances. | Lenders may misinterpret informal income sources without sufficient documentation. |
| **Perception of system-generated recommendations** | It uses them as secondary input but still prioritizes direct borrower data. | Prefers direct financial metrics like interest rates. | Skeptical of system recommendations, prefers manual evaluation by lenders. | Believes automated assessments do not reflect actual borrower capacity. Prefers human-based evaluations. |
| **Challenges in the lending process** | Hard to assess micro-enterprises due to limited financial history. | High interest rates mitigate risk but exclude weaker borrowers, limiting financial inclusion. | Lack of formal documentation results in unfavorable loan terms, increasing borrowing costs. | Informal income is difficult to verify, leading to frequent loan rejections. |

### Key Information Prioritized by Lenders and Borrowers

Lenders and borrowers show different priorities when assessing loans. Lender L1 emphasizes borrower loan history, demographics, and business details. These factors help L1 manage long-term risk, especially for micro-enterprises with low financial stability. While system-generated recommendations are considered, they are secondary in importance. Conversely, Lender L2, driven by profitability, prioritizes interest rates over borrower profiles, relying on high interest rates to mitigate perceived risk. This profitability-first preference may marginalize borrowers with weaker profiles, reflecting a tension between financial inclusion and profit maximization.

Borrowers B1 and B2, meanwhile, focus on providing complete financial documentation, such as credit history and salary slips. B1, an experienced borrower, emphasizes that these documents directly affect loan conditions, such as interest rates. B2, a first-time borrower, also highlights the role of credit checking mechanisms in influencing loan approval. Both borrowers recognize the importance of presenting comprehensive financial profiles to improve loan approvals.

**The Role of Additional Data**

L1 values enriched data sources, such as external databases and professional insights, to better assess high-risk borrowers. In contrast, L2 is less interested in detailed borrower assessments, focusing instead on interest rate adjustments to manage risk. For borrowers, complete and accurate financial documentation, including credit history, is critical to securing loans with better terms. B1 and B2 note that missing or incomplete information often leads to higher interest rates and lower loan limits.

**Impact of System Recommendations**

System-generated recommendations are viewed differently by lenders and borrowers. L1 uses these recommendations as supplementary information to support decisions based on loan history and borrower demographics. L2, however, places minimal emphasis on system recommendations, preferring to rely on interest rates as the primary metric for assessing risk. For borrowers, system recommendations are met with scepticism. B1 and B2 both express concerns about the accuracy of these recommendations, preferring decisions to be based on credit history rather than automated systems. This lack of trust in system-generated recommendations points to a significant gap in borrower confidence, which must be addressed to improve the adoption of lending systems. This view is also reflected in the findings related to the hypotheses in Section 7.3.

**Challenges and Opportunities for Enhancing the Lending Process**

The P2PLS ecosystem presents several challenges for both lenders and borrowers. L1 highlights the difficulty of assessing micro-enterprises with limited financial histories, while L2's reliance on interest rate flexibility may exclude borrowers with weaker profiles. For borrowers, the challenge lies in securing loans with favorable terms due to incomplete financial documentation, leading to higher interest rates.

The evaluation of each hypothesis based on interview insights is summarized in the following table.

*Table 25. Hypothesis Evaluation Based on Pre-survey Interviews*

| Hypothesis | Supported? | Explanation |
|---|---|---|
| **H1:** Lenders consider borrower financial data more critical for loan approval than system-generated recommendations. | **Yes** | Lender L1 prioritizes borrower history, demographics, and business stability over system recommendations. Even L2, while focused on interest rates, does not rely on system recommendations for risk assessment. |
| **H2:** Borrowers perceive financial and personal data as more critical for loan approval than system-generated recommendations. | **Yes** | Both borrowers emphasize credit history as essential for loan approval and distrust system-generated recommendations. They believe automated systems do not fully capture their financial reality. |

This analysis shows that lenders and borrowers emphasize financial and personal documentation more than system-generated recommendations, underscoring the importance of lending models prioritizing transparency in borrower assessments. The main survey experiment will further examine these insights to quantify their impact on lender behavior.

### 7.2.2. Piloting

Following the pre-survey interviews, several *pilot surveys* were conducted with respondents experienced and new in online surveys. Feedback from these pilots highlighted the need to streamline the information presented, as respondents reported fatigue when faced with too many questions. In response, the survey design was refined by reducing the types of information and the number of questions, ensured that the survey remained effective and reliable. This revision balanced the need for *statistically significant* data collection with *respondent attention span*.

*Three pilot tests* were conducted with researchers who have experience in quantitative research and survey experiments. Their feedback helped refine two key aspects: the number of profiles reviewed and the richness of information. Initially, respondents were asked to review 30 profiles across three cycles (one per hypothesis). However, all pilot participants noted that this was overwhelming, causing fatigue and random responses by the end. Based on this feedback, the number of profiles was reduced to ensure respondents could maintain focus and consistent responses.

Another important feedback point was on the *richness of information*, particularly in **Card B**, which contained *additional data*. Initially, the profiles included extensive details, such as business type, history, and multiple financial indicators. Pilot participants suggested reducing the information to prevent overload. As a result, the information in **Card B** was streamlined to three core factors: (1) business type (e.g., food vendor, mobile cart), (2) payment capacity (e.g., potential to earn over 100,000 rupiah per day), and (3) monthly income. This allowed for more manageable evaluations.

Despite feedback from pre-survey interviews highlighting *interest rates* as a critical factor, this element was excluded from the final survey. The rationale was that this research focuses on the impact of *information richness* and *system recommendations* rather than on financial metrics like interest rates. Including interest rates could have shifted the focus toward financial calculations, complicating the profiles and potentially overshadowing the intended exploration of data-driven decision-making.

It is important to note that this research focuses on how *information systems*, not deep credit analysis, affect loan decisions. The aim is to explore how the type and presentation of borrower information and system recommendations influence lending behavior. While not an expert study on credit risk, it offers valuable insights into how enriched information can improve decision-making in inclusive lending systems.

### 7.2.3. Survey Protocol

The survey was conducted entirely online using *the Qualtrics web-based application*, ensuring accessibility, randomization, and data consistency. Participants were assigned two out of four borrower profile cards, a decision informed by the piloting phase, where initial tests showed that evaluating all four profiles led to fatigue and inconsistent responses. Reducing the number of profiles improved engagement while maintaining reliable data collection. Figure 40 illustrates the four borrower profile variations used in the survey.

**Card A**


**Card B**

Card C


Card D

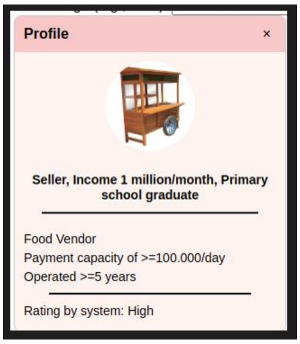



*Figure 40. The example of cards A, B, C, and D*

Each profile card was designed to systematically test different hypotheses by varying the type of borrower information presented. **Card A** serves as the baseline case, presenting only basic borrower details such as occupation, monthly income, and education level. For example, a borrower might be described as a seller earning 1 million IDR per month with a primary school education. This setup tests whether minimal borrower information is sufficient for loan approval, addressing **Hypothesis B1**. **Card B** expands on this by incorporating additional business-related attributes, such as specifying that the borrower is a food vendor, has a payment capacity of at least 100,000 IDR per day, and has been operating for over five years. This version evaluates whether enriched borrower data leads to higher approval rates, aligning with **Hypothesis B1**.

**Card C** introduces system-generated recommendations while keeping the borrower details at a basic level. In this case, the borrower profile remains the same as in **Card A**, but with an added automated rating indicating creditworthiness, classified as either "High" or "Low" based on predefined evaluation criteria. This structure tests whether lenders rely on system recommendations when making loan decisions, corresponding to **Hypothesis B2**. **Card D** combines enriched borrower data and system-generated recommendations, providing the most comprehensive borrower profile by including business details and an automated rating. This format assesses whether combining these two factors results in a higher loan approval rate than using either one alone, addressing **Hypothesis B3**.

These structured variations create a direct link between the survey design and the research hypotheses, allowing for a systematic analysis of how different levels of borrower information influence lending decisions. Using *Qualtrics web-based application survey*, profile cards could be randomized for each respondent, ensuring unbiased exposure to different scenarios. The platform also supported *the ranking feature* for Card D, where respondents were asked to prioritize different types of borrower information based on their perceived importance. This functionality was essential for capturing how lenders weigh diverse informational attributes in decision-making processes. Furthermore, *Qualtrics' real-time data tracking* and advanced response management ensured consistent data quality.

To integrate perspectives from different fields, survey respondents were segmented into three groups: academics, finance professionals, and professionals from diverse sectors such as public service, entrepreneurship, and healthcare. Figure 41 illustrates the distribution of these cards among participants, where each respondent evaluated one of the profiles (A, B, or C) and the comprehensive profile (D), followed by fifteen reflection questions.

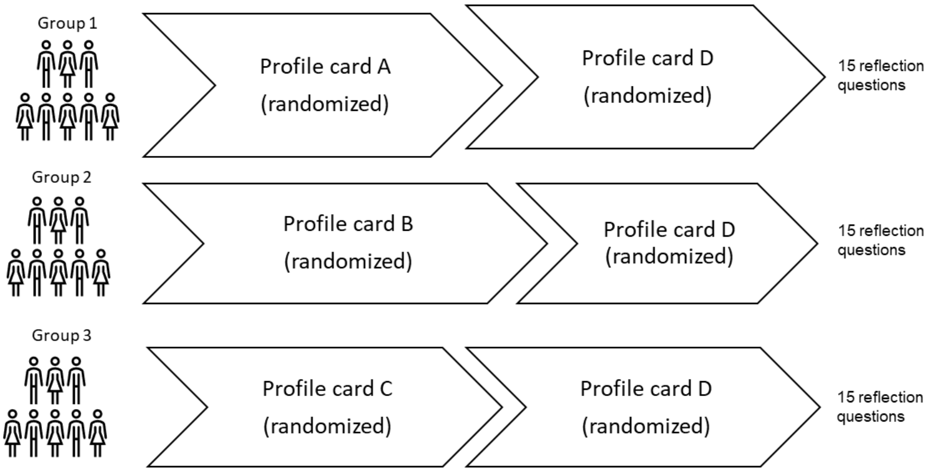



*Figure 41. Survey design*

The survey design incorporated key adjustments to ensure quality and reliability.

1. **Response fatigue** was avoided by limiting the number of profile cards each respondent evaluated. Response fatigue, also known as respondent fatigue, refers to the decline in the quality or completeness of survey responses as participants become tired or lose interest, particularly in lengthy surveys (Porter, Whitcomb, & Weitzer, 2024). Initially, respondents were exposed to 25–30 unique profile cards, which led to disengagement and saturation. Based on pilot feedback, the maximum number of cards per respondent was reduced to 5–8, ensuring better focus and engagement. To maintain statistical significance, each unique card was evaluated by a minimum of 30 different respondents.
2. **Statistical significance** was prioritized, with each profile type assessed 20–30 times by different respondents to meet reliability standards (Macchi, 2023) .
3. **Respondent feasibility** exceeded expectations; while 90 participants were initially targeted, 270 responses were collected (including 60 incomplete responses), significantly strengthening the study's dataset and findings.

### 7.2.4. Evaluation Metrics

This study applies four statistical methods to evaluate the impact of enriched borrower information and system-generated recommendations on loan acceptance rates: the T-test, ANOVA, Z-test, and Tukey's HSD. The **T-test** is used for initial pairwise comparisons, while **ANOVA** identifies overall differences across multiple groups. The **Z-test** supports mean comparisons in large samples, and **Tukey's HSD** is applied post hoc to pinpoint specific group differences. Combining these methods allows for a comprehensive analysis that accounts for individual group differences and overall trends in lender decision-making.

**The T-test** is employed for initial pairwise comparisons to test Hypotheses B1 and B2 by exploring basic differences in loan acceptance rates between the two groups. For *Hypothesis B1*, the T-test compares Card A (basic information only) with Card B (basic information plus additional data) to detect significant effects when these additional borrower variables are introduced. Similarly, for *Hypothesis B2*, the T-test compares Card A against Card C (basic information plus system recommendations), testing if system recommendations alone influence acceptance rates. This approach leverages the T-test's effectiveness in detecting mean differences between two independent groups, especially in early-stage analyses (Riina, Stambaugh, Stambaugh, & Huber, 2023). By isolating these pairwise differences, the T-test offers preliminary insight into how variations in borrower information influence lender decisions. Guo and Yuan (2017) offer broader perspectives on comparing means, especially in complex or partially paired data, supporting the choice of T-tests for initial, direct comparisons in experiments with two-group designs.

However, as T-tests only compare two groups at a time, **ANOVA** is necessary for examining multiple group interactions and verifying the broader applicability of these insights (Field, 2018). Given the study's multi-group design, ANOVA is used to determine whether significant differences exist across all four borrower profiles (A, B, C, D). For instance, in *Hypothesis B1*, ANOVA tests the overall effect of enriched information on loan acceptance by comparing groups exposed to varying levels of information (Cards A, B, and D). *Hypothesis B2* similarly requires comparing Cards A, C, and D to evaluate the effect of system recommendations. Field (2018) highlights that ANOVA is particularly effective in experimental designs with multiple treatment effects because it controls the likelihood of *Type I errors*, false positives arising from simultaneously testing multiple hypotheses. By analyzing overall variance across all groups, ANOVA minimizes the risk of erroneously detecting significant effects where none exist.

**The Z-test** is an additional metric for larger sample comparisons to confirm ANOVA results, particularly for examining mean differences across groups with higher sample sizes. This test complements ANOVA by offering a more straightforward, focused mean comparison for normally distributed data. Z-tests are advantageous in large-scale survey analyses, where confirming the consistency of mean differences across samples is essential, making them a robust alternative to T-tests when handling larger datasets (Field, 2018).

Following ANOVA, **Tukey's HSD test** is conducted as a *post hoc analysis* to determine specific group differences, which is crucial for hypotheses like B3, which examines combinations of information types. Tukey's HSD allows for a deeper understanding of how specific groupings (e.g., Cards A vs. D or B vs. C) differ. Field (2018) highlights that Tukey's HSD effectively controls *family-wise error rates*, which refer to the probability of making at least one false positive when conducting multiple pairwise comparisons. This makes it particularly suitable for analyzing the effects within a study's multi-group structure, providing a more accurate assessment of significant differences between individual groups.

These statistical methods provide a balanced approach, providing both initial insights and deeper multi-group comparisons. The T-test provides a straightforward comparison for pairwise differences to test Hypothesis B1's and B2's initial evaluation. ANOVA was applied across all hypotheses to assess group variances, given its effectiveness in managing multi-group comparisons (Field, 2018). Z-tests confirm larger sample sizes, while Tukey's HSD adds depth by identifying significant differences in pairwise comparisons following ANOVA.

## 7.3. Results and analysis

### 7.3.1. Demographics of Survey Respondents

The survey attracted 270 respondents, with a dropout rate of approximately 60 individuals. The dropouts were mainly due to timeouts from prolonged inactivity, prompting respondents to resume the survey on different devices. This was necessary because Qualtrics settings prevented the same device from being used after a timeout. The results of the survey is provided in **Appendix 4**.

The demographic distribution of participants is summarized in Table 26, detailing age groups, gender, professional background, and income levels. Most participants fell in the 35-44 age range, while the 25-34 age group comprised 75 respondents. A smaller segment consisted of younger individuals (12 respondents under 25), and 43 respondents were 45 and older.

*Table 26. Demographic Distribution of Respondents*

| **Group Distribution** | |
|---|---|
| Group 1 | 74 respondents |
| Group 2 | 103 respondents |
| Group 3 | 92 respondents |
| **Age Distribution** | |
| Under 25 | 12 respondents |
| 25-34 | 75 respondents |
| 35-44 | 140 respondents |
| 45-54 | 38 respondents |
| 55 and older | 5 respondents |

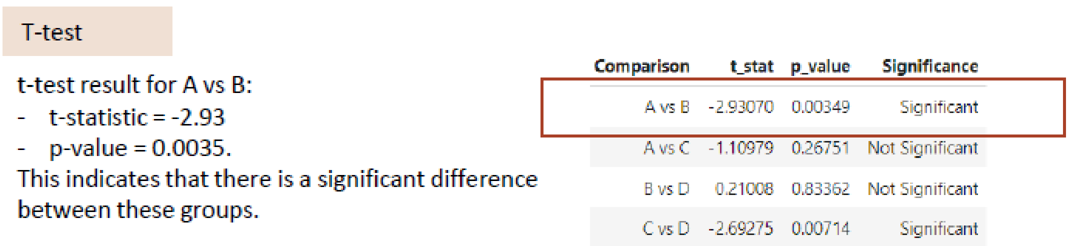
| **Gender** | |
|---|---|
| Female | 177 respondents |
| Male | 93 respondents |
| **Annual Income** | |
| < 5 million rupiah | 23 respondents |
| 5-10 million rupiah | 44 respondents |
| 11-20 million rupiah | 54 respondents |
| 21-30 million rupiah | 34 respondents |
| 31-40 million rupiah | 29 respondents |
| 41-50 million rupiah | 25 respondents |
| > 50 million rupiah | 62 respondents |

177 respondents were female, and 93 were male, showing a strong representation of women in the lending context. 141 worked in academia, financial regulation, and IT. Additionally, 39 respondents were from areas like law, healthcare, and engineering, while 51 came from other professions, reflecting the diversity in professional backgrounds. Annual income levels were also widely distributed. The largest income group included 62 respondents earning over 50 million rupiahs annually, while other respondents ranged from less than 5 million rupiahs (23 respondents) to various mid-level income brackets. This distribution ensured that the survey reflected socioeconomic diversity, offering valuable insights into how lending behaviors differ across income levels. In terms of professional background, the majority of the respondents were in the fields of Academics, Financial Regulators, IT, and Post-graduate Students (141 respondents), a minority in the fields of Law, Engineering, and Healthcare (39 respondents), and 51 respondents were from other fields. Furthermore, most respondents defined themselves as having a moderate understanding of lending issues, with a smaller segment familiar or completely unfamiliar with lending issues.

### 7.3.2. Hypothesis B1: Incorporating Additional Information Increases Loan Acceptance Rates.

**Hypothesis B1** investigates whether providing additional borrower information leads to higher loan acceptance rates. The null hypothesis ($H_0$) states *that additional borrower information does not influence loan acceptance rates*, while the alternative hypothesis ($H_1$) posits that additional borrower information increases acceptance rates. Three types of additional borrower information were tested: business type (e.g., mobile vendor vs. fixed-location shop), payment capacity (e.g., daily income threshold), and business duration (e.g., years in operation). These attributes were selected based on piloting feedback, indicating the need to avoid survey fatigue while maintaining statistical power. Expanding the information types further would have required longer surveys per respondent, leading to disengagement or necessitating a larger respondent pool, which was constrained by strict respondents' selection criteria.

A **T-test** was conducted comparing Group A (basic information only) and Group B (with additional borrower details) to test *whether additional borrower information influences loan acceptance rates*. The results yielded a t-statistic of -2.93 and a p-value of 0.0035 (Figure 42).


T-test

t-test result for A vs B:
- t-statistic = -2.93
- p-value = 0.0035.

This indicates that there is a significant difference between these groups.

| Comparison | t_stat | p_value | Significance |
|---|---|---|---|
| A vs B | -2.93070 | 0.00349 | Significant |
| A vs C | -1.10979 | 0.26751 | Not Significant |
| B vs D | 0.21008 | 0.83362 | Not Significant |
| C vs D | -2.69275 | 0.00714 | Significant |

*Figure 42. T-test for Hypothesis B1*

Since the p-value is below 0.05, it provides sufficient evidence to reject $H_0$, indicating that lenders are more likely to approve loans when additional borrower information is provided. A Z-test was conducted to validate the T-test findings by assessing differences in approval rates between Groups A and B. The Z-test produced a z-statistic of 2.9174 and a p-value of 0.0035 (Figure 43), further confirming that adding additional borrower data significantly impacts lender decisions. The result supports the generalizability and consistency of the findings.

Z-test

```
Z-test between Approval Rate A and Approval Rate B:
z-statistic: 2.9174
p-value: 0.0035
Result: The p-value is less than 0.05, suggesting a significant difference between Approval Rate A and Approval Rate B.
This supports the hypothesis that incorporating additional information increases loan acceptance rates for micro-enterprises.
```

*Figure 43. Z-test for hypothesis B1*

Given the multi-group design of the experiment, an ANOVA test was conducted to compare loan acceptance rates across all four borrower profile groups (A, B, C, and D). The analysis produced an F-statistic of 5.3967 and a p-value of 0.0011 (Figure 44), indicating significant variation in loan approvals between groups. A focused comparison between Groups A and B (F-statistic of 8.58, p-value 0.0035) reaffirmed that borrowers with enriched data profiles were significantly more likely to be approved.

ANOVA

```
ANOVA result between Approval Rate A, Approval Rate B, Approval Rate C, and Approval Rate D:
F-statistic: 5.3967
p-value: 0.0011
Result: The p-value is less than 0.05, suggesting significant differences between groups.
This supports the hypothesis that incorporating additional information increases loan acceptance rates for micro-enterprises.

ANOVA result between Approval Rate A and Approval Rate B:
F-statistic: 8.5890
p-value: 0.0035
Result: The p-value is less than 0.05, suggesting significant differences between groups.
This supports the hypothesis that incorporating additional information increases loan acceptance rates for micro-enterprises.
```

*Figure 44. ANOVA for hypothesis B1*

To pinpoint which specific group differences contributed to the ANOVA significance, Tukey's HSD post-hoc analysis was conducted. The results showed statistically significant differences between Group A vs. Group B and Group A vs. Group D (Figure 45), confirming that borrowers with additional information (Group B) and those with full information plus system recommendations (Group D) were more likely to be approved.

Tukey HSD

```
ANOVA result between Approval Rate A, B, C, and D:
F-statistic: 5.3967
p-value: 0.0011
Multiple Comparison of Means - Tukey HSD, FWER=0.05
====================================================
group1 group2 meandiff p-adj  lower  upper  reject
----------------------------------------------------
     A      B   0.1214 0.0188  0.0143 0.2284   True
     A      C   0.0461 0.7009 -0.0635 0.1558  False
     A      D   0.1162 0.0104    0.02 0.2125   True
     B      C  -0.0753 0.0829 -0.1568 0.0063  False
     B      D  -0.0051 0.9967 -0.0676 0.0574  False
     C      D   0.0701 0.0354  0.0033 0.1369   True
----------------------------------------------------
```

*Figure 45. Tukey HSD test for hypothesis B1*

Across all statistical tests (T-test, Z-test, ANOVA, and Tukey's HSD), $H_0$ was consistently rejected, supporting that ***providing additional borrower information significantly improves loan acceptance rates.*** These findings suggest that lenders value expanded borrower data when making loan decisions, reinforcing the importance of providing more borrowers' data in improving financial inclusion.

### 7.3.3. Hypothesis B2: Incorporating System Recommendations Increases Loan Acceptance Rates

Hypothesis B2 examines whether system-generated recommendations influence loan acceptance rates. The null hypothesis ($H_0$) states that *system recommendations do not affect loan acceptance*, while the alternative hypothesis ($H_1$) posits that system recommendations increase loan approval rates. Within the survey experiment, these recommendations were incorporated into Card C, which assigned borrowers a risk category of "Low" or "High" based on predefined scoring criteria. This design assessed whether lenders relied on automated recommendations when making decisions.

A T-test compared Group A (basic borrower information only) with Group C (basic information plus system-generated recommendations). The results yielded a t-statistic of -1.1098 and a p-value of 0.2675 (Figure 46), indicating no significant difference between the two groups.

T-test (groups)

t-test result for A vs C:
- t-statistic = -1.10
- p-value = 0.2675

This indicates that there is **NO** significant difference between these groups.

t-test result for B vs D:
- t-statistic = 0.21
- p-value = 0.8336.

This indicates that there is **NO** significant difference between these groups.

| Comparison | t_stat | p_value | Significance |
|---|---|---|---|
| A vs B | -2.93070 | 0.00349 | Significant |
| A vs C | -1.10979 | 0.26751 | Not Significant |
| B vs D | 0.21008 | 0.83362 | Not Significant |
| C vs D | -2.69275 | 0.00714 | Significant |

*Figure 46. T-test for hypothesis B2*

T-test (A vs C)

```
t-test result for A vs C: t-statistic = -1.1098, p-value = 0.2675.
This indicates that there is no significant difference between these groups.
```

*Figure 47. T-test for hypothesis B2*

We further explored these results using a Z-test. The Z-test, particularly sensitive to differences in larger samples, yielded a z-statistic of 1.1105 and a p-value of 0.2668 (Figure 48). Like the T-test, the Z-test confirmed no significant difference between the groups.

Z-test

```
Z-test between Approval Rate A and Approval Rate C:
z-statistic: 1.1105
p-value: 0.2668
Result: The p-value is greater than 0.05, suggesting no significant difference between the two groups.
This does not support the hypothesis that incorporating system recommendations enhances loan acceptance rates for micro-enterprises.
```

*Figure 48. Z-test for hypothesis B2*

We conducted an ANOVA comparing approval rates between Groups A and C to gain a broader perspective on the differences across groups. The ANOVA result, with an F-statistic of 1.2316 and a p-value of 0.2675 (Figure 49), reaffirmed the lack of significant differences between the groups.

ANOVA

```
ANOVA result between Approval Rate A and Approval Rate C:
F-statistic: 1.2316
p-value: 0.2675
Result: The p-value is greater than 0.05, suggesting no significant differences between the two groups.
This does not support the hypothesis that incorporating system recommendations enhances loan acceptance rates for micro-enterprises.
```

*Figure 49. ANOVA for hypothesis B2*

For further validation, we applied Tukey's HSD test as a post hoc analysis to check whether there were any pairwise differences between Groups A and C. The Tukey HSD results (Figure 50) showed no significant differences, as the p-adjusted value was 0.2675, well above the threshold for statistical significance. Therefore, the data strongly suggest that system recommendations provided on Card C do not significantly enhance loan acceptance rates compared to basic borrower information.

Tukey HSD

```
ANOVA result between Approval Rate A and Approval Rate C:
F-statistic: 1.2316
p-value: 0.2675
Multiple Comparison of Means - Tukey HSD, FWER=0.05
===================================================
group1 group2 meandiff p-adj   lower  upper  reject
---------------------------------------------------
     A      C   0.0461 0.2675 -0.0355 0.1278  False
---------------------------------------------------
```

*Figure 50. Tukey HSD for hypothesis B2*

The results across all statistical tests consistently failed to reject $H_0$, indicating that ***system recommendations, as presented in Card C, did not significantly impact lender decisions***. This suggests that lenders may not fully trust automated recommendations or may prioritize other borrower attributes over system-generated risk classifications.

### 7.3.4. Hypotheses B3: Combined Effect of Additional Information and System Recommendations

Hypothesis B3 examines whether combining additional borrower information and system-generated recommendations leads to higher loan acceptance rates than either factor alone. This hypothesis is tested through two comparisons: **Hypothesis B3.1** assesses whether Group D (both additional information and recommendations) outperforms Group B (additional information only), while **Hypothesis B3.2** evaluates whether Group D outperforms Group C (system recommendations only).

**For Hypothesis B3.1**, **$H_0$** stated *loan acceptance rates for borrowers with additional information and system recommendations (Group D) are not significantly different from those with additional information only (Group B)*; whereas **$H_1$** stated Loan acceptance rates for borrowers with additional information and system recommendations (Group D) are higher than those with additional information only (Group B).

The T-test (Figure 51) yielded a t-statistic of 0.210 and a p-value of 0.8336, indicating no statistically significant difference. The Z-test confirmed the absence of a significant difference (Figure 52), with a z-statistic of -0.2102 and a p-value of 0.8335, and the ANOVA result (Figure 53) shows an F-statistic of 0.0441 and a p-value of 0.8336.

T-test (groups)

t-test result for A vs C:
- t-statistic = 0.21
- p-value = 0.8336

This indicates that there is **NO** significant difference between these groups.

| Comparison | t_stat | p_value | Significance |
|---|---|---|---|
| A vs B | -2.93070 | 0.00349 | Significant |
| A vs C | -1.10979 | 0.26751 | Not Significant |
| B vs D | 0.21008 | 0.83362 | Not Significant |
| C vs D | -2.69275 | 0.00714 | Significant |

*Figure 51. T-test for hypothesis B3.1*

Z-test

```
z-test result for Group D vs Group B: z-statistic = -0.2102, p-value = 0.8335
Result: The p-value is 0.8335, suggesting no significant differences between the two groups. This does not support the hypothesis that incorporating bot
h additional information and system recommendations increases loan acceptance rates for micro-enterprises more than additional information alone.
```

*Figure 52. Z-test for hypothesis B3.1*

ANOVA

```
ANOVA result between Approval Rate A, Approval Rate B, Approval Rate C, and Approval Rate D:
F-statistic: 5.3967
p-value: 0.0011
Result: The p-value is less than 0.05, suggesting significant differences between groups.
This supports the hypothesis that incorporating additional information increases loan acceptance rates for micro-enterprises.
```

```
ANOVA result for Group D vs Group B: F-statistic = 0.0441, p-value = 0.8336
Result: The p-value is 0.8336, suggesting no significant differences between the two groups. This does not support the hypothesis that incorporating bot
h additional information and system recommendations increases loan acceptance rates for micro-enterprises more than additional information alone.
```

*Figure 53. ANOVA for hypothesis B3.1*

Additionally, Tukey test (Figure 54) confirmed the absence of significant differences between Group B and Group D, with a mean difference of -0.0051 and a p-value of 0.8336. These results lead to the failure to reject **$H_0$**, meaning ***loan acceptance rates for borrowers with additional information and system recommendations are not significantly different from those with additional information only***.

Tukey HSD

```
Multiple Comparison of Means - Tukey HSD, FWER=0.05
====================================================
group1 group2 meandiff p-adj   lower   upper  reject
----------------------------------------------------
     B      D  -0.0051 0.8336 -0.0531 0.0429  False
----------------------------------------------------
```

*Figure 54. Tukey HSD test for hypothesis B3.1*

For Hypothesis B3.2, **$H_0$** stated that *loan acceptance rates for borrowers with additional information and system recommendations (Group D) are not significantly different from those with system recommendations only (Group C)*; whereas **$H_1$** stated that loan acceptance rates for borrowers with additional information and system recommendations (Group D) are higher than those with system recommendations only (Group C).

The T-test results (Figure 55) indicate a significant difference, with a t-statistic of 2.6927 and a p-value of 0.0071, suggesting that combining both elements substantially increases acceptance rates. The Z-test (Figure 56) further confirms these findings, yielding a z-statistic of 2.6897 and a p-value of 0.0072, while the ANOVA test (Figure 57), with an F-statistic of 7.2509 and a p-value of 0.0071, shows significant differences between Groups C and D.

T-test (groups)

t-test result for A vs C:
- t-statistic = 0.269
- p-value = 0.0071

This indicates that there is a significant difference between these groups.

| Comparison | t_stat | p_value | Significance |
|---|---|---|---|
| A vs B | -2.93070 | 0.00349 | Significant |
| A vs C | -1.10979 | 0.26751 | Not Significant |
| B vs D | 0.21008 | 0.83362 | Not Significant |
| C vs D | -2.69275 | 0.00714 | Significant |

*Figure 55. T-test for hypothesis B3.2*

Z-test

```
z-test result for Group D vs Group C: z-statistic = 2.6897, p-value = 0.0072
Result: The p-value is less than 0.05, suggesting a significant difference between the two groups.
This supports the hypothesis that incorporating both additional information and system recommendations increases loan acceptance rates for micro-enterpr
ises more than system recommendations alone.
```

*Figure 56. Z-test for hypothesis B3.2*

ANOVA

```
ANOVA result for Group D vs Group C: F-statistic = 7.2509, p-value = 0.0071
Result: The p-value is less than 0.05, suggesting a significant difference between the two groups.
This supports the hypothesis that incorporating both additional information and system recommendations increases loan acceptance rates for micro-enterpr
ises more than system recommendations alone.
```

*Figure 57. ANOVA for hypothesis B3.2*

Tukey test (Figure 58) showing a significant mean difference of 0.0701 (p-value = 0.0071) between Groups C and D. All of the statistical tests for hypotheses B3.2 concluded that **$H_0$** is rejected, supporting **$H_1$** and confirming that ***loan acceptance rates for borrowers with additional information and system recommendations are higher than those with system recommendations only***.

```
Multiple Comparison of Means - Tukey HSD, FWER=0.05
===================================================
group1 group2 meandiff p-adj  lower  upper  reject
---------------------------------------------------
     C      D   0.0701 0.0071 0.0191 0.1212   True
---------------------------------------------------
```

*Figure 58. Tukey HSD test for hypothesis B3.2*

These results **do not support** Hypothesis B3.1 but **support** Hypothesis B3.2. This suggests that system recommendations alone do not significantly increase acceptance rates unless paired with additional borrower data. These findings emphasize that lending systems benefit more from enriched borrower profiles than standalone system-generated recommendations. The results suggest that achieving higher inclusion rates in lending frameworks demands *a layered approach* to borrower assessment, where system-generated recommendations are paired with field-enriched borrower profiles to yield more inclusive outcomes.

### 7.3.5. Hypothesis B4. Perception of Creditworthiness and Reliability of Information

Hypothesis B4 examines whether different types of borrower information influence lenders' perceptions of creditworthiness and data reliability. Respondents rated each profile from 1 to 5, assessing creditworthiness as the lender's confidence that the borrower can repay and information reliability as the lender's confidence in the information presented.

**Creditworthiness**

```
Welch t-test (pairwise):
            Metric Group 1 Group 2   mean1   mean2   t_stat     t_p  Significant (p<0.05)
Creditworthiness       A       B 3.07292 3.18113 -0.61099 0.54261                 False
Creditworthiness       A       C 3.07292 3.15402 -0.48775 0.62678                 False
Creditworthiness       A       D 3.07292 3.13747 -0.48344 0.63019                 False
Creditworthiness       B       C 3.18113 3.15402  0.15376 0.87810                 False
Creditworthiness       B       D 3.18113 3.13747  0.29928 0.76554                 False
Creditworthiness       C       D 3.15402 3.13747  0.12486 0.90092                 False

Z-test for mean difference (pairwise):
            Metric Group 1 Group 2   mean1   mean2   z_stat     z_p  Significant (p<0.05)
Creditworthiness       A       B 3.07292 3.18113 -0.60616 0.54441                 False
Creditworthiness       A       C 3.07292 3.15402 -0.48522 0.62752                 False
Creditworthiness       A       D 3.07292 3.13747 -0.49620 0.61975                 False
Creditworthiness       B       C 3.18113 3.15402  0.15415 0.87749                 False
Creditworthiness       B       D 3.18113 3.13747  0.33168 0.74013                 False
Creditworthiness       C       D 3.15402 3.13747  0.13192 0.89504                 False

One-way ANOVA (A–D):
            Metric  DF_between  DF_within  F_stat  p_value  Significant (p<0.05)
Creditworthiness           3        310 0.15102  0.92899                 False

Tukey HSD (post-hoc, p-adjusted):
group1 group2  meandiff   p_adj    lower   upper  Significant (p<0.05)
     A      B   0.10820 0.91550 -0.32180 0.53830                 False
     A      C   0.08110 0.96050 -0.34340 0.50560                 False
     A      D   0.06460 0.96590 -0.29140 0.42050                 False
     B      C  -0.02710 0.99830 -0.44070 0.38650                 False
     B      D  -0.04370 0.98770 -0.38650 0.29920                 False
     C      D  -0.01650 0.99930 -0.35250 0.31940                 False
```

*Figure 59. Perception of Creditworthiness*

Using pairwise t-tests and Z-tests for mean differences across Cards A, B, C, and D, followed by a one-way ANOVA and Tukey's HSD post-hoc, we found no statistically meaningful differences between groups (Figure 59). This non-significance may reflect that respondents formed creditworthiness judgments mainly from information already present on the basic card; the added field details and the system recommendation did not introduce new decisive facts for that judgment, so group means stayed close. This can still differ from earlier findings on loan acceptance (Hypothesis B1): acceptance may increase when extra information reduces uncertainty or makes approval feel safer, even if the stated creditworthiness rating does not change

Hypothesis B4.1 is **not supported** for the perception of creditworthiness: adding field data and/or a system recommendation does not significantly change perception of creditworthiness.

**Reliability**

```
Welch t-test (pairwise):
     Metric Group 1 Group 2   mean1   mean2   t_stat     t_p  Significant (p<0.05)
Reliability       A       B 2.76042 3.11887 -2.01428 0.04670                  True
Reliability       A       C 2.76042 3.54018 -4.47474 0.00002                  True
Reliability       A       D 2.76042 3.32431 -4.00002 0.00015                  True
Reliability       B       C 3.11887 3.54018 -2.40108 0.01808                  True
Reliability       B       D 3.11887 3.32431 -1.44206 0.15313                 False
Reliability       C       D 3.54018 3.32431  1.56632 0.12083                 False

Z-test for mean difference (pairwise):
     Metric Group 1 Group 2   mean1   mean2   z_stat     z_p  Significant (p<0.05)
Reliability       A       B 2.76042 3.11887 -2.00796 0.04465                  True
Reliability       A       C 2.76042 3.54018 -4.45806 0.00001                  True
Reliability       A       D 2.76042 3.32431 -4.12653 0.00004                  True
Reliability       B       C 3.11887 3.54018 -2.40206 0.01630                  True
Reliability       B       D 3.11887 3.32431 -1.53140 0.12567                 False
Reliability       C       D 3.54018 3.32431  1.64756 0.09944                 False

One-way ANOVA (A–D):
     Metric  DF_between  DF_within  F_stat  p_value  Significant (p<0.05)
Reliability           3        310 8.11324  0.00003                  True

Tukey HSD (post-hoc, p-adjusted):
group1 group2  meandiff   p_adj    lower   upper  Significant (p<0.05)
     A      B   0.35850 0.15760 -0.08390 0.80080                 False
     A      C   0.77980 0.00000  0.34310 1.21640                  True
     A      D   0.56390 0.00050  0.19770 0.93000                  True
     B      C   0.42130 0.05340 -0.00410 0.84670                 False
     B      D   0.20540 0.43590 -0.14720 0.55810                 False
     C      D  -0.21590 0.37240 -0.56140 0.12970                 False
```

*Figure 60. Perception of Data Reliability*

Applying t-tests, Z-tests, ANOVA, and Tukey's HSD, we observed clear differences (Figure 60). The ANOVA was significant. Tukey's HSD showed that Card A (basic info) was reliably lower than Card C (with system recommendations) and Card D (field data + recommendations). T-tests and Z-tests also flagged A vs B and B vs C at $p<0.05$, but these did not remain significant once multiple comparisons were controlled by Tukey's HSD. Directionally, the means increased A < B < D < C, indicating that presentations with recommendations (especially when combined with field data) were perceived as more reliable than basic information alone.

In this context, reliability reflects how clear, organized, and dependable the information appears to respondents. Cards that include a system recommendation (C) or the combined information (D) provide greater structure and transparency than the basic design (A). This standardization can make the information feel more consistent across cases and easier to appraise, which increases perceived reliability. The lift from field data alone (B) is modest; *the presence of a recommendation appears to be the dominant factor* in raising perceived reliability relative to A. The absence of a clear difference between C and D after adjustment suggests *diminishing returns*: once clarity and standardization are achieved, further detail does not meaningfully increase the perception of reliability.

Furthermore, these findings do not imply that higher perceived reliability necessarily raises loan acceptance (as in Hypothesis B2). Reliability concerns *confidence in the presentation and perceived quality of the information*; acceptance is a risk decision. Respondents may consider the information well-structured and dependable yet still apply cautious approval thresholds.

Hypothesis B4.2 is **supported** for reliability: presentations that include a system recommendation, especially when combined with field data, are perceived as more reliable than the basic presentation.

### 7.4. Conclusion

The table below summarizes the conclusions of hypothesis testing.

*Table 27. Summary of hypotheses testing (B1-B4)*

| Hypothesis | Conclusion | Explanation |
|---|---|---|
| **Hypothesis B1**: Incorporating additional information increases loan acceptance rates for micro-enterprises. | Significantly supported | Additional data elements like payment capacity and business duration significantly increase loan acceptance rates. |
| **Hypothesis B2**: Incorporating system recommendations enhances loan acceptance rates for micro-enterprises. | Significantly not supported | All statistical test results indicate no significant difference in loan acceptance rates with the addition of system recommendations alone. |
| **Hypothesis B3.1**: Combining additional information and system recommendations increases acceptance more than additional information alone. | Significantly not supported | All statistical test results show no significant increase in acceptance rates when combining additional information and system recommendations compared to additional information alone. This suggests that additional data has a significant impact on its own. |
| **Hypothesis B3.2**: Combining additional information and system recommendations increases acceptance more than system recommendations alone. | Significantly supported | All statistical test results show that combining additional information and system recommendations significantly enhances loan acceptance rates compared to system recommendations alone. |
| **Hypothesis B4.1**: Providing more detailed and comprehensive information increases the perceived creditworthiness. | Significantly not supported | Statistical analysis indicates no significant difference in perceived creditworthiness across the different types of information provided, suggesting that additional data or recommendations do not change perceptions of creditworthiness. |
| **Hypothesis B4.2**: Providing more detailed and comprehensive information enhances the perceived data reliability. | Significantly supported | Statistical analysis indicates that presentations that include a system recommendation, especially when combined with field data, are perceived as more reliable than the basic presentation. |

Table 27 summarises the hypotheses. Pairwise t- and z-tests were used as initial checks; the conclusions reported in the table rely on the comparisons that remain after adjusting for multiple testing with ANOVA followed by Tukey test.

For loan acceptance, **B1 is supported**: Additional Borrower Information increases approval rates. **B2 is not supported**: the System Recommendation, when presented on its own, does not increase approvals. When both are present, the result depends on the baseline: the combination surpasses the System Recommendation alone (**B3.2 supported**) but does not exceed Additional Borrower Information by itself (**B3.1 not supported**). In practical terms, lenders change decisions when verifiable borrower details are available; the System Recommendation helps mainly where such details are limited and does not substitute for them.

For perceptions, the two constructs diverge. **B4.1 is not supported**: perceived creditworthiness does not differ across cards, indicating that respondents keep their risk judgement steady despite presentation changes. **B4.2 is supported**: perceived data reliability increases when the System Recommendation is shown (Card C) and remains high when combined with Additional Borrower Information (Card D), with no further measurable gain beyond that. The repeated non-significance of B–D and C–D means that once a recommendation is present, adding the other element does not create an additional lift in perceived data reliability.

Where pairwise t- or z-tests marked A–B or B–C at $p<0.05$, these contrasts did not carry through Tukey's adjustment because several pairs were tested and the effective threshold is therefore stricter. The adjusted results isolate the differences that matter for interpretation: A–C and A–D on Reliability, and the superiority of the combined card over the recommendation alone for Acceptance (B3.2), alongside the primary effect of Additional Borrower Information (B1).

These findings translate directly into *design guidance for the Reference Architecture*. To increase acceptance rate, prioritise the capture and clear presentation of Additional Borrower Information (e.g., payment capacity, business duration, business type). Use the System Recommendation to standardise reading and provide short, transparent reasons so that the output is easy to trust; its effect is strongest when underlying data are sparse. In short, Additional Borrower Information (B) moves loan approvals, while the System Recommendation (C) raises perceived data reliability. For policy-makers and RA system designers, this implies a sequencing and governance choice: in the near term, expanding well-chosen, verifiable borrower fields (B) delivers the quickest gains in inclusion; in the medium-to-long term, durable scale depends on lenders' confidence that the information and its interpretation are consistent, auditable, and fair (C).

The next chapter is the last part of RA evaluation (part 3). We conduct the sensitivity analysis using machine learning by adding data attributes and tunning model parameters to evaluate the impact of model adjustment on reclassification of borrowers to improve inclusion.

# Chapter 8: Sensitivity Analysis on Improving Inclusion Scoring[4]

## 8.1. Introduction

This chapter builds upon the findings from Chapter 7, which explored how enriched borrower data influences lenders' decision-making in loan approval. Although the survey did not investigate attributes in isolation, it emphasized how enriched borrower profiles shaped lending approval. Chapter 8 extends this exploration by analyzing the impact of attributes through modeling. This analysis contributes to the development of inclusion scoring, which links borrower attributes to changes in risk classification and recommendation outcomes. Notably, several attributes highlighted by respondents in Chapter 7 were also found to affect borrower risk class shifts and system recommendations in this chapter. This reinforces the alignment between stakeholder intuitions and model-based insights, further validating the role of attributes in improving inclusion in the lending system.

This chapter investigates whether modifying borrower data and tuning model parameters can improve borrowers' risk classification and inclusion. Two hypotheses guide the analysis in this chapter: **Hypothesis A1** proposes that adding additional data variables increases the system's loan recommendations, while **Hypothesis A2** suggests that adjusting model parameters enhances the system's loan recommendations. These hypotheses reflect two design principles from the RA: Principle 2 (leveraging diverse data), which emphasizes incorporating a broader range of borrower attributes to improve loan recommendations, and Principle 1 (inclusion metrics), which advocates for metrics to measure impact on increasing inclusion.

The sensitivity analysis proceeds in three stages, as shown in Figure 61. *First*, a baseline model is built to represent the current system's borrower classification and to provide a reliable comparison model. *Next*, *Hypothesis A1* is tested by integrating additional borrower attributes into this baseline model to evaluate their impact on borrower classification. *In the third stage*, *Hypothesis A2* is tested by tuning model parameters using existing data to assess their effect on borrower reclassification.

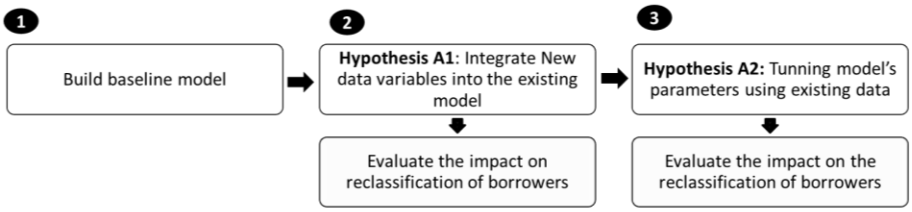



*Figure 61. Sensitivity analysis stages*

This chapter is organized as follows: Section 8.2 outlines the experimental setup and measurements. Section 8.3 explores Hypothesis A1 and analyzes the impact of additional data variables, while Section 8.4 examines Hypothesis A2, addressing model tuning. Section 8.5 concludes with key insights from the sensitivity analysis.

## 8.2. Experiment Setting and Measurements

To test these hypotheses, **a baseline model** was constructed using loan data from selected lending institutions in Indonesia. In the simulation, we compare borrower risk classifications from *the baseline model* with those from *the adjusted models* tested under hypotheses A1 and A2. The baseline model,

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[4] Parts of this chapter are based on the following publications:
Sulastri, Ding, Janssen, (2025). Sensitivity Analysis: Improving Inclusive Credit Scoring Algorithm through Feature Weight and Penalty-based Approach (ICEDEG 2025).

described in Section 8.2.2, functions as a reference point to assess whether changes in data or model parameters lead to meaningful improvements.

### 8.2.1. Existing Data

The dataset comprises anonymized borrower profiles and loan performance histories from selected Indonesian lending institutions. As real-world data drawn from actual lending practices, it reflects operational conditions in the field rather than simulated or experimental inputs. Initially, data from 2021 were considered; however, to reduce anomalies caused by the COVID-19 pandemic, the dataset was updated to 2022. This dataset primarily covers micro and ultra-micro enterprises, which play a significant role in Indonesia's economy. A key strength of this dataset is the completeness of its labeled classifications, eliminating the need for data imputation. Since the analysis is based on data from a particular borrower group in a specific country and period, the results may vary if applied to other datasets or population segments.

The lending system under examination utilizes a classification system that segments borrowers into *five risk categories* based on historical repayment behavior. This categorization influences lending decisions and often creates a barrier for microenterprises seeking credit. This study challenges the traditional classification approach by examining how data enrichment and model tuning can influence these classifications. Figure 62 displays the distribution of borrowers derived from the dataset provided by financial institutions participating in this study.

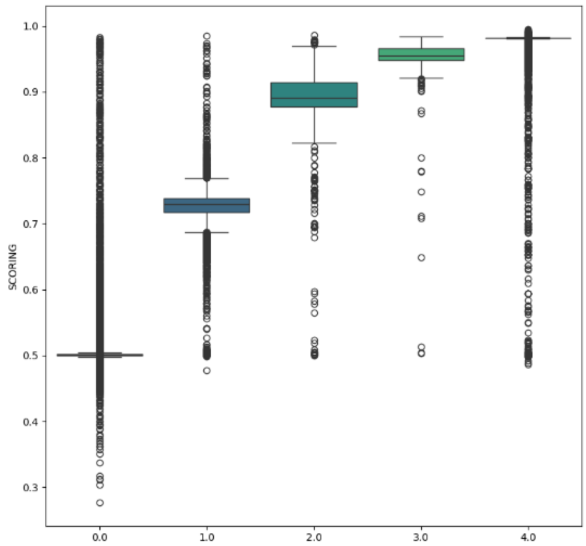


*Figure 62. Borrowers classification with loan samples from selected financial institutions (Sulastri, Ding, & Janssen, 2025)*

The x-axis represents borrower risk categories (0 to 4), where Category 0 is the lowest risk class (*most desirable*), and Category 4 is the highest risk class (*least desirable*). The y-axis shows the range of borrower scores within each category, and the box plots illustrate how much these scores vary. Categories 0 and 4 have broader distributions, meaning borrowers in these groups have more diverse characteristics, while Categories 2 and 3 have narrower ranges, indicating more consistent classifications. A borrower in Category 0 has a higher chance of getting approved for credit, while someone in Category 4 is more likely to face rejection. We aim to analyze how data and model adjustments impact these classifications, aiming to shift borrowers into lower-risk categories to improve their access to credit.

### 8.2.2. Baseline Model Construction

The baseline model serves as a reference point to evaluate whether adding new borrower attributes (**Hypothesis A1**) or adjusting model attributes (**Hypothesis A2**) leads to meaningful improvements in risk classification. The baseline model must be robust and reliable to ensure a credible benchmark. Comparisons are determined by tracking changes in borrower risk classifications between the baseline and adjusted models.

#### *1) Data Loading and Preprocessing*

The baseline model development began by *loading a dataset* filtered based on criteria like lending institutions and timeframe to align with the study's objectives. Missing values were addressed using mean or mode imputation to uphold data integrity. After data cleaning, *the dataset was split* into training and test sets. *Preprocessing pipelines were created* for numerical and categorical features: numerical features were standardized using *Standard Scaler* to maintain consistent value ranges, while categorical features were transformed through *One-hot Encoding* or *Label Encoder*. Applying these pipelines to both sets ensure uniform preprocessing and model readiness.

#### *2) Baseline Model Selection and Initial Testing*

To establish a strong baseline for borrower risk prediction, we evaluated multiple machine learning algorithms, including Gradient Boosting Classifier (GBC), XGBoost, CatBoost, Random Forest Classifier, and Decision Tree Classifier. The selection process utilized *PyCaret* to compare critical metrics such as accuracy, AUC, recall, precision, F1 score, Kappa, and MCC, ensuring the model could robustly predict borrower risk. Figure 63 shows initial comparisons highlighting each model's strengths and limitations. The final model choice was based not only on predictive accuracy but also on computational feasibility, as discussed in the next paragraph.

| | Model | Accuracy | AUC | Recall | Prec. | F1 | Kappa | MCC | TT (Sec) |
|---|---|---|---|---|---|---|---|---|---|
| gbc | Gradient Boosting Classifier | 0.9974 | 0.9993 | 0.9974 | 0.9974 | 0.9974 | 0.9926 | 0.9926 | 222.7033 |
| xgboost | Extreme Gradient Boosting | 0.9973 | 0.9995 | 0.9973 | 0.9973 | 0.9973 | 0.9923 | 0.9923 | 179.1567 |
| catboost | CatBoost Classifier | 0.9970 | 0.9995 | 0.9970 | 0.9970 | 0.9970 | 0.9914 | 0.9914 | 142.6000 |
| rf | Random Forest Classifier | 0.9965 | 0.9980 | 0.9965 | 0.9965 | 0.9965 | 0.9900 | 0.9900 | 12.3733 |
| dt | Decision Tree Classifier | 0.9950 | 0.9952 | 0.9950 | 0.9950 | 0.9950 | 0.9858 | 0.9858 | 3.8067 |
| lightgbm | Light Gradient Boosting Machine | 0.9906 | 0.9920 | 0.9906 | 0.9922 | 0.9911 | 0.9735 | 0.9736 | 6.9400 |
| et | Extra Trees Classifier | 0.9897 | 0.9980 | 0.9897 | 0.9894 | 0.9895 | 0.9706 | 0.9706 | 13.9267 |
| knn | K Neighbors Classifier | 0.9653 | 0.9781 | 0.9653 | 0.9672 | 0.9661 | 0.9023 | 0.9025 | 61.8933 |
| ada | Ada Boost Classifier | 0.8858 | 0.9869 | 0.8858 | 0.9135 | 0.8887 | 0.6859 | 0.7037 | 10.2000 |
| ridge | Ridge Classifier | 0.8369 | 0.0000 | 0.8369 | 0.8852 | 0.8575 | 0.5903 | 0.5996 | 1.0133 |
| lda | Linear Discriminant Analysis | 0.8093 | 0.8959 | 0.8093 | 0.8913 | 0.8445 | 0.5363 | 0.5487 | 2.6433 |
| dummy | Dummy Classifier | 0.7914 | 0.5000 | 0.7914 | 0.6263 | 0.6992 | 0.0000 | 0.0000 | 1.0933 |
| svm | SVM - Linear Kernel | 0.6760 | 0.0000 | 0.6760 | 0.8610 | 0.7186 | 0.4298 | 0.4774 | 1.6700 |
| nb | Naive Bayes | 0.2549 | 0.9553 | 0.2549 | 0.9280 | 0.3126 | 0.1463 | 0.3065 | 2.5333 |
| qda | Quadratic Discriminant Analysis | 0.1144 | 0.5600 | 0.1144 | 0.9199 | 0.1310 | 0.0860 | 0.2125 | 1.1633 |

*Figure 63. Performance Comparison of Machine Learning Models for Baseline Model (Sulastri, Ding, & Janssen, 2025)*

GBC delivered the highest accuracy (0.9974), narrowly surpassing XGBoost and CatBoost, yet its extended training time of over 2.5 hours per iteration under full-scale testing proved a major constraint. This extended runtime, significantly longer than the initial estimate of 222 seconds, was largely due to the increased dataset size and complexity in real experimental conditions, adding considerable strain to computational resources.

Similarly, XGBoost's processing time increased from an estimated 179 seconds to 1–2 hours per iteration. Given the extensive number of scenarios and model combinations required for this study, the prolonged training times of both GBC and XGBoost presented notable challenges for feasibility. Consequently, XGBoost was initially selected for its high accuracy (0.9973) combined with a relatively shorter runtime than GBC, offering a practical balance between accuracy and processing efficiency

***3) Experimentation with XGBoost and Transition to CatBoost***

As experimentation progressed, XGBoost's runtime constraints became increasingly apparent due to the experiment's extensive complexity. Each XGBoost model required around 1–2 hours to complete, which, combined with numerous approaches and scenarios, escalated computational demands to unfeasible levels. For instance, several scenarios involved 4–5 different setups, each containing 40–50 model combinations, resulting in processing times that strained the study's timeline.

In approximately 75% of the planned scenarios, CatBoost was introduced as a potential alternative to address these computational limitations. Initial tests showed CatBoost's performance comparable to XGBoost, with an accuracy of 0.9970 and an AUC of 0.9995, along with minimal differences in recall, precision, and F1 scores. The significant advantage of CatBoost, however, lay in its drastically reduced execution time, with each model iteration completing in just 1–2 minutes, far faster than XGBoost's 1–2 hours. This substantial reduction in computational time allowed us to maintain the required depth and rigor of analysis without compromising analytical reliability.

***4) Re-running Experiments with CatBoost***

Following the decision to adopt CatBoost as the algorithm or the baseline model, we re-ran all previous experiments to ensure consistency and accuracy across the different scenarios. Since earlier results were produced using XGBoost, re-running the experiments with CatBoost was necessary to ensure a valid comparison across all models tested under Hypotheses A1 and A2. This validation step was essential to confirm that the results were stable and reproducible under CatBoost's accelerated training times. By re-testing each scenario, we ensured that the transition to CatBoost did not introduce inconsistencies and that its performance was on par with, if not superior to, XGBoost.

In summary, the adaptive model selection process, from GBC to XGBoost and ultimately to CatBoost, reflects a deliberate approach to optimizing model performance while balancing computational feasibility. The adoption of CatBoost enabled the timely completion of experiments and allowed for comprehensive analysis of inclusion metrics without sacrificing model reliability. This final choice (CatBoost algorithm) provided the best alignment between performance, execution time, and the practical requirements of the study.

### 8.2.3. Measurement Metrics

The experiment operates under the assumption that a borrower's risk classification is indicative of future creditworthiness. A lower-risk class implies a higher likelihood of credit recommendation, while a higher-risk class suggests a lower likelihood. Based on this assumption, the primary analysis compares *the baseline model's classifications* with those from *the adjusted models* in Hypothesis A1 and Hypothesis A2. This study employs five key measurement metrics to evaluate the impact of model adjustments on borrower classification and inclusivity. Metrics related to class distribution (Metric 1 and Metric 2) are structured in an array format for direct comparison, while Metrics 3, 4, and 5 are presented as percentage values and ratios to quantify borrower movement and inclusivity effects.

### A. *Metric 1: Risk Class Distribution (array of %)*

This metric measures *the proportion of borrowers* in each risk class before and after model adjustments, expressed as a percentage of the total dataset, with the following formula.

$For\ each\ risk\ class\ i\ (where\ i = 0, 1, 2, 3, 4), the\ percentage\ of\ the\ borrower\ is\ calculated\ as:$

$$a_i = \frac{\#\ borrowers\ in\ Class\ i}{Total\ borrowers} \times 100\%$$

$The\ distribution\ for\ both\ models\ is\ represented\ as:$

$$Baseline\ model = [a, b, c, d, e]$$
$$Adjusted\ model = [a',\ b', c', d', e']$$

$Where$

- $a, b, c, d, e = percentage\ of\ borrowers\ in\ each\ risk\ class\ in\ the\ baseline\ model$
- $a',\ b', c', d', e' = percentage\ of\ borrowers\ in\ each\ risk\ class\ in\ the\ adjusted\ model$
- $The\ sum\ of\ percentages\ for\ both\ models\ must\ always\ equal\ 100\%$

An example of metric 1 is as follows.

| **Model name** | **Percentage of distribution in each risk class of adjusted model in comparison with total data** | | | | | |
|---|---|---|---|---|---|---|
| | **Risk class** | | | | | |
| | 0 (Lowest Risk) | 1 | 2 | 3 | 4 (Highest Risk) | Total data |
| Baseline Model (%) | 23.60% | 19.30% | 20.10% | 18.80% | 18.20% | 100.00% |
| Adjusted Model (%) | 25.10% | 18.90% | 19.70% | 17.50% | 18.80% | 100.00% |

### B. *Metric 2: Risk Class Shift (array of %)*

This metric quantifies the *relative percentage change* in each risk class compared to the baseline model. It highlights whether the proportion of borrowers in each category *increased or decreased* after model adjustments. The formula is as follows.

$For\ each\ risk\ class\ i, the\ percentage\ shift\ is\ computed\ as$

$$\Delta\%_i = \frac{(a'_i - a_i)}{a_i} \times 100\%$$

$where:$

- $a_i\ = baseline\ percentage\ of\ borrowers\ in\ class\ i$
- $a'_i = adjusted\ model\ percentage\ of\ borrowers\ in\ class\ i$
- $\Delta\%_i = relative\ percentage\ change\ for\ class\ i$

An example of metric 2 is as follows:

| **Model name** | **Percentage of shifting in each risk class of adjusted model in comparison with baseline models** | | | | |
|---|---|---|---|---|---|
| | **Risk class** | | | | |
| | 0 (Lowest Risk) | 1 | 2 | 3 | 4 (Highest Risk) |
| Adjusted Model (%) | 6.36% | -2.07% | -1.99% | -6.91% | 3.30% |

- Positive Δ% indicates more borrowers in this class after model adjustment.
- Negative Δ% indicates a reduction, meaning borrowers have moved to other risk classes.

### C. Metric 3: Borrower Shift to Lower Risk Classes (%)

This metric evaluates the proportion of borrowers who moved to a lower-risk class after the model adjustment. A high value in this metric indicates that the model improves financial inclusion by reducing risk classifications for many borrowers.

$$Formula:$$
$$Shift\ to\ lower\ risk\ class\ = \frac{\#\ borrowers\ who\ moved\ to\ lower\ classses}{Total\ Borrowers} \times 100\%$$

Example of calculation: If 245 out of 1,200 borrowers were reclassified into a lower-risk category:

$$Metric\ 3\ (Shift\ to\ lower\ risk\ class)\ = \frac{245}{1200} \times 100\%\ = 20.42\%$$

### D. Metric 4: Borrower Shift to Higher Risk Classes (%)

This metric evaluates the proportion of borrowers who moved to a higher-risk class after the model adjustment. A high percentage in this metric may indicate unintended consequences, as more borrowers are classified into higher risk categories.

$$Formula:$$
$$Shift\ to\ higher\ risk\ class\ = \frac{\#\ borrowers\ who\ moved\ to\ higher\ classses}{Total\ Borrowers} \times 100\%$$

Example of calculation: If 90 out of 1,200 borrowers were reclassified into a lower-risk category:

$$Metric\ 4\ (Shift\ to\ higher\ risk\ class)\ = \frac{90}{1200} \times 100\%\ = 7.5\%$$

### E. Metric 5: Inclusion Ratio

This metric quantifies the overall impact of model adjustments on inclusion by comparing the proportion of borrowers who moved to lower-risk classes against those who moved to higher-risk classes. A ratio above **1.0** suggests a *net positive impact* on inclusion, whereas a ratio below 1.0 indicates a *net negative effect* (more borrowers shifted to higher-risk classes than lower ones).

$$Formula:$$
$$Inclusion\ Ratio\ = \frac{\#\ borrowers\ shifted\ to\ lower\ classs}{\#\ borrowers\ shifted\ to\ higher\ classs}$$

Example of calculation: 20.42% of borrowers moved to a lower-risk class, and 7.50% of borrowers moved to a higher-risk class, results in,

$$Metric\ 5\ (Inclusion\ Ratio) = \frac{20.42\%}{7.5\%} = 2.72$$

Furthermore, to ensure the reliability of the adjusted models, we developed a baseline model to serve as a reference point, ensuring that the comparisons with the adjusted models are not based on a poorly performing model. To guarantee that all adjusted models consistently refer to the baseline model, the hyperparameters of the baseline model were recalled for each scenario, as below. The full explanation of the baseline model development process is provided in the next section.

```
param_grid_cat = {
  'iterations': [baseline_params['iterations']],
  'learning_rate': [baseline_params['learning_rate']],
  'depth': [baseline_params['depth']],
  'l2_leaf_reg': [baseline_params['l2_leaf_reg']]
}
```

*Figure 64. Baseline Model Hyperparameter Configuration*

While the dataset used in this study reflects real borrower records, the analysis involves structured experiments where model parameters, such as feature weights and penalty configurations, are deliberately varied to explore their effects on borrower classification. This controlled setup enables analysis of models' sensitivity, which cannot be observed from historical data alone. Historical loan decisions often reflect fixed model settings and unobserved institutional biases, making it difficult to isolate the influence of specific parameters. By simulating multiple model configurations on real data, this study aims to develop a practical method for identifying which adjustments lead to more inclusive outcomes rather than producing a single predictive model.

## 8.3. Experiment Results for Hypothesis A1

This section investigates the hypothesis of adding new attributes to the baseline model. The attributes tested were income (INCOME), income type (INCOME_S), degree (DEGREE), number of dependents (FAM), marital status (MAR), and job type (JOB). These attributes were selected based on their availability from lending institutions. Although obtaining sensitive data posed challenges, necessitating anonymization under strict NDAs, these attributes were identified as relevant and accessible for this study. The combinations of attributes tested were: (i) One attribute: 6 different combinations, (ii) Two attributes: 15 different combinations, (iii) Three attributes: 20 different combinations, (iv) Four attributes: 15 different combinations, (v) Five attributes: 6 different combinations, and (vi) Six attributes: 1 combination.

This results in 63 different models being executed. Each model execution requires 10-20 minutes, depending on the number of attributes added to the base model. To ensure the reliability of the result, we maintain the index number of data pairs compared in each execution. The overview of the results is shown in Figure 65, which shows an illustration of the movement to the lower class (metrics 3), movement to the higher class (metrics 4), and the inclusion ratio (metrics 5).

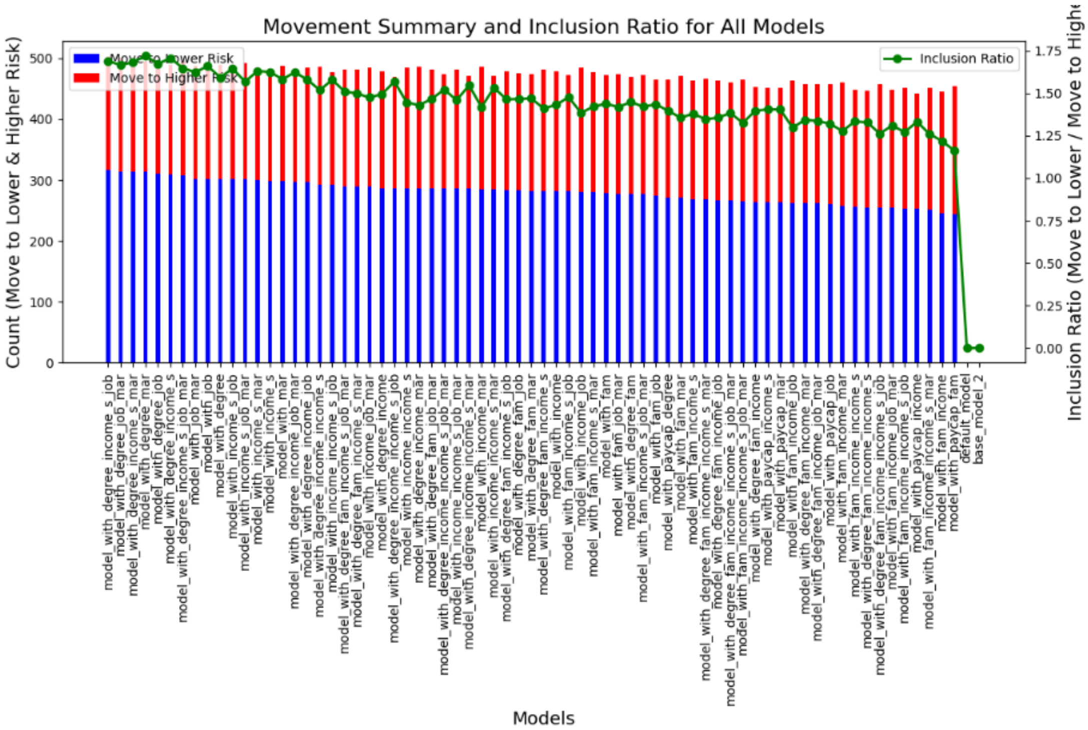


*Figure 65. Movement summary and inclusion ratio for Hypothesis A1*

The analysis of 63 experimental models revealed that adding attributes alone had a limited impact on borrower reclassification (See **Appendix 5**). The changes primarily resulted in modest movements between risk classes, with most borrowers retaining their original classifications. To address these limitations, a Payment Capacity (*Paycap*) feature was introduced to assess borrower repayment ability dynamically. *Paycap* integrates two critical variables: INCOME and OVER_TIME (the overdue payment duration).

*Feature importance test* revealed that OVER_TIME, which records the overdue payment time, held the highest weight among all predictors, significantly more than other variables. The *paycap* feature, therefore, builds upon OVER_TIME and income, adjusting for various risk sensitivities to provide a more comprehensive measure of financial stability. The *paycap* feature is calculated using multiple weights, as shown below:

$$Payment\_Capacity\_weight_w = \begin{cases} INCOME - (w \times normalized\_over\_time), & if\ INCOME > 0 \\ -(w \times normalized\_over\_time), & if\ INCOME \leq 0 \end{cases}$$

Here, INCOME represents the borrower's earnings, while *normalized_over_time* is a scaled overdue time calculated based on the dataset's minimum and maximum OVER_TIME values. The parameters w, 0.1, 0.25, 0.5, 0.75, and 1.0 represent different sensitivity levels in the paycap feature. This weighted approach allows the model to incorporate different risk tolerance levels, enabling it to capture borrower stability across multiple paycap variants. By introducing Paycap, we expect to provide a more nuanced assessment of repayment ability.

### *A. Metric 1: Risk Class Distribution (array of %)*

Metric 1 analyzes the distribution of borrowers across risk classes before and after integrating additional attributes in comparison with the total data. Table 28 highlights how different combinations influenced the reclassification of borrowers into risk classes (0 to 4). Detailed information about *each model's risk class distribution, movement, and inclusion ratio* is in appendix 5.

*Table 28. Risk class distribution in % (hypothesis A1)*

| # additional variables | # of scenario tested | Percentage of distribution in each risk class of adjusted model in comparison with total data | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0 | 1 | 2 | 3 | 4 | Total data |
| **Baseline model** | | 23.58% | 19.24% | 18.65% | 18.93% | 19.59% | 100% |
| **Adjusted model** | | | | | | | |
| 6 variables | 1 scenario | 23.57% | 19.31% | 18.64% | 18.91% | 19.57% | 100% |
| 5 variables | 6 scenarios | 23.57% | 19.30% | 18.65% | 18.91% | 19.58% | 100% |
| 4 variables | 15 scenarios | 23.57% | 19.31% | 18.64% | 18.90% | 19.58% | 100% |
| 3 variables | 20 scenarios | 23.57% | 19.31% | 18.64% | 18.91% | 19.57% | 100% |
| 2 variables | 15 scenarios | 23.56% | 19.34% | 18.61% | 18.91% | 19.57% | 100% |
| 1 variable | 6 scenarios | 23.57% | 19.37% | 18.58% | 18.91% | 19.58% | 100% |
| Models with payment capacity | 6 scenarios | 23.57% | 19.31% | 18.64% | 18.92% | 19.56% | 100% |

Table 28 shows that the overall distribution of borrowers across risk classes remains unchanged, mainly across different model scenarios, even the scenario with *payment capacity.* The baseline model assigns borrowers to risk classes with proportions ranging from 18.65% to 23.58%, while the adjusted models maintain a similar distribution, fluctuating within a narrow range of 18.58% to 23.57%. These results indicate that adding up to six additional attributes has only a minimal impact on classification distribution.

### *B. Metric 2: Risk Class Shift (array of %)*

Furthermore, we analyzed how adding more attributes impacts the changes in each risk class of the adjusted model compared to each risk class in the baseline model. The result is in the following table.

*Table 29. Risk class shifting in % (hypothesis A1)*

| # additional variables | # of scenario tested | Percentage of shifting in each risk class of adjusted model in comparison with base model | | | | |
|---|---|---|---|---|---|---|
| | | 0 | 1 | 2 | 3 | 4 |
| 6 variables | 1 scenario | -0.06% | 0.35% | -0.08% | -0.10% | -0.10% |
| 5 variables | 6 scenarios | -0.07% | 0.29% | -0.04% | -0.09% | -0.07% |
| 4 variables | 15 scenarios | -0.06% | 0.34% | -0.09% | -0.12% | -0.06% |
| 3 variables | 20 scenarios | -0.06% | 0.35% | -0.07% | -0.10% | -0.10% |
| 2 variables | 15 scenarios | -0.08% | 0.50% | -0.23% | -0.08% | -0.09% |
| 1 variables | 6 scenarios | -0.06% | 0.63% | -0.41% | -0.08% | -0.08% |
| Models with payment capacity | 6 scenarios | -0.05% | 0.34% | -0.10% | -0.02% | -0.16% |

*The adjusted models* demonstrated **minimal shifts** in borrower distributions across risk classes when additional data were integrated. As shown Table 29, the percentage differences across all classes remained small, generally within ±0.1% compared to the baseline model. Across all scenarios, the overall distribution remained largely unchanged, indicating that the additional attributes did not meaningfully alter borrower classification.

These results suggest that while adding more data introduces minor variations in borrower classifications, the effect is insufficient to improve risk class distributions substantially. This outcome highlights **the limited sensitivity** of the current model to additional attributes when applied in isolation. Advanced techniques such as feature engineering or algorithmic adjustments may be necessary to enhance the model's responsiveness to enriched borrower profiles to achieve more pronounced impacts on inclusion.

### *C. Metric 3: Borrower Shift to Lower Risk Classes (%)*

To evaluate the impact of additional attributes on borrower classification, we furthermore analyze borrower movements using *Metric 3 (Shift to Lower Risk Classes), Metric 4 (Shift to Higher Risk Classes),* and *Metric 5 (Inclusivity Ratio)*. These metrics are derived from the following two tables, summarizing borrower transitions between risk classes.

Table 30 presents the absolute number of borrowers who moved to lower or higher-risk classes after model adjustments alongside those whose classifications remained unchanged. The number of borrowers shifting to lower-risk classes is consistently higher than those shifting upward, contributing to an Inclusivity Ratio above 1.0 across all scenarios. However, the differences across models remain small, indicating that additional attributes did not significantly alter borrower movement.

*Table 30. Borrower movement across risk classes (Hypothesis A1)*

| # of Additional Variables | Number of borrowers move to lower class | Number of borrowers move to higher class | No Change | Inclusion Ratio |
|---|---|---|---|---|
| 6 variables | 267 | 193 | 85,147 | 1.38 |
| 5 variables | 255 | 202 | 85,150 | 1.26 |
| 4 variables | 255 | 192 | 85,160 | 1.33 |
| 3 variables | 264 | 189 | 85,154 | 1.40 |
| 2 variables | 278 | 192 | 85,137 | 1.45 |
| 1 variable | 301 | 189 | 85,117 | 1.59 |
| Models with pay_cap | 271 | 194 | 85142 | 1.40 |

Table 31 presents the percentage of borrowers shifting to lower-risk classes relative to the total dataset (Metric 3), providing a normalized view of borrower movement, Metric 4, and Metric 5.

*Table 31. Percentage of borrower movement and inclusivity ratio (Hypothesis A1)*

| # of additional variables | Metric 3 | Metric 4 | Metric 5 |
|---|---|---|---|
| | % of borrowers move to the lower class in comparison with total data | % of borrowers move to the higher class in comparison with total data | Inclusion Ratio |
| 6 variables | 0.31% | 0.23% | 1.38 |
| 5 variables | 0.30% | 0.24% | 1.26 |
| 4 variables | 0.30% | 0.22% | 1.32 |
| 3 variables | 0.31% | 0.22% | 1.39 |
| 2 variables | 0.32% | 0.23% | 1.44 |
| 1 variable | 0.35% | 0.22% | 1.59 |
| Models with pay_cap | 0.32% | 0.23% | 1.40 |

Metric 3 quantifies the percentage of borrowers who moved to a lower-risk class, indicating a positive financial inclusion outcome. As shown in Table 31, the percentage of borrowers shifting downward remains small, ranging from 0.30% to 0.35%. The highest downward movement (0.35%) is observed when only one additional variable is included, whereas the lowest (0.30%) occurs in models using four or five additional variables. This suggests that increasing the number of attributes does not necessarily lead to stronger borrower reclassification into lower-risk categories.

Models incorporating payment capacity also show a limited impact, with 0.32% of borrowers shifting downward, indicating that financial indicators alone do not meaningfully improve borrower movement to lower-risk classes. These findings align with Metric 1 and Metric 2, reinforcing that additional data have a minimal effect on risk class reclassification.

*D. Metric 4: Borrower Shift to Higher Risk Classes (%)*

As shown in Table 31, the percentage of borrowers shifting upward remains low, ranging from 0.22% to 0.24%. The highest shift (0.24%) occurs in the five-variable model, while other scenarios fluctuate within 0.22%–0.23%, showing minimal variation. The model with payment capacity (0.23%) aligns with most other cases, confirming that additional attributes, including financial indicators, do not significantly increase borrower reclassification into higher-risk classes.

*E. Metric 5: Inclusivity Ratio*

Metric 5 compares the number of borrowers shifting to lower-risk classes versus those moving to higher-risk classes, with a ratio above 1.0 indicating a net positive impact on inclusion. As shown in Table 31 and Figure 65 (green line), the inclusion ratio remains consistently above 1.0 across all models, ranging from 1.26 to 1.59. The highest ratio (1.59) is observed when only one additional variable is used, while the lowest (1.26) occurs in the five-variable model. The model with payment capacity (1.40) follows the general trend, reinforcing that additional attributes have a limited effect on overall inclusivity, with small variations across scenarios.

***Summary Analysis for Hypothesis A1***

Hypothesis A1 tested the impact of adding up to six new attributes (INCOME, DEGREE, FAM, MAR, JOB, INCOME_S) to a baseline credit scoring model. Across 63 adjusted models, results showed minimal reclassification effects, with most borrowers remaining in their original risk categories. Even with enriched data, shifts to lower-risk classes were modest, and inclusion ratios remained slightly above 1. While attributes like OVER_TIME and INCOME, integrated through the *Paycap* feature, provided more nuanced borrower assessments, their impact on inclusion remained limited. *Paycap-enabled* models improved inclusion ratios slightly (1.16–1.40) but failed to deliver significant reclassification.

***These findings show that data enrichment alone does not substantially enhance financial inclusion.*** Advanced methods such as feature engineering or parameter tuning might be needed to achieve meaningful improvements, which is explored in Hypothesis A2. This is because raw attribute additions had minimal effect, suggesting that more refined transformations or derived features may better capture borrower risk profiles.

### 8.4. Experiment Results for Hypothesis A2

As indicated in the findings from the previous section, merely adding the data does not significantly create a more inclusive outcome. Therefore, this section investigates the impact of tuning model parameters. The experimental setup for Hypothesis A2 is like used in Hypothesis A1, involving data loading, preprocessing, and splitting into training and test sets. However, unlike Hypothesis A1, Hypothesis A2 does not introduce new attributes but relies on the original dataset.

We selected parameter-tuning methodologies that align with inclusion goals and the nature of the dataset. These methodologies are *Feature Weight Adjustment* and *Penalty-Based Models*. In addition, we developed a novel approach by combining the strengths of the previous two approaches, which we called *Hybrid Feature Penalty Tuning (HFPT)*.

The Penalty-Based Model approach is widely supported in the literature as an effective method for controlling classification bias and improving fairness in risk assessment. For example, Tang et al. (2021) propose a penalty-adjusted loss function to handle credit default imbalances, aligning closely with this study's approach. Similarly, Ali et al. (2019) and Grari et al. (2020) incorporate fairness constraints directly into the optimization process using penalty mechanisms, ensuring equitable treatment across groups. Meanwhile, Feature Weight Adjustment is a practical and straightforward technique for evaluating how different attributes influence borrower classification. By integrating both, HFPT enhances inclusivity by balancing feature sensitivity with penalty constraints, offering a more adaptive way to refine borrower classification outcomes.

**1) Feature Weight Adjustment**

This approach systematically changes the weight of features to examine the impact on borrower classification and distribution. Two features are selected based on the *feature importance test,* which is *delayed debt payment* (OVER_TIME) and *interest rate* (OVER_INT). By tweaking the emphasis on these variables, the models are expected to be able to reclassify more borrowers into lower-risk categories, making credit more accessible.

We conduct a sensitivity analysis to understand how these changes affect model performance. This involves adjusting the weight of these features at various levels (reduction factors of 0.1, 0.25, 0.5, 0.75, and 1) to see how sensitive the model is to each change. With **15 model variations** tested, this approach helps us find the potential scenarios for improving inclusion.

**2) Penalty-Based Models**

This approach applies penalties to one or more risk classes (class 0 to 5) to observe the impact on borrower classification and distribution. A penalty is intended to change the cost function for specific class(es). We design eight ***penalty types***, each targeting different sets of risk classes. For example, *Pen0* penalty type penalizes class 0 only; *Pen0-1* penalizes class 0 and class 1; *Pen0-2* penalizes class 0, 1, and 2; and *Pen4* applies penalties to class 4. Each configuration is tested with seven ***penalty values*** (100, 500, 1000, 1500, 2000, 3000, and 5000), that shows the magnitude of the penalty to corresponding class(es). Lower values means lower or moderate penalties, whereas higher means a high magnitude of penalty is applied to particular class(es). This combination of scenarios results in **56 model variations**. Additionally, eight default models without penalties serve as a control group to measure the effect of penalties against a neutral benchmark.

**3) Hybrid Feature Penalty Tuning (HFPT)**

The HFPT approach combines the previous two approaches: Feature Weight Adjustment and Penalty-Based Models. Feature Weight Adjustments focus on analyzing the impact of reducing the weight of two important features; whereas Penalty-Based models are applying *penalty type* and *penalty values* to various scenario to analyze the impact on borrowers' classification and distribution.

The HFPT approach is introduced as a novel approach that involve four key components: *penalty types*, *penalty levels*, *feature reductions*, and *features to modify*. *The penalty types* consists of 17 types of penalty configurations that determine how penalties are distributed across borrower risk classes. For example, Pen4 penalizes only class 4; and Pen0-2 applies penalties across classes 0, 1, and 2. *Penalty levels* consistes of four values, 500, 1000, 3000, and 5000, to evaluate the model's sensitivity to varying penalty intensities. We reduce *the penalty levels* range in order to limit the number of model variations. *Feature reductions* are applied at factors of 0.1, 0.5, and 1, to be applied to feature OVER_INT, OVER_TIME, and combination of both, This scenario generates a total of **629 model variations,** as in

The complete results of simulations for hypotheses A1 and A2 are provided in **Appendix 5, 6, 7, 8, and 9,** whereas the source code of the programming are provided in in **Appendix 10, 11, 12, and 13.**

Table 32, including 17 default models.

The complete results of simulations for hypotheses A1 and A2 are provided in **Appendix 5, 6, 7, 8, and 9**, whereas the source code of the programming are provided in in **Appendix 10, 11, 12, and 13**.

*Table 32. Scenarios for Hybrid Feature Penalty Tuning (HFPT) Approach*

| **Scenario Component** | **Number of Combinations** |
|---|---|
| Penalty Types | 17 (see Appendix 8) |
| Penalty Levels | 4 [500, 1000, 3000, 5000] |
| Feature Reductions | 3 [0.1, 0.5, 1] |
| Features to Modify | 3 [OVER_TIME, OVER_INT, OVER_TIME & OVER_INT] |
| **Total Combinations** | **629** |

### 8.4.1. Results of Feature Weight Adjustment Approach

The feature weight adjustments approach shows us the impact of reducing the weight of several features towards risk classification. We apply five types of *reduction factors* (0.1, 0.25, 0.5, 0.75, and 1) to each feature individually and in combination. Each reduction factor represents a degree of weighting reduction. The lower the value, the lower we expect the feature's impact on classification outcomes. Table 33 provides a detailed overview of the distribution of borrowers across risk classes. However, the results are presented in an absolute number, which might not be easily understood. Therefore, we will provide an analysis using metrics 1,2,3,4, and 5 in the following section.

*Table 33. The distribution of risk classes with the absolute number (feature weight)*

| **Reduction Factor** | **Model name** | **Number of people in each risk class** | | | | | |
|---|---|---|---|---|---|---|---|
| | | **0 (low risk)** | **1** | **2** | **3** | **4 (very high risk)** | **Total** |
| **A. Base model** | | | | | | | |
| Base model | | 20253 | 21200 | 18930 | 20071 | 20196 | 100650 |
| **B. Adjusted models to test Hypothesis A2 – Approach Feature Weight** | | | | | | | |
| 0.1 | inc_f0.1['INT'] | 20254 | 21202 | 18940 | 20043 | 20211 | 100650 |
| | inc_f0.1['TIME'] | 34572 | 47153 | 115 | 219 | 18591 | 100650 |
| | inc_f0.1['TIME', 'INT'] | 46316 | 35729 | 101 | 171 | 18333 | 100650 |
| 0.25 | inc_f0.25['INT'] | 20253 | 21248 | 18891 | 20089 | 20169 | 100650 |
| | inc_f0.25['TIME'] | 34419 | 46841 | 176 | 361 | 18853 | 100650 |
| | inc_f0.25['TIME', 'INT'] | 42756 | 38682 | 163 | 375 | 18674 | 100650 |
| 0.5 | inc_f0.5['INT'] | 20253 | 21254 | 18884 | 20097 | 20162 | 100650 |
| | inc_f0.5['TIME'] | 33794 | 46662 | 293 | 535 | 19366 | 100650 |
| | inc_f0.5['TIME', 'INT'] | 40877 | 39680 | 276 | 549 | 19268 | 100650 |
| 0.75 | inc_f0.75['INT'] | 20239 | 21209 | 18945 | 20064 | 20193 | 100650 |
| | inc_f0.75['TIME'] | 27796 | 43930 | 7641 | 1478 | 19805 | 100650 |
| | inc_f0.75['TIME', 'INT'] | 29704 | 42275 | 7441 | 1481 | 19749 | 100650 |

#### *A. Metric 1: Risk Class Distribution (array of %)*

To assess how adjusting feature weights influences borrower classification, Table 34 presents the percentage distribution of borrowers across risk classes under different weight reduction scenarios. The baseline model serves as a reference, while the adjusted models apply reduction factors to the OVER_TIME and OVER_INT features either separately or in combination.

*Table 34. Risk class distribution in % (hypothesis A2 - Feature Weight)*

| **Reduction Factor** | **Model name** | **Percentage of distribution in each risk class of adjusted model in comparison with total data** | | | | | |
|---|---|---|---|---|---|---|---|
| | | **0** | **1** | **2** | **3** | **4** | **Total data** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **A. Base model** | | | | | | | |
| Base model | | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **B. Adjusted models to test Hypotesis 2 - Approach Feature Weight** | | | | | | | |
| Reduction Factor | | | | | | | |
| 0.1 | inc_f0.1['INT'] | 20.12% | 21.07% | 18.82% | 19.91% | 20.08% | 100% |
| | inc_f0.1['TIME'] | 34.35% | 46.85% | 0.11% | 0.22% | 18.47% | 100% |
| | inc_f0.1['TIME', 'INT'] | 46.02% | 35.50% | 0.10% | 0.17% | 18.21% | 100% |
| 0.25 | inc_f0.25['INT'] | 20.12% | 21.11% | 18.77% | 19.96% | 20.04% | 100% |
| | inc_f0.25['TIME'] | 34.20% | 46.54% | 0.17% | 0.36% | 18.73% | 100% |
| | inc_f0.25['TIME', 'INT'] | 42.48% | 38.43% | 0.16% | 0.37% | 18.55% | 100% |
| 0.5 | inc_f0.5['INT'] | 20.12% | 21.12% | 18.76% | 19.97% | 20.03% | 100% |
| | inc_f0.5['TIME'] | 33.58% | 46.36% | 0.29% | 0.53% | 19.24% | 100% |
| | inc_f0.5['TIME', 'INT'] | 40.61% | 39.42% | 0.27% | 0.55% | 19.14% | 100% |
| 0.75 | inc_f0.75['INT'] | 20.11% | 21.07% | 18.82% | 19.93% | 20.06% | 100% |
| | inc_f0.75['TIME'] | 27.62% | 43.65% | 7.59% | 1.47% | 19.68% | 100% |
| | inc_f0.75['TIME', 'INT'] | 29.51% | 42.00% | 7.39% | 1.47% | 19.62% | 100% |

Table 34 shows that the baseline model assigns borrowers across risk classes in relatively balanced proportions, and when adjustments are applied, the distribution shifts considerably. The changes are minimal for models where OVER_INT is adjusted alone, with risk class proportions closely mirroring the baseline model across all reduction factors. However, models where OVER_TIME is adjusted, either separately or in combination with OVER_INT, show a substantial reallocation of borrowers. At a 0.1 reduction factor, the share of Risk Class 0 increases to 34.35% when adjusting OVER_TIME alone and 46.02% when both features are adjusted together, indicating a significant movement of borrowers into lower-risk categories. Correspondingly, Risk Class 2 and 3 nearly disappear, reinforcing the dominant influence of OVER_TIME in reclassification.

As the reduction factor increases, the effect of OVER_TIME remains strong but becomes less extreme. At 0.5, for instance, Risk Class 0 reaches 33.58% in the OVER_TIME-only model and 40.61% in the combined model, still far above the baseline distribution. By 0.75, the effect diminishes further, with Risk Class 2 and 3 partially restored, indicating that higher reduction factors lessen the impact on reclassification.

The results confirm that adjusting OVER_TIME significantly influences class distribution, shifting many borrowers into lower categories while nearly eliminating those in mid risk-classes at the most extreme reduction levels. In contrast, adjustments to OVER_INT alone have negligible effects, reinforcing that it does not substantially impact borrower classification. These findings indicate that feature weighting, particularly for OVER_TIME, is a major driver of borrower reclassification in the model.

### *B. Metric 2: Risk Class Shift (array of %)*

Table 35 presents the percentage changes in risk class distribution compared to the baseline model. A positive percentage refers to an increase in borrowers within a given risk class, while a negative percentage indicates a reduction, meaning borrowers have transitioned to other risk classes.

*Table 35. Risk class shifting in % (hypothesis A2 - Feature Weight)*

| **Reduction Factor** | **Model name** | **Percentage of shifting in each risk class of adjusted model in comparison with base model** | | | | |
|---|---|---|---|---|---|---|
| | | **0** | **1** | **2** | **3** | **4** |
| 0.1 | inc_f0.1['INT'] | 0.005% | 0.009% | 0.053% | -0.140% | 0.074% |
| | inc_f0.1['TIME'] | 70.701% | 122.420% | -99.392% | -98.909% | -7.947% |

| | | | | | | |
|---|---|---|---|---|---|---|
| | inc_f0.1['TIME', 'INT'] | 128.687% | 68.533% | -99.466% | -99.148% | -9.225% |
| 0.25 | inc_f0.25['INT'] | 0.000% | 0.226% | -0.206% | 0.090% | -0.134% |
| | inc_f0.25['TIME'] | 69.945% | 120.948% | -99.070% | -98.201% | -6.650% |
| | inc_f0.25['TIME', 'INT'] | 111.109% | 82.462% | -99.139% | -98.132% | -7.536% |
| 0.5 | inc_f0.5['INT'] | 0.000% | 0.255% | -0.243% | 0.130% | -0.168% |
| | inc_f0.5['TIME'] | 66.859% | 120.104% | -98.452% | -97.334% | -4.110% |
| | inc_f0.5['TIME', 'INT'] | 101.832% | 87.170% | -98.542% | -97.265% | -4.595% |
| 0.75 | inc_f0.75['INT'] | -0.069% | 0.042% | 0.079% | -0.035% | -0.015% |
| | inc_f0.75['TIME'] | 37.244% | 107.217% | -59.635% | -92.636% | -1.936% |
| | inc_f0.75['TIME', 'INT'] | 46.665% | 99.410% | -60.692% | -92.621% | -2.213% |

The baseline model remains the reference point, with no change across risk classes. OVER_INT adjustments alone produce minimal shifts, with variations staying within ±0.25%, confirming a limited effect on borrower classification. In contrast, adjusting OVER_TIME results in dramatic shifts, particularly at 0.1 and 0.25 reduction factors, where Risk Class 0 expands significantly (70.70% and 69.95%, respectively), while Risk Classes 2 and 3 shrink by nearly 99%. This extreme reallocation indicates that reducing the influence of OVER_TIME drastically shifts borrowers into lower-risk classes.

The shifts are even more pronounced when both OVER_TIME and OVER_INT are adjusted together. At a 0.1 reduction factor, Risk Class 0 increases by 128.69%, confirming that OVER_TIME drives the strongest reclassification effect. As the reduction factor increases to 0.5 and 0.75, the impact softens but remains substantial, with Risk Class 0 increasing by 101.83% and 46.67%, respectively. Notably, adjustments at 0.75 show less dramatic shifts, suggesting a diminishing effect as weight reductions become less extreme.

The results highlight that reducing OVER_TIME leads to significant movement into lower-risk categories, whereas OVER_INT alone has little to no impact. The strongest shifts occur at lower reduction factors (0.1 and 0.25), reinforcing that feature weight adjustments can influence borrower reclassification but are highly dependent on the variable selected and weight reduction applied.

### *C. Metric 3: Borrower Shift to Lower Risk Classes (%)*

To further evaluate the impact of Feature Weight Adjustment on borrower classification, we analyze borrower movements using Metric 3 (Shift to Lower Risk Classes), Metric 4 (Shift to Higher Risk Classes), and Metric 5 (Inclusivity Ratio). The results are presented in Table 36 and Table 37.

*Table 36. Borrower movement across risk classes (hypothesis A2 - Feature Weight)*

| Reduction factor | Model name | Number of borrowers move to lower class | Number of borrowers move to higher class | No Change | Inclusion Ratio |
|---|---|---|---|---|---|
| 0.1 | inc_f0.1['INT'] | 106 | 109 | 100,435 | 0.97 |
| | inc_f0.1['TIME'] | 48,127 | 331 | 52,192 | 145.40 |
| | inc_f0.1['TIME', 'INT'] | 51,537 | 244 | 48,869 | 211.22 |
| 0.25 | inc_f0.25['INT'] | 121 | 40 | 100,489 | 3.03 |
| | inc_f0.25['TIME'] | 47,865 | 331 | 52,454 | 144.61 |
| | inc_f0.25['TIME', 'INT'] | 50,583 | 314 | 49,753 | 161.09 |
| 0.5 | inc_f0.5['INT'] | 122 | 30 | 100,498 | 4.07 |
| | inc_f0.5['TIME'] | 47,352 | 331 | 52,967 | 143.06 |
| | inc_f0.5['TIME', 'INT'] | 49,871 | 318 | 50,461 | 156.83 |
| 0.75 | inc_f0.75['INT'] | 95 | 104 | 100,451 | 0.91 |
| | inc_f0.75['TIME'] | 45,680 | 181 | 54,789 | 252.38 |
| | inc_f0.75['TIME', 'INT'] | 47,740 | 153 | 52,757 | 312.03 |

Table 36 provides the absolute number of borrowers who moved to lower or higher-risk classes after model adjustments alongside those whose classifications remained unchanged. To better interpret these movements in terms of inclusion performance, Table 37 summarizes the results using Metrics 3 (Borrower Shift to Lower Risk Classes), Metric 4 (Shift to Higher Risk Classes), and Metric 5 (Inclusivity Ratio), which will be the basis of the analysis in the next section.

*Table 37. Percentage of borrower movement and inclusivity ratio (hypothesis A2 - Feature Weight)*

| Reduction factor | Model name | Metric 3 | Metric 4 | Metric 5 |
|---|---|---|---|---|
| | | % of borrowers move to the lower class in comparison with total data | % of borrowers move to the higher class in comparison with total data | Inclusion Ratio |
| 0.1 | inc_f0.1['INT'] | 0.11% | 0.11% | 97.25% |
| | inc_f0.1['TIME'] | 47.82% | 0.33% | 14539.88% |
| | inc_f0.1['TIME', 'INT'] | 51.20% | 0.24% | 21121.72% |
| 0.25 | inc_f0.25['INT'] | 0.12% | 0.04% | 302.50% |
| | inc_f0.25['TIME'] | 47.56% | 0.33% | 14460.73% |
| | inc_f0.25['TIME', 'INT'] | 50.26% | 0.31% | 16109.24% |
| 0.5 | inc_f0.5['INT'] | 0.12% | 0.03% | 406.67% |
| | inc_f0.5['TIME'] | 47.05% | 0.33% | 14305.74% |
| | inc_f0.5['TIME', 'INT'] | 49.55% | 0.32% | 15682.70% |
| 0.75 | inc_f0.75['INT'] | 0.09% | 0.10% | 91.35% |
| | inc_f0.75['TIME'] | 45.38% | 0.18% | 25237.57% |
| | inc_f0.75['TIME', 'INT'] | 47.43% | 0.15% | 31202.61% |

Table 37 shows that models adjusting OVER_TIME exhibit the highest downward movement, particularly at lower reduction factors. At a 0.1 reduction factor, 51.20% of borrowers shifted to lower-risk classes when both OVER_TIME and OVER_INT were adjusted, compared to only 0.11% when only OVER_INT was adjusted. This reinforces that OVER_TIME plays a dominant role in borrower reclassification.

At a 0.25 reduction factor, borrower movement remains substantial, with 50.26% of borrowers shifting downward when both features were adjusted, and 47.56% when adjusting OVER_TIME alone. This trend continues for reduction factors of 0.5 and 0.75, though the extent of reclassification decreases slightly as reduction factors increase. The findings suggest that adjusting OVER_TIME is the most effective method for increasing borrower movement toward lower-risk categories.

### *D. Metric 4: Borrower Shift to Higher Risk Classes (%)*

This metric measures the proportion of borrowers who moved to higher-risk classes, highlighting potential unintended effects of the feature weight approach. As shown in Table 37, the percentage of borrowers shifting upward remains minimal across all scenarios. The results are visually reinforced in Figure 66 which compares movements to lower and higher-risk classes across different reduction factors and feature combinations. The blue line (representing shifts to lower-risk classes) spikes dramatically for scenarios involving **OVER_TIME**, particularly at reduction factors of 0.1, 0.25, and 0.5. In contrast, scenarios involving **OVER_INT** alone show modest movement, as indicated by the near-flat blue line in these cases. At the same time, we can maintain a low movement to the higher-risk class (unintended result) in all scenarios.

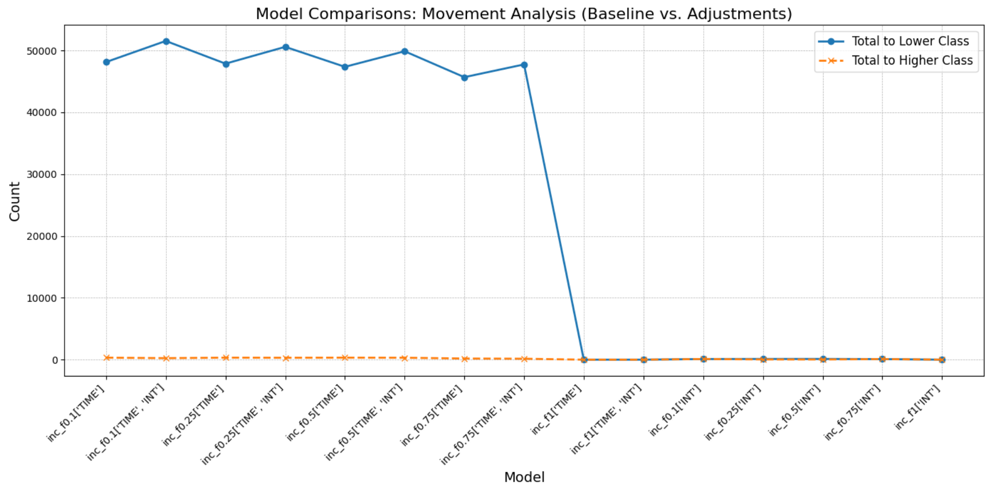


*Figure 66. Movement analysis – Feature Weight Approach*

### E. Metric 5: Inclusivity Ratio

The inclusion ratio, depicted in Table 37 and Figure 67, compares movements into lower-risk classes to higher-risk classes. Models adjusted for OVER_TIME consistently exhibit exceptionally high inclusion ratios, with values exceeding 200 in scenarios with reduction factors of 0.1 and 0.25. This indicates a strong and desirable movement toward lower-risk categories while maintaining minimal reclassification to higher-risk categories. As shown in the green line, the inclusion ratio sharply declines when the reduction factor approaches 1 (no reduction). Conversely, models that adjust only OVER_INT show inclusion ratios close to 1, highlighting their limited impact on borrower reclassification.

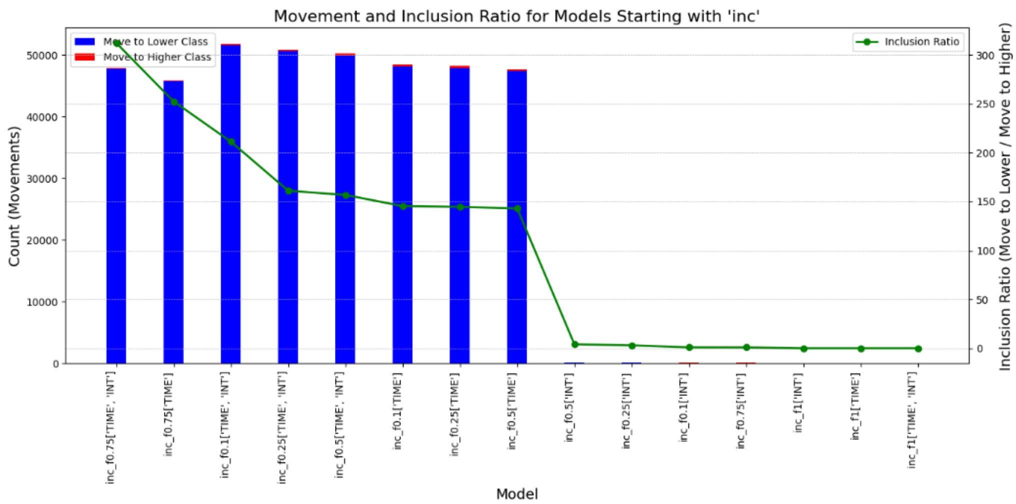


*Figure 67. Movement summary and inclusion ratio for feature weight approach*

### F. Summary and Implications of Feature Weight Approach

The Feature Weight Adjustment approach shows that reducing the influence of certain attributes helps to move borrowers to lower-risk classes. This shift is particularly significant when reducing the weight of the OVER_TIME feature, indicating a strong reclassification effect. Metric 3 indicates that adjusting OVER_TIME leads to over 50% of borrowers being reclassified into lower-risk classes, while OVER_INT alone has little effect. At the same time, Metric 4 confirms that the number of borrowers moving to higher-risk categories remains very small, meaning this approach does not cause unintended negative shifts. Metric 5, which measures Inclusivity Ratio, also supports this, as models adjusting OVER_TIME have the highest ratios, showing that feature adjustments can make credit more accessible.

These findings provide significant support for Hypothesis A2, suggesting that tuning feature weights can be an effective approach for improving inclusion outcomes. However, the effectiveness of this approach depends on which feature is adjusted, with OVER_TIME having the biggest impact. This means that when applying this method, it is essential to choose the right features carefully to ensure that the changes align with the overall risk structure of the borrowers.

### 8.4.2. Results of Penalty-based Approach

The penalty-based approach assigns penalties to designated risk classes, altering the cost function during training to encourage borrowers' reclassification. Experiments began by testing *penalty values* incrementally, starting from 1, 10, 20, and so on, to observe their effect on borrower classification. Initial trials revealed that penalty values below 100 had minimal impact on reclassification patterns. Significant changes were observed only when **penalty values** exceeded 100, prompting the selection of a focused range: 1, 100, 500, 1000, 1500, 2000, 3000, and 5000. This range ensures that the analysis captures both the upper and lower bounds of penalty intensity, enabling a comprehensive evaluation of its effects. Penalties are selectively applied based on penalty exclusions, targeting only specific classes to preserve risk integrity. Each configuration's penalty weight $w_i$ for class C is determined by:

$$w_i = \begin{cases} \lambda \; if \; C \notin excluded\_classes \\ 1 \; if \; C \in excluded\_classes \end{cases}$$

where λ represents the *penalty value*.

The experiments involve various *penalty types*, labeled Pen0, Pen0-1, Pen0-2, Pen0-3, etc., to target specific risk classes. Higher penalty values (e.g., 5000) apply a stronger push towards penalized classes, while lower values (e.g., 100) test the model's sensitivity to less aggressive interventions. This structured approach allows us to analyze how different penalty types and values impact borrower reclassification. We develop 8x7 = 56 models with eight default models to evaluate the simulations.

#### *A. Metric 1: Risk Class Distribution (array of %)*

The purpose of Metric 1 is to evaluate how different penalty configurations influence the distribution of borrowers across risk classes. The complete table of the penalty-based model consists the absolute value are presented in the appendix for understanding the scale of changes. Table 38 converts these absolute numbers into percentage distributions for the analysis.

*Table 38. Risk class distribution in % (hypothesis A2 - Penalty Based Approach)*

| **Penalty types** | **Model name** | **Percentage of distribution in each risk class of adjusted model in comparison with total data** | | | | | |
|---|---|---|---|---|---|---|---|
| | | **0** | **1** | **2** | **3** | **4** | **Total data** |
| **A. Base model** | | | | | | | |
| Base model | | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **B. Adjusted models to test Hypothesis 2 (Approach Penalty Based)** | | | | | | | |
| **Pen4** | Pen4_VAL5000 | 0.03% | 0.01% | 0.00% | 0.00% | 99.96% | 100% |
| | Pen4_VAL3000 | 0.03% | 0.01% | 0.00% | 0.00% | 99.96% | 100% |
| | Pen4_VAL2000 | 0.03% | 0.01% | 0.00% | 0.00% | 99.96% | 100% |
| | Pen4_VAL1500 | 0.03% | 0.01% | 0.00% | 0.00% | 99.96% | 100% |
| | *Pen4_VAL1000* | *0.03%* | *0.01%* | *0.00%* | *0.00%* | *99.96%* | *100%* |
| | *Pen4_VAL500* | *20,11%* | *20,70%* | *18,99%* | *18,41%* | *21,79%* | *100%* |
| | Pen4_VAL100 | 20.10% | 20.59% | 18.97% | 17.89% | 22.45% | 100% |
| | Pen4_VAL1 | 20.11% | 20.70% | 18.99% | 18.41% | 21.79% | 100% |
| **Pen4-3** | Pen4-3_VAL5000 | 0.00% | 0.00% | 0.00% | 78.06% | 21.94% | 100% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Pen4-3_VAL3000 | 0.00% | 0.00% | 0.00% | 80.68% | 19.32% | 100% |
| | Pen4-3_VAL2000 | 0.00% | 0.00% | 0.00% | 80.03% | 19.97% | 100% |
| | Pen4-3_VAL1500 | 0.00% | 0.00% | 0.00% | 80.05% | 19.95% | 100% |
| | Pen4-3_VAL1000 | 0.00% | 0.00% | 0.00% | 80.05% | 19.94% | 100% |
| | Pen4-3_VAL500 | 20.12% | 20.49% | 18.73% | 20.22% | 20.45% | 100% |
| | Pen4-3_VAL100 | 20.13% | 20.85% | 18.82% | 20.09% | 20.11% | 100% |
| | Pen4-3_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen4-2** | Pen4-2_VAL5000 | 0.00% | 0.00% | 59.81% | 20.89% | 19.31% | 100% |
| | Pen4-2_VAL3000 | 0.00% | 0.00% | 60.25% | 20.25% | 19.50% | 100% |
| | Pen4-2_VAL2000 | 0.00% | 0.00% | 59.77% | 20.71% | 19.52% | 100% |
| | Pen4-2_VAL1500 | 0.00% | 0.00% | 59.77% | 20.85% | 19.38% | 100% |
| | Pen4-2_VAL1000 | 0.00% | 0.00% | 59.99% | 20.42% | 19.58% | 100% |
| | Pen4-2_VAL500 | 0.00% | 0.00% | 60.02% | 20.26% | 19.71% | 100% |
| | Pen4-2_VAL100 | 20.10% | 19.37% | 20.46% | 19.94% | 20.12% | 100% |
| | Pen4-2_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen4-1** | Pen4-1_VAL5000 | 0.00% | 40.91% | 18.53% | 21.90% | 18.66% | 100% |
| | Pen4-1_VAL3000 | 0.00% | 41.14% | 18.47% | 21.50% | 18.89% | 100% |
| | Pen4-1_VAL2000 | 0.00% | 41.57% | 18.20% | 20.75% | 19.49% | 100% |
| | Pen4-1_VAL1500 | 0.00% | 41.16% | 18.61% | 20.36% | 19.87% | 100% |
| | Pen4-1_VAL1000 | 0.00% | 40.68% | 19.28% | 20.22% | 19.82% | 100% |
| | Pen4-1_VAL500 | 0.00% | 40.37% | 19.65% | 20.22% | 19.75% | 100% |
| | Pen4-1_VAL100 | 19.58% | 21.59% | 18.82% | 19.94% | 20.07% | 100% |
| | Pen4-1_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen3_** | Pen3_VAL5000 | 0.06% | 0.03% | 0.00% | 99.90% | 0.01% | 100% |
| | Pen3_VAL3000 | 0.06% | 0.03% | 0.00% | 99.90% | 0.01% | 100% |
| | Pen3_VAL2000 | 0.06% | 0.03% | 0.00% | 99.90% | 0.01% | 100% |
| | *Pen3_VAL1500* | *0.06%* | *0.03%* | *0.00%* | *99.90%* | *0.01%* | *100%* |
| | *Pen3_VAL1000* | *20.13%* | *20.56%* | *18.81%* | *20.75%* | *19.75%* | *100%* |
| | Pen3_VAL500 | 20.13% | 20.73% | 18.87% | 20.50% | 19.77% | 100% |
| | Pen3_VAL100 | 20.13% | 20.90% | 18.85% | 20.25% | 19.87% | 100% |
| | Pen3_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen3_2** | Pen3-2_VAL5000 | 0.00% | 0.00% | 60.28% | 39.72% | 0.00% | 100% |
| | Pen3-2_VAL3000 | 0.00% | 0.00% | 60.28% | 39.72% | 0.00% | 100% |
| | Pen3-2_VAL2000 | 0.00% | 0.00% | 60.28% | 39.72% | 0.00% | 100% |
| | Pen3-2_VAL1500 | 0.00% | 0.00% | 60.28% | 39.72% | 0.00% | 100% |
| | Pen3-2_VAL1000 | 0.00% | 0.00% | 60.28% | 39.72% | 0.00% | 100% |
| | Pen3-2_VAL500 | 20.08% | 17.94% | 22.01% | 20.33% | 19.64% | 100% |
| | Pen3-2_VAL100 | 20.11% | 19.99% | 19.92% | 20.18% | 19.80% | 100% |
| | Pen3-2_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen3-1** | Pen3-1_VAL5000 | 0.00% | 41.50% | 18.04% | 40.46% | 0.00% | 100% |
| | Pen3-1_VAL3000 | 0.00% | 41.66% | 18.59% | 39.74% | 0.00% | 100% |
| | Pen3-1_VAL2000 | 0.00% | 40.36% | 19.91% | 39.74% | 0.00% | 100% |
| | Pen3-1_VAL1500 | 0.00% | 40.29% | 19.96% | 39.75% | 0.00% | 100% |
| | Pen3-1_VAL1000 | 0.00% | 40.31% | 19.95% | 39.74% | 0.00% | 100% |
| | Pen3-1_VAL500 | 0.00% | 40.90% | 19.36% | 38.33% | 1.41% | 100% |
| | Pen3-1_VAL100 | 19.68% | 21.56% | 18.80% | 20.22% | 19.75% | 100% |
| | Pen3-1_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen3-0** | Pen3-0_VAL5000 | 20.28% | 20.08% | 19.17% | 40.46% | 0.00% | 100% |
| | Pen3-0_VAL3000 | 20.27% | 20.46% | 19.03% | 40.23% | 0.00% | 100% |
| | Pen3-0_VAL2000 | 20.08% | 21.17% | 18.85% | 20.89% | 19.02% | 100% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Pen3-0_VAL1500 | 20.08% | 21.16% | 18.87% | 20.77% | 19.12% | 100% |
| | Pen3-0_VAL1000 | 20.09% | 21.12% | 18.87% | 20.59% | 19.33% | 100% |
| | Pen3-0_VAL500 | 20.09% | 21.12% | 18.85% | 20.43% | 19.50% | 100% |
| | Pen3-0_VAL100 | 20.09% | 21.16% | 18.79% | 20.24% | 19.73% | 100% |
| | Pen3-0_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen2_** | Pen2_VAL5000 | 0.03% | 0.03% | 99.75% | 0.02% | 0.17% | 100% |
| | Pen2_VAL3000 | 0.03% | 0.03% | 99.75% | 0.02% | 0.17% | 100% |
| | Pen2_VAL2000 | 0.03% | 0.03% | 99.75% | 0.02% | 0.17% | 100% |
| | Pen2_VAL1500 | 0.03% | 0.03% | 99.75% | 0.02% | 0.17% | 100% |
| | Pen2_VAL1000 | 0.03% | 0.03% | 99.75% | 0.02% | 0.17% | 100% |
| | *Pen2_VAL500* | *0.03%* | *0.03%* | *99.75%* | *0.02%* | *0.17%* | *100%* |
| | *Pen2_VAL100* | *20.11%* | *19.60%* | *20.55%* | *19.74%* | *20.00%* | *100%* |
| | Pen2_VAL1 | 20.12% | 20.09% | 19.92% | 19.84% | 20.04% | 100% |
| **Pen2-1** | Pen2-1_VAL5000 | 0.00% | 43.09% | 56.91% | 0.00% | 0.00% | 100% |
| | Pen2-1_VAL3000 | 0.00% | 43.09% | 56.91% | 0.00% | 0.00% | 100% |
| | Pen2-1_VAL2000 | 0.00% | 40.37% | 59.63% | 0.00% | 0.00% | 100% |
| | Pen2-1_VAL1500 | 0.00% | 40.37% | 59.63% | 0.00% | 0.00% | 100% |
| | Pen2-1_VAL1000 | 0.00% | 40.37% | 59.63% | 0.00% | 0.00% | 100% |
| | Pen2-1_VAL500 | 0.00% | 40.37% | 59.63% | 0.00% | 0.00% | 100% |
| | Pen2-1_VAL100 | 19.70% | 21.50% | 18.92% | 19.92% | 19.95% | 100% |
| | Pen2-1_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen2-0** | Pen2-0_VAL5000 | 20.23% | 20.69% | 59.08% | 0.00% | 0.00% | 100% |
| | Pen2-0_VAL3000 | 20.34% | 20.58% | 59.08% | 0.00% | 0.00% | 100% |
| | Pen2-0_VAL2000 | 20.34% | 20.58% | 59.08% | 0.00% | 0.00% | 100% |
| | Pen2-0_VAL1500 | 20.36% | 20.56% | 59.08% | 0.00% | 0.00% | 100% |
| | Pen2-0_VAL1000 | 20.20% | 20.72% | 59.08% | 0.00% | 0.00% | 100% |
| | Pen2-0_VAL500 | 20.14% | 20.78% | 59.08% | 0.00% | 0.00% | 100% |
| | Pen2-0_VAL100 | 20.08% | 21.14% | 18.88% | 19.98% | 19.92% | 100% |
| | Pen2-0_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen1_** | Pen1_VAL5000 | 0.00% | 99.90% | 0.00% | 0.00% | 0.10% | 100% |
| | Pen1_VAL3000 | 0.00% | 99.90% | 0.00% | 0.00% | 0.10% | 100% |
| | Pen1_VAL2000 | 0.00% | 99.90% | 0.00% | 0.00% | 0.10% | 100% |
| | Pen1_VAL1500 | 0.00% | 99.90% | 0.00% | 0.00% | 0.10% | 100% |
| | *Pen1_VAL1000* | *0.00%* | *99.90%* | *0.00%* | *0.00%* | *0.10%* | *100%* |
| | *Pen1_VAL500* | *19.28%* | *22.33%* | *18.54%* | *19.88%* | *19.97%* | *100%* |
| | Pen1_VAL100 | 19.79% | 21.74% | 18.53% | 19.95% | 19.98% | 100% |
| | Pen1_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen1-0** | Pen1-0_VAL5000 | 20.22% | 79.78% | 0.00% | 0.00% | 0.00% | 100% |
| | Pen1-0_VAL3000 | 20.45% | 79.55% | 0.00% | 0.00% | 0.00% | 100% |
| | Pen1-0_VAL2000 | 20.23% | 79.77% | 0.00% | 0.00% | 0.00% | 100% |
| | Pen1-0_VAL1500 | 20.16% | 79.81% | 0.00% | 0.00% | 0.03% | 100% |
| | Pen1-0_VAL1000 | 20.06% | 21.56% | 18.48% | 19.99% | 19.90% | 100% |
| | Pen1-0_VAL500 | 20.07% | 21.53% | 18.49% | 19.98% | 19.93% | 100% |
| | Pen1-0_VAL100 | 20.07% | 21.45% | 18.55% | 19.97% | 19.96% | 100% |
| | Pen1-0_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen0_** | Pen0_VAL5000 | 20.19% | 20.73% | 19.11% | 20.05% | 19.92% | 100% |
| | Pen0_VAL3000 | 20.17% | 20.75% | 19.10% | 20.03% | 19.94% | 100% |
| | Pen0_VAL2000 | 20.18% | 20.75% | 19.09% | 20.04% | 19.94% | 100% |
| | Pen0_VAL1500 | 20.15% | 20.78% | 19.09% | 20.03% | 19.95% | 100% |
| | Pen0_VAL1000 | 20.15% | 20.83% | 19.04% | 20.01% | 19.97% | 100% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Pen0_VAL500 | 20.14% | 20.85% | 19.02% | 19.97% | 20.02% | 100% |
| | Pen0_VAL100 | 20.13% | 20.88% | 19.00% | 19.91% | 20.08% | 100% |
| | Pen0_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Extend Pen0_** | Pen0_VAL100000 | 97.26% | 0.03% | 0.00% | 0.62% | 2.09% | 100% |
| | Pen0_VAL50000 | 99.96% | 0.00% | 0.00% | 0.00% | 0.04% | 100% |
| | Pen0_VAL40000 | 99.96% | 0.00% | 0.00% | 0.00% | 0.04% | 100% |
| | Pen0_VAL30000 | 99.96% | 0.00% | 0.00% | 0.00% | 0.04% | 100% |
| | Pen0_VAL20000 | 99.95% | 0.00% | 0.00% | 0.00% | 0.05% | 100% |
| | Pen0_VAL15000 | 99.84% | 0.00% | 0.00% | 0.05% | 0.11% | 100% |
| | Pen0_VAL10000 | 99.70% | 0.00% | 0.00% | 0.11% | 0.20% | 100% |
| | Pen0_VAL9800 | 99.68% | 0.00% | 0.00% | 0.11% | 0.21% | 100% |
| | Pen0_VAL9700 | 99.66% | 0.00% | 0.00% | 0.11% | 0.22% | 100% |
| | Pen0_VAL9200 | 99.64% | 0.00% | 0.00% | 0.12% | 0.23% | 100% |
| | Pen0_VAL9100 | 99.64% | 0.00% | 0.00% | 0.12% | 0.24% | 100% |
| | Pen0_VAL9090 | 99.64% | 0.00% | 0.00% | 0.12% | 0.24% | 100% |
| | **Pen0_VAL9060** | **99.64%** | **0.00%** | **0.00%** | **0.12%** | **0.24%** | **100%** |
| | **Pen0_VAL9050** | **20.22%** | **20.68%** | **19.13%** | **20.10%** | **19.87%** | **100%** |
| | Pen0_VAL9040 | 20.23% | 20.68% | 19.11% | 20.11% | 19.86% | 100% |
| | Pen0_VAL9030 | 20.23% | 20.69% | 19.11% | 20.11% | 19.86% | 100% |
| | Pen0_VAL9020 | 20.23% | 20.68% | 19.12% | 20.11% | 19.86% | 100% |
| | Pen0_VAL9010 | 20.23% | 20.68% | 19.12% | 20.11% | 19.86% | 100% |
| | Pen0_VAL9000 | 20.23% | 20.68% | 19.12% | 20.11% | 19.86% | 100% |
| | Pen0_VAL6000 | 20.20% | 20.72% | 19.11% | 20.07% | 19.90% | 100% |
| | Pen0_VAL5000 | 20.19% | 20.73% | 19.11% | 20.05% | 19.92% | 100% |
| | Pen0_VAL3000 | 20.17% | 20.75% | 19.10% | 20.03% | 19.94% | 100% |
| | Pen0_VAL2000 | 20.18% | 20.75% | 19.09% | 20.04% | 19.94% | 100% |
| | Pen0_VAL1500 | 20.15% | 20.78% | 19.09% | 20.03% | 19.95% | 100% |
| | Pen0_VAL1000 | 20.15% | 20.83% | 19.04% | 20.01% | 19.97% | 100% |
| | Pen0_VAL500 | 20.14% | 20.85% | 19.02% | 19.97% | 20.02% | 100% |
| | Pen0_VAL100 | 20.13% | 20.88% | 19.00% | 19.91% | 20.08% | 100% |
| | Pen0_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen0-1** | Pen0-1_VAL5000 | 20.22% | 79.78% | 0.00% | 0.00% | 0.00% | 100% |
| | Pen0-1_VAL3000 | 20.45% | 79.55% | 0.00% | 0.00% | 0.00% | 100% |
| | Pen0-1_VAL2000 | 20.23% | 79.77% | 0.00% | 0.00% | 0.00% | 100% |
| | Pen0-1_VAL1500 | 20.16% | 79.81% | 0.00% | 0.00% | 0.03% | 100% |
| | Pen0-1_VAL1000 | 20.06% | 21.56% | 18.48% | 19.99% | 19.90% | 100% |
| | Pen0-1_VAL500 | 20.07% | 21.53% | 18.49% | 19.98% | 19.93% | 100% |
| | Pen0-1_VAL100 | 20.07% | 21.45% | 18.55% | 19.97% | 19.96% | 100% |
| | Pen0-1_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen0-2** | Pen0-2_VAL5000 | 20.23% | 20.69% | 59.08% | 0.00% | 0.00% | 100% |
| | Pen0-2_VAL3000 | 20.34% | 20.58% | 59.08% | 0.00% | 0.00% | 100% |
| | Pen0-2_VAL2000 | 20.34% | 20.58% | 59.08% | 0.00% | 0.00% | 100% |
| | Pen0-2_VAL1500 | 20.36% | 20.56% | 59.08% | 0.00% | 0.00% | 100% |
| | Pen0-2_VAL1000 | 20.20% | 20.72% | 59.08% | 0.00% | 0.00% | 100% |
| | Pen0-2_VAL500 | 20.14% | 20.78% | 59.08% | 0.00% | 0.00% | 100% |
| | Pen0-2_VAL100 | 20.08% | 21.14% | 18.88% | 19.98% | 19.92% | 100% |
| | Pen0-2_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |
| **Pen0-3** | Pen0-3_VAL5000 | 20.28% | 20.08% | 19.17% | 40.46% | 0.00% | 100% |
| | Pen0-3_VAL3000 | 20.27% | 20.46% | 19.03% | 40.23% | 0.00% | 100% |
| | Pen0-3_VAL2000 | 20.08% | 21.17% | 18.85% | 20.89% | 19.02% | 100% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Pen0-3_VAL1500 | 20.08% | 21.16% | 18.87% | 20.77% | 19.12% | 100% |
| | Pen0-3_VAL1000 | 20.09% | 21.12% | 18.87% | 20.59% | 19.33% | 100% |
| | Pen0-3_VAL500 | 20.09% | 21.12% | 18.85% | 20.43% | 19.50% | 100% |
| | Pen0-3_VAL100 | 20.09% | 21.16% | 18.79% | 20.24% | 19.73% | 100% |
| | Pen0-3_VAL1 | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | 100% |

Key Findings from Metric 1:

**1. *Penalty types* drive borrower reclassification into penalized classes**
Across all penalty configurations (as reflected in model name), borrowers tend to migrate toward the specific risk classes that are penalized. In Pen4, where penalties are applied to Class 4, almost all borrowers are pushed into this category, with models such as Pen4_VAL5000 showing an extreme concentration of 99.96% in Class 4. Similarly, in Pen4-3, where penalties are applied to class 4 and 3, borrowers move toward these two categories, resulting in 78.06% in Class 3 and 21.94% in Class 4 at Pen4-3_VAL5000. The same pattern appears in Pen4-2, where penalties applied to Class 4, 3, and 2 cause a 59.81% concentration in Class 2 and a significant proportion remaining in Classes 3 and 4. In Pen4-1, which penalizes Classes 4 to 1, the effect is more distributed, but still, borrowers overwhelmingly shift into the penalized classes.

A similar movement is observed in Pen0-based penalties. For instance, Pen0-2, which penalizes Classes 0, 1, and 2, results in 59.08% of borrowers being concentrated in Class 2 when the penalty is set at Pen0-2_VAL5000. Pen0-1, which penalizes Classes 0 and 1, leads to an extreme case where 79.78% of borrowers are classified in Class 1 at Pen0-1_VAL5000. This pattern confirms that the primary impact of penalties is *to push borrower classification into the penalized classes* rather than promoting a balanced redistribution across risk categories.

**2. Higher *penalty values* increase the strength of the reclassification effect**
The magnitude of *the penalty value* directly influences the intensity of borrower movement into penalized classes. At relatively high *penalty values* (5000, 3000, 2000, 1500), the concentration effect is strongest, leading to extreme shifts such as 99.96% of borrowers in Class 4 under Pen4_VAL5000 and 78.06% in Class 3 under Pen4-3_VAL5000. As the *penalty value* decreases, the effect weakens. For example, in Pen4-3, when the penalty value is reduced from 5000 to 100, the proportion of borrowers in Class 3 drops significantly from 78.06% (Pen4-3_VAL5000) to 20.09% (Pen4-3_VAL100), while *the base model distribution starts to reemerge*. Similarly, in Pen0-2, where penalties were applied to Classes 0, 1, and 2, the proportion in Class 2 decreases from 59.08% (Pen0-2_VAL5000) to a more balanced 18.88% (Pen0-2_VAL100).

This trend confirms that while penalties effectively drive borrowers into penalized categories at high values, *the effect becomes less dominant at lower penalty values,* allowing for a more proportional class distribution. From an inclusion perspective, this means that overly high penalty values may disproportionately push borrowers, particularly those on the borderline, into higher-risk categories. In contrast, moderate penalty levels enable a more equitable classification outcome, which better supports inclusion goals by avoiding unnecessary exclusion of borrowers who might otherwise qualify. Therefore, the magnitude of the penalty plays a crucial role in determining whether penalties reinforce risk concentrations or allow for a balanced classification.

**3. The importance of extended observations.**
While most *penalty types* immediately show clear effects on borrower classification, some configurations exhibit delayed responses, necessitating extended observation ranges to fully capture the penalty's impact. A notable example is Pen0, which does not trigger significant reclassification at

standard penalty values up to 5000. Unlike other penalties, where borrowers rapidly move toward penalized classes, the distribution of borrowers in Pen0-based models remains nearly identical to the base model at standard penalty levels.

To further investigate this behavior, *an extended set of penalty values was tested*, reaching up to 100,000. Only at extreme penalty values, such as Pen0_VAL10000, does a meaningful shift occur, with 99.70% of borrowers reclassified into Class 0. This delayed response suggests that Class 0 exhibits resistance to penalty-induced reclassification, likely due to its inherent borrower characteristics. Unlike higher-risk classes, where penalties quickly lead to movement, Class 0 requires substantially larger penalties before significant shifts occur.

This finding highlights the importance of designing experiments that extend beyond conventional penalty ranges when unexpected stability is observed. In standard scenarios, penalty effects can be detected at values below 5000, but for some cases, higher penalty values may be necessary. This has implications for borrower acceptance systems, where certain borrower groups, particularly low-risk ones, may appear unaffected by penalty strategies unless their reclassification thresholds are fully explored. Therefore, failing to extend the penalty range might lead to the incorrect conclusion that a penalty has no effect when, whereas, in reality, its impact is simply delayed.

### 4. Detecting *Thresholds Values* Where Penalties Alter Borrower Classification

Building on the insight from **Pen0**, we observed that the distribution only shifts behaviorally at a specific penalty threshold. In the case of Pen0, the behavioral change occurs between VAL9050 and VAL9060, as shown in the following table and figure. Please note that the table is presented in percentage while the figure uses absolute value instead.

| Configuration | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 | Total |
|---|---|---|---|---|---|---|
| Pen0_VAL9060 | 99.64% | 0.00% | 0.000% | 0.12% | 0.24% | 100% |
| Pen0_VAL9050 | 20.22% | 20.68% | 19.13% | 20.10% | 19.87% | 100% |

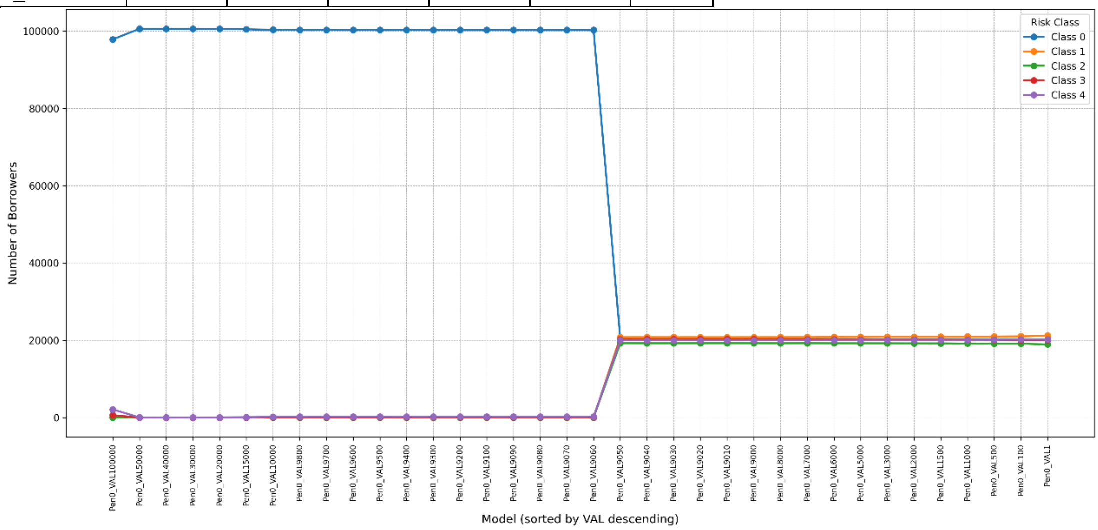


*Figure 68. Borrowers' class distribution in Pen0*

At *Pen0_VAL9060*, the distribution changes drastically, with 99.64% of borrowers now in Class 0. Guided by this insight, we then attempted to determine thresholds across other penalty types. Due to the space concern, we only show the analysis for Pen0, Pen1, Pen2, Pen3, Pen4, and Pen5. The results for other penalty types are placed in Appendix 7.

Starting with **Pen4**, after rerunning simulations between these values, we found that the actual threshold lies between *Pen4_VAL690* and *Pen4_VAL700*, as shown below:

| Configuration | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 | Total |
|---|---|---|---|---|---|---|
| Pen4_VAL700 | 0.03% | 0.01% | 0.00% | 0.00% | 99.96% | 100% |
| Pen4_VAL690 | 20.10% | 20.59% | 18.97% | 17.89% | 22.45% | 100% |

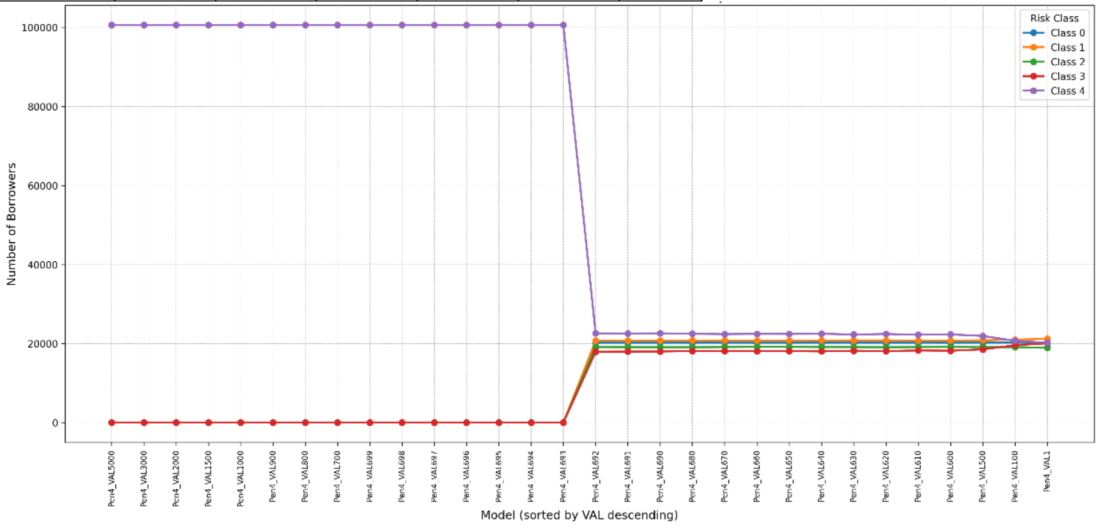


*Figure 69. Borrowers' class distribution in Pen4*

Figure 69 illustrates a sharp transition at Pen4_VAL700, where nearly all borrowers are reclassified into Class 4, marks the tipping point of the penalty's impact.

We continued with **Pen3**, additional simulations revealed the exact turning point between *Pen3_VAL1280* and *Pen3_VAL1290*:

| Configuration | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 | Total |
|---|---|---|---|---|---|---|
| Pen3_VAL1290 | 0.06% | 0.03% | 0.00% | 99.90% | 0.01% | 100% |
| Pen3_VAL1280 | 20.14% | 20.41% | 18.75% | 20.96% | 19.74% | 100% |

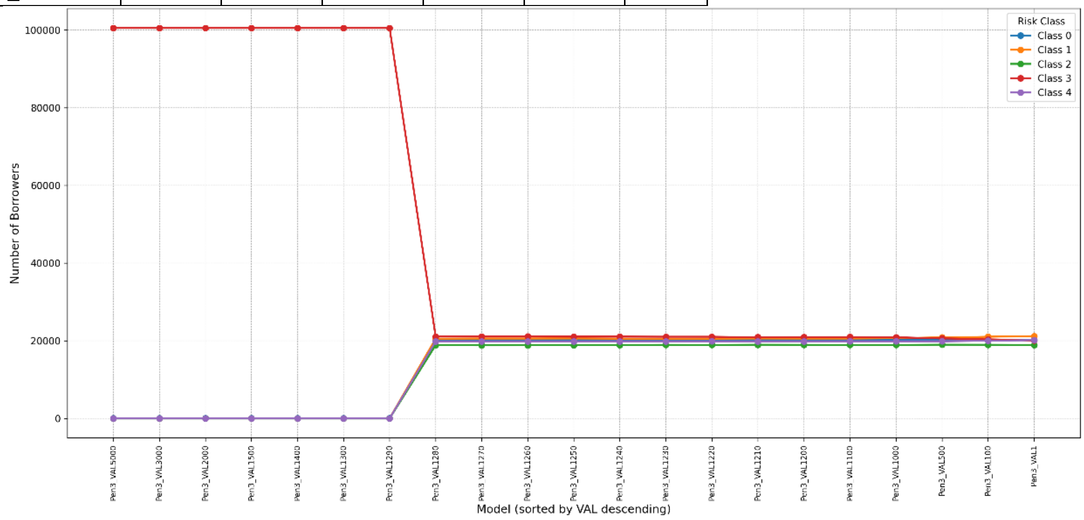


*Figure 70. Borrowers' class distribution in Pen3*

Figure 70 shows a sharp shift to Class 3 at Pen3_VAL1290, marking the threshold where the penalty begins to dominate the classification.

For **Pen2**, the distribution change was detected between *Pen2_VAL480* and *Pen2_VAL490*:

| Configuration | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 | Total |
|---|---|---|---|---|---|---|
| Pen2_VAL490 | 0.03% | 0.03% | 99.75% | 0.02% | 0.17% | 100% |
| Pen2_VAL480 | 20.09% | 18.26% | 22.08% | 19.63% | 19.93% | 100% |

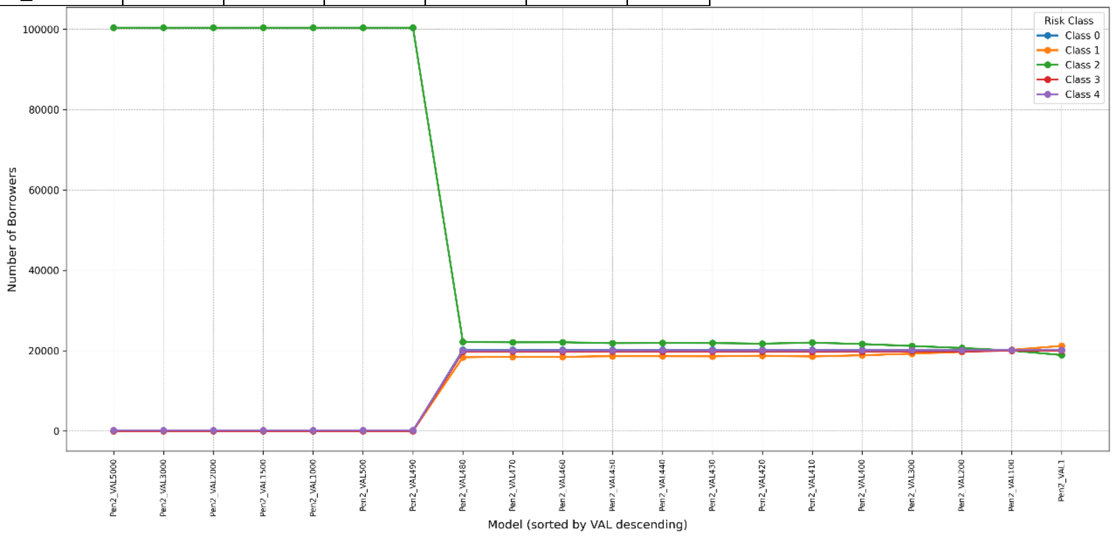


*Figure 71. Borrowers' class distribution in Pen2*

For **Pen1**, the behavioral shift was found between *Pen1_VAL750* and *Pen1_VAL760*:

| Configuration | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 | Total |
|---|---|---|---|---|---|---|
| Pen1_VAL760 | 0.00% | 99.90% | 0.00% | 0.00% | 0.10% | 100% |
| Pen1_VAL750 | 19.05% | 22.57% | 18.52% | 19.91% | 19.95% | 100% |

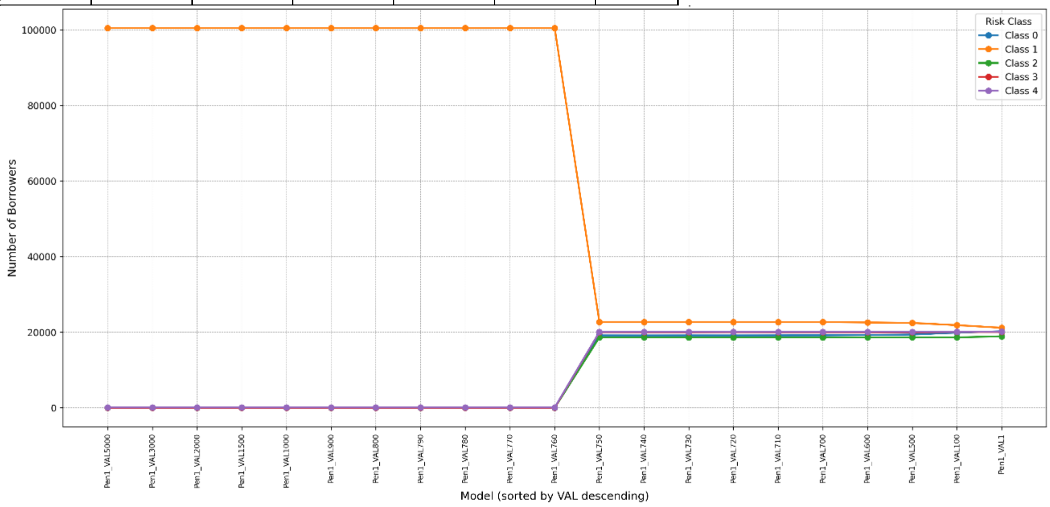


*Figure 72. Borrowers' class distribution in Pen1*

In summary, these *threshold values* represent the exact penalty points at which classification behavior begins to shift significantly for each penalty type. These thresholds are crucial for designing penalty configurations that avoid unintended borrower concentration, therefore, helping preserve inclusion by ensuring that reclassification does not disproportionately exclude borderline applicants.

Metric 1 reveals that penalty-based approaches predominantly reinforce borrower movement into penalized classes. The strength of this effect is highly dependent on *penalty values*, where higher values result in stronger reclassification effects, while lower values allow for a more balanced risk class distribution. Some effects only became visible when penalty ranges were extended beyond standard levels. For example, Pen0 initially appeared to have no effect until the simulation range was expanded, revealing a clear reclassification pattern at a specific threshold value. This highlights the importance of identifying *exact threshold points*, *specific penalty values where borrower distribution shifts significantly*.

### *B. Metric 2: Risk Class Shift (array of %)*

Unlike Metric 1, which focuses on the proportion of individuals in each class *compared to the total data*, Metric 2 directly quantifies the percentage change in class composition *compared to the base model*. Table 39 presents the percentage shift in distribution for each risk class relative to the base model. A negative percentage indicates fewer individuals remain in that class compared to the base model, whereas a positive percentage reflects an increase.

*Table 39. Risk class shifting in % (hypothesis A2 - Penalty based)*

| Penalty types | Model name | Percentage of shifting in each risk class of adjusted model in comparison with base model | | | | |
|---|---|---|---|---|---|---|
| | | 0 | 1 | 2 | 3 | 4 |
| **Pen4** | Pen4_VAL5000 | -99.86% | -99.95% | -100.00% | -100.00% | 398.17% |
| | Pen4_VAL3000 | -99.86% | -99.95% | -100.00% | -100.00% | 398.17% |
| | Pen4_VAL2000 | -99.86% | -99.95% | -100.00% | -100.00% | 398.17% |
| | Pen4_VAL1500 | -99.86% | -99.95% | -100.00% | -100.00% | 398.17% |
| | Pen4_VAL1000 | -99.86% | -99.95% | -100.00% | -100.00% | 398.17% |
| | Pen4_VAL500 | -0.05% | -1.73% | 0.95% | -7.66% | 8.60% |
| | Pen4_VAL100 | 0.005% | -0.95% | 0.92% | -2.41% | 2.53% |
| | Pen4_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen4-3** | Pen4-3_VAL5000 | -100% | -100% | -100% | 291.47% | 9.32% |
| | Pen4-3_VAL3000 | -100% | -100% | -100% | 304.58% | -3.71% |
| | Pen4-3_VAL2000 | -100% | -100% | -100% | 301.34% | -0.49% |
| | Pen4-3_VAL1500 | -100.00% | -100% | -100% | 301.41% | -0.56% |
| | Pen4-3_VAL1000 | -99.98% | -100% | -100% | 301.43% | -0.60% |
| | Pen4-3_VAL500 | -0.02% | -2.74% | -0.41% | 1.40% | 1.89% |
| | Pen4-3_VAL100 | 0.02% | -1.00% | 0.07% | 0.76% | 0.22% |
| | Pen4-3_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen4-2** | Pen4-2_VAL5000 | -100% | -100% | 218.00% | 4.73% | -3.78% |
| | Pen4-2_VAL3000 | -100% | -100% | 220.37% | 1.53% | -2.82% |
| | Pen4-2_VAL2000 | -100% | -100% | 217.78% | 3.88% | -2.72% |
| | Pen4-2_VAL1500 | -100% | -100% | 217.78% | 4.56% | -3.40% |
| | Pen4-2_VAL1000 | -100% | -100% | 218.97% | 2.42% | -2.40% |
| | Pen4-2_VAL500 | -100% | -100% | 219.14% | 1.61% | -1.76% |
| | Pen4-2_VAL100 | -0.10% | -8.03% | 8.79% | 0.00% | 0.29% |
| | Pen4-2_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen4-1** | Pen4-1_VAL5000 | -100% | 94.21% | -1.48% | 9.83% | -6.99% |
| | Pen4-1_VAL3000 | -100% | 95.33% | -1.80% | 7.82% | -5.88% |
| | Pen4-1_VAL2000 | -100% | 97.35% | -3.23% | 4.04% | -2.89% |
| | Pen4-1_VAL1500 | -100% | 95.43% | -1.08% | 2.09% | -0.96% |
| | Pen4-1_VAL1000 | -100% | 93.15% | 2.54% | 1.38% | -1.24% |
| | Pen4-1_VAL500 | -100% | 91.68% | 4.48% | 1.41% | -1.56% |
| | Pen4-1_VAL100 | -2.70% | 2.50% | 0.08% | -0.02% | 0.03% |
| | Pen4-1_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen3_** | Pen3_VAL5000 | -99.72% | -99.83% | -100% | 400.98% | -99.96% |
| | Pen3_VAL3000 | -99.72% | -99.83% | -100% | 400.98% | -99.96% |
| | Pen3_VAL2000 | -99.72% | -99.83% | -100% | 400.98% | -99.96% |
| | Pen3_VAL1500 | -99.72% | -99.83% | -100% | 400.98% | -99.96% |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Pen3_VAL1000 | 0.05% | -2.41% | 0.03% | 4.05% | -1.58% |
| | Pen3_VAL500 | 0.06% | -1.59% | 0.33% | 2.79% | -1.48% |
| | Pen3_VAL100 | 0.01% | -0.75% | 0.24% | 1.55% | -0.99% |
| | Pen3_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen3_2** | Pen3-2_VAL5000 | -100% | -100% | 220.51% | 99.18% | -100% |
| | Pen3-2_VAL3000 | -100% | -100% | 220.51% | 99.18% | -100% |
| | Pen3-2_VAL2000 | -100% | -100% | 220.51% | 99.18% | -100% |
| | Pen3-2_VAL1500 | -100% | -100% | 220.50% | 99.19% | -100% |
| | Pen3-2_VAL1000 | -100% | -100% | 220.50% | 99.19% | -100% |
| | Pen3-2_VAL500 | -0.19% | -14.81% | 17.01% | 1.94% | -2.14% |
| | Pen3-2_VAL100 | -0.07% | -5.09% | 5.93% | 1.21% | -1.33% |
| | Pen3-2_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen3-1** | Pen3-1_VAL5000 | -100% | 97.00% | -4.07% | 102.90% | -100% |
| | Pen3-1_VAL3000 | -100% | 97.81% | -1.15% | 99.30% | -100% |
| | Pen3-1_VAL2000 | -100% | 91.59% | 5.84% | 99.28% | -100% |
| | Pen3-1_VAL1500 | -100% | 91.30% | 6.13% | 99.31% | -100% |
| | Pen3-1_VAL1000 | -100% | 91.36% | 6.07% | 99.30% | -100% |
| | Pen3-1_VAL500 | -100% | 94.16% | 2.94% | 92.22% | -92.97% |
| | Pen3-1_VAL100 | -2.22% | 2.34% | -0.06% | 1.42% | -1.58% |
| | Pen3-1_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen3-0** | Pen3-0_VAL5000 | 0.80% | -4.65% | 1.93% | 102.90% | -100% |
| | Pen3-0_VAL3000 | 0.76% | -2.85% | 1.18% | 101.75% | -100% |
| | Pen3-0_VAL2000 | -0.23% | 0.51% | 0.22% | 4.74% | -5.22% |
| | Pen3-0_VAL1500 | -0.23% | 0.47% | 0.34% | 4.17% | -4.73% |
| | Pen3-0_VAL1000 | -0.17% | 0.29% | 0.32% | 3.23% | -3.64% |
| | Pen3-0_VAL500 | -0.16% | 0.27% | 0.25% | 2.46% | -2.81% |
| | Pen3-0_VAL100 | -0.17% | 0.47% | -0.11% | 1.47% | -1.68% |
| | Pen3-0_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen2_** | Pen2_VAL5000 | -99.86% | -99.83% | 430.35% | -99.92% | -99.13% |
| | Pen2_VAL3000 | -99.86% | -99.83% | 430.35% | -99.92% | -99.13% |
| | Pen2_VAL2000 | -99.86% | -99.83% | 430.35% | -99.92% | -99.13% |
| | Pen2_VAL1500 | -99.86% | -99.83% | 430.35% | -99.92% | -99.13% |
| | Pen2_VAL1000 | -99.86% | -99.83% | 430.35% | -99.92% | -99.13% |
| | Pen2_VAL500 | -99.86% | -99.83% | 430.35% | -99.92% | -99.13% |
| | Pen2_VAL100 | -0.03% | -4.62% | 5.90% | -0.50% | -0.15% |
| | Pen2_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen2-1** | Pen2-1_VAL5000 | -100% | 104.58% | 202.59% | -100% | -100% |
| | Pen2-1_VAL3000 | -100% | 104.58% | 202.59% | -100% | -100% |
| | Pen2-1_VAL2000 | -100% | 91.65% | 217.07% | -100% | -100% |
| | Pen2-1_VAL1500 | -100% | 91.65% | 217.07% | -100% | -100% |
| | Pen2-1_VAL1000 | -100% | 91.65% | 217.07% | -100% | -100% |
| | Pen2-1_VAL500 | -100% | 91.65% | 217.07% | -100% | -100% |
| | Pen2-1_VAL100 | -2.08% | 2.06% | 0.62% | -0.10% | -0.56% |
| | Pen2-1_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen2-0** | Pen2-0_VAL5000 | 0.52% | -1.76% | 214.14% | -100% | -100% |
| | Pen2-0_VAL3000 | 1.09% | -2.32% | 214.14% | -100% | -100% |
| | Pen2-0_VAL2000 | 1.09% | -2.32% | 214.14% | -100% | -100% |
| | Pen2-0_VAL1500 | 1.16% | -2.38% | 214.14% | -100% | -100% |
| | Pen2-0_VAL1000 | 0.38% | -1.63% | 214.14% | -100% | -100% |
| | Pen2-0_VAL500 | 0.06% | -1.33% | 214.14% | -100% | -100% |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Pen2-0_VAL100 | -0.23% | 0.35% | 0.40% | 0.20% | -0.71% |
| | Pen2-0_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen1_** | Pen1_VAL5000 | -99.99% | 374.27% | -100% | -100% | -99.49% |
| | Pen1_VAL3000 | -99.99% | 374.27% | -100% | -100% | -99.49% |
| | Pen1_VAL2000 | -99.99% | 374.27% | -100% | -100% | -99.49% |
| | Pen1_VAL1500 | -99.99% | 374.27% | -100% | -100% | -99.49% |
| | Pen1_VAL1000 | -99.99% | 374.27% | -100% | -100% | -99.49% |
| | Pen1_VAL500 | -4.20% | 6.01% | -1.42% | -0.31% | -0.47% |
| | Pen1_VAL100 | -1.63% | 3.22% | -1.45% | 0.05% | -0.44% |
| | Pen1_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen1-0** | Pen1-0_VAL5000 | 0.48% | 278.77% | -100% | -100% | -100% |
| | Pen1-0_VAL3000 | 1.62% | 277.68% | -100% | -100% | -100% |
| | Pen1-0_VAL2000 | 0.51% | 278.73% | -100% | -100% | -99.99% |
| | Pen1-0_VAL1500 | 0.19% | 278.92% | -100% | -100% | -99.86% |
| | Pen1-0_VAL1000 | -0.29% | 2.36% | -1.72% | 0.23% | -0.81% |
| | Pen1-0_VAL500 | -0.28% | 2.24% | -1.71% | 0.19% | -0.66% |
| | Pen1-0_VAL100 | -0.26% | 1.82% | -1.37% | 0.16% | -0.53% |
| | Pen1-0_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen0_** | Pen0_VAL5000 | 0.35% | -1.58% | 1.59% | 0.54% | -0.73% |
| | Pen0_VAL3000 | 0.25% | -1.49% | 1.57% | 0.46% | -0.61% |
| | Pen0_VAL2000 | 0.27% | -1.48% | 1.52% | 0.47% | -0.61% |
| | Pen0_VAL1500 | 0.16% | -1.36% | 1.51% | 0.45% | -0.59% |
| | Pen0_VAL1000 | 0.14% | -1.12% | 1.26% | 0.33% | -0.47% |
| | Pen0_VAL500 | 0.11% | -1.03% | 1.15% | 0.14% | -0.24% |
| | Pen0_VAL100 | 0.02% | -0.85% | 1.01% | -0.15% | 0.07% |
| | Pen0_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **EXTEND Pen0_** | Pen0_VAL100000 | 383.34% | -99.84% | -99.97% | -96.91% | -89.61% |
| | Pen0_VAL50000 | 396.76% | -100% | -99.98% | -99.99% | -99.82% |
| | Pen0_VAL40000 | 396.76% | -100% | -99.98% | -99.99% | -99.82% |
| | Pen0_VAL30000 | 396.76% | -100% | -99.98% | -99.99% | -99.82% |
| | Pen0_VAL20000 | 396.72% | -100% | -100% | -99.99% | -99.77% |
| | Pen0_VAL15000 | 396.17% | -100% | -100% | -99.74% | -99.47% |
| | **Pen0_VAL10000** | **395.46%** | -100% | -100% | -99.47% | -99.01% |
| | Pen0_VAL9800 | 395.39% | -100% | -100% | -99.47% | -98.95% |
| | Pen0_VAL9700 | 395.29% | -100% | -100% | -99.43% | -98.89% |
| | Pen0_VAL9200 | 395.19% | -100% | -100% | -99.39% | -98.83% |
| | Pen0_VAL9100 | 395.17% | -100% | -100% | -99.39% | -98.81% |
| | Pen0_VAL9090 | 395.17% | -100% | -100% | -99.39% | -98.81% |
| | **Pen0_VAL9060** | **395.16%** | -100% | -100% | -99.39% | -98.80% |
| | Pen0_VAL9050 | 0.51% | -1.82% | 1.69% | 0.77% | -0.95% |
| | Pen0_VAL9040 | 0.51% | -1.80% | 1.63% | 0.86% | -1.02% |
| | Pen0_VAL9030 | 0.51% | -1.79% | 1.63% | 0.86% | -1.02% |
| | Pen0_VAL9020 | 0.51% | -1.83% | 1.66% | 0.85% | -1.01% |
| | Pen0_VAL9010 | 0.51% | -1.83% | 1.68% | 0.86% | -1.03% |
| | Pen0_VAL9000 | 0.51% | -1.81% | 1.65% | 0.86% | -1.02% |
| | Pen0_VAL6000 | 0.38% | -1.61% | 1.60% | 0.66% | -0.84% |
| | Pen0_VAL5000 | 0.35% | -1.58% | 1.59% | 0.54% | -0.73% |
| | Pen0_VAL3000 | 0.25% | -1.49% | 1.57% | 0.46% | -0.61% |
| | Pen0_VAL2000 | 0.27% | -1.48% | 1.52% | 0.47% | -0.61% |
| | Pen0_VAL1500 | 0.16% | -1.36% | 1.51% | 0.45% | -0.59% |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Pen0_VAL1000 | 0.14% | -1.12% | 1.26% | 0.33% | -0.47% |
| | Pen0_VAL500 | 0.11% | -1.03% | 1.15% | 0.14% | -0.24% |
| | Pen0_VAL100 | 0.02% | -0.85% | 1.01% | -0.15% | 0.07% |
| | Pen0_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen0-1** | Pen0-1_VAL5000 | 0.48% | 278.77% | -100% | -100% | -100% |
| | Pen0-1_VAL3000 | 1.62% | 277.68% | -100% | -100% | -100% |
| | Pen0-1_VAL2000 | 0.51% | 278.73% | -100% | -100% | -99.99% |
| | Pen0-1_VAL1500 | 0.19% | 278.92% | -100% | -100% | -99.86% |
| | Pen0-1_VAL1000 | -0.29% | 2.36% | -1.72% | 0.23% | -0.81% |
| | Pen0-1_VAL500 | -0.28% | 2.24% | -1.71% | 0.19% | -0.66% |
| | Pen0-1_VAL100 | -0.26% | 1.82% | -1.37% | 0.16% | -0.53% |
| | Pen0-1_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen0-2** | Pen0-2_VAL5000 | 0.52% | -1.76% | 214.14% | -100% | -100% |
| | Pen0-2_VAL3000 | 1.09% | -2.32% | 214.14% | -100% | -100% |
| | Pen0-2_VAL2000 | 1.09% | -2.32% | 214.14% | -100% | -100% |
| | Pen0-2_VAL1500 | 1.16% | -2.38% | 214.14% | -100% | -100% |
| | Pen0-2_VAL1000 | 0.38% | -1.63% | 214.14% | -100% | -100% |
| | Pen0-2_VAL500 | 0.06% | -1.33% | 214.14% | -100% | -100% |
| | Pen0-2_VAL100 | -0.23% | 0.35% | 0.40% | 0.20% | -0.71% |
| | Pen0-2_VAL1 | 0% | 0% | 0% | 0% | 0% |
| **Pen0-3** | Pen0-3_VAL5000 | 0.80% | -4.65% | 1.93% | 102.90% | -100% |
| | Pen0-3_VAL3000 | 0.76% | -2.85% | 1.18% | 101.75% | -100% |
| | Pen0-3_VAL2000 | -0.23% | 0.51% | 0.22% | 4.74% | -5.22% |
| | Pen0-3_VAL1500 | -0.23% | 0.47% | 0.34% | 4.17% | -4.73% |
| | Pen0-3_VAL1000 | -0.17% | 0.29% | 0.32% | 3.23% | -3.64% |
| | Pen0-3_VAL500 | -0.16% | 0.27% | 0.25% | 2.46% | -2.81% |
| | Pen0-3_VAL100 | -0.17% | 0.47% | -0.11% | 1.47% | -1.68% |
| | Pen0-3_VAL1 | 0% | 0% | 0% | 0% | 0% |

Analysis and key findings of Metric 2:

1. ***Penalty types drive systematic shifts across risk classes***

Each penalty type follows a predictable distribution pattern, confirming that the design of penalties influences how individuals are reassigned. The Pen4 series causes a massive shift of individuals into class 4, effectively eliminating lower-class populations. The percentage shift shows nearly -100% in classes 0, 1, 2, and 3, with a corresponding +398% increase in class 4 for higher penalty values. The Pen4-3 series introduces a dual redistribution into classes 4 and 3, splitting the relocated individuals across both. Compared to Pen4, these models retain a fraction of individuals in class 3, seen in a ~300% increase in class 3 and a high but slightly lower increase in class 4.

The Pen4-2 and Pen4-1 categories gradually extend this shift further downward, moving individuals into classes 4, 3, 2, and even 1, following a layered effect that distributes individuals in a more stepwise manner. The inverse effect is observed for Pen0-2, Pen0-1, and Pen0-3, where individuals from higher risk classes (4, 3, and 2) migrate into lower classes (0, 1, and 2), indicating that lowering penalties effectively redistributes risk populations downward. The pattern is remarkably consistent across penalty types, proving that each penalty structure enforces a targeted movement pattern rather than arbitrary redistribution.

2. ***Penalty values influence the magnitude of shifts***

While *penalty type* determines the direction of movement, *penalty values* control the intensity of these shifts. Higher penalty values (5000, 3000) cause almost complete depletion of some risk classes. For instance, Pen4_VAL5000 shows nearly -100% in classes 0, 1, 2, and 3, indicating that almost all individuals have been forced into class 4. Similarly, Pen2-1_VAL5000 results in a +202% shift into class 2, reinforcing its strong migration effect. Lower penalty values (1500, 1000, 500, 100) weaken the impact, with risk classes retaining a portion of their original populations. For example, Pen4_VAL100 results in only minor changes across all risk classes compared to higher values, with less than ±2% shifts observed. This progressive weakening suggests that *penalty values* act as ***a control mechanism***, adjusting whether population shifts occur suddenly and aggressively or gradually and proportionally.

### 3. *The importance of extended observation in certain cases*

One crucial finding is that Pen0 does not initially produce a visible shift into class 0 at conventional penalty values. Unlike other penalty types, Pen0_VAL5000 and lower show no significant increase in class 0, suggesting that the expected effect of Pen0 is absent at these penalty levels. To investigate further, the observation range was extended to penalties beyond 10,000, revealing that only at Pen0_VAL10000 and higher does the anticipated effect appear, with a dramatic **+395%** increase in class 0 for Pen0_VAL50000. This highlights that ***some penalties require a threshold*** before their impact becomes measurable.

### 4. *Detecting Thresholds Where Penalties Trigger Significant Shifts from the Baseline Distribution*

Similar to Metric 1, Metric 2 confirms that borrower movements across risk classes only after passing a specific threshold. All thresholds observed here match those identified in Metric 1, reinforcing their consistency. For instance, Pen0 shows minimal change at Pen0_VAL9050 but triggers a drastic +395.16% shift into Class 0 at Pen0_VAL9060. Pen4 sees a +398.17% in Class 4 between Pen4_VAL690 and Pen4_VAL700. The same pattern holds for other penalty types, as shown in the table below.

*Table 40. Threshold shifting for penalty-based approach (Metric 2)*

| Penalty Type | Threshold Before | Key Shift After | Dominant Class |
|---|---|---|---|
| Pen0 | Pen0_VAL9050 | Pen0_VAL9060 | Class 0 (+395%) |
| Pen1 | Pen1_VAL750 | Pen1_VAL760 | Class 1 (+374%) |
| Pen2 | Pen2_VAL480 | Pen2_VAL490 | Class 2 (+430%) |
| Pen3 | Pen3_VAL1280 | Pen3_VAL1290 | Class 3 (+401%) |
| Pen4 | Pen4_VAL690 | Pen4_VAL700 | Class 4 (+398%) |

Metric 2 results show that *penalty types* influence the direction of shifts, *penalty values* control the magnitude, and certain penalties require extended observation. Moreover, each penalty type has a clear ***threshold value*** at which borrower reclassification accelerates, and these thresholds are consistent with those identified in Metric 1.

### *C. Metric 3: Borrower Shift to Lower Risk Classes (%)*

Table 41 presents the percentage-based analysis of borrower movements across different penalty configurations for evaluating Metric 3, Metric 4, and Metric 5. To maintain focus on the relative impact of each penalty adjustment, the absolute values of borrower shifts are moved to appendix 7.

*Table 41. Percentage of borrower movement and inclusivity ratio (hypothesis A2 - Penalty-based)*

| Penalty Types | Model name | Metric 3 | Metric 4 | Metric 5 |
|---|---|---|---|---|
| | | % of borrowers move to the lower class in comparison with total data | % of borrowers move to the higher class in comparison with total data | Inclusion ratio |
| **Pen4** | Pen4_VAL5000 | 0.01% | 79.91% | 0.00014 |
| | Pen4_VAL3000 | 0.01% | 79.91% | 0.00014 |
| | Pen4_VAL2000 | 0.01% | 79.91% | 0.00014 |

| | | | | |
|---|---|---|---|---|
| | Pen4_VAL1500 | 0.01% | 79.91% | 0.00014 |
| | Pen4_VAL1000 | 0.01% | 79.91% | 0.00014 |
| | Pen4_VAL500 | 0.07% | 1.98% | 0.03614 |
| | Pen4_VAL100 | 0.07% | 0.73% | 0.09202 |
| **Pen4-3** | Pen4-3_VAL5000 | 0.57% | 62.44% | 0.009 |
| | Pen4-3_VAL3000 | 0.82% | 59.99% | 0.014 |
| | Pen4-3_VAL2000 | 0.22% | 60.01% | 0.004 |
| | Pen4-3_VAL1500 | 0.22% | 60.01% | 0.004 |
| | Pen4-3_VAL1000 | 0.22% | 60.00% | 0.004 |
| | Pen4-3_VAL500 | 0.12% | 0.98% | 0.127 |
| | Pen4-3_VAL100 | 0.11% | 0.43% | 0.257 |
| | Pen4-3_VAL1 | 0% | 0% | 0/e |
| **Pen4-2** | Pen4-2_VAL5000 | 0.99% | 41.63% | 0.024 |
| | Pen4-2_VAL3000 | 0.88% | 41.26% | 0.021 |
| | Pen4-2_VAL2000 | 0.63% | 41.52% | 0.015 |
| | Pen4-2_VAL1500 | 0.69% | 41.44% | 0.017 |
| | Pen4-2_VAL1000 | 0.49% | 41.22% | 0.012 |
| | Pen4-2_VAL500 | 0.37% | 41.20% | 0.009 |
| | Pen4-2_VAL100 | 0.03% | 1.73% | 0.018 |
| | Pen4-2_VAL1 | 0% | 0% | 0/e |
| **Pen4-1** | Pen4-1_VAL5000 | 1.67% | 21.24% | 0.079 |
| | Pen4-1_VAL3000 | 1.40% | 20.79% | 0.067 |
| | Pen4-1_VAL2000 | 1.04% | 20.45% | 0.051 |
| | Pen4-1_VAL1500 | 0.75% | 20.95% | 0.036 |
| | Pen4-1_VAL1000 | 0.38% | 20.80% | 0.018 |
| | Pen4-1_VAL500 | 0.38% | 20.99% | 0.018 |
| | Pen4-1_VAL100 | 0.08% | 0.62% | 0.134 |
| | Pen4-1_VAL1 | 0% | 0% | 0/e |
| **Pen3_** | Pen3_VAL5000 | 20.08% | 59.95% | 0.33 |
| | Pen3_VAL3000 | 20.08% | 59.95% | 0.33 |
| | Pen3_VAL2000 | 20.08% | 59.95% | 0.33 |
| | Pen3_VAL1500 | 20.08% | 59.95% | 0.33 |
| | Pen3_VAL1000 | 0.39% | 0.86% | 0.45 |
| | Pen3_VAL500 | 0.38% | 0.57% | 0.67 |
| | Pen3_VAL100 | 0.26% | 0.32% | 0.80 |
| | Pen3_VAL1 | 0% | 0% | 0/e |
| **Pen3-2** | Pen3-2_VAL5000 | 20.33% | 41.19% | 0.49 |
| | Pen3-2_VAL3000 | 20.33% | 41.19% | 0.49 |
| | Pen3-2_VAL2000 | 20.33% | 41.19% | 0.49 |
| | Pen3-2_VAL1500 | 20.33% | 41.19% | 0.49 |
| | Pen3-2_VAL1000 | 20.33% | 41.19% | 0.49 |
| | Pen3-2_VAL500 | 0.46% | 3.16% | 0.15 |
| | Pen3-2_VAL100 | 0.28% | 1.10% | 0.26 |
| | Pen3-2_VAL1 | 0% | 0% | 0/e |
| **Pen3-1** | Pen3-1_VAL5000 | 20.66% | 20.88% | 0.99 |
| | Pen3-1_VAL3000 | 20.89% | 20.23% | 1.03 |
| | Pen3-1_VAL2000 | 20.35% | 21.00% | 0.97 |
| | Pen3-1_VAL1000 | 20.35% | 21.05% | 0.97 |
| | Pen3-1_VAL1500 | 20.34% | 21.06% | 0.97 |
| | Pen3-1_VAL500 | 18.96% | 20.48% | 0.93 |

| | | | | |
|---|---|---|---|---|
| | Pen3-1_VAL100 | 0.40% | 0.48% | 0.82 |
| | Pen3-1_VAL1 | 0% | 0% | 0/e |
| **Pen3-0** | Pen3-0_VAL5000 | 20.28% | 1.34% | 15.08 |
| | Pen3-0_VAL3000 | 20.27% | 0.75% | 27.06 |
| | Pen3-0_VAL2000 | 1.12% | 0.08% | 13.59 |
| | Pen3-0_VAL1500 | 1.00% | 0.07% | 13.45 |
| | Pen3-0_VAL1000 | 0.77% | 0.07% | 10.37 |
| | Pen3-0_VAL500 | 0.61% | 0.06% | 9.70 |
| | Pen3-0_VAL100 | 0.43% | 0.07% | 6.48 |
| | Pen3-0_VAL1 | 0% | 0% | 0/e |
| **Pen2_** | Pen2_VAL5000 | 39.83% | 41.26% | 0.97 |
| | Pen2_VAL3000 | 39.83% | 41.26% | 0.97 |
| | Pen2_VAL2000 | 39.83% | 41.26% | 0.97 |
| | Pen2_VAL1500 | 39.83% | 41.26% | 0.97 |
| | Pen2_VAL1000 | 39.83% | 41.26% | 0.97 |
| | Pen2_VAL500 | 39.83% | 41.26% | 0.97 |
| | Pen2_VAL100 | 0.18% | 1.02% | 0.18 |
| | Pen2_VAL1 | 0% | 0% | 0/e |
| **Pen2-1** | Pen2-1_VAL5000 | 41.91% | 20.12% | 2.08 |
| | Pen2-1_VAL3000 | 41.91% | 20.12% | 2.08 |
| | Pen2-1_VAL2000 | 40.05% | 20.98% | 1.91 |
| | Pen2-1_VAL1500 | 40.05% | 20.98% | 1.91 |
| | Pen2-1_VAL1000 | 40.05% | 20.98% | 1.91 |
| | Pen2-1_VAL500 | 40.05% | 20.98% | 1.91 |
| | Pen2-1_VAL100 | 0.29% | 0.49% | 0.59 |
| | Pen2-1_VAL1 | 0.0% | 0.0% | 0/e |
| **Pen2-0** | Pen2-0_VAL5000 | 40.18% | 0.33% | 120.0 |
| | Pen2-0_VAL3000 | 40.29% | 0.34% | 120.0 |
| | Pen2-0_VAL2000 | 40.29% | 0.34% | 120.0 |
| | Pen2-0_VAL1500 | 40.31% | 0.34% | 120.0 |
| | Pen2-0_VAL1000 | 40.15% | 0.34% | 119.6 |
| | Pen2-0_VAL500 | 40.09% | 0.33% | 119.7 |
| | Pen2-0_VAL100 | 0.28% | 0.10% | 2.7 |
| | Pen2-0_VAL1 | 0.0% | 0.0% | 0/e |
| **Pen1_** | Pen1_VAL5000 | 58.71% | 20.16% | 2.91 |
| | Pen1_VAL3000 | 58.71% | 20.16% | 2.91 |
| | Pen1_VAL2000 | 58.71% | 20.16% | 2.91 |
| | Pen1_VAL1500 | 58.71% | 20.16% | 2.91 |
| | Pen1_VAL1000 | 58.71% | 20.16% | 2.91 |
| | Pen1_VAL500 | 0.49% | 0.89% | 0.54 |
| | Pen1_VAL100 | 0.42% | 0.36% | 1.17 |
| | Pen1_VAL1 | 0% | 0% | 0/e |
| **Pen1-0** | Pen1-0_VAL5000 | 58.91% | 0% | 58%/e |
| | Pen1-0_VAL3000 | 59.14% | 0% | 59%/e |
| | Pen1-0_VAL2000 | 58.92% | 0% | 58%/e |
| | Pen1-0_VAL1500 | 58.82% | 0% | 58%/e |
| | Pen1-0_VAL1000 | 0.57% | 0.11% | 5.05 |
| | Pen1-0_VAL500 | 0.53% | 0.10% | 5.55 |
| | Pen1-0_VAL100 | 0.43% | 0.08% | 5.18 |
| | Pen1-0_VAL1 | 0% | 0% | 0/e |

| | | | | |
|---|---|---|---|---|
| **Pen0_** | Pen0_VAL5000 | 0.34% | 0.38% | 0.90 |
| | Pen0_VAL3000 | 0.30% | 0.39% | 0.79 |
| | Pen0_VAL2000 | 0.29% | 0.37% | 0.80 |
| | Pen0_VAL1500 | 0.27% | 0.37% | 0.74 |
| | Pen0_VAL1000 | 0.25% | 0.33% | 0.76 |
| | Pen0_VAL500 | 0.19% | 0.31% | 0.62 |
| | Pen0_VAL100 | 0.10% | 0.27% | 0.36 |
| | Pen0_VAL1 | 0% | 0% | 0/e |
| **EXTEND Pen0_** | Pen0_VAL100000 | 77.36% | 0.98% | 78.9 |
| | Pen0_VAL50000 | 79.84% | 0.00% | 40179.5 |
| | Pen0_VAL40000 | 79.84% | 0.00% | 40179.5 |
| | Pen0_VAL30000 | 79.84% | 0.00% | 40179.5 |
| | Pen0_VAL20000 | 79.83% | 0.00% | 20087.5 |
| | Pen0_VAL15000 | 79.73% | 0.07% | 1146.3 |
| | Pen0_VAL10000 | 79.59% | 0.11% | 715.2 |
| | Pen0_VAL9800 | 79.58% | 0.12% | 690.5 |
| | Pen0_VAL9700 | 79.56% | 0.12% | 645.8 |
| | Pen0_VAL9200 | 79.54% | 0.13% | 625.4 |
| | Pen0_VAL9100 | 79.53% | 0.13% | 625.4 |
| | Pen0_VAL9090 | 79.53% | 0.13% | 625.4 |
| | **Pen0_VAL9060** | 79.53% | 0.13% | 625.4 |
| | **Pen0_VAL9050** | 0.41% | 0.39% | 1.1 |
| | Pen0_VAL9040 | 0.42% | 0.38% | 1.1 |
| | Pen0_VAL9030 | 0.42% | 0.38% | 1.1 |
| | Pen0_VAL9010 | 0.42% | 0.39% | 1.1 |
| | Pen0_VAL9000 | 0.42% | 0.38% | 1.1 |
| | Pen0_VAL8000 | 0.40% | 0.39% | 1.0 |
| | Pen0_VAL7000 | 0.39% | 0.40% | 1.0 |
| | Pen0_VAL6000 | 0.38% | 0.39% | 1.0 |
| | Pen0_VAL5000 | 0.34% | 0.38% | 0.9 |
| | Pen0_VAL3000 | 0.30% | 0.39% | 0.8 |
| | Pen0_VAL2000 | 0.29% | 0.37% | 0.8 |
| | Pen0_VAL1500 | 0.27% | 0.37% | 0.7 |
| | Pen0_VAL1000 | 0.25% | 0.33% | 0.8 |
| | Pen0_VAL500 | 0.19% | 0.31% | 0.6 |
| | Pen0_VAL100 | 0.10% | 0.27% | 0.4 |
| | Pen0_VAL1 | 0% | 0% | 0/e |
| **Pen0-1** | Pen0-1_VAL5000 | 0.34% | 0.00% | 0.34%/e |
| | Pen0-1_VAL3000 | 0.30% | 0.00% | 0.30%/e |
| | Pen0-1_VAL2000 | 0.29% | 0.00% | 0.29%/e |
| | Pen0-1_VAL1500 | 0.27% | 0.00% | 0.27%/e |
| | Pen0-1_VAL1000 | 0.25% | 0.11% | 2.21 |
| | Pen0-1_VAL500 | 0.19% | 0.10% | 1.99 |
| | Pen0-1_VAL100 | 0.10% | 0.08% | 1.19 |
| | Pen0-1_VAL1 | 0% | 0% | 0/e |
| **Pen0-2** | Pen0-2_VAL5000 | 40.18% | 0.33% | 120 |
| | Pen0-2_VAL3000 | 40.29% | 0.34% | 119.99 |
| | Pen0-2_VAL2000 | 40.29% | 0.34% | 119.99 |
| | Pen0-2_VAL1500 | 40.31% | 0.34% | 120.03 |
| | Pen0-2_VAL1000 | 40.15% | 0.34% | 119.56 |

| | | | | |
|---|---|---|---|---|
| | Pen0-2_VAL500 | 40.09% | 0.33% | 119.73 |
| | Pen0-2_VAL100 | 0.28% | 0.10% | 2.72 |
| | Pen0-2_VAL1 | 0% | 0% | 0/e |
| **Pen0-3** | Pen0-3_VAL5000 | 20.28% | 1.34% | 15.08 |
| | Pen0-3_VAL3000 | 20.27% | 0.75% | 27.06 |
| | Pen0-3_VAL2000 | 1.12% | 0.08% | 13.59 |
| | Pen0-3_VAL1500 | 1.00% | 0.07% | 13.45 |
| | Pen0-3_VAL1000 | 0.77% | 0.07% | 10.37 |
| | Pen0-3_VAL500 | 0.61% | 0.06% | 9.70 |
| | Pen0-3_VAL100 | 0.43% | 0.07% | 6.48 |
| | Pen0-3_VAL1 | 0% | 0% | 0/e |

The percentage of borrowers moving to lower-risk classes is determined mainly by *the penalty type* and *penalty value*. Penalties that primarily target the highest-risk classes, such as Pen4, naturally show limited downward movement. In contrast, penalties targeting the lower-risk spectrum (e.g., Pen0, Pen0-1, Pen0-2) exhibit much stronger downward movement.

*The penalty value* also plays a crucial role in determining the magnitude of borrower reclassification. At high penalty values, downward movement is amplified, whereas borrower movement is minimal at lower values (e.g., VAL100 or below). This threshold effect is particularly evident in Pen2-0, where penalty values of 5000 and above result in over 40% of borrowers moving to lower-risk classes. However, at lower penalty values (VAL100 and below), borrower movement remains under 1%. This confirms that penalties must exceed a certain magnitude to trigger significant downward shifts.

Finally, an extended observation of penalty values further validates this threshold effect. In many penalty types, including Pen0 and its variants, significant borrower reclassification is only observed when penalty values surpass 9000. This suggests that borrower movement is not immediate and requires a sufficiently large penalty value to become apparent.

***D. Metric 4: Borrower Shift to Higher Risk Classes (%)***

The proportion of borrowers moving to higher-risk classes is influenced by *the penalty type*. Penalty types with higher-risk categories (e.g., Pen4, Pen3, Pen2) exhibit substantial upward borrower movement. In particular, Pen4 consistently shows nearly 80% of borrowers shifting into higher-risk categories when penalty values reach 5000 or more. In contrast, penalty types with lower-risk categories (e.g., Pen0, Pen0-1, Pen0-2) exhibit minimal upward movement. For example, Pen0-3_VAL1000 records only 0.07% of borrowers shifting upward, while 0.77% move downward, resulting in a net positive impact on financial inclusion.

*Penalty value* further influences the extent of higher-risk borrower movement. At lower penalty values, shifts to higher-risk categories are negligible, while at high values, borrower movement increases significantly. However, when penalty values are minimal (VAL100 and below), borrower movement in either direction is limited. This reinforces the conclusion that penalty-based borrower reclassification requires a sufficiently large penalty value to manifest.

***E. Metric 5: Inclusivity Ratio***

The inclusion ratio measures how well penalty configurations promote inclusion by comparing movements to lower-risk and higher-risk classes. An ideal inclusion ratio is greater than 1, indicating that more borrowers are reclassified to lower-risk categories than to higher-risk ones. However, it must be evaluated alongside Metrics 3 and 4 to account for the magnitude of movements and with Metric 1 and 2 to assess how well risk class distribution supports inclusion goals.

*A good example of inclusion* is observed in *Pen0-2_VAL5000*, which achieves an inclusion ratio of 120.00. Here, 40.18% of borrowers are reclassified to lower-risk categories, while only 0.33% move to higher-risk classes. This high ratio reflects targeted adjustments that effectively promote financial inclusion without causing excessive upward reclassification or system instability. Moreover, as confirmed by Metric 1, the distribution across risk classes improves significantly, showing that the penalty configuration balances reclassification dynamics while maintaining system integrity. In contrast, *a poor example of inclusion* is seen in *Pen4_VAL5000*, where the inclusion ratio is nearly zero (0.00014). Although this low ratio already signals poor inclusion, the magnitude of movements makes it even more concerning: only 0.01% of borrowers move to lower-risk classes, while 79.91% are shifted to higher-risk categories. This creates an undesirable outcome where penalties reinforce upward retention in the highest-risk classes thereby reducing borrowers' access to credit and directly undermining inclusion goals.

Furthermore, the extended observation of penalty values is critical. The Pen0 extended models show that inclusion ratios remain below 1.0 for lower penalty values but increase dramatically when the penalty exceeds 9000. This finding underscores the necessity of testing broader penalty ranges, as their effects may only become apparent at certain thresholds, which in turn affects the system's ability to identify configurations that meaningfully improve borrower inclusion.

**Detecting Thresholds in Metrics 3 to 5**

An important observation across Metrics 3, 4, and 5 is that the turning points, where borrower movement to lower or higher risk classes begins to change drastically, occur at **the same penalty values previously identified as thresholds in Metrics 1 and 2**. This alignment confirms that each *penalty type* has a consistent penalty value where its behavioral effect becomes significant, regardless of the metric used. The table below summarizes thresholds, showing the penalty values at which the inclusion begins to shift. At these thresholds, we observe a steep increase in downward movement (Metric 3), a decline in upward movement (Metric 4), and a sharp rise in the inclusion ratio (Metric 5).

*Table 42. Threshold shifting for penalty-based approach (Metric 3-5)*

| Penalty Type | Penalty Value | % Shift to Lower Risk (M3) | % Shift to Higher Risk (M4) | Inclusion Ratio (M5) |
|---|---|---:|---:|---:|
| Pen4 | 690 | 0.07% | 2.67% | 0.026 |
| | *700* | *0.01%* | *79.91%* | *0.00014* |
| Pen3 | 1280 | 0.42% | 1.12% | 0.37 |
| | *1290* | *20.08%* | *59.95%* | *0.33* |
| Pen2 | 480 | 0.58% | 2.89% | 0.20 |
| | *490* | *39.83%* | *41.26%* | *0.97* |
| Pen1 | 750 | 0.50% | 1.11% | 0.45 |
| | *760* | *58.71%* | *20.16%* | *2.91* |
| Pen0 | 9050 | 0.41% | 0.39% | 1.10 |
| | *9060* | 79.53% | 0.13% | 625.40 |

### *F. Summary and Implications of Penalty-based Approach*

The penalty-based approach reveals distinct patterns in borrower movement across all five metrics, demonstrating how penalty structures impact risk classification and financial inclusion.

**Metric 1** and **Metric 2** confirm the fundamental effect of penalty structures on *class distribution*. The percentage shifts show borrowers systematically move toward the risk class influenced by *the penalty type*. For instance, Pen4 models induce mass movement into class 4, while Pen0-2 causes a shift into classes 0, 1, and 2. The trend is highly consistent across all penalty types. Additionally, *penalty value* influences the intensity of these shifts, with stronger penalties amplifying movement while weaker penalties produce weaker effects. The most notable exception is Pen0 models, where no significant movement occurred initially. This anomaly led to an extended observation, which revealed that penalty values above 10,000 were required to trigger substantial migration into class 0.

**Metric 3**, **Metric 4**, and **Metric 5** provide insight into *class movement*. **Metric 3** shows that penalties targeting low-risk classes (such as Pen0-2 and Pen1-0) create substantial downward movement. In contrast, high-risk class penalties (such as Pen4) result in minimal movement to lower classes, forcing borrowers to remain in or move toward higher-risk classifications. **Metric 4** confirms that upward shifts are primarily concentrated in penalty types targeting higher-risk classes. However, the extent of these shifts is heavily influenced by penalty magnitude, with small values leading to weak reclassification effects and large values causing dramatic shifts.

The inclusion ratio (**Metric 5**) further validates the influence of penalty structures on financial inclusion. Models where penalties push borrowers downward, especially in extended Pen0 cases, demonstrate high inclusion ratios, reaching values above 40,000. Meanwhile, penalties targeting higher-risk classes yield low inclusion ratios.

Importantly, Metrics 1 to 5 analyses also revealed ***specific threshold values for each penalty type at which borrower reclassification behavior shifts significantly***. For example, in Pen0, a dramatic change was observed between Pen0_VAL9050 and Pen0_VAL9060, where classification suddenly concentrated into Class 0. Similar threshold points were detected for Pen1 through Pen4, with comparable behavioral shifts occurring between Pen1_VAL750–760, Pen2_VAL480–490, Pen3_VAL1280–1290, and Pen4_VAL690–700. These consistent thresholds were not only evident in distributional metrics (Metric 1 and 2) but also in movement metrics (Metric 3, 4, and 5). This alignment across all metrics reinforces the reliability of these thresholds and highlights their value for guiding future penalty calibration.

These findings suggest that ***penalty-based models are effective for borrower reclassification and redistribution*** but *must be carefully tuned to align with inclusion objectives*. The results confirm that penalties targeting low-risk classes with sufficiently large values drive significant borrowers to the lower class. Additionally, extended observations highlight the importance of testing models beyond conventional ranges to capture their full impact. The broader implication of this study is that penalty-based mechanisms can shape borrower risk distribution, but their effectiveness depends on *penalty type* and *penalty value*.

### 8.4.3. Results of Hybrid Feature Penalty Tuning (HFPT) Approach

The HFPT approach integrates the Feature Weight and Penalty-based approaches to explore how their combination can influence borrower reclassification. The HFPT experiment evaluates 629 models by combining different *penalty types*, *penalty values*, *feature reductions*, and *feature configurations*. 17 **penalty types** define how penalties are distributed across risk classes, from narrowly targeting specific classes (e.g., Pen4 penalizing only Class 4) to broader setups like Pen0-2 targeting Classes 0–2. **Penalty values** are set at four values (500, 1000, 3000, 5000) to test degrees of intensity. **Feature reductions** are applied at factors of 0.1, 0.5, and 1, altering the influence of OVER_TIME and OVER_INT. *The complete table of all 629 models* is provided in **Appendix 8 and 9**.

### *A. Metric 1: Risk Class Distribution (array of %)*

Metric 1 examines how the two approaches interact in redistributing borrowers across risk classes. In this section, we visualize redistribution for each penalty's dominant class (e.g., Class 4 for Pen4. Class 3 for Pen3, etc) to simplify analysis. Due to space constraints, only five *penalty types* (Pen4, Pen3, Pen2, Pen1, and Pen0) are shown here. The visualization for all class distributions and complete results are provided in Appendix 8 and 9, which confirms consistent patterns across all penalty types.

#### *1. Penalty Targeting Class 4 (Pen4)*

HFPT consistently mirrors the pattern in Penalty-Only models, reaffirming that penalty configurations remain the dominant force in reclassification. In cases with *high penalty values* like Pen4_VAL10000 or VAL3000, nearly all borrowers are assigned to Class 4 regardless of feature reductions. As shown in Figure 73, the number of borrowers in Class 4 remains unchanged, indicating that even substantial reductions in OVER_TIME or OVER_INT have a negligible impact under high *penalty values*.

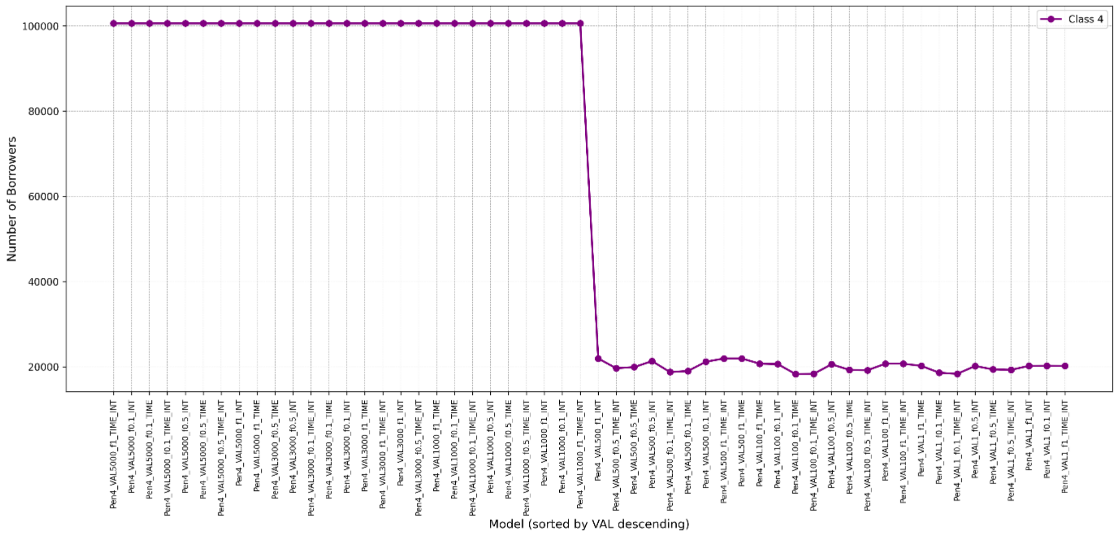


*Figure 73. Distribution of Dominant Class 4 in HFPT Pen4*

However, *when penalties are reduced* to VAL500 or VAL100, feature modifications become more influential. The introduction of OVER_TIME reductions significantly shifts borrowers toward lower-risk classes. For instance, in Pen4_VAL500_f0.1_TIME_INT, Class 1 becomes dominant (53.59%), replacing the originally concentrated distribution in Class 4. This shift is especially visible in the middle portion of the curve in Figure 73, where borrower distribution becomes more varied and responsive to feature weight adjustments. The following table shows several examples of the impact of feature reduction.

| Pen4 examples | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 | Explanation |
|---|---|---|---|---|---|---|
| Pen4_VAL5000 (Penalty-Only) | 0.03% | 0.01% | 0.00% | 0.00% | 99.96% | With relatively ***high penalty values***, feature reduction gives no impact |
| Pen4_VAL5000_f0.1_TIME_INT | 0.03% | 0.01% | 0.00% | 0.00% | 99.96% | |
| Pen4_VAL500 (Penalty-Only) | 20.11% | 20.70% | 18.99% | 18.41% | 21.79% | With relatively ***low penalty values***, feature reduction becomes more influential in HFPT models. |
| Pen4_VAL500_f0.1_TIME_INT | 27.26% | 53.59% | 0.43% | 0.10% | 18.64% | |
| Pen4_VAL100 (Penalty-Only) | 20.12% | 20.86% | 18.98% | 19.46% | 20.57% | |
| Pen4_VAL100_f0.1_TIME_INT | 21.75% | 59.65% | 0.35% | 0.05% | 18.20% | |

This pattern suggests that HFPT is a flexible tuning mechanism under ***moderate penalties values***. While penalties still shape the distribution movement, feature reductions provide more influence when there is still room for class redistribution.

#### *2. Penalty Targeting Class 3 (Pen3)*

A similar pattern emerges in Pen3. With high penalty values like Pen3_VAL5000, borrower distribution is heavily concentrated in Class 3. Figure 74 shows that configurations above a particular threshold yield stable distributions. However, as the penalty decreases, particularly below that threshold, feature reductions drive more volatility depending on the magnitude of feature reductions.

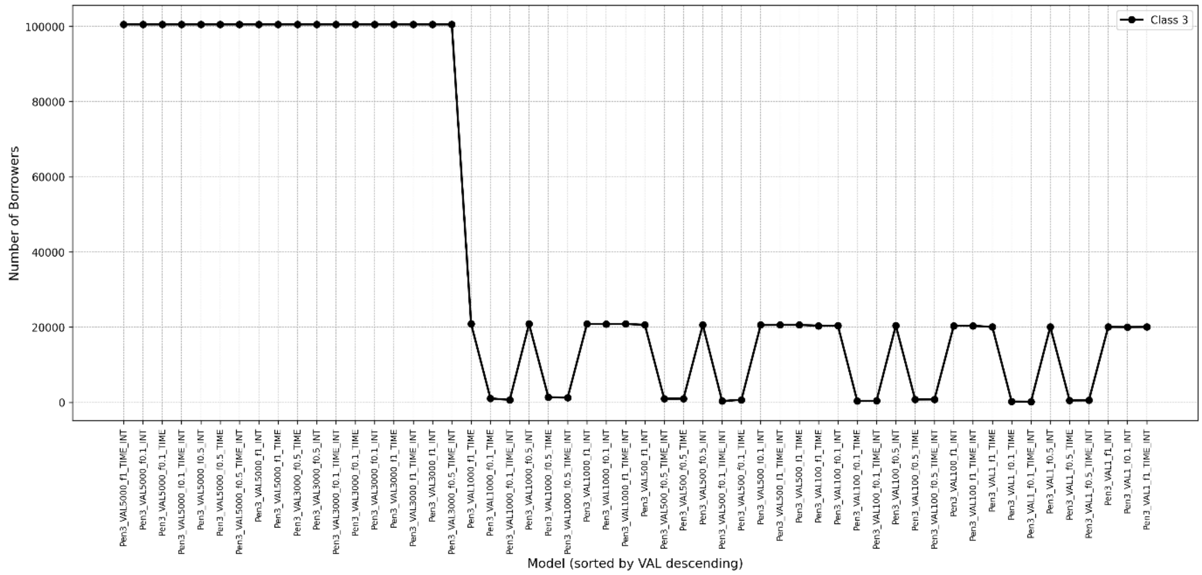


*Figure 74. Distribution of Dominant Class 3 in HFPT Pen3*

The following table shows several examples of the impact of feature reduction on Pen3.

| Pen3 examples | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 | Explanation |
|---|---|---|---|---|---|---|
| Pen3_VAL5000 (penalty only) | 0.06% | 0.03% | 0.00% | 99.90% | 0.01% | With relatively ***high penalty values***, feature reduction gives no impact |
| Pen3_VAL5000_f0.1_TIME | 0.06% | 0.03% | 0.00% | 99.90% | 0.01% | |
| Pen3_VAL500 (penalty only) | 20.13% | 20.73% | 18.87% | 20.50% | 19.77% | With relatively ***low penalty values***, feature reduction becomes more influential in HFPT models. |
| Pen3_VAL500_f0.1_TIME_INT | 74.20% | 7.27% | 0.32% | 0.37% | 17.84% | |
| Pen3_VAL100 (penalty only) | 20.13% | 20.90% | 18.85% | 20.25% | 19.87% | |
| Pen3_VAL100_f0.1_TIME_INT | 41.61% | 39.90% | 0.21% | 0.42% | 17.85% | |

### 3. *Penalty Targeting Class 2 (Pen2)*

In Pen2, severe penalty values (VAL3000, VAL1000) produce a uniform concentration in Class 2. This changes drastically after a particular threshold. In Figure 75, a sharp drop is observed just after the threshold value, reflecting a more dynamic role of features in reshaping class distribution.

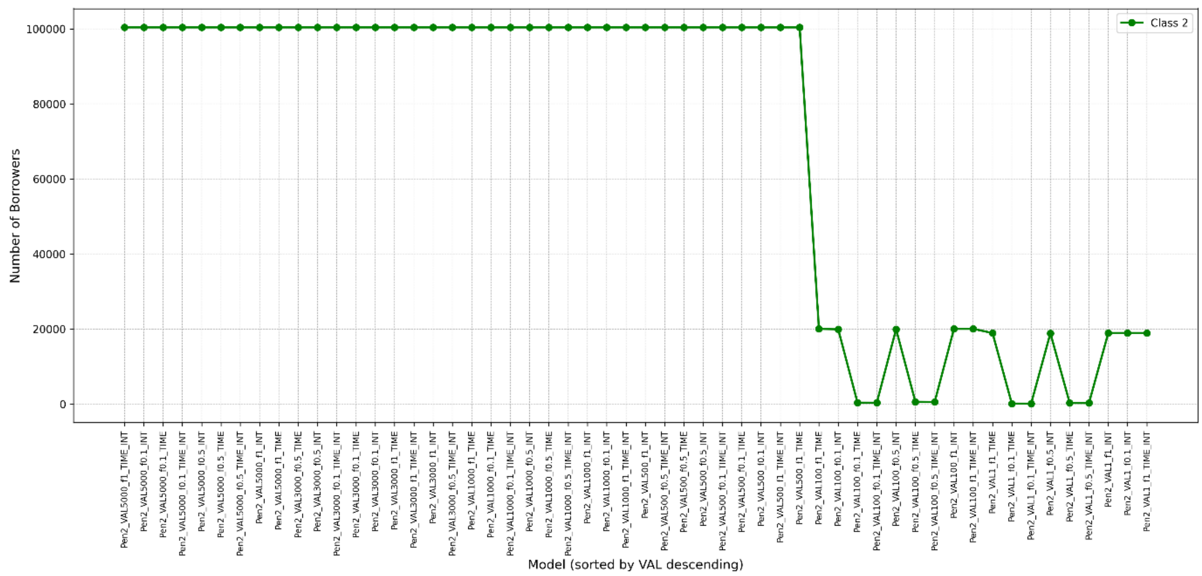


*Figure 75. Distribution of Dominant Class 2 in HFPT Pen2*

The following table shows several examples of the impact of feature reduction on Pen2.

| Pen2 examples | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 | Explanation |
|---|---|---|---|---|---|---|
| Pen2_VAL5000 (penalty-Only) | 0.03% | 0.03% | 99.75% | 0.02% | 0.17% | With relatively ***high penalty values***, feature reduction gives no impact |
| Pen2_VAL5000_f0.1_TIME_INT | 0.03% | 0.03% | 99.75% | 0.02% | 0.17% | |
| Pen2_VAL100 (Penalty-Only) | 20.12% | 20.09% | 19.92% | 19.84% | 20.04% | With relatively ***low penalty values***, feature reduction becomes more influential in HFPT models. |
| Pen2_VAL100_f0.1_TIME_INT | 37.59% | 43.90% | 0.36% | 0.36% | 17.80% | |
| Pen2_VAL1(Penalty-Only) | 20.12% | 21.06% | 18.81% | 19.94% | 20.07% | |
| Pen2_VAL1_f0.1_TIME_INT | 46.02% | 35.50% | 0.10% | 0.17% | 18.21% | |

### *4. Penalty Targeting Class 1 (Pen1)*

The same phenomenon is present in Pen1. High penalties dominate classification toward Class 1 (Figure 76). However models below a threshold display distribution changes.

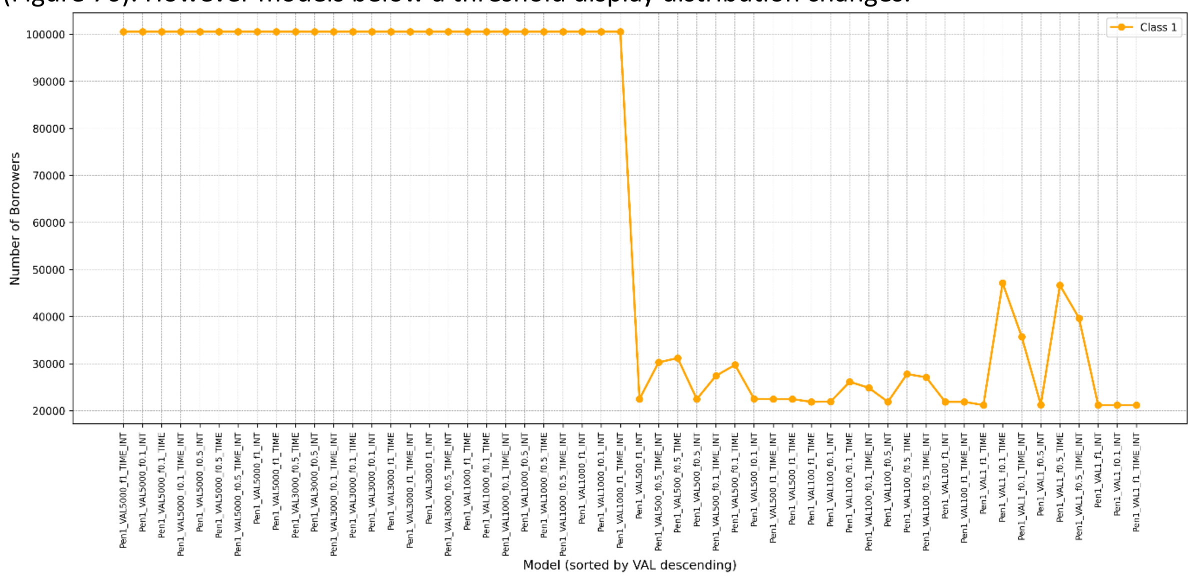


*Figure 76. Distribution of Dominant Class 1 in HFPT Pen1*

The following table shows several examples of the impact of feature reduction on Pen1.

| Pen1 examples | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 | Explanation |
|---|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| Pen1_VAL5000 (penalty-only) | 0.002% | 99.90% | 0.00% | 0.00% | 0.10% | With relatively ***high penalty values***, feature reduction gives no impact |
| Pen1_VAL5000_f0.1_TIME_INT | 0.002% | 99.90% | 0.00% | 0.00% | 0.10% | |
| Pen1_VAL500(penalty-only) | 19.28% | 22.33% | 18.54% | 19.88% | 19.97% | With relatively ***low penalty values***, feature reduction becomes more influential in HFPT models. |
| Pen1_VAL500_f0.5_TIME_INT | 50.61% | 30.08% | 0.20% | 0.39% | 18.72% | |
| Pen1_VAL100 (penalty-only) | 19.79% | 21.74% | 18.53% | 19.95% | 19.98% | |
| Pen1_VAL100_f0.1_TIME_INT | 57.42% | 24.71% | 0.03% | 0.05% | 17.79% | |

### *5. Penalty Targeting Class 0 (Pen0)*

Pen0 follows the same pattern as other penalty types: HFPT becomes effective only when penalty values fall below a certain threshold. However, the required penalty value to shift borrower distributions is substantially higher than in other configurations. As a result, HFPT only begins to produce visible reclassification effects when penalty values drop below Pen0_VAL9060, making this the highest threshold across all penalty types.

To capture this pattern, we include more models in the analysis (Figure 77) to reflect the broader penalty range needed before HFPT effects can be observed. In high-penalty settings, such as Pen0_VAL100000, borrower distribution remains concentrated in Class 0 regardless of any feature weight adjustment. Once the value drops below ~9000, feature reductions, especially on OVER_TIME, begin to influence classification, pushing borrowers into neighboring classes. The gradual shift in the figure confirms that Pen0 behaves like other penalty types but requires a much wider penalty scale to observe comparable transitions.

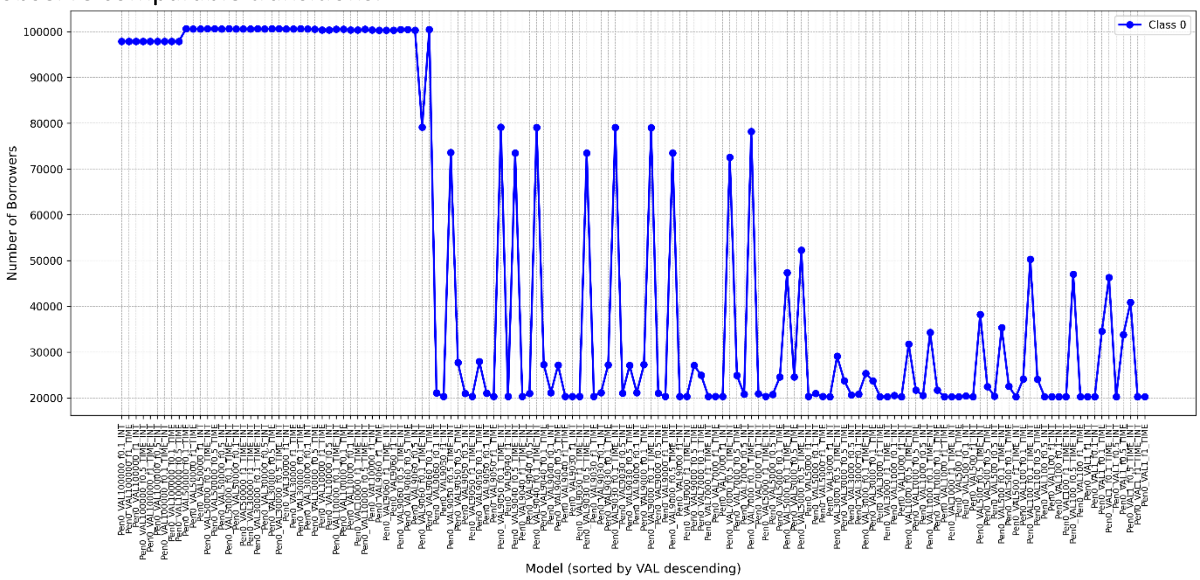


*Figure 77. Distribution of Dominant Class 0 in HFPT Pen0*

The following table shows several examples of the impact of feature reduction on Pen0.

| **Pen0 examples** | **Class 0** | **Class 1** | **Class 2** | **Class 3** | **Class 4** | **Explanation** |
|---|---|---|---|---|---|---|
| Pen0_VAL100000 (Penalty-only) | 97.26% | 0.03% | 0.005% | 0.62% | 2.09% | With relatively ***high penalty values***, feature reduction gives no impact |
| Pen0_VAL100000_f0.1_TIME_INT | 97.26% | 0.03% | 0.005% | 0.62% | 2.09% | |
| Pen0_VAL500 (Penalty-only) | 20.14% | 20.85% | 19.02% | 19.97% | 20.02% | With relatively ***low penalty values***, feature reduction becomes more influential in HFPT models. |
| Pen0_VAL500_f0.1_TIME_INT | 35.11% | 46.91% | 0.06% | 0.12% | 17.80% | |
| Pen0_VAL100 (Penalty-only) | 20.13% | 20.88% | 19.00% | 19.91% | 20.08% | |
| Pen0_VAL100_f0.1_TIME_INT | 49.98% | 32.04% | 0.03% | 0.12% | 17.81% | |

In conclusion, Metric 1 confirms that *penalty configurations remain the dominant factor in shaping borrower distribution*, while feature weight reductions act as *a refinement tool* that becomes effective only when penalty values are below certain thresholds. This threshold behavior in HFPT *mirrors the patterns observed in penalty-only models*, with reclassification effects emerging most visibly once penalty values drop below critical points, specifically VAL9060 for Pen0, VAL760 for Pen1, VAL490 for Pen2, VAL1290 for Pen3, and VAL700 for Pen4. Pen0 requires the highest penalty value before any distributional shift occurs due to the disproportionately large share of borrowers' data in Class 0. These insights are valuable for inclusion by design, as they provide empirical guidance on configuring penalty values to avoid excessive concentration in specific classes while enabling HFPT to redistribute borrowers more equitably. These findings reinforce *the role of HFPT not as a replacement for a penalty-based approach but as a complementary tuning mechanism* that can improve borrower inclusion outcomes when structural penalty pressure is moderated.

However, this study does not further investigate the specific patterns of redistribution that occur in the moderate-penalty where feature reductions begin to influence outcomes. For example, while we observe that feature tuning can shift borrower distributions away from penalized classes under moderate penalty values, we do not analyze *why these shifts occur* at certain magnitudes or *why particular risk classes experience more significant movement than others*. Future research must examine these dynamics more systematically.

***B. Metric 2: Risk Class Shift (array of %)***

Metric 2 measures how HFPT models shift borrower distributions relative to the base model rather than just examining their internal distributions. The HFPT approach, like the penalty-based approach, heavily restructures borrower distributions in proportion to *the penalty type* and *value*. High penalty values (e.g., 5000 or 3000) create substantial deviations from the base model, particularly in models that target specific risk classes. HFPT does not alter outcomes in these cases, as the underlying penalty already drives near-total concentration. For example, in Pen4 models with high penalty values, Class 4 absorbs nearly the entire borrower population, and this holds for both Penalty-Only and HFPT configurations, as in the following table.

| Configuration | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 |
|---|---|---|---|---|---|
| Pen4_VAL5000 (Penalty-Only) | -99.86% | -99.95% | -100% | -100% | 398.17% |
| Pen4_VAL5000_f0.1_TIME | -99.86% | -99.95% | -100% | -100% | 398.17% |
| Pen4_VAL1000 (Penalty-only) | -99.86% | -99.95% | -100% | -100% | 398.17% |
| Pen4_VAL1000_f0.5_TIME_INT | -99.86% | -99.95% | -100% | -100% | 398.17% |

This pattern confirms that feature-based changes are ineffective once penalties fully dominate reclassification. The same holds for Pen2 high-value models, as in the following table.

| Configuration | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 |
|---|---|---|---|---|---|
| Pen2_VAL5000 (Penalty-Only) | -99.9% | -99.8% | +430.3% | -99.9% | -99.1% |
| Pen2_VAL5000_f0.5_TIME | -99.86% | -99.83% | 430.35% | -99.92% | -99.13% |

Furthermore, **feature reductions only become relevant when penalty effects are relatively lower.** When penalty values are moderate or low, HFPT affects borrower shifts meaningfully. In these settings, feature reductions drive deviation patterns that diverge sharply from the penalty-only version. For example, Pen4_VAL500's penalty-only model shows only slight upward movement into Class 4, while the HFPT version shifts many borrowers downward.

| Configuration | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 |
|---|---|---|---|---|---|
| Pen4_VAL500 (Penalty-Only) | -0.05% | -1.73% | +0.95% | -7.66% | +8.60% |
| Pen4_VAL500_f0.1_TIME_INT | 35.49% | 154.44% | -97.74% | -99.52% | -7.19% |
| Pen4_VAL500_f0.5_TIME | 15.24% | 166.17% | -96.70% | -98.24% | -1.45% |

Similar effects are observed in Pen2_VAL100 as in the following table. In these models, HFPT reinforces reclassification away from the penalized class, pushing borrowers toward lower classes.

| Configuration | Class 0 | Class 1 | Class 2 | Class 3 | Class 4 |
|---|---|---|---|---|---|
| Pen2_VAL100 (Penalty-Only) | 0.00% | -4.60% | +5.90% | -0.50% | -0.10% |
| Pen2_VAL100_f0.1_TIME_INT | 86.79% | 108.42% | -98.09% | -98.22% | -11.30% |
| Pen2_VAL100_f0.5_TIME_INT | 86.45% | 101.78% | -97.16% | -96.35% | -6.71% |

The comparison with the base model confirms ***that penalties remain the dominant factor in altering borrower distributions****, while feature-based modifications only introduce additional deviation when penalty values are moderate*.

### *C. Metric 3: Borrower Shift to Lower Risk Classes (%)*

Borrower movement toward lower risk classes in the HFPT approach remains primarily influenced by *penalty type* and *penalty value*, similar to the penalty-based approach. High penalty values that already force borrowers into specific classes leave little room for feature modifications to further influence movement. In these cases, any feature adjustments do not alter borrower distributions significantly. For example, Pen4_VAL5000's penalty-only configuration results in only 0.01% of borrowers moving to a lower class. When HFPT is applied, even under substantial feature adjustments (e.g., TIME_INT at f0.1), the result remains the same, indicating that feature-based adjustments cannot override penalty-dominated outcomes.

| Configuration | Move to Lower Class (%) |
|---|---|
| Pen4_VAL5000 (Penalty-Only) | 0.01 |
| Pen4_VAL5000_f0.1_TIME_INT | 0.01 |

However, when penalties allow more flexibility in borrower placement, typically under moderate penalty values, HFPT shows a much stronger effect. In Pen4_VAL500, the penalty-only model moves 0.07% of borrowers downward. With HFPT adjustments using TIME_INT at f0.1, the proportion rises sharply to 45.90%.

| Configuration | Move to Lower Class (%) |
|---|---|
| Pen4_VAL500 (Penalty-Only) | 0.07 |
| Pen4_VAL500_f0.1_TIME_INT | 45.90 |

A similar pattern emerges in Pen2, where extreme penalty configurations also show minimal downward reclassification, limiting the influence of HFPT. For example, Pen2_VAL3000's penalty-only model yields only 39.83% downward movement. Applying HFPT, the outcome remains at 39.83%.

| Configuration | Move to Lower Class (%) |
|---|---|
| Pen2_VAL3000 (Penalty-Only) | 39.83 |
| Pen2_VAL3000_f0.1_TIME_INT | 39.83 |

However, when the penalty values are more moderate, feature adjustments sharply increase the proportion of borrowers reclassified into lower-risk classes. In Pen2_VAL100, the penalty-only model records a 0.18% downward movement. HFPT with TIME_INT at f0.1 pushes this to 49.29%, a significant jump that clearly illustrates the fine-tuning power of TIME-based adjustments when the penalty structure is permissive.

| Configuration | Move to Lower Class (%) |
|---|---|
| Pen2_VAL100 (Penalty-Only) | 0.18 |
| Pen2_VAL100_f0.5_TIME_INT | 49.29 |

The same interaction appears in Pen0-1. Under high penalty configurations such as Pen0-1_VAL3000, the penalty-only model yields a 59.14% downward shift. Even with strong HFPT settings (e.g., TIME_INT at f0.1), the result does not change much to 60.06%.

| Configuration | Move to Lower Class (%) |
|---|---|
| Pen0-1_VAL3000 (Penalty-Only) | 59.14 |
| Pen0-1_VAL3000_f0.1_TIME_INT | 60.06 |

In contrast, Pen0-1 exhibits a sharp increase in downward movement when the penalty value is reduced. In Pen0-1_VAL100, the penalty-only model sees only **0.43%** lower movement. This increases dramatically under HFPT: applying TIME_INT at f0.1 shifts **52.96%** of borrowers downward.

| Configuration | Move to Lower Class (%) |
|---|---|
| Pen0-1_VAL100 (Penalty-Only) | 0.43 |
| Pen0-1_VAL100_f0.1_TIME_INT | 52.96 |

Even at the lowest penalty (VAL1), where the penalty-only model still yields just **0.00%** downward movement, HFPT introduces a massive shift. Applying TIME_INT at f0.1 results in a **51.20%** downward movement, underscoring that HFPT only becomes effective when penalties are not already saturated.

| Configuration | Move to Lower Class (%) |
|---|---|
| Pen0-1_VAL1 (Penalty-Only) | 0.00 |
| Pen0-1_VAL1_f0.1_TIME_INT | 51.20 |

This pattern is consistent across all 17 penalty types explored in this study, including Pen0, Pen0-1, Pen0-2, Pen2, and Pen4. In every case, feature-based reductions only introduce visible changes in borrower distribution when the underlying penalty effect is moderate. This confirms that ***HFPT operates as a refinement mechanism, with its influence constrained or enabled by the severity of penalty configurations***.

### *D. Metric 4: Borrower Shift to Higher Risk Classes (%)*

As in penalty-based models, the penalty type and value also largely determine borrower movement to higher-risk classes in HFPT. When high penalty values are applied to push borrowers toward a target class, the penalty-only configuration already dictates most of the shift. HFPT does not exacerbate these movements. Instead, it mimics the pattern observed under penalty-only conditions, even when feature reductions are applied. This behavior is particularly important, as it confirms that ***HFPT does not introduce additional upward shifts that might be undesirable in inclusive lending contexts***.

Pen4's penalty-only models, such as Pen4_VAL5000, already generate high upward movement (e.g., 79.91%) with negligible downward movement, resulting in a low Inclusion Ratio. When HFPT is applied the proportion of upward movement remains similar or only slightly changes. In more moderate penalty settings like Pen4_VAL500, HFPT introduces sharper feature-driven changes, but ***upward shifts are still small***. For example, while penalty-only at Pen4_VAL500 yields just 1.98% upward movement, applying HFPT at f0.5_TIME_INT even reduces this to 0.5%.

| Configuration | Movement to higher risk class (%) |
|---|---|
| Pen4_VAL5000 (Penalty-Only) | 79.91 |
| Pen4_VAL5000_f0.1_TIME_INT | 79.91 |
| Pen4_VAL5000_f0.5_TIME_INT | 79.91 |
| Pen4_VAL500 (Penalty-Only) | 1.98 |
| Pen4_VAL500_f0.5_TIME_INT | 0.50 |
| Pen4_VAL500_f0.1_TIME | 0.67 |

Similar results are found in Pen2. When penalty values are high, penalty-only and HFPT models result in a similar upward movement. For example, Pen2_VAL3000's penalty-only model causes 41.26% of borrowers to move up. This figure remains stable across all HFPT variants, including those with strong TIME reductions. When penalties are moderate (e.g., Pen2_VAL100), HFPT introduces more visible changes. Still, the shift to higher classes remains controlled. Pen2_VAL100_f0.5_TIME_INT shows only 0.12% upward movement, confirming that HFPT does not introduce unwanted surges.

| Configuration | Upward Shift (%) |
|---|---:|
| Pen2_VAL3000 (Penalty-Only) | 41.26 |
| Pen2_VAL3000_f0.5_TIME_INT | 41.26 |
| Pen2_VAL100 (Penalty-Only) | 1.02 |
| Pen2_VAL100_f0.5_TIME_INT | 0.12 |
| Pen2_VAL100_f0.1_TIME_INT | 0.14 |

In Pen0-1, upward movement is inherently minimal under penalty-only settings, and HFPT preserves this favorable behavior. For instance, the penalty-only version of Pen0-1_VAL1000 yields 0.11% upward movement. With HFPT at f0.5_TIME_INT, the movement even reduced to 0.06%, showing that **HFPT does not trigger unexpected shifts**. Across all Pen0-1 variants, upward movement under HFPT remains low, even with aggressive feature reduction value.

| Configuration | Upward Shift (%) |
|---|---:|
| Pen0-1_VAL1000 (Penalty-Only) | 0.11 |
| Pen0-1_VAL1000_f0.5_TIME_INT | 0.06 |
| Pen0-1_VAL100 (Penalty-Only) | 0.08 |
| Pen0-1_VAL100_f0.5_TIME_INT | 0.05 |
| Pen0-1_VAL100_f0.1_TIME_INT | 0.05 |

In conclusion, Metric 4 confirms that ***HFPT does not amplify undesirable shifts toward higher-risk classes***. Even with strong feature reductions, the upward movement remains consistent with, or only slight changes, the levels induced by penalty-only models. This indicates that HFPT models follow the original penalty-driven structure and preserve desirable risk allocation patterns.

### *E. Metric 5: Inclusivity Ratio*

The Inclusivity Ratio is inherently shaped by the factors determining Metrics 3 and 4. Since Metric 3 tends to increase only when the initial borrower distribution is moderate, and Metric 4 generally remains stable under HFPT, it follows that Metric 5 behaves similarly. When penalties already dominate the distribution, leaving no room for additional downward shifts, HFPT minimally affects the Inclusion Ratio. However, when the penalty value is moderate and borrower distribution remains flexible, especially toward lower-risk categories, ***HFPT significantly boosts downward movement*** while suppressing upward shifts. This leads to substantial increases in the Inclusion Ratio, often nonlinearly, depending on how strongly the feature reductions are applied.

This pattern is evident in Pen4. In penalty-only settings with extreme values such as Pen4_VAL5000, the Inclusion Ratio remains flat at 0.00014, reflecting negligible downward movement and overwhelming upward reclassification. Applying HFPT in these same configurations does not change the outcome, Inclusion Ratios remain low regardless of reduction type or strength. However, once penalties are reduced to a moderate level (e.g., Pen4_VAL500 or VAL100), the influence of feature reductions becomes visible. For example, Pen4_VAL500's ratio under penalty-only is 0.036. When HFPT is applied with f0.5_TIME_INT, this ratio jumps to 91.63. In more aggressive settings like Pen4_VAL100_f0.5_TIME_INT, the ratio exceeds 200.

| Configuration | Inclusion Ratio |
|---|---|
| Pen4_VAL5000 (Penalty-Only) | 0.0001 |
| Pen4_VAL5000_f0.1_TIME_INT | 0.0001 |
| Pen4_VAL500 (Penalty-Only) | 0.0360 |
| Pen4_VAL500_f0.5_TIME_INT | 91.6300 |
| Pen4_VAL100 (Penalty-Only) | 0.0920 |
| Pen4_VAL100_f0.5_TIME_INT | 207.1400 |

A similar effect is observed in Pen2. With high penalty values (e.g., Pen2_VAL1000 or Pen2_VAL500), the Inclusion Ratio remains at 0.97 in penalty-only and HFPT configurations. However, the shift is dramatic when the penalty is reduced to Pen2_VAL100. HFPT raises the Inclusion Ratio from just 0.18 (penalty-only) to over 400 in Pen2_VAL100_f0.5_TIME_INT, with similarly high results in other TIME-based variants.

| Configuration | Inclusion Ratio |
|---|---|
| Pen2_VAL1000 (Penalty-Only) | 0.97 |
| Pen2_VAL1000_f0.1_TIME_INT | 0.97 |
| Pen2_VAL100 (Penalty-Only) | 0.18 |
| Pen2_VAL100_f0.5_TIME_INT | 406.66 |

This behavior is observed consistently across all 17 penalty types used in this study, including Pen0, Pen0-1, Pen0-2, and others. **The Inclusion Ratio under HFPT is primarily driven by Metric 3**, which reflects the proportion of borrowers moving to lower-risk classes. Importantly, the value of Metric 3 under HFPT is itself shaped by the initial distribution and degree of movement observed in the penalty-only models. That is when the penalty-only configuration creates a more distributed or moderate shift, HFPT adjustments, especially those involving TIME reductions, can amplify downward movement and lead to significantly higher Inclusion Ratios. Conversely, when penalty-only models already induce concentrated distributions with little downward movement, the impact of HFPT on inclusion remains limited. This dynamic consistently appears across all penalty types examined.

### *F. Summary and Implications of HFPT*

The HFPT approach combines feature weight adjustments with penalty-based approaches and clearly shows how these two approaches interact in shaping borrower reclassification. The findings across Metrics 1 to 5 reveal consistent distribution, movement, and inclusion patterns, highlighting the boundaries and opportunities of this hybrid approach.

**Metric 1** and **Metrics 2** confirm that penalties remain the dominant force in shaping borrower distribution. When penalties are relatively high, the penalty structure almost entirely dictates borrower movement, leaving little room for feature-based adjustments to introduce further shifts. However, in models with *moderate penalties*, where borrowers are more evenly spread across risk classes, HFPT modifications, especially those reducing OVER_TIME, begin to show influence by pushing more borrowers toward lower-risk categories. This effect serves as **a *fine-tuning mechanism*** that works within the structural space left by the penalties. By leveraging HFPT in this moderate zone, designers can improve access for borderline borrowers who would otherwise remain in higher-risk classes under rigid penalty settings.

**Metric 3** and **Metric 4** further clarify how HFPT behaves under varying penalty settings. For **Metric 3**, HFPT amplifies movement to lower-risk classes with moderate penalties. For instance, in Pen4_VAL500, the downward movement increased from just 0.07% of borrowers under penalty-only to over 45.90% with HFPT. In contrast, even strong feature reductions do not trigger additional downward movement when penalties are already high. In **Metric 4**, the results are more stable: HFPT does not increase undesirable upward movement to higher-risk classes. Even with aggressive feature adjustments, the proportion of borrowers moving upward remains consistent with, or even lower than, the results in penalty-only models.

**Metric 5** ties these outcomes together by examining the Inclusion Ratio. Because this metric depends on Metric 3 and 4, its pattern closely follows the combined downward and upward shifts behavior. The results highlight that HFPT's effect on the Inclusion Ratio depends on the penalties' magnitude and moderate distributional shifts. When penalties have induced extreme movement, HFPT modifications contribute little to inclusion. However, when penalties allow some flexibility in distribution, particularly in lower-risk classes, feature reductions amplify downward movement and lead to significantly higher Inclusion Ratios.

***The HFPT approach offers a practical tool for exploring how penalties and features jointly shape borrower distribution and movement***. By simulating reductions in feature weight across different penalty settings, HFPT helps identify which features significantly affect reclassification outcomes. This makes HFPT especially valuable for adapting risk-scoring models to new datasets, as *users can replicate the same testing logic to detect impactful features and conduct further sensitivity analysis*.

### 8.5. Conclusion

The simulations demonstrate that Hypotheses A1 and A2 offer valuable insights for improving inclusion in financial lending. The table below summarizes the hypothesis results.

*Table 43. Summary of Hypotheses and Results for Hypotheses A1 and A2*

| Hypothesis | Description | Conclusion | Result |
|---|---|---|---|
| Hypothesis A1 | Adding additional data variables increases loan recommendations, shifting more borrowers to lower-risk classification. | Not Supported | Small, consistent shifts to lower-risk categories were observed. However, these changes alone did not yield substantial increases in inclusion. |
| Hypothesis A2 | Tuning model parameters increases loan recommendations, shifting more borrowers to lower-risk classification. | Supported | Parameter tuning significantly improved loan inclusion, enabling a broader range of micro-enterprises to access credit. |

The connection between these hypotheses and the findings from Chapter 7 becomes particularly evident during the testing of Hypothesis A2. The analysis reveals that certain borrower data features significantly influence loan recommendations. Notably, the influence of these features aligns with insights shared by stakeholders during the survey, reinforcing the importance of considering diverse borrowers' data in the loan approval process.

For **Hypothesis A1**, the results indicate that adding additional data attributes leads to small and consistent shifts toward lower-risk classifications. However, these changes were limited in magnitude and did not result in meaningful increases in inclusion across the tested models. While data enrichment contributes to finer borrower differentiation, its isolated effect was insufficient to confirm the hypothesis. Therefore, Hypothesis A1 is not confirmed, and complementary methods are needed to achieve substantial reclassification and inclusion improvements

For **Hypothesis A2**, the results highlight the impact of parameter tuning through three approaches: Feature Weight Adjustment, Penalty-Based Models, and Hybrid Feature Penalty Tuning (HFPT).

In ***the Feature Weight Adjustment***, reducing the influence of selected features, particularly OVER_TIME (delayed payment time) and OVER_INT (interest rate), affects borrower classification. The results show that decreasing the weight of OVER_TIME has a more pronounced effect than OVER_INT, particularly when reduction factors are small (e.g., 0.1 or 0.5). Parameter OVER_INT reduction has a weaker effect than OVER_TIME, indicating that *the OVER_TIME parameter is more influential in determining risk reclassification*. However, the precise redistribution patterns are difficult to control, as the effect does not exhibit a consistent or interpretable pattern across risk classes. While feature weight adjustment is highly effective in assessing the sensitivity of individual features, it does not provide sufficient insight into how borrowers are redistributed across risk classes. This limitation necessitates further experimentation with penalty-based models, which excel in analyzing class distribution sensitivity.

In ***the Penalty-Based Models*** experiment, *penalty type* and *penalty value* play interdependent roles in shaping borrower reclassification. ***Penalty type*** determines which risk classes experience forced borrower movement. Narrowly focused penalties, such as Pen4, concentrate shifts into a single class, whereas broader penalties, such as Pen0-2, distribute borrower movement across multiple risk categories. Meanwhile, ***penalty value*** controls the magnitude of borrower shifts. At high penalty values (e.g., 5000), the penalty assignment almost entirely influences borrower placement, creating extreme concentration effects. In contrast, the redistribution effect remains more balanced at lower penalty values (e.g., 500), allowing a wider spread of borrower movements across classes.

Furthermore, the analysis across all five metrics reveals that borrower behavior changes sharply at **specific penalty thresholds**, which differ for each penalty type. These thresholds represent critical points where borrower reclassification patterns change substantially. This consistency across metrics confirms that penalty effectiveness is not linear but instead depends on surpassing a critical value to trigger structural changes in borrower distribution. These findings highlight that ***penalty type*** sets *the structure of borrower classification changes*, **penalty value** controls *the intensity of the shift*, and ***penalty threshold*** is essential to *unlocking the actual impact of a given penalty configuration*.

During experimentation, several ***inclusion metrics were refined*** to more accurately reflect the effects of borrower reclassification. For instance, after observing unexpected distribution patterns at certain penalty thresholds, we refine the formulation of Metrics 3 and 5 to provide a more meaningful analysis. This process required re-running selected model configurations to confirm whether the metric adjustments aligned with observed behavior. As a result, the development of the metrics and the modeling process progressed iteratively, with each informing the other.

**The HFPT approach**, which integrates feature weight adjustments with penalty-based modifications, reveals that *penalties continue to dominate borrower movement*, but feature adjustments *serve as an amplifying mechanism*. When penalty values are high, feature modifications have little additional effect, as the penalty assignment already determines the borrower distribution. However, when penalties are moderate and low, feature reductions create additional redistribution effects, further enhancing movement. HFPT does not introduce new patterns of borrower movement but amplifies and extends penalty-driven trends. The largest inclusion gains are observed in models where penalties create partial borrower reclassification, allowing feature-based modifications to shift distributions further.

These results show that ***structured penalty-based approaches are an effective tool for controlling borrower classification, with feature adjustments acting as a secondary mechanism*** that enhances but does not replace penalty-driven effects. The most effective configurations for financial inclusion combine *moderate penalty values* with *targeted feature weight reductions*. This configuration enables controlled borrower movement while preserving balanced risk class distribution.

It is important to emphasize that the goal of this chapter is ***not to develop a new algorithm*** but to establish a practical method for analyzing sensitivity in borrower classification and understanding how inclusion outcomes shift under different model configurations. The focus lies in designing and testing a configurable framework that helps identify which parameters influence reclassification, how they interact, and how they can be adjusted to support the goal of improving inclusion.

**For policy-makers**, these findings underscore *the importance of setting clear feature selection and weighting guidelines*. Since minor adjustments to certain features can significantly alter borrower classification, regulations should promote transparency in selecting and weighing features. This ensures that credit assessments remain inclusive while preventing unintended distortions disadvantaging specific borrower segments. *Standardized evaluation criteria* and periodic audits can help maintain the integrity of these models while allowing for adaptive improvements.

Policy-makers should focus on *preventing extreme borrower concentration* by encouraging balanced penalty structures in regulating penalty-based approaches. Instead of relying solely on rigid penalties, frameworks should support hybrid strategies like HFPT, which integrates moderate penalties with feature-based adjustments. *Incentives for financial institutions* to adopt dynamic scoring mechanisms, ones that adjust based on borrower behavior rather than fixed penalty rules, can further improve access to credit while maintaining responsible lending standards.

Accordingly, ***we recommend using the HFPT tool as a practical instrument for policy-makers and practitioners to explore how penalty configurations influence borrower distribution***. This tool is particularly useful in ***identifying which features are most influential in driving borrower reclassification***, by leveraging the threshold values we have provided. For instance, in our dataset, the features OVER_TIME and OVER_INT emerged as key drivers influencing classification outcomes. When applied to different datasets, the tool can help users detect important features specific to their context. Moreover, since our dataset involves five classification outputs, we could define and test multiple penalty types, and this logic can be replicated for datasets with different classification schemes. While penalty types should be adapted to reflect each dataset's output structure, we specifically recommend the following threshold values as a reference: Pen0 (9050–9060), Pen1 (750–760), Pen2 (480–490), Pen3 (1280–1290), and Pen4 (690–700). These thresholds mark the points at which penalties begin to produce significant changes in borrower classification, offering a calibrated starting point for designing an inclusive scoring model.

# PART V: EPILOGUE

## Chapter 9: Conclusion

This study designs a Reference Architecture (RA) to improve the inclusion of marginalized borrowers in lending systems. The RA embeds the concept of inclusion by design, which integrates inclusion into all aspects of system development and evaluation. This study has three main objectives: *first*, to design a Reference Architecture that addresses the challenges faced by underserved borrower segments; *second*, to establish measurable inclusion indicators; and *third*, to respond to socio-technical challenges by incorporating design principles and architectural elements. Through this approach, this research seeks to create actionable pathways for improving financial inclusion.

This research used the Design Science Research (DSR) methodology to design a Reference Architecture through an iterative approach combining theoretical rigor and practical relevance. This study is guided by four research questions: RQ1: What are the socio-technical challenges to achieving inclusion in lending systems? RQ2: What indicators can measure inclusion within these systems? RQ3: What elements make up a Reference Architecture (RA) for an inclusive lending system? RQ4: What is the impact of the proposed RA on inclusion?

This chapter is divided into three sections. Section 9.1 presents the answers to the research questions. Section 9.2 discusses scientific and practical contributions. Section 9.3 addresses limitations and future research directions.

### 9.1. Addressing the Research Questions

#### 9.1.1. RQ1: What are the Socio-technical Challenges to Achieving Inclusion in Lending Systems?

This study identifies six categories of challenges to achieving inclusion in lending systems: Technology and Data, Financial lending, Organization, Regulation and Governance, Social and Cultural, and Literacy. Although a number of challenges are related to the RA development, the broad range of challenges shows the complexity of inclusion. A Reference Architecture, the goal of this research, is not sufficient alone. There are many challenges, ranging from technical to institutional, and they can be interdependent. While the literature emphasizes systemic and theoretical barriers, interview results highlight practical issues and stakeholders' concerns.

The literature highlights several issues in the **Technology and Data challenges** category; for example, many systems operate on fragmented infrastructures that lack scalability and modularity. Interview results show that borrower data is often incomplete, outdated, or unverifiable, especially for individuals outside the formal financial system. Furthermore, the inability to process or integrate alternative data sources restricts the ability to represent diverse borrower profiles. These limitations hinder the development of inclusive scoring systems. Furthermore, data issues reinforce information asymmetry, where borrowers lack access to and control over how their data is used in credit decisions.

The **financial lending challenges** category addresses the trade-off between profitability for lenders and lending platforms and affordability for marginalized segments. Lenders are more interested in profitability, whereas marginalized borrowers often cannot afford to pay high interest rates, high fees, or have rigid repayment terms. The literature highlights the challenge of creating fair assessment models with special attention to high-risk borrowers, proving that the lending terms can still be profitable even when providing loans to high-risk borrowers. However, lending systems tend to prioritize low-risk segments.

In the **Organization challenges** category, fintech companies face challenges as they balance operational feasibility and the goal of improving inclusion. For example, fintech companies have difficulty responding to limited and incomplete borrower information, particularly in informal sectors or underserved regions. Often, borrower profiles are insufficient to support meaningful assessment or are unavailable. Chapter 7 shows that lenders rely on available contextual data to make decisions on loan approval. Chapter 8 further demonstrated that borrower classifications shift significantly when data variables are enriched or adjusted. This underscores the need for fintech companies to implement organizational strategies that not only address data limitations but are also capable of integrating new data sources to improve profitability and inclusion. These challenges are complicated by reputational risks concerning data privacy and borrower protection.

One of the **regulatory challenges** categories contains the lack of coordination between regulators and financial institutions. The literature stresses the importance of having strong data protection laws and consistent policies. Interview results echoed this, focusing on how misaligned rules make it harder for borrowers in underserved areas to access credit, such as overlapping mandates among regulatory bodies. Interviews also emphasized how rigid rules, such as inflexible loan criteria, hinder inclusive product development. While the literature often frames these issues as systemic and long-term, interviews stressed the urgent need for practical adjustments, such as simplifying regulatory processes and fostering coordination among authorities.

**The social and cultural challenges** category in the literature contains social issues like systemic discrimination, such as gender biases that limit women's access to credit. The interviews added that illegal lending practices could impact trust in the lending system and discourage involvement. **Literacy challenges** category impact borrowers and lenders, limiting their ability to understand the financial terms and to navigate the digital systems. The literature emphasizes that low literacy often leads to poor loan management and higher default rates. Interviews revealed similar concerns about the limited understanding of interest rates, repayment terms, and financial planning.

The categories show many different challenges; however, not all identified challenges are addressed within the scope of this study. As stated in Chapter 1, this research focuses on challenges that can be directly addressed through a reference architecture. Future research is suggested to address broader socio-cultural, educational, and policy challenges. The following categories of challenges are within the focus of this study.

*The first* is **the Technology and Data challenges** category**.** Lending systems often operate in fragmented environments that lack scalable infrastructure, which results in challenges to process or integrate alternative data sources. The dependence on conventional data excludes marginalized groups, such as informal workers and micro-entrepreneurs. Data quality also remains a critical issue, as interviews highlight that borrower data is frequently outdated, incomplete, or unverifiable. This is further complicated by information asymmetry between borrowers and lenders, where borrowers do not understand how their data affects credit eligibility, while lenders, in turns, struggle to build sufficient confidence in risk assessments and become reluctant to extend credit to high-risk borrowers.

*The second* is **the Financial Lending challenges** category**,** which addresses the loan products and scoring models. *Loan products* are typically designed for borrowers with predictable incomes, disadvantaging those with irregular cash flows, such as farmers, daily laborers, and microenterprises. This situation is complicated by rigid repayment schedules that do not align with marginalized segments. Moreover, institutional policies are more focused on providing incentives to fintech companies with low default rates rather than those that improve inclusion. Therefore, the systems are designed to prioritize low-risk segments. Interviews confirm that current financial lending lacks the flexibility to serve diverse borrower profiles.

This study aims to address these challenges by developing a reference architecture, a structured design artifact that embeds inclusion by design and guide lending systems in overcoming these challenges.

### 9.1.2. RQ2: What indicators can measure inclusion within these systems?

Achieving financial inclusion in lending systems requires addressing the architectural challenges and developing a way to assess inclusion outcomes. While a widely acknowledged goal, inclusion remains an abstract concept without well-defined metrics to evaluate it. This study proposes a set of inclusion indicators to assess how the designed Reference Architecture (RA) supports inclusion. Research Question 2, "What indicators measure inclusion within these systems?" aims to translate inclusion into measurable indicators.

This study categorized inclusion metrics into four categories: ***penetration, financial, analytical,*** *and* ***literacy***. Penetration and Financial metrics address *who* is reached and *how equitable* the access is. Analytical metrics monitors *how inclusive* the data representation and scoring mechanisms are. Literacy metrics assess borrowers' and lenders' ability *to understand* the system. These categories are complementary: reaching a population (penetration) is insufficient if services are unaffordable (financial access), unfairly scored (analytical inclusion), or misunderstood by users (literacy).

Although this research *does not address literacy gaps* in the design of the RA, literacy metrics are included for evaluation purposes. While the architecture does not aim to provide education or overcome literacy, the RA includes features, such as contestation mechanisms and transparent scoring, that require a basic level of borrower understanding, which education can facilitate. Including literacy metrics helps ensure that the system is not only accessible but also usable to its intended users.

The proposed framework adopts the four metrics categories because each reflects a different requirement. *Penetration* focuses on who is reached; *Financial Access* considers what terms borrowers receive credit; *Analytical Inclusion* considers how borrowers are assessed by scoring mechanisms; and *Literacy* relates to whether users can understand and engage with the system. The explanation of each metric type is as follows.

***Penetration metrics*** consist of the indicators of physical access and digital access to monitor whether marginalized groups are excluded due to geographic or demographic structure. ***Financial Access metrics*** examine affordability issues to monitor whether marginalized segments can access based on their payment capacity. ***Analytical Inclusion metrics*** consist of data representation, algorithmic design for the scoring system, and transparency and interpretability of the outcome. ***Literacy metrics*** capture whether borrowers and lenders can understand and use the system. Although RA does not directly address literacy gaps, we keep providing literacy metrics for evaluation purposes. RA features such as contested decision-making and transparent scoring require a basic level of borrower understanding.

The answer to RQ2 transforms inclusion from *an abstract concept* into becoming *measurable and actionable*. These metrics support policy-makers in tracking progress, practitioners in refining the system, and researchers in advancing inclusion measurement. The metrics also reflect borrower and lender perspectives, as outlined in Chapter 4. Metrics like interest affordability, literacy, and algorithm transparency are designed to evaluate whether borrowers can access, understand, and benefit from the system. Meanwhile, indicators such as loan approval rates help assess lenders' behavior.

Furthermore, this research proposes a structured set of inclusion metrics based on the literature review and interviews. However, only three types of metrics were used in the evaluation of the RA: loan approval rates (Chapter 7), the inclusion ratio that compares movement of borrowers to lower and higher risk classes (Chapter 8), and the perceived impact of system features on inclusion (Chapter 6). These metrics were selected because they match the focus of each evaluation stage and can be assessed within the prototype, survey, and simulation settings. Chapter 6 explores perceived inclusion of RA features, Chapter 7 captures how enriched borrower profiles affect loan approval, and Chapter 8 assesses how algorithmic tuning changes borrower classification. In each case, the results indicate that the RA contributes to more inclusive outcomes within the scope of the study.

Other metrics, such as those related to regional equity, affordability, and literacy, require longitudinal data, real-world deployment, or user-level monitoring and were therefore excluded from the current evaluation scope. Moreover, these metrics are less suited to short-term or simulated testing and do not directly assess the architectural features of the RA.

### 9.1.3. RQ3: What elements make up a Reference Architecture for inclusive lending?

RQ3 is answered by identifying three elements that form the foundation of the architecture: Value-Based Requirements (VBRs), Design Principles (DPs), and Architectural Components. These elements form the RA as the design artifact of this research. The VBRs are about *the what*: the core values and requirements that are mandatory in the system. The DPs and Architectural Components are about *the how*: the DPs guide how the values are embedded into system design, while the components operationalize these principles through concrete functionalities and interactions across the architecture to support inclusion.

#### *A. Value-Based requirements*

The VBRs in this study are built around the concept of **inclusion by design**, which refers to *integrating inclusion concepts throughout the development and evaluation of lending systems*. The elicitation of VBRs in this study followed an inductive approach within the Value-Based Engineering (VBE) framework. This framework was selected because it provides a structured method to translate abstract inclusion values into concrete architectural requirements. It aligns with the study's goal to embed values systematically into system design. To guide this elicitation, we used *use-case diagrams* and *sequence diagrams* to identify the inclusion requirements. These diagrams helped identify potential exclusion points and define where specific system requirements should intervene. Following this step, stakeholder interviews were conducted to evaluate and expand the identified requirements. This research formulated **seven VBRs** as follows.

**Equal Access** highlights the need to ensure that borrowers, regardless of where they live or who they are, have comparable opportunities to obtain credit. This study defines the requirement equality of access as *the capacity to provide access based on an individual's creditworthiness, which is linked to their payment capacity, despite demographic profiles*. Achieving this requires addressing systemic challenges such as infrastructure limitations, data biases, and digital divides. Leveraging alternative data sources is expected to address these challenges.

**Inclusive Scoring** is a topic that is hardly addressed in the literature. This study defines the requirement of an inclusive scoring system as *having the ability to implement adaptive scoring algorithms that account for heterogeneous financial behaviors, particularly for marginalized segments*. Inclusive scoring uses alternative data to create a more complete picture of each borrower, especially for those often left out by traditional models. Processing this kind of data often relies on advanced machine learning, but technical sophistication alone is insufficient.

**Equitable distribution** examines whether credit goes mainly to certain borrowers while others are left out. In many systems, credit tends to flow more easily to urban areas or borrowers with established profiles, while others, such as rural households, small enterprises, or women, remain underserved. This study defines equitable distribution as avoiding this kind of concentration. The goal is to make credit allocation more balanced so that different groups have a fair chance of being included.

**Credit Schema for Marginalized Segments** tailors financial products to the specific needs of underserved populations, including microenterprises, smallholder farmers, and low-income households. This study defines the requirement for credit schema for marginalized segments as *the ability to develop flexible loan products with repayment structures that accommodate diverse borrower needs.* Some examples are seasonal loans, profit-sharing for small businesses, and microloans with lower interest rates for low-income groups.

**Perceived Societal Benefit** balances inclusion with financial sustainability, ensuring that lending systems benefit all stakeholders. This study defines the requirement for perceived societal benefit as *the ability to provide sustainable benefits for all parties involved.* This requirement focuses on designing financial models that optimize lender profitability while maintaining borrowers' affordability. For instance, dynamic interest rate structures that adjust based on the borrower's repayment capacity.

**Information Exchange Trust** highlights the centrality of trust in improving engagement among borrowers and lenders. In many lending interactions, trust issues arise because borrowers often doubt whether their data will be used fairly, while lenders question the accuracy and integrity of borrower-submitted information. This study defines the requirement for information exchange trust as *the ability to implement secure, tamper-proof audit mechanisms to reinforce trust in financial transactions.* Features like clear communication of loan terms and dispute resolution mechanisms are essential. For borrowers, trust reduces fears of exploitation or unfair treatment. For lenders, it ensures confidence in the integrity of borrower data.

**Transparent operational processes** aim to make system decisions easier to follow. In this study, transparency means that borrowers and lenders can understand how lending outcomes are determined. Borrowers should understand the reasons behind approvals or rejections and be able to respond when necessary. Dashboards that show credit information and explain decision factors may help reduce bias and support more inclusive outcomes.

### *B. Design Principles*

Design principles (DP) offer a way to translate inclusion goals into actual system design. Unlike Value-Based Requirements, which describe *what* the system should achieve, these principles focus on *how* those goals can be built into its structure. They were developed step by step, drawing from existing studies and insights gathered during interviews. The DPs are focused on creating inclusion-by-design, which embeds inclusion into the system's structure and processes to enable equitable participation and sustained engagement.

**Principle 1: Integrate inclusion metrics for evaluating access and performance.** This principle emphasizes the importance of incorporating inclusion metrics into lending systems to assess and enhance their ability to reach underserved populations. As detailed in Chapter 4, these metrics consist of four categories: penetration, financial access, analytical inclusion, and literacy. By embedding these metrics, systems can monitor their progress in expanding access, identify areas lacking inclusion, and adjust strategies to improve outcomes. This ensures that inclusion remains a measurable and actionable goal throughout the system's design and implementation.

**Principle 2: Leverage alternative data to reduce information asymmetry.** Alternative data, such as digital transaction histories, utility payments, and behavioral patterns, can help include borrowers often excluded by traditional systems. This principle focuses on using such data to create more accurate borrower profiles while ensuring privacy and reliability through data governance.

**Principle 3: Enhancing inclusion through transparency in loan terms, approval explanations, and borrower appeals.** Transparency in processes, such as explaining reasons for loan rejection and mechanisms for borrowers to contest decisions, is central to this principle. These measures build user trust, improve engagement, and promote fairness in decision-making. Transparency also helps overcome information asymmetry between lenders and borrowers by making system decisions visible and understandable. For instance, simulation tools can help borrowers understand their credit eligibility, reducing misunderstandings and fostering greater confidence in the system.

**Principle 4: Tailor credit solutions to empower underserved borrowers.** This principle advocates for designing credit products that address the unique challenges of marginalized groups. Examples include flexible repayment schemes for informal workers or seasonal loans for agricultural borrowers. Customized solutions empower marginalized borrowers to participate in the financial ecosystem.

**Principle 5: Balance inclusion with long-term sustainability.** Expanding access alone is insufficient; lending systems must balance inclusion with risk management to remain viable. This principle highlights the need to address challenges such as high default rates and limited repayment capacity, which, if ignored, could destabilize systems in the long run. Rather than treating risk as a barrier, this principle frames it as a way to support inclusion sustainably. Here, sustainability refers to the long-term viability of inclusive lending systems, ensuring they can continue to operate while serving high-risk borrowers. Strategies like cross-subsidization and real-time repayment monitoring help lenders manage risk while continuing to serve high-risk borrowers. This principle connects short-term access goals with long-term resilience by embedding stability mechanisms into inclusive system designs.

These design principles are essential guidelines for embedding inclusion into lending systems. Without them, *the requirements risk becoming merely operational features* without achieving the intended outcomes. For instance, a system without inclusion metrics (DP1) could leave inclusion outside the focus. Similarly, ignoring alternative data guidelines (DP2) might hinder the fulfillment of VBRs like Equal Access and Equitable Distribution, as traditional data alone may fail to capture diverse profiles.

While the system could operate without it, Transparency and borrowers' appeal (DP3), borrower engagement would suffer due to a lack of transparency and opportunities to challenge inaccuracies. For tailored credit schemas (DP4), while a system could technically operate without customizing loan terms for marginalized groups, it would likely fall short of addressing their unique needs. Similarly, balancing inclusion and risk (DP5) is crucial; ignoring this principle might lead to systems that either over-prioritize inclusion at the expense of portfolio stability or implement overly rigid risk controls that undermine access for underserved groups.

### *C. Architectural Components*

The Reference Architecture is structured into four blocks, each grouping together multiple architectural components that collectively support a specific inclusion function. In this structure, *a block* refers to a higher-level grouping (e.g., Loan Assessment Block), while *components* refer to the specific functionalities within each block (e.g., Contestation Component, Inclusive Credit Scoring Component). This block-based organization clarifies the roles of different system parts while preserving modularity. Furthermore, these components are not intended to replace existing architectures. Instead, they are designed to integrate with current systems, emphasizing their value-added role as core elements to improve inclusion.

The **Loan Assessment Block** is for creating an inclusive decision-making, integrating borrower data, lender ratings, and alternative financial indicators to assess loan eligibility. This block ensures inclusion through multiple subcomponents, such as the *Contestation Component*, which allows borrowers to challenge assessments by submitting verified corrections, and the *Inclusive Credit Scoring Component*, which leverages alternative financial data to expand borrower evaluation beyond traditional credit histories. Additionally, the *Inclusive Loan Distribution Component* actively monitors lending patterns to prevent systemic exclusion, while the *Custom Schema Component* enables flexible loan structures tailored to borrower-specific needs. Finalized loan decisions are recorded in the *Distributed Ledger Block*, ensuring transparency and immutability.

The **Data Collection Block** is for ensuring that only verified borrower information is incorporated into the loan assessment process. Data is gathered from multiple sources, including borrower-submitted corrections, external financial contributors, and institutional data providers. The *Distributed Data Capturing Component* collects these inputs, while the *Validator Dashboard* enforces verification before integrating the data. *The Audit Logging Component* records all data modifications.

The **Distributed Ledger Block** stores all finalized lending activities, ensuring transparency, accountability, and tamper-proof record-keeping. The blocks contains two main components: *the Transaction Ledger*, which stores approved loan transactions, borrower ratings, and credit scoring results, and the *Audit Ledger*, which maintains a structured history of past assessments for compliance purposes. The *Consensus Mechanism* governs data validation, requiring *Validator Nodes* to approve each transaction before it is permanently recorded. This decentralized validation approach prevents fraudulent modifications while reinforcing trust in the lending system.

The **User Dashboard Block** provides structured interfaces for stakeholders (borrowers, lenders, validators, regulators, and collaborators), ensuring role-based access to relevant information. By enabling borrowers to review and correct their information, lenders to view borrower profiles and system scores, and validators and regulators to verify and monitor assessments, the dashboards reduce information asymmetry and embed inclusion into decision-making. *The Borrower Dashboard* allows users to apply for loans, submit data corrections, and track repayments, with all updates subject to validation before influencing credit decisions. *The Lender Dashboard* supports application review, borrower risk assessment, and rating submission and contributes to the dual-rating mechanism. *The Validator Dashboard* maintains data integrity by verifying borrower-submitted and external records before they are integrated into the system. *The Regulator Dashboard* includes tools for oversight, such as the Scoring Dashboard for monitoring model performance and the Inclusion Rule Component for setting eligibility criteria. *The Collaborator Dashboard* enables data contributors, such as distributed agents and external providers, to supply borrower information, expanding data diversity.

### 9.1.4. RQ4: What is the impact of the proposed Reference Architecture on inclusion?

RQ4 evaluates the extent to which the RA addresses the inclusion challenges identified in RQ1, e.g. the *technology and data* and the *financial lending* challenges. In the Technology and Data challenges category, the RA addresses challenges of data integration, low data quality, and information asymmetry that limit borrower visibility and hinder lender trust. In the Financial lending challenges category, the RA addresses rigid scoring, rigid loan terms, and incentive structures that prioritize low-risk borrowers over equitable access.

To examine whether the RA effectively addresses these challenges, the research conducted three complementary evaluations: prototype development and feature testing (Chapter 6), controlled behavioral surveys (Chapter 7), and machine learning simulations with sensitivity analysis (Chapter 8). While all RA components were established as mandatory in RQ3, the testing scope for RQ4 was focused on evaluating the essential concepts. These include the contested decision-making, dual rating system, and collaborative data collection features tested in Chapter 6, which aim to increase borrower agency, support evaluation for those with limited credit histories, and improve data diversity. Chapter 7 evaluates how enriched borrower profiles and system-generated recommendations affect lender decisions, reflecting how the RA influences behavioral aspects of inclusion. Chapter 8 tests whether adjusting model parameters leads to more inclusive reclassification for underserved borrowers, demonstrating the impact of adaptive scoring. Indeed, the evaluation was necessarily *limited* due to time and feasibility constraints for developing a full-fledged architecture that would be used over time in practice. This study prioritized features that could be evaluated within the research timeline, focusing on their operational relevance and contribution to inclusion.

Each evaluation phase is directly linked to the challenges outlined in RQ1. The prototype development and feature testing (Chapter 6) evaluate whether the *contested decision-making*, *collaborative data collection*, and *dual rating systems* features improve user agency, expand borrower evaluation options for lenders, and data diversity. The controlled behavior survey (Chapter 7) evaluates how enriched borrower profiles affect lender approval behavior. Finally, the simulation (Chapter 8) evaluates how model configurations and scoring parameters influence borrower reclassification to gain higher inclusion. While further testing is needed for unassessed components, the results confirm that the RA offers practical and scalable solutions to improve inclusion in lending systems.

### *A. Evaluation of Prototype Features*

To evaluate the proposed Reference Architecture (RA), this study developed a prototype using Hyperledger Besu, a DLT platform selected to support transparency and verifiability within a simulated lending system. DLT was used here to demonstrate how decentralized infrastructure can support traceable interactions. Besu was chosen because it supports more efficient transaction processing, allowing only authorized participants to validate data. This makes DLT suitable for addressing inclusion challenges identified in this study, such as limited transparency, unverifiable borrower data, and a lack of accountable decision records. Compared to other DLT platforms, Besu is simpler to manage, cheaper, and easier to integrate with widely used development tools.

The prototype developed was used to test specific features in Chapter 6 and also supported the experimental configurations in Chapters 7 and 8. Several RA components were implemented in four functional blocks: user dashboards, a loan assessment system, data collection components, and the underlying distributed ledger infrastructure. Although the full RA was not implemented due to time and resource constraints, the prototype prioritized components that allowed user interaction and data processing within a simulated peer-to-peer lending environment. The same prototype environment was also used to run the experiments and simulations in Chapters 7 and 8, enabling consistent testing across evaluation stages. The use of a prototype, rather than a full-fledged system, was a deliberate choice to focus on testing the essential concepts of the RA that were ready for operational evaluation within the study's scope.

Chapter 6 evaluated three features (contested decision-making, dual rating systems, and data collaboration) through interactive simulations followed by Focus Group Discussions (FGDs) with two groups: IT and macroprudential and credit risk professionals. The prototype enabled participants to submit borrower corrections, rate borrowers, and upload data as external collaborators. This phase emphasized how these features *improve the perception of inclusion*. The results are as follows.

*The contested decision-making feature* was proposed to enhance inclusion by enabling borrowers to revise inaccuracies in their data. This feature fosters inclusion by correcting inaccurate data that often leads to the exclusion of underserved borrowers. While participants acknowledged its relevance and value, they also raised concerns about scalability, institutional commitment to validating borrower inputs, and risks of manipulation. These concerns underscore the importance of establishing practical workflows and clear validation protocols, without undermining the feature's potential to improve borrower representation in the system.

*The dual rating system* was seen as a promising feature to build multidimensional borrower profiles by combining input from lenders and community members. This feature is perceived as valuable for borrowers with limited credit histories, offering a broader evaluation framework. Despite these advantages, issues related to ambiguous rating criteria were identified. Addressing these concerns requires clear mechanisms for resolving discrepancies and regular validation of rating models to help inform future refinement of the feature.

*The data collaboration feature* used a DLT-based setup to demonstrate how data from diverse sources could be aggregated and verified. While not dependent on DLT, the feature highlights the potential of decentralized validation to support data integrity. This feature addresses challenges to inclusion by incorporating alternative data and creating a decentralized validation framework. However, several implementation issues were observed during testing, such as unstructured data, representation gaps, and data obsolescence, indicating the need for robust data governance frameworks.

The findings from FGDs revealed complementary insights. *IT professionals* emphasized the technical feasibility of the RA features and the need to focus on scalability, DLT configurations, and user-centric designs when used in practice. *Macroprudential and credit risk professionals* found the features relevant, but also pointed to broader regulatory and systemic considerations, including risk management, borrower awareness, and collaboration with financial institutions. While both groups acknowledged the inclusion potential of the features, they stressed that successful implementation would require attention to long-term sustainability to ensure the lending system remains viable and impactful over time.

Overall, the results suggest that the RA features can contribute to financial inclusion by operationalizing inclusion principles across different aspects of the lending process. However, their practical feasibility will depend on how scalability, data quality, and stakeholder coordination are managed. This would require organizational responsibilities and changes in the institutional system, which were outside the scope of this research.

This prototype and features will be used in Chapters 7 and 8, where the RA's inclusion potential will be assessed through a controlled survey and sensitivity analysis of scoring models.

***B. Assessing Lender Behavior and the Impact of Enriched Borrower Profiles on Loan Acceptance***

This evaluation phase addresses RQ4 by examining lender behavior through online surveys using *a Qualtrics web application*. This survey involved 270 respondents, significantly exceeding the original target of 90 participants. Respondents were lenders or financial professionals evaluating borrower profiles under various information conditions. Of the 270 respondents who initiated the survey, 60 did not fully complete the experiment, leaving 210 complete responses for analysis. The evaluation focused on behavioral changes in loan approval decisions, creditworthiness judgments, and the perceived reliability of borrower data when enriched information and system recommendations were provided. These behavioral indicators are directly linked to the challenges identified in RQ1, particularly those related to incomplete data and inconsistent decision-making. For evaluating the behavior, six hypotheses were formulated.

**Hypothesis B1: Incorporating additional information increases loan acceptance rates for micro-enterprises.**

Hypothesis B1 tests whether incorporating additional borrower data improves loan acceptance rates. The results consistently demonstrate that additional borrower details, such as payment capacity, business type, and duration, positively influence lender decisions. Statistical analyses, including T-tests, Z-tests, ANOVA, and Tukey's HSD, confirm significant differences in loan acceptance rates between profiles with and without enriched information. The additional data elements enable lenders to reassess borrower risks more confidently, supporting the RA's principle of leveraging diverse and contextual data to expand financial access.

**Hypothesis B2: Incorporating system recommendations increases loan acceptance rates for micro-enterprises.**

Hypothesis B2 evaluates whether system-generated recommendations enhance loan acceptance rates. The results do not support this claim: the statistical analysis shows no significant increase in acceptance rates when only system recommendations are provided. These findings indicate a potential trust gap or hesitation among lenders regarding algorithmic assessments, especially when additional contextual borrower data does not complement such recommendations. This underlines the importance of combining system-generated insights with enriched data to build trust and influence lender decisions.

**Hypothesis B3.1: Combining additional information and system recommendations increases acceptance more than additional information alone,** and

**Hypothesis B3.2: Combining additional information and system recommendations increases acceptance more than system recommendations alone.**

Hypotheses B3.1 and B3.2 test whether combining enriched borrower data and system recommendations enhances loan acceptance rates compared to using each element independently. Hypothesis B3.1 *is not supported*, so combining both elements does not outperform additional information. This result suggests that the additional borrower information carries sufficient weight in influencing lender decisions, with system recommendations offering minimal incremental value. In contrast, Hypothesis B3.2, evaluating whether combining both elements outperforms system recommendations alone, *is found to be significant*. These results highlight the importance of enriched borrower profiles in amplifying the effectiveness of system recommendations.

**Hypothesis B4.1: Providing more detailed and comprehensive information increases the perceived creditworthiness**; and

**Hypothesis B4.2: Providing more detailed and comprehensive information enhances the perceived data reliability.**

Hypothesis B4 examines how enriched borrower information affects lenders' perceptions. While it does not significantly change their view of borrower creditworthiness (B4.1), it does improve their trust in the reliability of the data significantly (B4.2). This helps explain why loan acceptance rates increase (B1): not because borrowers are seen as more qualified, but because lenders feel more confident in the accuracy of the information provided.

These findings help to explain the behavior of lenders making decisions under uncertainty. Enriched borrower profiles (B1) lead to higher loan approvals, even when lenders do not view borrowers as more creditworthy (B4.1). What makes the difference is the perceived reliability of the information (B4.2). Lenders may not trust the borrower more, but they trust that the information is reliable enough to estimate the risk and justify their decision.

### *C. Sensitivity Analysis of Borrower Reclassification through Adding Data Attributes and Parameter Tuning*

This section explores how data enrichment and parameter tuning can impact the reclassification of borrowers to lower-risk categories, thereby enhancing financial inclusion. Through sensitivity analysis, two hypotheses were tested: *Hypothesis A1*, which tested the effect of additional data attributes, and *Hypothesis A2*, which assessed the impact of parameter tuning. We use machine learning to develop the scoring models and to conduct the simulations within the Loan Assessment Block of the prototype, specifically the inclusive scoring component for evaluation. This research applied ***five measurement metrics*** to conduct the analysis, which included the risk class distribution (metric 1), risk class shift (metric 2), movement to lower risk class (metric 3), movement to higher risk class (metric 4), and inclusion ratio (metric 5). These metrics are directly related to inclusion as they assess how data enrichment and parameter tuning influence the redistribution of borrowers across risk categories, particularly focusing on moving underserved borrowers into lower-risk classes.

**Hypothesis A1: Adding additional data variables increases loan recommendations, shifting more borrowers to lower-risk classification.**

Hypothesis A1 examined whether enriching borrower profiles with additional data attributes could drive reclassification into lower-risk categories. The results revealed that while these variables provided more detailed borrower profiles, their overall impact on risk classifications was not found to be significant. Across numerous models tested, most borrowers remained in their original risk categories, with only minor reclassifications observed. Introducing the ”paycap” feature, leveraging dynamic repayment capacity measures, enhanced the granularity of borrower evaluations. Although models incorporating *paycap* demonstrated modest improvements, such as reclassification ratios exceeding 1.4, the absolute scale of borrower movements *remained small*. Although additional data attributes improve borrower evaluations, they do not substantially increase the movement of borrowers to lower-risk categories, meaning that data alone **does not significantly enhance inclusion**.

**Hypothesis A2: Tuning model parameters increases loan recommendations, shifting more borrowers to lower-risk classification.**

Hypothesis A2 was found to have a significant impact on borrower redistribution, highlighting the impact of advanced parameter-tuning techniques. Three distinct approaches—*Feature Weight Adjustment, Penalty-Based Models,* and *Hybrid Feature Penalty Tuning (HFPT)*—were tested to assess their ability to reclassify borrowers and enhance inclusion. We developed 755 modelling experiments to observe the outcomes of all adjustments in detail. This extensive scope ensured that the emerging patterns were not coincidental but rather the result of deliberate adjustments. The results of the three approaches tested under Hypothesis A2 are as follows.

<u>**The feature weight adjustments**</u> approach plays a critical role in influencing ***borrower reclassification***. By *reducing the influence* of key features like OVER_TIME (delayed loan payment), the model *becomes*

*more sensitive* to shifts in borrower class, allowing significant reclassification to lower-risk categories. For example, configurations with low *reduction factors* (e.g., 0.1 or 0.25) consistently produce high inclusion ratios. However, adjustments to OVER_INT (interest rate) alone have minimal impact, highlighting its limited role in improving inclusion outcomes. These simulations show the impacts of *feature* and *reduction factors* on borrowers' risk classification. A more sensitive feature provides more impact, which depends on the reduction factor setting.

**The penalty-based** approach is crucial in influencing ***borrower redistribution*** (not only reclassification as in the feature weight approach). This approach adjusts borrower distribution through two parameters: *penalty type* (which risk classes are penalized, such as Pen0 penalized Class 0, Pen1 penalized Class 1, etc) and *penalty value* (the severity of the penalty). Each risk class represents a group of borrowers with similar creditworthiness, with lower-risk classes typically comprising borrowers perceived as more likely to repay loans. When penalties are targeted at lower-risk classes and assigned sufficiently high *penalty values*, they effectively reclassify borrowers into more favorable risk categories (lower-risk classes). Empirical results across *five evaluation metrics* confirm that these settings lead to substantial downward borrower shifts, minimal upward movement, and high inclusion ratios. In contrast, penalties targeting only high-risk classes tend to concentrate borrowers in high-risk classes, failing to improve inclusion.

A novel insight from the penalty-based approach in this study is the ability to identify ***penalty threshold,*** precise penalty values at which borrower classification changes significantly. In this context, penalty thresholds refer to *the minimum penalty values at which the model starts to push borrowers into different risk categories in a consistent and measurable way*. When *penalty values* are below these thresholds, the model's output remains similar to the baseline, with minimal redistribution. Once the threshold is crossed, borrower movement becomes sharp and systematic, leading to meaningful shifts in inclusion metrics. These thresholds were consistently observed across all metrics in each *penalty type* (Pen0, Pen1, Pen2, etc). The following threshold values are identified: Pen0 with the threshold *value* of **9060**, Pen1 at **760**, Pen2 at **490**, Pen3 at **1290**, and Pen4 at **700**. Identifying these values provides a concrete reference point for designing scoring systems that respond only when penalties are strong enough to drive redistribution. For policy-makers and system designers, these thresholds offer actionable guidance for calibrating scoring systems. They enable targeted experimentation, helping avoid ineffective settings and ensuring penalties only take effect once they are strong enough to drive meaningful redistribution.

Furthermore, the differences in threshold values across penalty types can be partially explained by the class proportions in *the training data*. For example, Class 0 includes more than 50% of the data, making it the most dominant category. As a result, shifting borrowers out of or into this class requires relatively high *penalty values* because the model must overcome a strong baseline distribution. In contrast, *penalty types* that target classes with smaller data portions produce reclassification effects at lower *penalty values*. The classes that contain less than 10% of the borrower population required smaller adjustments to influence distribution. This pattern reflects an important aspect of model explainability: the more significant the class share in the training data, the more effort is needed to shift borrowers in or out of it. This impacts inclusion because large classes require higher penalties to reclassify borrowers, which may limit the redistribution potential. In contrast, smaller classes are easier to shift, but their redistribution has less impact on improving overall inclusion. These outcomes highlight that model responses are not arbitrary but emerge from the interaction between model structure, penalty configuration, and data distribution.

This may also reflect a broader challenge in machine learning, where the distribution of its training data can shape the behavior of a model. In this study, the observed pattern suggests that models might respond differently to the same type of adjustment depending on the relative size of each class. While this was not directly tested, the variation in penalty thresholds across classes indicates that underlying data structure likely plays a role in shaping model sensitivity.

Compared to the feature adjustment approach, which modifies the weight of specific variables, penalty-based models offer ***more explicit control over inclusion dynamics*** and are ***easier to interpret*** in policy contexts. While the feature adjustment approach requires knowledge of feature behavior, the penalty-based approach can be implemented as rule-based overlays, making them more transparent and adaptable, particularly when inclusion outcomes must be explainable and policy-aligned.

<u>**Hybrid Feature Penalty Tuning (HFPT)**</u> is a novel method introduced in this study to improve borrower reclassification by combining two previous approaches: feature weight reduction and penalty-based. *Feature adjustment* reduces the influence of selected variables, while *penalty-based tuning* alters the classification outcome by enforcing reallocation into specific risk categories. HFPT systematically integrates both approaches in a single setup, enabling flexible control over borrower movement across risk classes. Unlike earlier approaches that apply penalties or feature tuning in isolation, HFPT was designed to investigate whether their combination could yield greater inclusion effects.

Results across Metrics 1 to 5 confirm that HFPT delivers consistent inclusion gains, especially when *penalty values* are set at **moderate levels**. In these scenarios, borrower distributions remain sufficiently open, allowing feature reductions, particularly on OVER_TIME, to shift more borrowers into lower-risk categories without increasing upward movement. This effect is not marginal; it amplifies inclusion when penalties alone do not create full reclassification. This behavior differentiates HFPT from penalty-only approaches, where the penalty configuration largely determines borrower movement. In penalty-based models with relatively high penalty values, reclassification occurs uniformly once a threshold is crossed, leaving little flexibility for further refinement. In contrast, *HFPT enables continued borrower movement and redistribution* within the available structural space, particularly in models with relatively moderate penalty values.

Rather than acting as a secondary element, feature adjustment in HFPT plays a decisive role when penalties leave space for redistribution. However, when penalties are set at **relatively high levels**, HFPT effects converge with penalty-only outcomes, indicating that penalty value remains the dominant factor in those configurations.

As a key innovation of this research, HFPT is proposed as a modeling technique and a practical tool for policy-makers and practitioners. ***It enables controlled exploration of which features influence borrower classification meaningfully under varying penalty scenarios***. In this study, the OVER_TIME variable emerged as a consistently impactful driver. When applied to new datasets, HFPT can help detect influential features, support localized model calibration, and guide the design of scoring systems that balance inclusion and risk. For policy contexts, it provides a transparent and testable mechanism to align technical adjustments with inclusion goals, making it a scalable option for adaptive credit policy development.

In conclusion, the findings from RQ1 to RQ4 show that several focused challenges identified in this study were addressed through developing the RA, while others were only partially covered by the scope of testing. In the **Technology and Data** challenge category, the problem of *low data quality* was addressed through contested decision-making and collaborative input, both of which were tested and shown to improve data credibility and traceability. The issue of *limited borrower control* over data was addressed by allowing borrowers to submit and correct their information, with each update verified through a structured validation process. Structural limitations, such as *fragmented infrastructure* and challenges in *integrating alternative data*, were addressed in the RA through distributed design components; however, these aspects were not fully tested in the evaluation scope.

In the **Financial Lending challenges category**, the RA addressed exclusion caused by *rigid eligibility criteria* and *overreliance on traditional features* through dual rating and scoring flexibility. These mechanisms were evaluated through sensitivity analysis of parameter settings and behavioral experiments and found to improve borrower reclassification and approval likelihood. Challenges related to *rigid repayment schedules* and *unaffordable loan terms* were designed for in the RA under tailored credit solutions but were not tested in this study. Finally, *the persistent preference among lenders* for low-risk profiles was not addressed by system design and remains outside the scope of this research. Some challenges were not evaluated, not because the RA lacks the relevant mechanisms but because the components designed to address them were not included in the testing. The decision to exclude certain components from the evaluation was driven by the need to focus on evaluating essential parts of the RA, particularly where the impact on inclusion was not yet clear or required further refinement.

## 9.2. Contributions to Knowledge and Practices

This research contributes to scientific knowledge and practical applications by introducing *inclusion by design*. Embedding inclusion into the core design of financial systems addresses complex socio-technical challenges in underserved populations.

### *A. Scientific Contributions*

This study contributes to the design of inclusive lending systems by designing a Reference Architecture (RA) that places inclusion at the center of system design. At the beginning of this research, there was no reference architecture available, nor was there any clear guidance on designing lending systems with inclusion as a core objective. It was unclear what components were needed, how inclusion should be embedded, and how to measure the improvement of inclusion. Through this study, we designed an RA consisting of Value-Based Requirements, Design Principles, and Architectural Components. By embedding *the inclusion by design* concept, this study presents **a new way of designing architectures for inclusion**, treating inclusion as part of system architecture rather than as an external concern.

Another starting point of this research was the lack of clarity on how to measure inclusion in lending systems. Existing indicators mostly focus on basic access or usage, without addressing the magnitude, structure, or analytical interpretation of inclusion. This study responds to that gap by **designing a set of inclusion metrics** across four categories: *penetration, financial access, analytical inclusion,* and *literacy*. While not all were empirically tested in this research, their conceptual development provides a structured framework for assessing financial inclusion across multiple categories. These metrics extend beyond traditional financial access indicators by considering technological capabilities, financial metrics, and digital literacy, offering a more context-aware evaluation method.

Another scientific contribution of this study demonstrates that **financial inclusion is not a binary state but a continuum** encompassing access, usage, and empowerment. This perspective, aligned with Sen's Capability Theory, redefines financial inclusion beyond conventional indicators such as account ownership or transaction volume. By incorporating socio-economic categories and technology, this study highlights the necessity of context-aware and adaptable policy interventions. The findings emphasize that providing access to financial services does not guarantee meaningful participation; inclusion should be assessed as an iterative process.

The literature often assumes that improving borrower profiles with more data will naturally lead to better credit decisions and improved inclusion. As discussed in Chapter 3, many studies emphasize the importance of alternative data to reduce information asymmetry and expand access; however, findings from Chapter 8 challenge this assumption. The simulations show that adding more borrower data only resulted in modest improvements in reclassification outcomes. The effect was usually limited, especially when scoring models were not adjusted. This suggests that **alternative data sources alone may not be sufficient for inclusion unless coupled with systemic adjustments** in scoring models. Simply increasing the amount of borrower data does not guarantee broader access to credit, as classification outcomes remain primarily dependent on existing scoring mechanisms. This highlights the importance of rethinking how alternative data is integrated into lending systems, ensuring that additional information contributes meaningfully to risk assessment rather than simply increasing data volume without substantive impact.

At the same time, this study finds that the **sensitivity of the algorithmic parameters plays a significant role in inclusion outcomes**, particularly in how model parameters are tuned. The results from Chapter 8 demonstrate that even *small adjustments* in model parameters can lead to substantial shifts in borrower reclassification. These findings suggest that inclusion is not just about adding more borrower data but about ensuring that risk models properly utilize this data. Without careful calibration, even the most extensive borrower profiles may fail to shift classification outcomes in a way that benefits underserved groups.

While additional borrower information does not significantly improve inclusion outcomes in the scoring models (Chapter 8), **lenders show a higher likelihood of approving loans when they receive more contextual borrower details** (Chapter 7). The behavior results from Chapter 7 show that borrower profiles containing enriched contextual information are more likely to be approved by lenders compared to profiles with limited data supplemented by system recommendations. This underscores the importance of transparency, interpretability, and explainability in lending systems, ensuring that enriched data is available and perceived as reliable by lenders.

***B. Contributions to Practice***

The **Reference Architecture**, developed and evaluated in this study, demonstrates how technologies can be used to address marginalized segments and improve inclusion. By focusing on modularity and adaptability, the RA ensures that inclusion is not merely a conceptual idea but can be translated into tangible system features. This approach bridges the gap between theoretical models and practical applications.

**A prototype** was developed and tested through FGDs to operationalize the RA and assess whether its inclusive features improved participants' perception of inclusion. The results confirmed their practical relevance, with participants recognizing their potential to foster borrower agency, data diversity, and system transparency. They also noted scalability, data quality, and model robustness challenges. To support these features, DLT, secure databases, or synchronized cloud platforms can enable shared access and data traceability. In this study, DLT was employed as a demonstrative implementation to support inclusive system features, without being positioned as a central solution.

The hypotheses tested in Chapters 7 and 8 (A1-A2, B1-B4) provide evidence of how **enriched borrower profiles and parameter tuning impact inclusion**. For example, the study finds that additional data significantly increases loan acceptance rates (B1), while combining such data with system-generated recommendations amplifies these effects (B3). Moreover, the RA integrates adaptive mechanisms, such as penalty-based adjustments and feature tuning, to balance expanding access and managing credit risk. This practical contribution equips policy-makers and practitioners with tools to improve financial inclusion without compromising systemic resilience.

In conclusion, this research contributes to scientific knowledge and industry practice by addressing the complexities of designing inclusive financial systems. *From a scientific perspective*, it advances the understanding of designing lending architectures by integrating inclusion as a fundamental concept rather than a secondary outcome. It also introduces inclusion metrics and highlights the role of borrower data, model sensitivity, and transparency in improving inclusion. *From a practical standpoint*, this study equips policy-makers, practitioners, and system designers with actionable approaches to foster inclusion for underserved populations by offering an evaluated architecture that aligns theoretical principles with real-world implementation.

## 9.3. Limitations and Future Directions

While the findings offer significant contributions to theory and practice, several limitations were encountered. These limitations highlight areas requiring further refinement and suggest pathways for future exploration.

### *A. Limitations*

This research focuses on Indonesia's lending ecosystem, using its specific regulatory and socio-economic conditions for detailed analysis. While this focus enabled the development of tailored solutions, it **limits the generalizability** of the findings to other contexts. Key components of the RA, such as the Contested Decision-Making feature, were adapted to address local challenges that may differ in other cultural or regulatory settings. For instance, the design elements that work in Indonesia might require substantial modifications to align with the needs of regions with different infrastructure, governance, or borrower characteristics. This highlights the need for future studies to explore how the RA can be adapted and scaled across diverse contexts.

This research primarily focused on challenges that could be addressed through the RA. While several challenges related to the broader lending ecosystem, including systemic issues, regulatory constraints, and cultural factors, were recognized, the study concentrated on the aspects that could be addressed within the scope of the RA. As a result, some challenges were not fully explored due to their complexity or the RA's current design limitations. Future research could explore these broader issues, particularly the social and cultural factors influencing borrower behavior and their interaction with lending systems.

**Institutional differences** also influence the effectiveness of lending models. The level of regulatory oversight varies between countries, impacting how inclusion mechanisms are implemented. A regulation-light environment, such as Indonesia’s evolving fintech sector, may produce different outcomes compared to a highly regulated system like in the U.S., where strict lending criteria and consumer protection laws bind financial institutions. In loosely regulated markets, digital lending platforms may expand access rapidly but face challenges related to borrower protection, fraud prevention, and systemic risk management. Future research should examine how different regulatory environments influence the scalability and effectiveness of the RA.

Furthermore, **cultural factors** may influence how borrowers in Indonesia engage with lending systems. In many low-income communities, people often rely on informal borrowing based on social ties. Local culture might shape borrowing decisions, such as sharing repayment responsibility with family, avoiding formal loan agreements, and preferring to borrow from people they know rather than using digital platforms. While this study focuses on designing a Reference Architecture to address technical challenges, it does not explore how these cultural practices affect system design. Understanding how the systems align with local values remains important for future research.

This study also faces selection and response bias limitations, which may have influenced data collection and interpretation. **Selection bias** may have affected the results because borrowers willing to participate might systematically differ, such as possessing higher financial literacy, from those who declined participation. This demographic skewness can limit the representativeness of the findings (Heckman, 1979). Meanwhile, **response bias** might arise due to the stigma surrounding online lending in Indonesia, where many borrowers associate it with predatory practices or perceive it as damaging their reputation. Response bias generally occurs when respondents alter their answers due to perceived social expectations (Furnham, 1986).

Regarding the design principle, **Principle 4** (Tailored Credit Solutions), which emphasizes designing credit schemas to meet the diverse needs of borrowers, was **not included** in the testing scope due to time and resource constraints. While this principle is essential for ensuring that the RA accommodates a wide range of borrower profiles and supports customized loan terms, its testing was excluded. The need for tailored credit solutions is recognized, but testing of this principle would require extensive data and further integration with lending institutions, which was beyond the scope of this study.

Moreover, developing multidimensional inclusion metrics was a key methodological achievement. However, **translating these conceptual frameworks into actionable indicators** revealed challenges in measurement, particularly due to data constraints and varying stakeholder expectations. While the metrics served as practical evaluative tools, their applicability depended on data availability, technical feasibility, and institutional willingness to adopt new assessment methods.

### *B. Future Research Directions*

Building on the localized insights from Indonesia, future research can explore the RA's adaptability to diverse socio-economic and regulatory contexts. **Comparative studies** across regions with differing levels of financial development could identify universal design principles while tailoring components for specific environments. For example, investigating how the RA performs in high-income countries or low-resource settings would provide insights into its global scalability and adaptability.

Beyond adapting the RA to different contexts, future research should explore **potential extensions** of the RA's components. The core architecture established in this study provides a foundation, but new system components may be required to enhance its functionality. **Adding components** could refine the RA's ability to assess and respond to borrower needs dynamically. Future iterations of the RA should investigate how these additional components interact with existing components and whether they contribute to more inclusive outcomes.

Several aspects of the RA were not evaluated due to practical constraints, and future research can address these gaps through expanded testing and iterative refinements. The exclusion of Principle 4 from empirical validation represents a key limitation that can be revisited through experiments to assess customized loan products across different borrower segments. Future studies are recommended to adopt *controlled or quasi-experimental* designs comparing tailored versus standardized loan structures to measure impacts on borrower inclusion.

Future research can test the RA components that were not evaluated in this research, including the Inclusion Engine and the Inclusive Distribution Mechanism. *The Inclusion Engine* serves as a rule-setting mechanism that allows regulators to define credit inclusion criteria. This component ensures lending decisions align with recent policies by adjusting parameters, such as minimum financial thresholds, risk tolerance levels, or credit assessment factors. Future research should develop adaptive rule-based algorithms for the Inclusion Engine and test how this feature impacts inclusion. *The Inclusive Distribution Mechanism* ensures that loans are not disproportionately concentrated in specific groups. Empirical testing should evaluate whether the mechanism successfully diversifies loan approvals and improves access for underserved segments.

Sensitivity analysis reveals that even small changes in model parameters can significantly impact borrower classification and inclusion outcomes. Further research can expand the scope of these analyses by **conducting more extensive sensitivity tests**. The short-term evaluations conducted in this research provided valuable insights into the RA's immediate impact; however, **longitudinal studies** are necessary to assess its long-term effects on inclusion, systemic stability, and borrower empowerment. Future research should examine how borrower behaviors change over extended periods, identifying unintended consequences or long-term benefits that were not captured in short-term assessments.

While these directions address the current RA's limitation, broader challenges in inclusive lending can also be investigated beyond the boundaries of this study, such as algorithmic explainability, regulatory integration, borrower engagement, and data interoperability.

The first cluster, ***algorithmic explainability***, focuses on how the interaction between model parameters and training data shapes borrower classification outcomes. While this study revealed consistent threshold patterns, the internal mechanisms remain partially opaque. Future research can investigate how credit scoring models can be more interpretable and predictable. Work in this area can address the black-box nature of current systems by developing methods that explain not just *what* a model predicts but *how* and *why* outcomes change under different configurations.

The second cluster, ***regulatory integration***, considers how inclusive tools can be embedded into institutional workflows. Future studies can explore *who* defines inclusion parameters, *how* rule-setting aligns with public goals, and *what* forms of enforcement or incentives support adoption. This process involves both governments and regulators defining inclusion parameters to align with public goals, while financial institutions are responsible for implementing these guidelines.

The third cluster, ***borrower engagement***, addresses how users' interaction with system features (such as score explanations, contestation tools, or custom loan offers) can improve inclusion. Experimental and qualitative studies, such as interviews, field trials, or behavioral surveys, can be used to test how these features affect borrowers with low literacy.

The fourth cluster, ***data interoperability***, highlights the foundational role of data in enabling inclusion. Many underserved borrowers remain invisible due to fragmented data, limited digital records, or a lack of mechanisms for data sharing across institutions. Future research can explore how alternative data can be integrated into credit scoring. Technical questions around standardization, data quality, and privacy must be addressed alongside governance issues such as consent and access rights.

These four cluster research directions reflect that achieving inclusion requires continued work across many dimensions, including refining system features and addressing institutional issues, borrower experience, and data availability. The RA designed in this study serves as a foundation providing requirements, principles, and components that can be adapted across contexts. This research provides a solid foundation for future research in inclusion.

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## Appendices

The online appendices can be accessed online at https://doi.org/10.4121/7c3083a2-8229-45c4-a57f-233007b75e8b. The online appendices consist of:

1. Source code of Smart Contract layer (P2PLending.sol) - solidity
2. Source code of the middleware layer of DLT services (P2PLendingService.js) - JavaScript
3. Source code of back-end API layer (P2PLendingAPI.js) - JavaScript
4. An Excel file of raw data of survey results
5. An Excel file of Metric 1-5 for hypothesis A1: Additional attributes
6. An Excel file of Metric 1-5 for hypothesis A2: Feature weight approach
7. An Excel file of Metric 1-5 for hypothesis A2: Penalty-based approach
8. An Excel file of Metric 1-2 for hypothesis A2: Hybrid Feature Penalty Tuning Approach (HFPT)
9. An Excel file of Metric 3-5 for hypothesis A2: Hybrid Feature Penalty Tuning Approach (HFPT)
10. Python source code for hypothesis A1
11. Python source code for hypothesis A2 (Feature weight approach)
12. Python source code for hypothesis A2 (Penalty-based approach)
13. Python source code for hypothesis A2 (HFPT)
14. All Interview Protocols

## Curriculum vitae

Reni Sulastri is a PhD candidate at Delft University of Technology, the Netherlands, in the ICT section of the Department of Engineering Systems and Services (ESS), Faculty of Technology, Policy and Management (TPM). Her research is under the supervision of Prof. Dr. Ir. Marijn Janssen and Dr. Aaron Ding, focusing on developing a *Reference Architecture (RA) to address financial inclusion challenges in lending systems.* Her work applies *Design Science Research (DSR)* to design and evaluate systemic interventions that enhance financial access for underserved populations. Her research explores inclusion metrics, machine-learning-driven adaptive credit scoring, and system architectures that operationalize inclusion-by-design. Through prototyping, simulation, and behavioral experiments, she evaluates how algorithmic interventions and enriched borrower profiles impact lending decisions.

She holds a Master of Science in Management of Technology from TU Delft, the Netherlands (2016) and a Bachelor's degree in Computer Engineering from Nanyang Technological University, Singapore (2004).

She has extensive professional experience at **Bank Indonesia**, the central bank of Indonesia, where she has worked for over 15 years in various IT system development and digital transformation roles. Her last position involved enterprise initiatives to support AI-based projects in the central bank. Before this, she was an Enterprise Application Architect responsible for designing strategic IT frameworks for enterprise-wide solutions. From 2013 to 2020, she served as a System Analyst, overseeing system analysis, IT operations, and IT compliance. Between 2010 and 2013, her roles focused on system development. Earlier in her career, she managed the IT infrastructure and digital information systems for Bank Indonesia's museum projects (2006–2010), supporting the digital transformation of historical and financial archives.

Before joining Bank Indonesia, she worked as a Senior IT Analyst at the **Inland Revenue Authority of Singapore** (2004–2005), where she developed IT solutions for tax processing and digital services in Singapore's taxation system.

Her research interests include machine learning for government policy, inclusion in AI-based credit scoring, peer-to-peer (P2P) lending systems, and digital governance. She is interested in exploring how technology-driven financial systems can be designed to enhance inclusion while ensuring sustainability in automated decision-making.

## List of Publications

**Journal Articles**

**Sulastri, R., Janssen, M., van de Poel, I., & Ding, A.** (2024). *Transforming towards inclusion-by-design: Information system design principles shaping data-driven financial inclusion*. Government Information Quarterly, 41, 101979. https://doi.org/10.1016/j.giq.2024.101979

**Conference Proceedings**

**Sulastri, R., Janssen, M., & Ding, A.** (2025). *Sensitivity Analysis: Improving Inclusive Credit Scoring Algorithm through Feature Weight and Penalty-based Approach*. *2025 ICEDEG*, Bern, Switzerland, 2025, pp. 54-61. https://doi.org/10.1109/ICEDEG65568.2025.11081606

**Sulastri, R., & Janssen, M.** (2023). *Challenges in designing an inclusive Peer-to-peer (P2P) lending system*. In *24th Annual International Conference on Digital Government Research (DGO 2023)*, July 11–14, Gdańsk, Poland. ACM. https://doi.org/10.1145/3598469.3598475

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**Draft (Journal article)**

**Sulastri, R., Janssen, M., & Ding, A.** (NA). *Evaluating Inclusive Credit Scoring: The Effect of New Information, Information Quality, and Sensitivity on Algorithmic Decision Making* (IEEE Engineering Management).

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**Sulastri, R (2023).** *Inclusion-by-Design: Designing a Reference Architecture for Inclusive Lending Systems. The 19th International Conference on Design Science Research in Information Systems and Technology (DESRIST 2024),* June 3-5, Trollhättan, Sweden.

**Previous publications**

**Praditya, D., Sulastri, R., Bharosa, N., & Janssen, M.** (2016). *Exploring XBRL-Based Reporting System: A Conceptual Framework for System Adoption and Implementation*. In *15th IFIP Conference on e-Business, e-Services, and e-Society (I3E 2016)*. Lecture Notes in Computer Science, Vol. 9844, pp. 305–316. Springer.

**Praditya, D., Janssen, M., & Sulastri, R.** (2017). *Determinants of Business-to-Government Information Sharing Arrangements*. The Electronic Journal of e-Government, 15(1), 44–55.