Machine Learning in KYC and the Amplification of Social Trade-offs

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by

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Preface

As a person, I've always been interested in many different things. When this topic landed in my lap, at the intersection of ML, AML, and social costs and benefits, my curiosity was immediately sparked. I was eager to dive in and learn more. Talking to the nine respondents was not only insightful for my thesis, but it also deepened my personal interest in the subject. I'm very grateful to them for their valuable time and contributions.

I wrote my thesis in the PwC FS Tech team, where I met such a diverse and unique group of people. I learned a lot from them. My weekly meetings with Koen always started with a good catch-up before getting to the feedback, which I really appreciated. The rest of the team was also always ready to help, asking critical questions or sharing practical advice, so thank you for that.

A special thanks to my supervisors: one guiding me through the SCBA method, and the other with deep privacy technology knowledge. Both are very smart and inspiring people, and I could still learn so much from them. Their feedback was sharp, constructive, and always helped me move forward.

Then, my dearest friends, especially those who were also writing their theses this summer. It can be a bit demotivating when others are on holiday, but having a few fun study buddies around made all the difference. Thanks also to my "extra thesis committee", my father and two brothers, who were always just a call away in thesis emergencies. And of course, my sweetest boyfriend, who went through this whole period alongside me.

Looking back, the thesis writing period was challenging at times, and sometimes a little monotonous. But meeting so many new people with different backgrounds and stories made it a great experience. This marks the end of my master's and the beginning of something new and unknown. To end with a quote from a great writer, Dr. Seuss: "Oh! The places you'll go!"

A.V. Kerkhoven
Delft, August 2025

Summary

Context and Problem Statement

As financial crime grows more complex, governments have tightened Anti-Money Laundering (AML) regulations, with banks serving as the first line of defense. The Know Your Customer (KYC) process, used to identify and monitor clients, is central to this effort. To keep up with the resource intensive process, banks are beginning to turn to machine learning (ML), hoping to improve detection while lowering costs. However, this shift raises new concerns: opaque algorithms may introduce bias, reduce transparency, and unintentionally exclude vulnerable groups from the financial system. In the Netherlands, recent reports have shown how well-intentioned AML measures can lead to discriminatory practices. As the EU prepares to implement the new AML Regulation (AMLR) in 2027, which will further tighten compliance. While policy and technical discourse continues, there is little understanding of how these changes affect society as a whole.

Research Gap and Question

The literature showes that while AML policies and the integration of ML have been widely studied from regulatory, technical, and institutional perspectives, their broader societal effects remain underexplored. Most research focuses on costs and benefits for banks and governments, mostly neglecting the indirect impact on society. This thesis addresses that gap by systematically analyzing how ML integration into KYC processes shifts the societal costs and benefits of AML compliance. While most evaluations of ML in finance focus on technical or regulatory performance, this research applied a qualitative Social Cost-Benefit Analysis (SCBA) to examine broader social consequences such as exclusion, inequality, and institutional trust. By analyzing current practices and exploring how ML changes these dynamics, the study contributes to a more balanced understanding of innovation in financial compliance. The main research question was therefore formulated as follows:

"How does the implementation of machine learning in the KYC process alter the relevant social costs and benefits of the current KYC process under AML regulation?"

Methodology

This thesis applies a qualitative SCBA framework (Romijn and Renes, 2013) to explore the societal effects of AML regulation through the KYC process, with a specific focus on the impact of ML. The research followed the first five SCBA steps as outlined in Dutch policy guidelines (Romijn and Renes, 2013), including problem definition, establishing a baseline, defining the policy alternative, identifying social effects, and identifying costs. The social effects and costs were not quantified in this research due to the qualitative nature of the identified effects. Due to data limitations the final three SCBA steps were excluded. Primary data was collected through 9 semi-structured interviews with experts from the corporate sector, academia, and human rights advocacy. Interviewees were selected based on their expertise in AML, KYC, and/or ML, and their ability to reflect on broader societal implications. A preliminary KYC process diagram and stimulus texts based on literature were used to structure and enrich the interviews.

Interview data was analyzed using thematic analysis in ATLAS.ti, following the six-step method of Willig and Rogers (2017). Emerging codes were grouped into themes and translated into nine key social effects, e.g. inequality, crime reduction, and consumer surplus. These effects were then visualized in a conceptual model showing their interrelations and the impact of ML. Triangulation with existing literature was used to enhance validity.

Key Insights

The following key findings highlight the most important insights regarding the social costs and benefits of the KYC process and the impact of machine learning within AML compliance.

- *The KYC Process Has Dual Social Impacts*

This thesis examined the social costs and benefits of KYC processes under European AML regulation. Using thematic analysis of expert interviews, the study identified a wide range of interconnected social effects. The candidate positive effects include reduced crime and improved government financial health. Identified potential negative effects include increased administrative burdens on consumers, reduced economic participation, and rising inequality.

- *Machine Learning Amplifies Both Benefits and Harms*

  The introduction of ML into the KYC process intensifies many of these effects. For the benefits, ML can improves the detection of financial crime and may enhance the efficiency of public enforcement and private compliance. The identified harms that ML can raise were opportunity costs due to legal uncertainty, introduces privacy risks, and may increase stress among consumers.

- *The KYC Process can Intensify Social Harm and Unequal Burden Distribution*

  A central finding is that society bears the weight of the costs, even though financial institutions and governments control the design and implementation of AML systems. ML expands the surveillance function of banks, blurring the line between private and public roles and potentially reducing accountability. Vulnerable groups can be disproportionately affected through exclusion, algorithmic bias, and stress. This points to a structural imbalance in who benefits from technological innovation and who suffers from its unintended consequences.

Conclusions

This thesis explored how machine learning reshapes the social costs and benefits of KYC processes under AML regulation. Based on expert interviews and qualitative SCBA, the study found that ML amplifies both the benefits, such as improved crime detection, and the risks, including legal uncertainty, exclusion, and inequality. The effects are interconnected, with societal consequences often falling disproportionately on the public. By framing KYC as a socio-technical system, this research highlights the need for ethical oversight and systems thinking. ML introduces not just technological change; it also creates a responsibility to ensure that its effects are fair and beneficial to society as a whole.

Actionable Recommendations

This study highlights the need for a more balanced and accountable approach to integrating machine learning in AML compliance. Policymakers should move beyond a narrow enforcement focus by embedding social impact assessments into AML policy design and collaborating with academic experts. Regulation must ensure that ML systems are not only legally compliant but also socially fair and explainable. Financial institutions must take responsibility for the real-world effects of ML in KYC, prioritizing explainability, bias mitigation, and transparent vendor oversight. Close engagement with regulators and researchers is key to setting fair and practical standards. Finally, society, though not directly involved in implementation, bears many of the negative impacts. Public awareness, advocacy, and participation in digital finance policy debates are crucial to safeguarding fairness, privacy, and accountability.

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Nomenclature

Abbreviations

Abbreviation	Definition
AML	Anti-Money Laundring
ML	Machine Learning
FI	Financial Institutions
KYC	Know Your Customer
AI	Artificial Intelligence
CFT	Counter-Financing of Terrorism
AMLD	Anti-Money Laundering Directive (EU)
CDD	Customer Due Diligence
DNB	De Nederlandsche Bank (Dutch central bank)
AFM	Autoriteit Financiële Markten (Netherlands Authority for the Financial Markets) EU
European Union	
HCBS	FATF
Financial Action Task Force	
FIU	Financial Intelligence Unit
SCBA	Social Cost-Benefit Analysis
UBO	Ultimate Beneficial Owner
UK	United Kingdom
UN	United Nations
EPA	Engineering & Policy Analysis

1
Introduction

This chapter introduces the context, motivation, and structure of the thesis. It begins by outlining the social and regulatory challenges of money laundering and the central role of financial institutions in enforcing anti-money laundering (AML) measures, particularly through the Know Your Customer (KYC) process. It then presents the growing role of machine learning (ML) in this process and the emerging need to assess its broader societal effects. The chapter defines the problem, research objectives, and main research question, and explains the decision to use a qualitative social cost-benefit analysis (SCBA) as an exploratory framework. Finally, it outlines the relevance of the study for academic, societal, and policy audiences and provides an overview of the thesis structure.

1.1. Background

Money Laundering and its Social Consequences

"Money laundering is the process by which criminals "clean" the benefits of their activities to hide their illegal origin. It is usually associated with the types of organised crime that generate huge profits in cash, such as trafficking in drugs, weapons and human beings as well as fraud." (European Commission, n.d.). Criminals use a series of transactions to disguise the source of their funds. The consequences of money laundering can be detrimental to economies, governments, and societies worldwide. It distorts markets, undermines financial institutions, and enables the expansion of organized crime (McDowell and Novis, 2001). Masciandaro et al. (2007) show that criminals can create unfair competition by money laundering by driving up purchase prices. A report by the Australian Government (Schmidt, 2024) describes how money laundering presents social risks by eroding trust in public institutions. This is because money laundering often goes hand in hand with tax evasion and fraud, reducing the money available for public services (Schmidt, 2024). It also helps corrupt individuals hide and enjoy the profits of their crimes, which can encourage further corruption and unfairness in society (Schmidt, 2024). The Dutch central bank, De Nederlandsche Bank (DNB), which is responsible for supervising financial institutions, states that integrity is a basic requirement for a healthy financial sector, and that money laundering is a central risk to the sector's integrity (De Nederlandsche Bank, 2020).

Regulatory Landscape of AML in EU and the Netherlands

To mitigate the risks of money laundering, the European Union has developed a series of anti-money laundering (AML) directives since 1991, gradually expanding their scope to include terrorist financing and beneficial ownership transparency (Pavlidis, 2023a; Alexander, 2001). However, these directives, such as AMLD5, faced limitations, including fragmented enforcement due to national transposition and challenges in regulating emerging technologies like cryptocurrencies (Haffke et al., 2019; Van Roomen and De Jonge, 2024). To address these shortcomings, the upcoming Anti-Money Laundering Regulation (AMLR), set to apply from 2027, introduces a directly binding framework across all EU member states. It strengthens due diligence requirements, expands the range of obliged entities, and aims to improve consistency (Kaiser, 2024). This thesis is set in the context of an evolving regulatory framework. The stricter and more uniform requirements under the AMLR are likely to increase the compliance burden on financial institutions. As a result, finding efficient and scalable compliance solutions becomes even more important. The Netherlands implements the European requirements through it's own law: ”Wet ter voorkoming van witwassen en financieren van terrorisme” (De Nederlandsche Bank, 2020).

Financial Institutions as Gatekeepers of the Financial System

Banks are particularly susceptible to money laundering activities. This susceptibility arises from several inherent factors. Banks offer a wide range of financial services, including deposits, loans, discounts, and foreign exchange, which inherently creates numerous opportunities for money laundering activities to occur (He, 2009). Moreover, due to the central role that banks play within both national and international economic systems, they frequently serve as intermediaries for substantial volumes of financial transactions. Consequently, they become primary targets for money launderers aiming to integrate illicit funds into the formal financial system (He, 2009). Given this context, banks provide a logical and valuable point of entry to analyze social effects in the context of AML compliance measures.

KYC process in Financial Institutions

The KYC process forms a central component of AML compliance frameworks within banks. It defines what documents banks must collect and how they should monitor customer transactions. By tracking account activity, banks can detect unusual or suspicious behavior (Bilali, 2012). When such behavior is identified, banks are legally obligated to report it to authorities (Bilali, 2012). While KYC serves to prevent money laundering and terrorist financing, it is resource-intensive for banks, and non-compliance can result in severe penalties, such as the fines of 1.9 billion dollars and 775 million euros paid respectively by HSBC and ING for regulatory breaches (Mollenkamp, 2012; FIOD, 2018). The KYC process is one of the most important parts of AML compliance. Because KYC is both central to AML regulation and one of the areas where banks are actively exploring the use of machine learning, it serves as a logical and focused object of study in this thesis.

Unintended Effects of AML Compliance

A recent article by the Ministerie van Binnenlandse Zaken en Koninkrijksrelaties (2025) pointed out serious faults in a Dutch bank's execution of AML regulation. The KYC process was found to result in discriminatory profiling and exclusion, where customers with a migration background, dual nationality, or non-Dutch names were disproportionately subjected to account blocks, service denials, or excessive documentation demands. This example highlights how AML measures can have unintended negative side effects on society. Additionally, implementation of AML regulations significantly increases regulatory burden on banks, impacting their operational efficiency and customer relationships (Harvey, 2004; Unger et al., 2013). Regulatory pressures have led to a rise in de-risking, where banks refuse services to customers from high-risk areas, resulting in a decline of up to 10% in cross-border payments in grey listed countries (Collin et al., 2016). De-risking refers to when banks terminate or restrict financial services to clients perceived as high risk for money laundering. This is often done to avoid regulatory consequences. The societal risk of this practice is excluding groups from the financial system potentially caused by discrimination (Malakoutikhah, 2020) and enhancing inequality. Furthermore, the AML compliance raises concerns about privacy and surveillance, particularly where financial intelligence is shared widely or misused, creating social harm that is difficult to quantify but may undermine public trust (Levi and Reuter, 2006; Schmidt, 2024).

ML in the KYC Process

Despite growing interest in the potential of ML to improve AML processes, its actual use within financial institutions (FIs) remains limited due to small and outdated training datasets, fragmented customer data, and regulatory constraints (Canhoto, 2021). Rather than detecting actual criminal activity, ML is primarily used to flag unusual behavior for manual investigation, highlighting the gap between its perceived and realized value in AML applications (Canhoto, 2021). Financial institutions face significant barriers, including high implementation costs, concerns about transparency, fairness, and regulatory alignment (Turksen et al., 2024; Pavlidis, 2023b). The lack of explainability in ML systems, often seen as “black boxes”, raises questions about trust, legal defensibility, and accountability in AML enforcement (Barbierato and Gatti, 2024). Regulatory bodies, such as DNB and the Netherlands Authority for the Financial Markets (AFM), have acknowledged both the opportunities and risks of AI, stressing the need for harmonized oversight to prevent unintended harms (AFM & DNB, 2024). As ML slowly becomes more incorporated in compliance processes like KYC, it is essential to assess its broader societal implications.

1.2. Problem statement

In response to the global threat of financial crime, AML regulations have become increasingly strict, placing significant compliance demands on financial institutions. At the heart of AML efforts lies the KYC process, a legally required but resource-intensive system for identifying and monitoring customers. To cope with growing regulatory pressure, banks are turning to ML as a tool to automate and enhance KYC procedures. FIs are looking for improved detection and operational efficiency in ML. However, it also introduces new risks, including algorithmic bias, reduced transparency, and the exclusion of vulnerable groups. As ML becomes more embedded in compliance systems, it is no longer sufficient to evaluate it solely based on technical performance. There is a need to assess its broader societal impact. However, current literature rarely addresses the full spectrum of social costs and benefits associated with ML-driven KYC. This lack of insight creates uncertainty for banks and policymakers seeking to balance innovation with social welfare. There are indications that social costs might outweigh the benefits, but no comprehensive overview from a welfare economics perspective currently exists. An outline of the social effects can provide this overview, guiding policymakers and FIs toward reforms that enhance social welfare.

1.3. Research Objectives

This thesis investigates the implications of integrating ML into KYC processes, with a particular focus on how the integration affects the social costs and benefits associated with compliance with AML regulation. Rather than conducting a full social cost-benefit analysis (SCBA), the study aims to develop a set of relevant criteria and considerations that could inform such an assessment. This study focuses on ML as a tool used by banks to meet existing AML requirements. Framed in this way, the research is guided by the following central question:

“How does the implementation of machine learning in the KYC process alter the relevant social costs and benefits of the current KYC process under AML regulation?”

To answer this question, the study applies a qualitative approach and follows the first five steps of a SCBA, as outlined in the Dutch SCBA guidelines by Romijn and Renes (2013). This method allows for a structured examination of the broader societal implications of AML regulation, and how these implications could shift depending on the way of implementation. To answer the main research question the first five steps of the SCBA are carried out qualitatively. To employ the SCBA method there needs to be a baseline situation and policy alternative. In this study, the baseline is a situation where no AML regulation is enforced. The policy alternative is where there is AML regulation which requires the KYC process. Steps 4 & 5 in the SCBA, respectively identify the effects and benefits of the policy alternative. These two parts are usually also monetized, however this is outside the scope of this research. The choice and further explanation of the method is detailed in section 1.4 and section 3.3. The geographic scope of this question is limited to the European context, with a particular focus on the Netherlands, where this research is conducted. This study does not conduct a full SCBA, but rather identifies and analyzes the types of social effects that should be considered in such an assessment, offering a structured foundation for future evaluation.

What are the current KYC operations and compliance practices used by banks under AML regulation?

This question provides a base of how banks currently perform KYC processes to comply with AML regulation. It outlines the operational steps involved in the process. This step is essential for the SCBA, as it defines the policy alternative against which the use of machine learning will be assessed. To answer this, a literature review was conducted to capture relevant industry insights, supplemented by semi-structured expert interviews with professionals involved in compliance.

How is machine learning currently applied in the identified KYC process?

This question identifies where and how ML is applied or can be applied in current KYC procedures. The purpose of this analysis is to define the object of change in the research to understanding how ML modifies the social effects of AML compliance with and without its use. The question is addressed through a review of recent literature on technological developments in AML/KYC, complemented by expert interviews. Interviewees were asked to reflect on their experience with the use of ML, including perceived benefits, limitations, and implementation challenges. These insights provide the foundation for assessing how the integration of ML might influence the costs and benefits identified in the qualitative SCBA.

What candidate social effects need to be considered in a SCBA of the current KYC process under AML regulation?

This question identifies the relevant social costs and benefits associated with the implementation of AML regulation through current KYC practices. This part of the research is based on the SCBA framework and maps out which effects, both positive and negative, should be taken into account for the monitization step in a future SCBA. For this sub-question, step 4 and 5 of the SCBA are carried out qualitatively. This is, the identification of the effects and costs of the policy alternative compared to the baseline of no AML regulation. To answer this sub-question, the study combines several methods. Effects are derived from thematic coding of expert interviews and also from academic and policy literature on AML. This approach ensures that the resulting effect categories are both theoretically grounded and reflect real world experience. Together, they provide the foundation for later assessing how these effects might shift with the introduction of machine learning in the KYC process.

How does the introduction of machine learning alter the identified candidate social costs and benefits of the current KYC process?

Building on the previously identified societal effects of current KYC practices, this sub-question examines how those effects change qualitatively when machine learning is used as part of the compliance process. This sub-question is not part of the SCBA method as ML is not a policy alternative enforced by the government. ML can potentially improve or decline the social costs and benefits of the KYC process. By analyzing expert interviews, this study identifies how practitioners perceive changes in these societal categories after ML implementation. The interviews indicate a positive or negative effect on the identified social effects because of ML use in the KYC process. This understanding will reveal new opportunities, hidden risks, or unintended consequences of ML compliance. The resulting conceptual framework will provide insights, enabling policymakers and financial institutions to make informed decisions on how best to leverage machine learning in KYC practices, ensuring effective compliance while minimizing potential social harms.

1.4. Perspective and SCBA Approach

During the writing of this thesis I was doing a thesis internship at PwC. PwC supports this research project and offers access to valuable expertise, people, and internal knowledge that I wouldn't easily find elsewhere. I'm writing this thesis from within the Financial Services Technology team, which naturally gives the research a consultancy perspective. This might shape how certain issues are viewed or framed. PwC has been advising financial institutions for many years on how to deal with increasingly complex AML requirements, and how to adapt to new technologies like machine learning. Being part of this firm has given me practical insight into how banks handle these challenges and what kinds of trade-offs they face.

Additionally, the researcher chose a welfare economics and utilitarian perspective to analyze the social consequences of ML in the KYC-process. In the economics of welfare, the welfare gains or losses of government actions are measured and aim to achieve maximum well-being in society (Just et al., 2004). SCBA is a tool rooted in welfare economics that helps support policy decisions by comparing the broad societal costs and benefits of proposed measures (Romijn and Renes, 2013). It aims to express even non-market effects, such as health, safety, or social cohesion, in monetary terms to enable a consistent and transparent comparison (Romijn and Renes, 2013). Although full quantification in some projects is not always possible, SCBA remains valuable by clearly outlining known and unknown effects and helping to structure complex policy discussions. The approach can also highlight how costs and benefits are distributed across groups. This clear way of evaluating makes the perspective well suited for assessing complex interventions, such as those in the KYC process.

The decision to use a SCBA in this thesis is both practical and exploratory. It is practical because

SCBA offers a structured way to assess the broad societal effects of the research topic, making it a suitable method for evaluating social consequences of the KYC process under AML regulation. At the same time, it is exploratory because SCBA is not commonly applied in the context of financial compliance. This thesis therefore contributes to academic research by showing how SCBA can be adapted to evaluate how regulations are put into practice, not just in terms of technical performance, but also in terms of societal impact. To ensure a clear understanding of how social effects are distributed, this thesis categorizes the identified costs and benefits by stakeholder group: society, government, and FIs. This division helps clarify who is affected by the KYC process

This thesis takes a broad welfare perspective on the SCBA by going beyond purely financial effects and including societal, ethical, and distributional impacts of using machine learning in KYC. While a SCBA usually focuses on expressing and comparing effects in monetary terms, the broad welfare perspective also considers non-monetary aspects like fairness, and effects on different stakeholders (Bos et al., 2022). By including qualitative insights and looking at how benefits and burdens of the KYC process are distributed, this thesis supports efforts to make SCBA more suitable for effects that can't easily be expressed in money.

1.5. Relevance

1.5.1. Academic Relevance

Current literature covers the effectiveness of current KYC processes as well as the potential effects that ML can bring. However they often examine the perspective of government, and FIs. Social costs or benefits are either discussed as subsections within broader studies, or each article focuses on one specific social cost or benefit. This study addresses that gap by applying elements of a SCBA a method widely used in public policy and infrastructure evaluation, but rarely, if ever, applied to AML compliance or financial sector technology adoption. In this sense, the thesis introduces a novel and exploratory use of SCBA, offering a new welfare economics perspective on how to assess AML's broader impact on society. The thesis contributes to new insights on the use of the SCBA methodology in the context of financial regulation.

Existing research has yet to fully map or compare the social trade-offs associated with the impact of ML on the social effects of KYC. This thesis fills that gap by offering a broad view of the societal impact, adding to academic knowledge while also supporting real-world decision-making. The results are especially useful for policymakers, and financial institutions, who are under growing pressure to consider not just policy effectiveness, but also the fairness and social effects of new technologies in compliance.

1.5.2. Societal Relevance

The results of this thesis are socially relevant because they help identify which design or policy choices in AML enforcement may unintentionally harm the people the system is meant to protect. The shift in social effects brought about by machine learning is complex. This thesis aids people to understand the complexity of the issue. By doing so, the research supports public debate and knowledge on how to ensure that the fight against financial crime does not come at the cost of fairness, and financial accessibility. The findings can be used by financial institutions, society, and policymakers to make more informed decisions.

1.6. Outline Thesis

This thesis is structured as follows. Chapter 2 provides an overview of the existing literature on the effects of AML processes and the use of machine learning, identifying key knowledge gaps. Chapter 3 explains the methodology, including the use of qualitative social cost-benefit analysis and thematic interview analysis. Chapter 4 presents the results, exploring the social costs and benefits of both the current KYC process and the implementation of machine learning. Chapter 5 summarizes and visualizes the conceptualized social effects. Chapter 6 discusses and evaluates the findings, and Chapter 7 concludes with the answers to the research questions and practical implications.

2 Related Work

This literature review details the current state of knowledge on the social costs and benefits of implementing ML in AML practices in banks. The review provides key aspects necessary for understanding the context of the research questions. Despite extensive research on AML regulations and compliance costs, a critical gap remains in assessing the social costs and benefits of AML compliance. Moreover, little is known about how different compliance strategies, such as the use of ML, affect the overall societal costs and benefits of AML enforcement. This review highlights the need to first evaluate AML as a regulatory intervention, before examining whether the adoption of ML amplifies or mitigates its effects. The AML process is central to this literature review even though the research objectives are focused on the KYC process. This is because the AML process/compliance is a more broad term encompassing the KYC process, which makes it mentioned more often in literature.

This review draws on academic studies, government reports, and consultancy analyses to examine the social costs and benefits of AML processes in banks. Academic sources offer critical and theoretical insights, while policy and consultancy reports provide practical perspectives on implementation, compliance burdens, and operational impact. Together, they offer a comprehensive view of both systemic issues and real-world effects.

First, the search strategy is elaborated. Then, the review combines findings from academic and grey literature in two main areas: (1) studies assessing the costs and benefits of AML compliance, and (2) studies analyzing the effects of ML applications in AML processes. The aim is to identify key gaps in the existing research and to establish a foundation for assessing the social costs and benefits of ML in the AML context. The literature review investigates what is known about the social costs and benefits of AML compliance in the banking sector, and explores the social effects of machine learning in the same context.

2.1. Search Strategy

To identify relevant literature, three targeted database searches were conducted using Scopus, Web of Science, and Google Scholar. Each search was structured around one of the following conceptual groups: (1) AML policy in Europe, (2) machine learning in AML practices, and (3) the economic and social costs and benefits of AML measures. The first group, AML policy in Europe, was used in contextualizing the topic and substantiated the introduction chapter. The other two queries resulted in the articles for the literature review. The specific boolean queries used are summarized in Table 2.1. After these searches backward and forward snowballing was carried out. The resulting papers were included based on their relevance to the research questions. The screening resulted in 25 articles being included in the literature review which can be seen in Table 2.2 and Table 2.4.

These are categorized thematically into two main groups:

- Studies discussing the costs and benefits of AML processes in banks.
- Studies assessing the implementation and effects of ML in AML processes.

Table 2.1: Literature search strategy

Concept Groups	Keywords	Truncations
AML policy in Europe	anti-money laundering, AML policy, banks, compliance, policy evaluation, EU, Europe	("anti-money laundering" OR "AML policy")AND("bank*")AND("compliance" OR "policy evaluation") AND ("EU" OR "Europe")
Social costs and benefits of machine learning in AML	machine learning, artificial intelligence, effects, impacts, risks, anti-money laundering, AML, social, society	(("machine learning" OR "artificial intelligence") AND ("effect*" OR "impact*" OR "risk*) AND ("anti-money laundering" OR "AML") AND ("social" OR "society"))
Costs and benefits of AML	cost-benefit analysis, anti-money laundering, AML compliance, financial regulation, effectiveness, costs, unintended consequences	("cost-benefit analysis") AND ("anti-money laundering" OR "AML compliance" OR "financial regulation") AND ("effect*" OR "cost*" OR "benefit*" OR "unintended consequences")

2.2. Studies on the costs and benefits of AML regulation

The current gray, academic and government literature contribute insights on the costs and benefits of AML compliance as seen in Table 2.2. Several articles highlight that there are significant known costs to AML compliance with little known benefits.

Crime Reduction and Deterrence Effects

Gerbrands et al. (2022) demonstrate that AML regulation can disrupt money laundering networks, ultimately reducing money laundering. Ferwerda (2009) argues that the implementation of AML regulation contributes to the reduction in crime. The authors argue that AML policies deter criminals from illegal behavior and therefore lower crime levels (Ferwerda, 2009). Ferwerda (2009) found that international cooperation is the only policy area significantly associated with lower crime rates. This suggests that even though AML policy is related to lower crime, not all AML measures are equally effective.

Unintended Consequences: De-risking and Financial Exclusion

Some sources recognize significant unintended consequences, particularly financial exclusion, overregulation, and institutional inefficiencies. Pavlidis (2023b) critiques the AML policies for aggrevating de-risking behaviours, especially against non-profit organisations and marginalized communities. Although AML policy encourages proportionality, the implementation of its risk-based approach often lacks nuance, causing institutions to default to broad avoidance rather than tailored risk mitigation. Similarly, Malakoutikhah (2020) stresses that AML regulations have led to widespread financial exclusion. Banks, fearing regulatory penalties, withdraw services from groups deemed high-risk, including charities and money transfer operators. These effects are counterproductive, driving financial activity underground and weakening the formal financial system's integrity (Malakoutikhah, 2020).

Economic Costs and Unclear Benefits

In a project funded by the European Commission, Unger et al. (2013) developed a cross-country cost-benefit analysis of AML/CTF policy in the EU. It highlights that while compliance efforts cost Member States an estimated €2 billion annually, mostly borne by the private sector, the benefits remain largely unmeasured. Unger et al. (2013) highlight costs and benefits of AML policy at a national level, touching on financial costs and benefits, as well as a few social ones. The study supports the relevance of a social cost-benefit perspective, especially one that questions whether current efforts are proportionate and effective.

Government and consultancy reports offer insight into institutional and business-level effects. The New Zealand Ministry of Justice study on AML reforms (New Zealand Ministry of Justice, 2017) highlights mixed cost outcomes, while a Deloitte report (Deloitte, 2016) finds that financial institutions bear disproportionate compliance burdens with uncertain benefits. Harvey (2004) highlights the distribution of the costs. The author states that while states seek to demonstrate regulatory control to satisfy international expectations, the compliance costs are disproportionately absorbed by banks and society at large, rather than by governments themselves. According to Harvey (2004) these include not only direct financial burdens, but also exclusion and erosion of customer trust. Moreover, Harvey (2004) suggests that the private benefits to financial institutions, such as penalty avoidance or reputational protection, may be overstated, indicating a weak cost-benefit rationale for current AML compliance strategies.

An article by Ferwerda (2018) also devised several costs and benefits for AML(e.g. supervision costs, reduction in privacy, reduced damage effect on real economy and confiscated proceeds). In addition to the studies discussed above, a broader overview of the identified positive and negative effects of AML compliance across the literature is presented in Table 2.3.

Challenges in Evaluating AML Effectiveness

A central concern in the literature is whether AML policies achieve their intended goals, and at what cost. A major challenge in assessing AML effectiveness is the hidden nature of money laundering, which makes reliable measurement difficult Ferwerda (2018) and Harvey (2004). Both Ferwerda (2018) and Harvey (2004) emphasize the lack of empirical evidence substantiating a clear correlation between AML compliance and a reduction in money laundering or associated criminal activities. In the absence of reliable data, governments often justify increasingly stringent regulatory frameworks on the presumption that more regulation equates to less money laundering (Harvey, 2004). However, Harvey (2004) argues that this presumption is not supported by empirical research and fails to account for how laundering methods adapt in response to regulation. With a similar critical view, Ferwerda (2018) concludes their article with the dilemma whether unknown benefits are worth a very expensive AML policy with reduction of privacy and efficiency costs. In a frequently cited study, Pol (2020) offers an interesting critique of AML, stating that it is "the world's least effective policy experiment". The analysis demonstrates that the proportion of criminal proceeds seized on a global scale is less than 0.1%, while compliance costs significantly exceed the sums recovered. This argument is reinforced by Saperstein et al. (2015), who contend that AML policies lack a solid economic foundation and are largely ineffective. These articles hint at questioning the proportionality of AML policies.

Privacy and Surveillance Concerns

Several studies express concern about privacy violations and the broader societal consequences of AML surveillance. Van Roomen and De Jonge (2024) explore tensions between privacy rights and AML enforcement. They argue that cross-border data sharing and surveillance, while essential for disrupting illicit financial flows, can compromise democratic accountability and human rights if not properly balanced. Amicelle and Favarel-Garrigues (2012) show how financial surveillance practices tied to AML and counter-terrorist financing rules can produce overlooked social harms. The authors compare two cases. First, the public sanction lists, which have sparked public discussions. Second, the largely unnoticed internal profiling practices in banks. The authors also point to effects as violations of the right to due process, reputational damage, and the erosion of human dignity. This happens when people are wrongly flagged or excluded from financial services without knowing why. The authors stress that these harms are often invisible. The aforementioned harms are rarely discussed or challenged, as individuals are unaware of the profiling (Amicelle and Favarel-Garrigues, 2012). The authors argue that this is caused by little transparency or oversight provided by banks (Amicelle and Favarel-Garrigues, 2012). The article shows that while AML measures aim to improve security, they can also threaten human rights when carried out by private actors without proper safeguards. Brewczyńska (2024) challenges the legitimacy of the legal grounds on which the data is collected by banks and in turn the government with her book "Policing via banks: the question of legitimacy of personal data sharing". Data protection is mentioned as a potential area of improvement on the European AML regulations and recommends that AML legislation should go further than just following legal rules and should implement safeguards to protect individual rights. The author also explains the way banks enforce the AML regulations, is done by the KYC process. The KYC process is chosen as the object of analysis in this thesis as it is the specific operation that carries out the AML regulation.

Financial Inclusion and Inequality

A persistent theme in the literature is how AML regulation can lead to financial exclusion and deepen inequality. De Koker (2006) shows how strict AML/CFT customer due diligence (CDD) rules can lead to financial exclusion, especially in countries with large informal sectors. In both the UK and South Africa, people without formal ID were often denied basic banking, despite simplified rules being available. This limits access to financial services for vulnerable groups and weakens AML/CFT systems by pushing activity into the informal economy, where detection is harder. These findings highlight a key social cost of AML regulation: reduced financial inclusion. De Koker (2006) argues that CDD systems should be adjusted to local contexts to balance crime prevention with access. This supports the view that AML rules can have both social benefits (e.g. crime reduction) and costs (e.g. exclusion), which need to be weighed in policy design.

2.2.1. Gaps in Literature on Social Effects AML policy

Key literature reveals that while AML policies may contribute to crime deterrence and the disruption of laundering networks, especially through international cooperation, their effectiveness remains largely unproven due to a persistent lack of reliable data and measurable outcomes. At the same time, significant negative effects of AML regulations are well-documented. The disconnect between assumed benefits and demonstrated harms raises critical questions about the proportionality and justification of current AML compliance frameworks. Current literature concentrates particularly on banks, governments or policy effectiveness. While current research covers negative and positive effects of AML regulation, it lacks focus on society. This thesis builds on the insights of this literature review by focusing specifically on the KYC process, which operationalizes AML regulation in practice and it's social effects. Table 2.2 presents a comparative overview of key studies evaluating the costs, benefits, and unintended consequences of AML policies across jurisdictions and methods. It can be noted that the studies listed in Table 2.2 are based in various countries, which points to the international relevance of the challenges associated with AML policy. The studies in this table primarily rely on theoretical models, legal analysis, literature reviews, and stakeholder-based methods such as surveys and consultations.

Table 2.2: Summary of Literature on AML Cost-Benefit and Effectiveness

Reference	Purpose	Method	Findings	Limitations	Future Research Recommendations	Country
1. Pol, 2020	Evaluate AML policy as a failed public policy experiment	Literature review and synthesis	AML recovers less than 0.1% of criminal funds	Poor data quality and inconsistent methodologies	Interdisciplinary policy redesign with better metrics	Global
2. Deloitte, 2016	Analyze business compliance impacts of AML Phase 2	Stakeholder consultations and cost modelling	Financial sector bears high cost; benefits unclear	Estimates rely on assumptions; low empirical backing	Ongoing evaluation of real business effects	New Zealand
3. New Zealand Ministry of Justice, 2017	Evaluate Phase 2 AML reform impacts	Government policy analysis	Reforms created mixed business cost effects	Based on projected rather than real costs	Longitudinal impact monitoring	New Zealand
4. Ferwerda, 2009	Test whether AML policy reduces crime	Theoretical model and an empirical panel analysis using Mundlak specification	International co-operation in AML policy is significantly associated with lower crime rates	Data on AML enforcement quality and causality is limited; results show association, no cause relationship	Include more countries, better AML data, and use instruments or time-series to test causality	Europe, Canada, US, Australia
5. Harvey, 2004	Estimate AML compliance costs in UK banks	Survey-based study	Compliance burdens are high and rising	Limited sample; early-stage estimates	Broader cost analysis across EU	UK
6. Unger et al., 2013	Assess legal/economic effectiveness of AML in 27 EU states	Mixed methods: surveys, interviews, workshops	Varies by country; weak CBA data hinders full assessment	Incomplete statistics and survey responses	Improve cross-country comparability and statistical reliability	EU-wide
7. Malakoutikhah, 2020	Analyze how CTF regulation causes financial exclusion and undermines its own effectiveness	Qualitative legal research drawing on international frameworks	Financial exclusion undermines CTF effectiveness and violates human rights	Paper is based on other literature, no empirical research done	Flexible, proportionate CDD and risk-based financial inclusion measures	Global
8. Pavlidis, 2023a	Examine the unintended consequences of FATF standards	Legal analysis with inter-disciplinary perspectives	FATF standards contribute to de-risking, financial exclusion, and NPO targeting	Misapplication of the risk-based approach; insufficient emphasis on proportionality and financial inclusion	Promote correct implementation of FATF's RBA; strengthen data quality and stakeholder coordination	Global
9. Van Roomen and De Jonge, 2024	Analyze human rights vs. AML enforcement tension	Legal analysis and case study	Strong privacy norms hinder cross-border enforcement	Difficulty accessing third-country data	Propose human dignity as legal counterbalance	Netherlands
10. Ferwerda, 2018	Assess AML policy effectiveness from a cost-benefit view	Theoretical and economic framework	Policy effectiveness varies; costs are high relative to gains	Lack of data for precise monetization	Include more empirical assessments; refine CBA methods	Multiple (EU focus)
11. Saperstein et al., 2015	Argue AML policy lacks economic justification	Legal critique	AML is costly and largely ineffective	No empirical data; focused on US legal system	Include empirical analysis to support legal claims	USA
12. Brewczyńska, 2024	Uncover the legitimacy of networked data sharing as per AML regulations	Legal analysis	Legitimacy should be implemented into a feature of law	Scoped to Europe and laws before 2023	The development fo legitimacy within law	EU-wide
13. Gerbrands et al., 2022	Investigate whether anti-money laundering policies affect money launderers' behavior	Network analysis	AML policies can affect criminal networks	Lacking robust theoretical underpinning	Track and measure criminal networks over time	EU-wide
14. Amicelle and Favarel-Garrigues, 2012	Exploration of FI surveillance practices	Comparative case study	There are harms tied to AML policy through bank surveillancea	Reliance on secondary data and limited scope of researched actorsan	Include privacy as a collective social value in policy making	France, Switzerland
15. De Koker, 2006	Explore link between AML/CFT regulations and financial exclusion	Conceptual analysis	Policy makers should consider the impact of these AML processes on financial exclusion	Lack of multidisciplinary research	More research on the needs and profile of the financially excluded	UK & South Africa

2.2.2. Literature-Based Overview of AML Effects by Stakeholder

The specific positive and negative effects that are stated in the literature in Table 2.2 can be found in Table 2.3, structured by three stakeholder groups: society, financial institutions, and the government. This categorization offers a structure to the effects and helps show a distributed across each group and is elaborated more in section 3.3. The effects in Table 2.3 are based on the current KYC processes that are still largely fulfilled through manual processes, rule-based systems, and human oversight.

Table 2.3: Positive and Negative Effects of AML Policy Measures

Stakeholder	Negative Effects (Costs)	Positive Effects (Benefits)
Society	Compliance burden legit. customers[6,5] Discrimination[7, 14] Fees and rates[1] Financial exclusion[1,6,5,8,7,14] Data protection risk [12] Human dignity risk[9, 14] Reputational dagmage [14] Human security risk[9] Proportionality[7] Lack of fair trial[14] Reduction privacy[6,10,14] Shift to unregulated financial systems[8,7] Tax[1] Transaction delays[6,5]	Public safety[1,6,3] Reduction in crime[6,3,4,7] Reduction damage on real economy[6,10] Reduction money laundering[6,3,10,13] Reduction terrorism[6]
Financial Institutions	Compliance costs[1,2,3,5] Penalties[1] Reporting costs[6,5] Training costs[6,5]	Attraction of quality customers[5,2] Financial risk reduction[6,2,5,10] Improvement in governance[2] Reputation risk reduction[6,2,3,5]
Government	Administrative & staff costs[6,3,5,10] Ongoing policy making costs[6] FIU budget & staff[6,10] Supervisor budget & staff[6,10]	Confiscated proceeds[6,3,10] International reputation[3,5] ML deterrence[3] Preventive fines (FI)[6] Repressive fines (criminals)[6,10]

The literature shows that traditional KYC procedures offer important societal benefits, such as increased public safety and reduced financial crime. However, they also carry considerable costs particularly for society, financial institutions, and the government. The effects are varied and distributed across three stakeholder groups. The effects are largely distributed upon society and less across the other two groups. Additionally, society often experiences downstream consequences of impacts on both financial institutions and governments, making it essential to comprehensively analyse how AML regulation and the KYC process in particular affects society as a whole. This thesis addresses that need by systematically mapping these social effects. This section has reviewed the literature on the current KYC process, which is largely manual and reliant on rule-based algorithms. The following section explores the introduction of ML algorithms which can learn from data, allowing them to perform tasks without explicit instructions.

2.3. Studies on the cost and benefits of machine learning in AML processes

The current literature mainly acknowledges the positive and negative effects that ML can bring to the effectiveness of AML compliance within banks. The literature also covers the known inherent risks and challenges that ML brings.

Machine Learning in AML Context

A central theme across several studies is the dual nature of this technological innovation in AML: it promises increased efficiency in detecting suspicious transactions but also raises significant concerns e.g. about fairness, transparency, and regulatory alignment. In this review, the term AI is used as an umbrella concept that includes ML. ML in this thesis differs from rule based algorithms as they are able to learn from data without following explicit instructions. Including AI as a term for research broadens the amount of findings in both academic and grey literature relevant to technological developments in AML. Table 2.4 displays the sources and key attributes of the literature discussed in the review related to ML in AML processes. The methods of the literature in this table are largely conceptual, literature-based, or descriptive, ranging from policy reviews and legal analysis to bibliometric studies. The full list of all negative and positive effects found in these studies can be found in Table 2.5.

Promises and Challenges of ML

Positive and negative effects of ML are well covered in current literature. Lyeonov et al. (2024) describe both promises and challenges of ML in AML processes. They note that ML may support real-time detection of suspicious activities, improve prediction accuracy, reduce false positives, and optimize the allocation of human resources according to Lyeonov et al. (2024). The down side of ML use is the risk of infringing on privacy, and facing data quality and explainability issues. The authors emphasize the importance of promoting and improving transparency in the AML system.

Dzingirai (2024) conducts a structured literature review to examine the relationship between artificial intelligence and money laundering, focusing specifically on developments in the Southern African context. The study summarizes a set of potential effects mentioned in existing literature, including real-time detection of suspicious transactions, automated compliance checks, and the use of customer behavior data for risk profiling. The review also identifies risks such as infringements on privacy and challenges related to poor data quality (Dzingirai, 2024).

Yi et al. (2023) offer a broader overview of AI applications in finance, emphasizing how AI can address conventional inefficiencies and improve decision-making. However, they also stress that the quality of input data and explainability are major concerns. The implementation of AI in credit risk assessment and fraud detection is promising but may introduce biases if not properly controlled.

A recurring concern across the literature is the interpretability and explainability of AI systems used in AML contexts. Barbierato and Gatti (2024) argue that despite their predictive power, machine learning algorithms, particularly neural networks, are often ”black boxes” that cannot provide explanations. This opacity can undermine user trust, regulatory compliance, and the legal defensibility of AI-driven decisions. Their review questions whether machine learning should be seen as a true science. Barbierato and Gatti (2024) argue that we need to look more closely at ML’s limits, how it works and how reliable its methods really are.

Mehrabi et al. (2021) offer a comprehensive and interdisciplinary survey of how bias arises and manifests in ML systems. Bias in training data or model design can lead to discriminatory outcomes (Mehrabi et al., 2021). In the case of the KYC process it can result in disproportionately flagging individuals from specific ethnic backgrounds as high risk. While the system may not be explicitly designed to discriminate, it can do so if biased correlated variables (e.g., ZIP code, nationality) are used. They also emphasized how fairness is very important, especially when used in sectors like the judicial sector (Mehrabi et al., 2021). This is also very relevant for the KYC process because if a model is unfair, individuals can be unjustly excluded from the financial system.

Maxwell et al. (2020) provide a detailed legal analysis of the compatibility of AI-enhanced AML systems with EU fundamental rights, arguing that current systems often violate the proportionality principle. Anther problem identified in the article is the lack of explainability in certain machine learning models.

Pavlidis (2023b) considers how AI might revolutionize AML and asset recovery but stresses the need for robust regulatory frameworks. The study highlights the importance of balancing technological efficiency with safeguarding fundamental rights, stating concerns about over-surveillance and under-accountability. The paper is notable for framing digital transformation in AML as a ”game changer” but warns that this transformation is incomplete without new safeguards.

ML Adoption in AML

Turksen et al. (2024) provide a detailed exploration of how banks in Eastern Europe are navigating AI and ML implementation for suspicious transaction monitoring. Their qualitative study highlights banks’ growing interest in AI tools due to operational efficiency gains but notes persistent trust and explainability challenges. The regulatory uncertainty and cost of integrating explainability into AI systems emerged as critical barriers. Their findings suggest a tension between innovation and compliance, especially under expanding policies.

Borrellas and Unceta (2021) bring an economic perspective to these concerns, framing the social value of machine learning in terms of aggregate welfare. Their study identifies interpretability, fairness, safety, and privacy as the four main barriers to socially optimal adoption of AI in economic decision-making. They argue that current laws and business incentives might not be enough to make sure AI is fair, safe, and clear. New rules may be needed to deal with the negative side effects that AI can cause.

2.3.1. Gaps in Literature on the Social Effects of ML in AML Processes

The literature on AML policy, particularly in the context of AI and ML deployment, is evolving. It reflects an assumption that ML could improve AML effectiveness, though this promise remains largely unproven. Additionally, ML also introduces new social and economic risks. The trade-off between innovation and accountability is central to current debates. Contributions like those of Turksen et al. (2024) and Pavlidis (2023b) show that the field is moving toward greater integration of legal, ethical, and technical perspectives. While the literature highlights both risks and benefits of ML in AML, it doesn't yet show how this affects the social costs and benefits of the KYC process. This thesis fills that gap.

Table 2.4: Summary of literature related to machine learning in AML

Reference	Purpose	Method	Findings	Limitations	Future Research Recommendations	Country
16. Pavlidis, 2023b	Assess AI impact on AML and asset recovery policy.	Literature review	Regulatory framework that acts as a base for risk mitigation for technology in AML.	Largely theoretical and legal in scope, it does not evaluate implementation or effectiveness of proposed safeguards.	New operational governance structures for AI implementation.	Greece
17. Turksen et al., 2024	Investigate legal and trust challenges of AI in suspicious transaction monitoring	Qualitative interviews with banks and tech developers	AI valuable but hindered by costs, explainability issues, and regulation gaps	Limited generalizability due to regional scope	Promote transparency, build explainable models, align with legal standards	UK
18. Barbierato and Gatti, 2024	Critically assess ML's scientific status and epistemological foundations.	Conceptual analysis, review of ML approaches and literature.	ML lacks causal explanation and relies on statistical tools.	Theoretical only, lacks empirical validation.	Clarify epistemological grounding, Further advancement in imitation learning and reinforcement learning.	Italy
19. Mehrabi et al., 2021	Survey ML bias and fairness challenges.	Literature synthesis, taxonomy creation.	Bias in data, algorithms and user feedback loops are common in ML. Fairness in ML is when existing bias is avoided.	Conceptual, no empirical validation.	Address biases and other existing issues in AI.	USA
20. Maxwell et al., 2020	Assess if AI-based AML systems comply with EU fundamental rights	Legal-technical analysis using proportionality test	Finds AML systems legally problematic; many false positives, limited effectiveness	Theoretical focus; no performance data from real-world systems	Develop oversight, feedback systems, and rights-compliant AI frameworks	France
21. Yi et al., 2023	Review AI's challenges and opportunities in accounting and finance	Qualitative literature survey and taxonomy development	AI enhances forecasting and fraud detection but faces data and complexity issues	No empirical case studies; conceptual focus	Apply AI to real-world finance problems and develop hybrid models	China
22. Dzingirai, 2024	Examine AI's impact on money laundering in Southern Africa	Structured literature review	AI helps detect laundering, improve compliance, analyze behavior, compute risks, and guide policy	Relies solely on secondary sources; lacks empirical validation	Call for empirical studies on AI's effectiveness in AML	South-Africa
23. Borrellas and Unceta, 2021	Explore ML challenges from economic/regulatory perspective.	Economic theory, policy analysis.	ML models have issues that could impact the development and adoption of ML models which in turn could change overall social welfare.	Theoretical focus, lacks empirical data.	Interdisciplinary research on inefficiencies that externalities and monopolistic structures may generate.	Spain
24. Lyeonov et al., 2024	Analyze global trends in AI/ML use for financial crime prevention	Bibliometric analysis of 746 Scopus-indexed documents	Highlights international collaboration, growth, and ethical concerns in AML applications	Descriptive; lacks case-level or implementation evaluation	Explore fairness, ethics, and impact of AI/ML in national contexts	Poland
25. AFM & DNB, 2024	Explore AI trends in Dutch financial supervision.	Policy review, interviews with institutions.	AI is already used in KYC, fraud detection and cautious use of generative AI.	Regulatory perspective, limited access to confidential industry data, and insights based on selective interviews.	Increase supervisory knowledge, align EU regulation.	Netherlands

2.3.2. Literature-Based Overview of Effects of ML in AML by Stakeholder

Table 2.5 presents the developments in the AML domain by outlining the positive and negative effects of integrating ML, algorithms that learn from data instead of predefined rules, into compliance processes. As the literature increasingly explores the role of advanced analytics and automation, ML is considered to have the potential to enhance the effectiveness and efficiency of AML processes.

The table reveals that machine learning introduces a wider range of both opportunities and new risks. On the one hand, ML can significantly enhance compliance efficiency: improving detection of suspicious patterns, reducing manual workloads, and increasing overall AML effectiveness. These benefits are especially relevant for financial institutions that seek to manage growing volumes of data and regulatory pressure more intelligently.

On the other hand, ML based systems also bring complex technical and ethical challenges. Issues such as algorithmic bias, lack of transparency, explainability concerns, and data protection risks represent emerging costs that were largely absent in the analysis traditional, more manual based, compliance processes. These risks extend beyond financial institutions and begin to impact society more broadly.

Table 2.5: Positive and Negative Effects of Implementing Machine Learning in KYC Processes

Stakeholder	Negative Effects (Costs)	Positive Effects (Benefits)
Society	Data privacy risk[21,16,24,20] Data protection risks[25,16,24,22] Discrimination risk[20] Machine learning fairness[18,23,19] Algorithmic bias[16,17,18,19] Accountability model issues[16] Data quality algorithm issues [24] Explainability model gaps[20,17,21] Right to free expression[20] Susceptibility to cyber attacks[23] Transparency model flaws[16,17,18]	
Financial Institutions	High investment costs[22,17]	Anticipation of AML risks[22,20] Enhanced customer insight[22] Enhanced detection ML[21,22,20] Faster detection[16] Increase operational efficiency[22,24] Real-time detection[24] Reduced alert fatigue[16,24] Reduction in false positives[21,16,24] Reduction in manual work[21,16,17] Reduced non-compliance penalties[24]
Financial Institutions and Government		Efficiency AML[21,17] AML compliance[16,22,24] Compliance adaptability[16] Identification of complex patterns[20,22] More effective AML systems[16,17]
Government	Increased regulatory oversight[22]	

2.4. Conclusion and research gap

Most existing research focuses on AML compliance or machine learning from a government or a bank perspective, leaving a gap on how these developments affect society as a whole. While several studies assess the costs and benefits of AML, they typically focus on financial and administrative burdens for institutions, without considering broader social impacts. Moreover, there is little research on how machine learning might change the overall balance of costs and benefits in KYC processes, whether it contributes or not social welfare. Like many of the studies discussed in this literature review, this thesis also adopts a qualitative approach. This thesis contributes to the literature by identifying and structuring the key societal effects of KYC through a qualitative, exploratory approach grounded in welfare economics. The research aims to develop criteria that can be used to evaluate the societal costs and benefits of AML regulation through the KYC process. By combining ideas from AML regulation, ML technology, and SCBA methods, the study supports better policy and compliance decisions that take social impacts into account.

3 Methodology

This chapter outlines the research design, methods, and analytical approach used in this thesis. The objective of the study is to explore how the use of machine learning in the KYC process affects the social costs and benefits of compliance with AML regulation. Given the exploratory nature of the research, a qualitative approach was chosen. The study combines insights from literature and expert interviews and is structured using an SCBA framework. This chapter explains how the SCBA was adapted to fit the research context, describes how the interviews were prepared and conducted, and details the thematic analysis process. The chapter concludes with a description of how the findings were translated into a conceptual model that organizes and interprets the identified social effects.

3.1. Research design

This chapter will explore each methodological step of this research. It begins with an explanation on the argumentation of the chosen research methods in section 3.2. It continues with outlining the SCBA, the structure used for this thesis, in section 3.3. After, the interview preparation and setup are discussed in section 3.4. The data analysis of the interviews is detailed in 3.5. Finally, the conceptualization is explained in section 3.6.

Table 3.1: Overview of sub-questions and corresponding methods

No.	Sub-question	Methods
1.	What are the current KYC operations and compliance practices used by banks under AML regulation?	Literature review, Expert interviews, Conceptualization
2.	How is machine learning currently applied in the identified KYC processes?	Literature review, Expert interviews
3.	What candidate effects need to be considered in a SCBA of the current KYC process under AML regulation?	Literature review, SCBA, Thematic analysis, Expert interviews, Conceptualization
4.	How does the introduction of machine learning alter the identified social costs and benefits of the KYC process?	Expert interviews, Thematic analysis, Conceptualization

3.2. Approach

This research investigates the question: *"How does the use of machine learning in the KYC process affect the social costs and benefits of compliance with AML regulation?"* The aim is to explore an under-researched topic: the broader societal implications, of applying ML in AML, specifically in KYC procedures.

Given the exploratory nature of the research, a qualitative research design was chosen. The study relies on primary data, collected through semi-structured, open-ended interviews with professionals, scholars and a a human rights activist in the banking and compliance compliance context. This approach allows for in-depth insights into participants' experiences, perceptions, and concerns regarding the social costs and benefits of implementation of ML in KYC processes. The choice for open interview questions is motivated by the need to capture contextual, and subjective understandings of both positive (e.g., efficiency, accuracy) and negative (e.g., bias, exclusion) effects. This study uses a social cost-benefit analysis (SCBA) as a guiding analytical framework. However, due to the exploratory nature of this study and the limited availability of prior research on the social costs and benefits of this topic, the scope of the SCBA is necessarily constrained. As a result, the analysis is limited to the first five steps of the SCBA framework and are carried out qualitatively. A full quantification and monetization of these effects falls outside the scope of this research.

While prior studies often focus on specific technical, ethical, or regulatory aspects, they rarely provide a comprehensive, up-to-date overview of the broader societal implications. As a result, there was a need to generate new, grounded insights directly from professionals and scholars who are currently involved in or closely observing these developments. To process the interview data, a thematic analysis was conducted. Thematic analysis is used to understand a set of experiences and thoughts (Kiger and Varpio, 2020), which was the case in this research. The step-by-step approach outlined by Willig and Rogers (2017) was followed, allowing for a systematic identification of recurring themes and the development of a conceptual model based on the qualitative findings.

Participants were selected by targeting experts with practical or policy-level experience in banking compliance, financial crime prevention, and machine learning implementation. This ensured the data reflected both technical and societal perspectives. Interviews were conducted in a semi-structured format, allowing for open responses while ensuring consistency across key themes.

3.3. Social Cost Benefit Analysis

This research applies the social cost-benefit analysis (SCBA) structure to identify and compare the broader societal effects of AML regulation through the KYC processes. The SCBA steps used in this research are carefully outlined in the guideline by Romijn and Renes (2013). SCBA is typically used in public policy to assess and weigh the societal costs and benefits of alternative interventions. As Romijn and Renes (2013) argue, SCBA contributes to decision-making by illuminating the trade-offs and welfare effects of different policy options, even when monetization is difficult or incomplete.

Although SCBA is more commonly applied to infrastructure or environmental policy domains, this research adopts it for evaluating AML policy interventions in the financial sector. This is a justified choice given the broad social and institutional consequences of AML enforcement, including impacts on privacy, exclusion, institutional trust, and financial accessibility. The analysis offers a structured way to assess such effects in terms of public welfare.

Because many of the effects explored in this study, such as reductions in privacy, perceived discrimination, or improved trust, are not easily quantified in monetary terms, this research uses a qualitative SCBA approach. The aim is not to generate a net-present-value figure, but to systematically identify, categorize, and develop criteria for social costs and benefits of AML regulation and after assess its potential transformation via ML.

3.3.1. Analytical Boundaries and Scope

This thesis follows the SCBA methodology as outlined in Dutch general guideline (Romijn and Renes, 2013), but limits its scope to the first five steps. This boundary was set deliberately due to the exploratory and qualitative nature of the study, as well as the conceptual and data limitations surrounding AML outcomes. More specifically, the total volume of criminal proceeds is inherently uncertain, and many effects, such as ethical concerns around surveillance or financial exclusion, resist quantification altogether.

Table 3.2 outlines the standard SCBA steps and how they are interpreted in this research. The quantification of steps 4 and 5, and steps 6 to 8 (risk analysis, aggregation, and result presentation) are not completed in this thesis due to the qualitative nature of the data and lack of agreed-upon metrics for many effects. The output of the analysis remains valuable for insight and policy reflection because a qualitative interpretation of the first five steps already provide a structured understanding of how current and alternative systems impact social welfare.

Table 3.2: Interpretation SCBA explained per step with corresponding location in thesis

Step	SCBA Title	Interpretation	Corresponding Section
1	Problem analysis	Define the societal problem of ineffective or costly AML enforcement through KYC.	chapter 1 & chapter 2
2	Establish baseline	Describe the baseline, which is a situation with little to no AML regulation and therefore no KYC process. The measured effect is the policy alternative minus the reference scenario or baseline.	section 3.3
3	Define policy alternatives	Specify the introduction of AML regulation as an alternative approach through the KYC process.	section 4.2
4	Define effects and benefits	Identify the criteria for the social benefits of AML regulation. This step is carried out without monetizing the effects.	section 4.4 & chapter 5
5	Define costs	Identify the criteria for the social costs of AML regulation. This step is carried out without monetizing the social costs.	section 4.4 & chapter 5
6–8	(Omitted)	Not implemented due to lack of quantifiable benchmarks.	N/A

In this thesis, the SCBA is carried out for the policy alternative of the AML regulation, carried out through the KYC process. The base case for this analysis is little to no AML regulation. The potential criteria for a SCBA are identified through expert interviews and thematic analysis. This qualitative SCBA, forms the foundation against which the expected impact of ML implementation is evaluated.

It is important to clarify the baseline and policy alternative in steps 2 and 3. The baseline used in this research is a situation where there is little to no AML regulation and therefore also no KYC process. The policy alternative is the current KYC process which is required by AML regulations. This alternative is characterized as highly manual and rule-based. Social effects are identified relative to the baseline.

3.3.2. Stakeholder Division

An SCBA shows increased welfare if the total benefits exceed the total costs, regardless of how these are distributed. It is optional to incorporate the distribution of effects. In the context of AML/KYC processes, distributional effects are relevant: the costs and benefits are not evenly shared across society, financial institutions, and government. Therefore, this study explicitly discusses these three key stakeholder groups. This thesis employs the following definitions to describe the roles of the three stakeholder groups:

- **Society** captures the general public, including both consumers and individuals indirectly impacted by AML-related decisions.
- **Financial institutions (FIs)** are the operational enforcers of AML regulation through the KYC process (e.g. banks).
- **Government** refers to the public sector institutions responsible for policy design, supervision, and enforcement.

3.3.3. Selection and Definition of Social Effects

In order to identify and discuss social costs and benefits in a meaningful and consistent way, this thesis adopts a broad welfare-oriented interpretation grounded in welfare economics. This research adopts the definitions provided by the OECD report on cost-benefit analysis, where, as Pearce et al. (2006) state, "benefits are defined as increases in human wellbeing (utility) and costs are defined as reductions in human wellbeing." The selection of social costs and benefits in this SCBA is partly determined by their quantifiability. Intangible impacts such as surveillance, overreach, and privacy loss are difficult to express in monetary terms and may therefore be underrepresented in the quantified results; these are instead addressed qualitatively to acknowledge their potential significance.

The selection of social effects in this SCBA follows a clear principle: only those impacts that are both relevant to the societal consequences of AML regulation and capable of being measured or credibly estimated are included in the quantified analysis, while significant but non-quantifiable effects are addressed qualitatively. Broad institutional or legal concepts e.g. overreach, surveillance, presumption of innocence, or criminalization, were not incorporated in their abstract form, as they do not directly quantify changes in welfare. Instead, these concepts were only included insofar as they could be translated into specific, tangible, and monetizable consequences (e.g., additional compliance costs, inequality, or reduced participation in activities). This approach avoids including purely normative, institutional, or redistributional effects that cannot be reliably measured and ensures that all effects in the SCBA meet established inclusion criteria for social costs and benefits.

Where possible, effects are operationalised using established SCBA concepts. For instance, consumer surplus is used to describe net gains or losses for individuals relative to their payments or efforts (e.g. if KYC processes become cheaper, surplus increases). Government expenditures refer to the money spent on supervision, enforcement of compliance, and the implementation of AML policies. Opportunity costs reflect what government or institutions could have done instead with their time, money, or staff attention, had they not been spent on AML compliance.

3.4. Interview Process

The process for designing and conducting interviews is guided by the structure outlined by Weiss (1995). This includes:

- Defining the role of interviews within the research design;
- Selecting appropriate respondents based on well-defined criteria;
- Preparing the interview protocol, including question design;
- Conducting interviews in a consistent, ethical, and open-ended format;
- Analyzing the interview data through coding and thematic interpretation.

3.4.1. Interviewee Selection

As part of the research, semi-structured interviews were conducted to gain in-depth insights into the social costs and benefits of implementing ML in the KYC-processes. Guest et al. (2006) emphasize that the number of interviews should be based on the specific objectives and scope of the study. In this research, interviews continued until information saturation was reached, that is, when no new insights emerge. As Baker et al. (2012) note, “the old rule still applies: keep asking questions as long as you’re getting different answers.” The interviewees were contacted via university sites, Linkedin and the PwC network. To ensure that the collected data is directly relevant to the research objective, the respondents are selected based on criteria. First, they needed to be professionally involved in AML or KYC processes, either through advisory firms, academic research, or related organizations. Second, they have experience with or insight into technological developments in compliance, and third, they are able to reflect on the broader societal implications of these regulatory practices. Based on these criteria, the respondents presented in Table 3.3 were obtained.

Table 3.3: Interviewees with associated roles and organisations

No.	Role	Organisation
1	Partner Financial Services	Professional services firm
2	PhD Candidate Information and Computing Science	Dutch University
3	Manager AI and Data Science	Professional services firm
4	Postdoctoral Researcher Law, Technology and Society	Dutch University
5	Director Customer and Operations	Professional services firm
6	Director Financial Services	Professional services firm
7	Manager Financial Services	Professional services firm
8	Representative advocacy group	Financial and Human rights initiative
9	Consultant financial law and compliance	Freelance

3.4.2. Interview Preparation

In preparation for the semi-structured open ended interviews conducted in this study, several steps were taken to ensure methodological rigor, thematic relevance, and ethical compliance. The goal of the interviews was to explore expert perceptions regarding the societal effects associated with the implementation of ML in the KYC-process, complementing findings from the earlier literature review.

To keep in line with the study's objective of conducting a qualitative SCBA, the interview questions were structured around two key thematic areas, each of which was directly informed by the literature review. The following topics were questioned:

- Current KYC process in banks
- Costs of the current KYC process
- Benefits of the current KYC process
- Implementation of ML in the KYC process
- Costs associated with the implementation of ML in the KYC process
- Benefits associated with the implementation of ML in the KYC process

The first theme was included to establish the policy alternative required for the SCBA: understanding the current state of the KYC process as experienced by practitioners. The second and third theme were developed in order to establish the perceptions of the respondents on the social costs and benefits as an effect of AML regulation. The last three themes were designed to capture anticipated changes resulting from the introduction of ML technologies into the process, thereby enabling a comparative analysis between the foundation and the change of ML. These thematic areas were operationalized into open-ended interview questions, allowing respondents to elaborate freely on their experiences, perceptions, and expectations. The complete list of interview questions is provided in Appendix A.

To provide context for the interviews and inform the first subquestion ”What are the current KYC operations and compliance practices used by banks under AML regulation?” a preliminary process flow visualization was developed through desk research. This initial version drew primarily from industry reports, including a detailed overview in PwC documentation, which outlines typical compliance steps taken by financial institutions. The draft visualization served as a starting point to give context to the interview questions and validate the process flow.

During each interview, the visualization was presented to the respondents to clarify the terminology and establish a shared understanding of the operational steps involved. Respondents were explicitly invited to comment on the accuracy, completeness, and practical applicability of the diagram. Based on their feedback, which addressed both content and phrasing, iterative adjustments were made to improve the validity of the visual. This process allowed the researcher to both verify and refine the depicted KYC process and ensured that the resulting overview was grounded in actual practice within European banks. The artifact used in the interviews can be found in Appendix B.

A deductive step was incorporated to safeguard the relevance and clarity of the interviews. During the interviews, participants were presented with a researcher-constructed framework summarizing findings from the literature. This functioned as a stimulus text, used to invite reflection, validation, and critique. This stimulus summarized key potential risks and benefits of the current AML practices as well as on the implementation of ML found in literature. Following Törrönen (2002) idea of text stimulus, it was used as a way to help interviewees compare their own experiences to the ones found in literature. The stimulus was used at the end of the open questions, to avoid steering participants prematurely. The questions around these stimuli were in order to validate or challenge literature findings.

The interview guide and stimulus were reviewed in consultation with academic supervisors and subjected to a pilot interview with a colleague familiar with the domain but not directly involved in the study. This pilot allowed for refinement of both question phrasing and flow, helping ensure clarity, neutrality, and thematic coverage.

Finally, ethical considerations were addressed in line with the principles of informed consent, anonymity, and data protection. In line with TU Delft's guidelines, this research followed key privacy principles: data collection was kept to a minimum, identifying details were anonymized, and access was restricted. A

Data Management Plan has been approved by a TU Delft data steward. Interview data was be stored securely on TU Delft OneDrive, shared only with the thesis committee if needed. All participants have given informed consent, and data will be deleted after the project ends. Ethical approval for the data management plan and research design was obtained from Human Research Ethics Committee.

3.4.3. Interview Data Gathering and Processing

During the exploratory phase of this research, semi-structured interviews were conducted to gather insights that cannot be obtained solely through literature research. A semi-structured interview approach allows for a predefined set of questions while providing the flexibility to incorporate follow-up inquiries based on the responses of the interviewees (Edwards and Holland, 2013). This flexibility is particularly valuable in this study, as it enables a deeper exploration of the potential social costs and benefits of adopting machine learning in the KYC-process.

Interviews were held in the months of May and June 2025. Where possible, face-to-face interviews were preferred, as they allow for a more interactive exchange in which the interviewer can capture non-verbal cues, and confirm comprehension through rephrasing (Opdenakker, 2006). However, given practical constraints, including geographical dispersion and availability, interviews were also conducted via Microsoft Teams.

All interviews were recorded and transcribed via Microsoft Teams. The researcher started with getting familiar with the script by cleaning and correcting the automatic transcription. After transcription the interview was uploaded to a qualitative coding software.

3.5. Thematic Analysis

To analyze the qualitative data collected through expert interviews, a systematic thematic analysis was conducted using the qualitative data analysis software ATLAS.ti. The process closely followed the six-step model proposed by Willig and Rogers (2017), which is specifically designed to culminate in the development of a report grounded in empirical evidence. The analysis was extended into a conceptualization of the findings based on the qualitative analysis guide outlined by Naeem et al. (2023). Thematic analysis is a flexible and widely accepted method in qualitative research, particularly suited to exploring perceptions, practices, and institutional dynamics (Naeem et al., 2023). Its relevance to this study lies in its ability to uncover both latent and manifest themes that emerge from expert discourse and documentary evidence on AML processes.

Thematic analysis is described by Willig and Rogers (2017) as a six-step approach to analyzing qualitative data, emphasizing that the process is iterative rather than strictly sequential. The process begins with becoming deeply familiar with the data, which can start during data collection. Becoming familiar with the data was realized by cleaning and reading the transcripts. This set the foundation for the second phase: generating codes. Coding in interview transcripts is the process of systematically labeling segments of text with short descriptions or categories to identify patterns, or concepts in the data. Coding was fulfilled by highlighting quotes in the transcript in ATLAS.ti and developing a fitting code. Once the data was fully coded, the third phase involved clustering related codes into preliminary themes. These early themes serve as flexible, provisional concepts that are still open to revision. The fourth step is a critical review of these initial themes, ensuring they are coherent and meaningfully connected to the data. After reviewing, the fifth phase requires the researcher to define and clearly label each theme. Finally, in the sixth phase, the analysis is shaped into a coherent narrative through the writing of the report, as seen in chapter 4. This stage offers an opportunity to refine the insights and ensure the findings are communicated clearly and persuasively, presenting the researcher's interpretation of the data in a structured way.

3.6. Conceptualization

Conceptualization can be defined as "an abstract, simplified view of the world that we wish to represent for some purpose." (Gruber, 1993). In this study, conceptualization serves to translate thematic insights into a structured understanding of the social effects associated with the KYC process and its transformation through the use ML. The process began by establishing the foundation: the current implementation of the KYC process without the application of ML. Relevant themes were identified through interviews and structured according to their relationship with specific social effects. Each theme was assessed based on whether it contributed positively or negatively to these effects. The corresponding social costs and benefits, as identified in the literature, were then incorporated into a visual representation. In this baseline scenario, the status of each social effect was described in directional terms, either positive or negative, reflecting its overall societal impact under the current KYC process. Next, the analysis focused on the proposed change: the integration of machine learning (ML) into the KYC process. The impact of this alternative were assessed by examining how each previously identified social effect might shift, showing improvement, decline, or ambiguous outcomes.

Following the approach of Naeem et al. (2023), this stage of the analysis reflects the continuation of thematic coding into conceptual modeling. Codes derived from qualitative data were translated into broader social effects, which were then aligned with the research questions and positioned within the structure of a Social Cost-Benefit Analysis (SCBA).

In the final phase, these social effects were organized into a conceptual model that synthesizes the key insights of the research. This model represents the positve and negative relationships between the interview themes in AML regulation, interview themes in ML-based KYC implementation, and resulting societal impacts (see chapter 5.

3.6.1. Validity

Validity refers to the extent to which a study accurately captures the concepts it is intended to investigate. According to Borsboom et al. (2004), a study can be considered valid when the results genuinely reflect the variation in the concept being measured, and not just random or unrelated differences. In this research, validity means that the identified social costs and benefits of AML regulation and machine learning in the KYC process should meaningfully reflect reality. Namely, how these effects are perceived, experienced, or observed in practice. To ensure this, the study relies on existing literature to convert interview themes into social effects. Triangulation between interview data and existing academic and policy literature further supports the robustness of the findings. This ensures that the analysis was grounded in real-world developments, while still contributing to academic understanding of the topic.

4

Analysis of Interviews

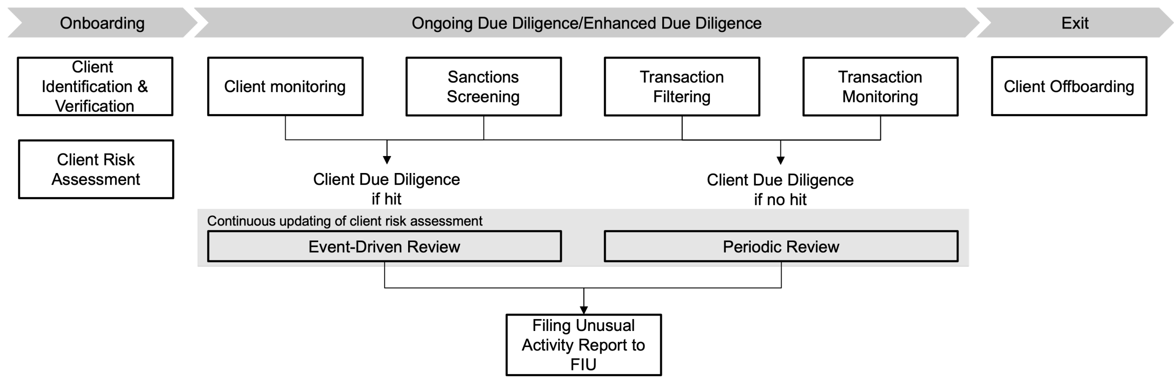
This chapter presents the results of the expert interviews conducted to explore the current KYC process, its associated social costs and benefits, and the impact of ML on the effects of AML compliance. The chapter is structured in four main sections. First, it outlines the current KYC process used by Dutch financial institutions, based on a combination of desk research and expert input. Second, it identifies how ML is currently applied in KYC and where it holds potential for future use. Third, it systematically analyzes the social costs and benefits of the existing KYC system by clustering insights into thematic categories. The chapter continues with a reflection on overall AML policy effectiveness, a theme that emerged spontaneously across almost all interviews. Interestingly, many respondents, while answering specific questions, ended up offering a broader judgment on the balance of costs and benefits of AML regulation. Finally, it evaluates how the use of ML in KYC may alter these effects, either by enhancing benefits or introducing new risks.

4.1. Current KYC Process

To establish the policy alternative in the SCBA of AML regulation, it is necessary to analyze the current KYC process, the main operational component through which AML compliance is realized in practice. Subquestion 1, “What are the current KYC operations and compliance practices used by banks under AML regulation?”, is therefore answered using a combination of desk research and expert interviews. This provides the foundation for understanding the costs and benefits of implementing AML regulation, compared to a baseline in which no formal KYC framework exists. The initial version of the KYC process diagram was based on an informal interview with an AML expert at a professional services firm. Subsequently, internal documentation outlining KYC procedures in banks was obtained, which served as the foundation for the preliminary diagram (see Appendix C).

This preliminary visualization was shown to all interviewees, who commented on its terminology, completeness, and implementation in practice. Their feedback was used to refine the diagram. All respondents recognized the process, and most agreed with its structure and wording. Two corporate experts offered specific revisions: Respondent 7 pointed out the absence of the so-called “hit” that initiates an event-driven review and emphasized the distinction between periodic and event-driven reviews. Respondent 6 shared a report detailing the legal basis for KYC procedures, including a more detailed process flow (Dutch Banking Association, 2023). This report was used to finalize the diagram shown in Figure 4.1, which presents the typical KYC trajectory used by Dutch banks.

Figure 4.1: Overview of the KYC-Process



The KYC process can be divided into three main stages: Onboarding, Ongoing Due Diligence/Enhanced Due Diligence, and Exit (Dutch Banking Association, 2023). The process begins with Customer Identification and Verification, during which the bank collects and authenticates identity documents to confirm the client's identity (Dutch Banking Association, 2023). Following this, the bank conducts a Client Risk Assessment, classifying the customer as low, medium, high, or unacceptable risk based on various factors including geography, sector, and ownership structure (in case of a business). This classification determines the depth and frequency of later due diligence procedures. This risk rating is updated during the whole client relationship.

Once onboarding is complete, the client enters the due diligence phase. This includes multiple monitoring activities aimed at identifying unusual or high-risk behavior over time. Client Monitoring refers to the ongoing observation of the client's structure, activity, and external signals to detect changes in risk. In parallel, Sanctions Screening ensures that customers and their transactions are not associated with sanctioned countries or prohibited individuals. Transaction Filtering takes place before sending money and blocks any transactions involving sanctioned subjects. In addition, Transaction Monitoring analyzes behavioral patterns over time to detect suspicious activity that deviates from the client's expected profile.

When any of these four mechanisms detect an unusual pattern, they generate a "hit," which triggers an Event-Driven Review. During the Event-Driven Review, the client's risk profile is reassessed and may be updated, or an Unusual Activity Report may be filed with the FIU. Periodic Reviews, conducted at set intervals based on the client's risk classification, are similar, if anomalies are identified, they too may result in a Unusual Activity Report.

Finally, in some cases, clients may be rejected during onboarding or offboarded during the relationship. Client Offboarding is the termination of the banking relationship due to an unacceptable risk level under anti-money laundering or counter-terrorism financing standards. This structured process highlights the ongoing and cyclical nature of KYC compliance, in which client relationships are continuously evaluated and may be escalated or terminated as risks evolve.

4.2. ML in the KYC Process

Based on the interviews conducted with a diverse set of stakeholders (see Table 3.3), several key patterns emerged regarding the current and potential use of ML in KYC processes. The following subquestion is answered in this section: *How is machine learning currently applied in the identified KYC processes?*. The codes and quotes used to answer the sub-question can be found in Appendix C. In this section the results are presented around recurring themes, each introduced with a key finding and followed by interpretation and supporting quotations.

Transaction monitoring as the primary application of ML in KYC

A strong consensus emerged among respondents that the most mature and widespread use of ML in KYC lies in transaction monitoring. Participants emphasized that ML is well-suited for high-volume, pattern-based detection tasks, aimed at identifying unusual or suspicious behavior. A respondent of a professional services firm explained, ”This is mainly in the transaction part: transaction monitoring and filtering. You use pattern recognition there: when is a transaction suspicious?” This view was shared with an academic respondent, who noted that ”client monitoring, transaction screening, sanctions screening, and transaction filtering and monitoring (...) all allow for deep learning solutions.” A respondent at a professional services firm shared a concrete example from practice: ”We used machine learning to reduce up to five thousand alerts per month to low-risk classification, we called it ‘alert filtering’ or ‘transaction reduction.’” These examples summarize how transaction monitoring is seen as the most fitting area in which to implement ML. This claim by the respondents is discussed in academic literature. Oztas et al. (2022) provide an overview of various machine learning approaches proposed in the literature for transaction monitoring. Oztas et al. (2022) note that although many machine learning methods for transaction monitoring have been proposed in academic literature, these techniques are often not adopted by financial institutions. A key reason is the lack of trust in their reliability and reproducibility, with many studies offering limited evaluation and insufficient information about the datasets used. This hesitancy contributes to continued high rates of false positives and rising regulatory fines, indicating a gap between research and real-world application.

A gap appears to exist between the literature and practice: while financial institutions are often presented in academic research as being cautious and hesitant to adopt ML methods in transaction monitoring, interviewees described this field as one of the most actively developed and applied areas of ML in KYC processes. This suggests that ML is currently used very little in general in FIs. However, the most prominent form of implementation at this moment is transaction monitoring.

Limited ML in client onboarding

In contrast, the use of ML in client onboarding is far less common and often met with caution. Respondents pointed to the relatively low case volume and higher risk of errors in early client assessment as key reasons why ML is not widely applied in this stage. A corporate respondent emphasized, ”I’ve never seen machine learning used in onboarding for risky customers. That seems like the least logical place to start.” An academic respondent added that although the use of large language models (LLMs) might offer potential in tasks like document parsing, ”onboarding doesn’t have the volume to justify deep learning, unlike transaction monitoring.” A corporate respondent did acknowledge some opportunities for support roles, such as assembling documentation: ”LLMs can speed up the process, but you still have to compile the file.” These responses suggest that while ML may have marginal use in onboarding, it is not seen as a priority area for automation. The use of ML for onboarding purposes was not found in academic literature. The lack of academic attention to ML in client onboarding reinforces respondents’ view that it remains a limited and cautiously approached area in practice.

ML in client risk assessment

Several respondents described how ML is being used not just for detection, but also for client assessment and operational efficiency. This approach focuses on identifying predictable, low-risk customers early in the process to avoid unnecessary manual reviews. As a corporate respondent explained, ”You want to pre-assess: which clients are so predictable that there’s almost no risk? You can catch those with an algorithm and reduce operational burden.” They also described how their team used ML to conduct ”pre-assessments” of client risk profiles, skipping full manual reviews when earlier patterns consistently indicated low risk. These practices illustrate how ML is being used as a resource allocation tool within KYC, enabling a more risk-based and proportionate approach. However, the use of ML for this purpose will probably depend on how much confidence the FI has in the model’s reliability and their risk appetite. Gupta et al. (2023) examine how ML can improve customer risk assessment in the context of financial crime compliance, showing that it is being explored academically.

ML techniques

The specific ML techniques employed vary across organizations, encompassing both classical models and more recent approaches. One respondent described the transition from basic tools to more complex ones: ”You no longer use simple Excel models, but algorithms running on graphs and vector databases that assess transaction linkage to money laundering.” The same respondent added that their firm used ”neural networks, combined with statistics, like Bayesian statistics” to detect suspicious behavior. Similarly, another corporate respondent reported using different methods: ”We used supervised learning models like gradient boosting and random forest. We also applied SHAP value analysis and autoencoders for anomaly detection." The breadth of techniques in use reflects a practical mindset: organizations are selecting tools based on their interpretability, technical feasibility, and fit to the task. An article by Chen et al. (2018) creates an overview of the different ML techniques used in AML. Similar to the respondents, the authors of the article assess Bayesian network and neural networks as potential tools in AML processes.

Current low implementation of ML in KYC process

Finally, respondents generally agreed that despite the attention ML is receiving, actual implementation remains limited. A representative from a financial and human rights advocacy group noted, "Everyone sees the potential, but true implementation is just beginning." Among the few concrete examples cited, the collaboration between HSBC and Google to fully automate transaction monitoring (May, 2023) was singled out as an exception rather than the rule. In a review of machine learning applications for transaction monitoring, it is noted that many of these methods are not adopted by financial institutions, in part due to a lack of trust in their reliability and reproducibility (Oztas et al., 2022). Financial institutions continue to be cautious as regulatory fines increase (Oztas et al., 2022). In practice, there are selective examples of ML being applied in KYC processes suggesting a limited but growing uptake. Yet academic literature largely emphasizes FIs' hesitancy. This divide highlights how academic literature may lag behind practical innovation, or alternatively, how practical implementation may outpace necessary critical scrutiny and regulation.

4.3. Exploration of the Social Costs and Benefits of the Current KYC-process

This section presents the analysis of the interviews on the social costs and benefits of the KYC process under AML regulation. The analysis is done by grouping the interview codes into themes and identifying the social effects they point to. The section opens with a brief overview of all themes and their associated social impacts in Figure 4.2, followed by an in-depth analysis of each theme. The themes are derived from coded data collected through the interviews (see Appendix C). The structure of each subsection is as follows: introduction of the theme, explanation of the codes from top to bottom, and a justification of the social effects. The codes are tested against the literature presented in chapter 2 as well as additional sources consulted during the analysis. Per theme, social costs or benefits are identified by using academic literature or analytical thinking. The social costs and benefits in this section are developed in order to establish the factors to be considered in a qualitative SCBA on AML regulation. The discovered themes are the following: crime prevention, social harm, financial burden government, indirect government incentives, reduced penalty risk FIs, financial burden FIs, and the indirect benefits FIs (see Figure 4.2). The order in which the interview themes are found in Figure 4.2 is the same as they are presented in this section. This section answers sub-question 3: "What candidate effects need to be considered in a SCBA of the current KYC process under AML regulation?" by identifying and justifying a set of concrete social effects based on interview findings and literature.

Figure 4.2: Visual of interview themes indicating a positive or negative impact of the KYC process on social effects relative to no KYC process

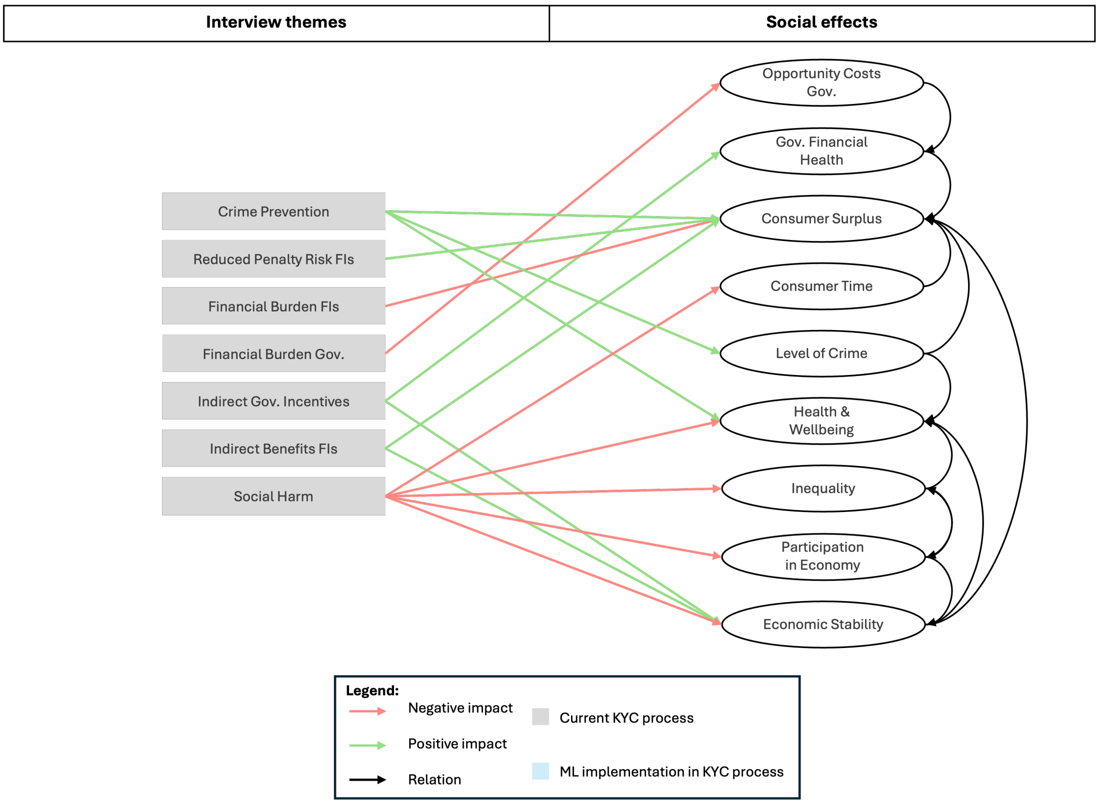
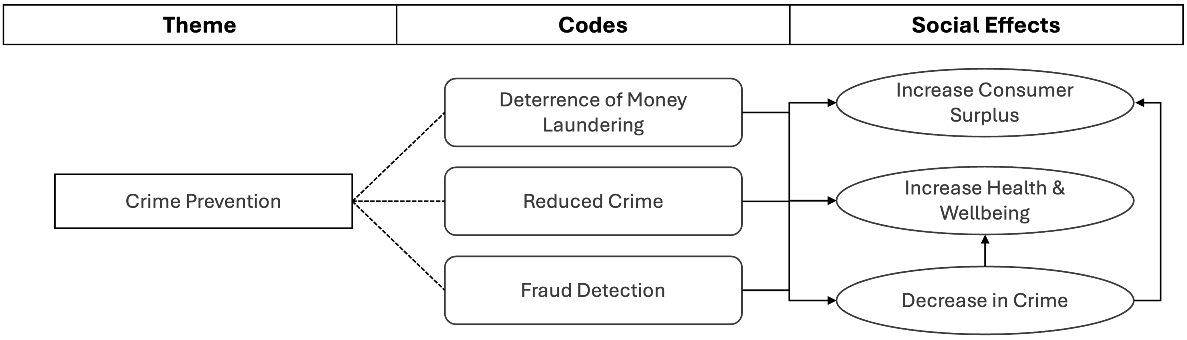


Figure 4.2 provides a summary of the identified social costs and benefits associated with the current KYC process under AML regulation. The themes on the left side are overarching themes found in the interview codes. They reflect the identified causes of a negative (red arrow) or positive (green arrow) impact on a certain social effect (on the right). The black arrows indicate a relation between two social effects with one effect influencing the other at the end of the arrow. Further explanation on the social effects and the relations between them can be found in section 5.2. Figure 4.2 offers a quick overview of the qualitative SCBA indicating the potential social effects of AML regulation which are listed on the right side of the figure. In doing so, it contributes to answering sub-question 3 by identifying candidate effects that can be considered in a SCBA of the current KYC process. The candidate effects being: Opportunity costs government, Government financial health, Consumer surplus, Consumer time, Level of crime, Health & wellbeing, Inequality, Participation in economy, and Economic stability. These nine identified potential criteria for an SCBA on the KYC process are influenced the most by crime prevention and social harm. This shows a key tension of the cause of the social costs and benefits: AML regulation intends to prevent crime and positively influence society however the social harm it creates is also significant.

4.3.1. Crime Prevention

Figure 4.3: Data Visual of Crime Prevention



The main purpose of the KYC-process identified by the interviewees is financial crime prevention. This theme highlights three main components: deterrence of money laundering, reduction in crime, and detection of fraud as can be seen in Figure 4.3. This theme is supported by quotes from four respondents with diverse backgrounds.

Reduction of Broader Crime

A respondent described how the KYC process can proactively prevent financial crime by discouraging high-risk or criminal entities from entering the financial system. Respondent 3 explained that setting stringent onboarding requirements can act as a barrier to entry for illicit actors, particularly if such standards are consistently applied across the market. New Zealand Ministry of Justice (2017) echoes this claim, by arguing that potential criminals are deterred, by AML practices, not only from money laundering, but also from the underlying criminal offenses.

The code, reduced crime, addresses the broader societal benefits of AML systems. Respondents drew connections between financial regulation and a wide array of criminal activities, ranging from terrorism and drug trafficking to tax evasion and sanctions evasion. Respondent 1, with a corporate background, noted that because all illicit money flows eventually intersect with the banking system, strong regulatory frameworks in that domain can have far-reaching effects on crime rates. Respondent 3, with a corporate background, emphasized the importance of sanctions screening, suggesting that effective enforcement makes it significantly harder for criminal and terrorist organizations to access funds. Respondent 5, also with a corporate background, echoed these points, stressing that money laundering is often connected to human trafficking and drug networks. The code of reduced crime is documented in multiple studies. Ferwerda (2009), Unger et al. (2013), New Zealand Ministry of Justice (2017), Malakoutikhah (2020) collectively indicate that improved AML practices, especially when international cooperation is prioritized, are associated with lower crime levels. Notably, respondents with academic or human rights backgrounds did not highlight these crime-related benefits of AML compliance in their responses.

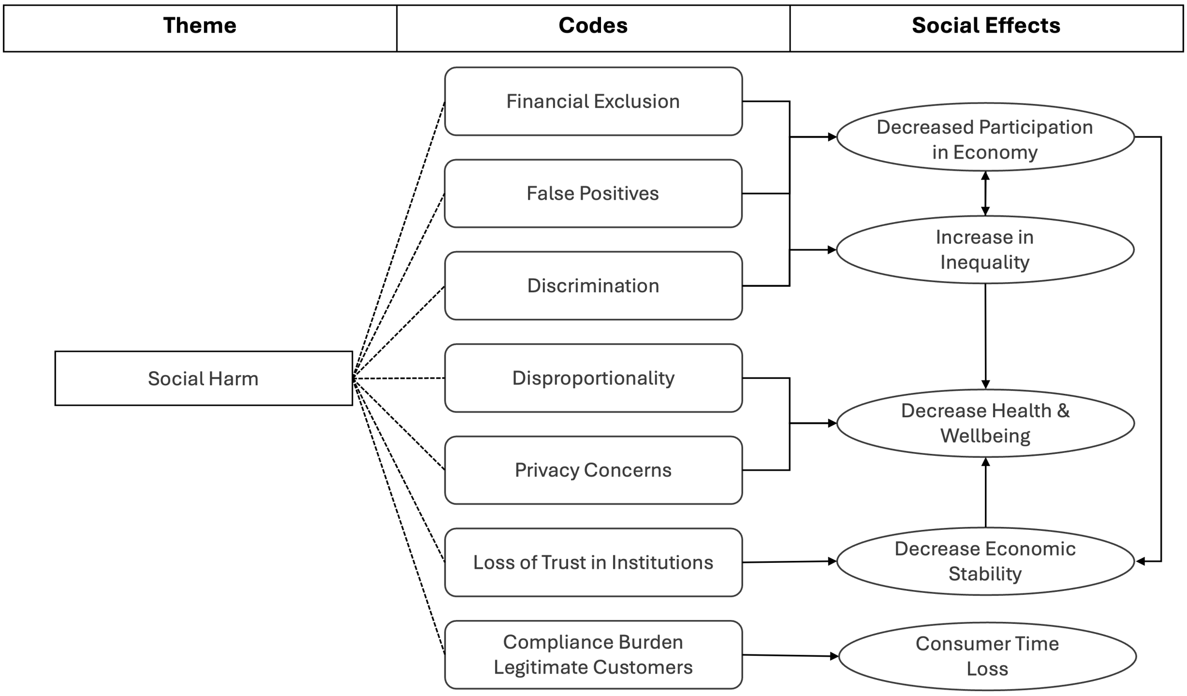
A more direct benefit is outlined in the code Fraud Detection. Respondent 2, with a academic background, emphasized how KYC-processes contribute to identifying and addressing fraud within the banking system. By uncovering fraudulent accounts and unusual transaction patterns, institutions can directly protect legitimate customers from financial harm. This code is in line with an article by Goecks et al. (2022). They note that AML and financial fraud detection are processes that use shared tools and models for detecting suspisious activities, including fraud.

Crime Prevention Linked to Social Welfare

The codes identified in this theme contribute directly to three key welfare-enhancing outcomes: increase in consumer surplus, public health gains, and reduced crime. Crime negatively impacts consumer surplus by increasing the costs associated with theft prevention, insurance, and security measures. This deters participation in the economy, as individuals may avoid certain areas or activities, reducing overall economic engagement and consumer confidence (Freeman, 1999). By reducing crime, the consumer surplus is increased. In this theme, reduced crime appears both as a code from the interviews and as a positive social effect. This shows that the respondents recognize the potential social benefit of the KYC process as the reduction in crime. The reduction of crime also reduces certain costs that are related to the consequences of crime like physical and/or emotional harm to the victims and people close to them (Heeks et al., 2018). Finally, as stated by Ferwerda (2009), the reduction in money laundering can be associated with lowers crime levels. There is also a relation seen between crime prevention and a higher consumer surplus. Through lower crime levels, the amount of money spent by individuals on insurance and security could be lower, resulting in a budget for other goods or services that they value. This connection between crime reduction, economic participation, and well-being underscores how effective KYC practices are perceived not only as regulatory tools, but as contributors to wider social welfare outcomes.

4.3.2. Social Harm

Figure 4.4: Data Visual of Social Harm in the Current KYC-Process



Social harm refers to the unintended negative social consequences that arise from the current KYC-processes. The theme of social harm encompasses six codes, as shown in Figure 4.4. This section of the results explores how these social harms are currently viewed in the existing KYC procedures, identifying recurring patterns and connections. Six respondents, with different professional backgrounds, highlighted the theme of social harm in their reflections.

Unjustified Flagging

The topic of financial exclusion is prominent in the responses, where respondents argued that the current KYC processes disproportionately affects vulnerable individuals. Respondent 8, from a human rights perspective, expressed concern about the social harm of exclusion, emphasizing that groups like migrants, self-employed individuals, and activists face difficulties due to overly stringent risk assessments. A corporate sector respondent (Respondent 6) also noted that the process, especially in the context of refugees from Ukraine, can unintentionally exclude individuals who lack the proper identification documents, preventing them from accessing benefits, working, or integrating into society. An interesting addition to the financial exclusion discussion comes from respondent 8 (human rights representative) stating that the KYC-process creates a loss in entrepreneurship due to the people being excluded by the financial system not being able to open an account or loan for their business. The perception of financial exclusion due to the KYC process aligns well with findings in literature by Pol

(2020), Unger et al. (2013), Harvey (2004), Pavlidis (2023a), Malakoutikhah (2020) who found that AML practices can result in restricting banking services to categories of clients.

The issue of false positives in the current KYC process also emerged as a source of social harm, highlighted by both a scholar and a corporate respondent. Respondent 6 stated that 95–99% of alerts generated by existing systems do not lead to meaningful AML follow-up, pointing to excessive over-flagging. Similarly, Respondent 2 emphasized the high rate of false positives in traditional KYC procedures. In literature it is also found that rule based algorithms, which is usually used in the current KYC process, create high amounts of false positives (Bakry et al., 2023).

Financial exclusion is closely related to discrimination which was identified as a significant issue tied to the KYC-process. An academic respondent (Respondent 4) pointed out that as KYC systems become more personalized, the risk of discrimination increases, especially when decisions are based on specific customer characteristics. For example, the case of Chinese students being denied bank accounts in the UK merely based on their nationality exemplifies how KYC-processes can unintentionally foster discrimination. This links directly to the issue of financial exclusion, as discriminatory practices often prevent certain groups from accessing banking services. A corporate employee (Respondent 5) further argued that the primary goal of these processes, combating criminal activities, can sometimes lead to the profiling of individuals based on nationality or other discriminatory factors, amplifying existing prejudices within society. The view of discrimination that emerged from the interviews is in line with Malakoutikhah (2020), who indicated that there are cases where banks have been sued over racial discrimination due to de-risking.

Disproportionate Surveillance

Two respondents discussed the issue of disproportionality, regarding the balance between the costs of compliance and the actual benefits of preventing illicit activities. Respondent 7 (private sector), who pointed out that individuals are subject to increasing levels of investigation, often without clear justification. These disproportionate actions not only harm individuals' rights but also undermine the fairness of the system as a whole. Respondent 8 (human rights advocate) explained that the question of proportionality, which is the idea that restrictions on an individual's rights should be in proportion to the severity of the threat, is often raised, especially when the benefits are uncertain. The discussion of proportionality concerning AML enforcement is also grounded in literature, with Malakoutikhah (2020) highlighting the potential over-compliance by banks that can be regarded as unfair. Amicelle and Favarel-Garrigues (2012) point out that the effectiveness of financial surveillance is often taken for granted, even though it is still uncertain. This leads to a structural imbalance, where heavy compliance demands are accepted without solid proof that they actually reduce crime.

Privacy concerns was a perception raised by two respondents. Respondent 9 (freelance consultant) shared an example where even small transactions, such as a Tikkie payment, could trigger investigations, highlighting the tension between privacy and compliance. Respondent 8 (human rights advocate) discussed how the enforcement of KYC processes often leads to heightened surveillance of individuals, which can be seen as an invasion of privacy. This issue resonates with insights from Ferwerda (2018) and Unger et al. (2013) who recognized the cost of reduction in privacy due to the screening of financial transactions and enhanced customer due diligence requirements. It is noteworthy that only two of the nine respondent commented on the privacy risk of these regulations. This could suggest that they are under-recognized in day-to-day compliance practices. It could also indicate that surveillance measures have become a routine part of financial compliance, making their impact on privacy less visible or actively questioned.

Distrust in Institutions and Democracy

Finally, the code of a loss of trust in institutions emerged throughout the interviews. A human rights advocate (Respondent 8) pointed out that the enforcement of KYC processes can erode trust in financial institutions, particularly when these institutions appear to be working more for governmental interests than for their customers. An academic respondent (Respondent 4) elaborated on this by explaining how the role of banks is shifting from being customer-centric to acting as agents of the state, which can undermine democracy. This shift, according to the respondent, contributes to a broader sense of distrust in institutions, as individuals begin to question the motivations behind these compliance processes and their broader implications for personal freedom and rights. This loss of trust in institutions was not found in literature within the literature review. Nevertheless, this creates a valid perspective for a social cost–benefit analysis because trust in institutions is a well-established factor in the functioning of financial systems and democratic government. Even if not explicitly addressed in the AML literature, recent studies show it is relevant. Ampudia and Palligkinis (2018) find that low trust in banks leads people to avoid or leave banks, which can harm financial inclusion. Chawla et al. (2023) also show that when people feel watched or treated unfairly, trust in banks drops, reducing engagement with the financial system.

Inconveniencing Customers

The compliance burden on legitimate customers is another code that has been identified in interviews and confirmed by literature. A corporate respondent (Respondent 1) discussed how the KYC process can be inconvenient for clients, particularly when small transactions are delayed or flagged unnecessarily. Another corporate respondent (Respondent 6) also highlighted the long delays in account openings, further stressing how the compliance system is often inefficient and burdensome, especially for individuals with legitimate needs. The compliance burden on legitimate customers, as highlighted in interviews, is also recognized in the literature. Harvey (2004) and Unger et al. (2013) note that AML measures affect all users equally, delaying transactions and requiring extensive due diligence, even when only targeting criminals.

Exclusion Linked to Health and Inequality

The codes that fall under the theme social harm lead to several negative social effects. Exclusion from financial services, due to discriminatory profiling or false positives, limits individuals' ability to participate in economic life. Koku (2015) notes that those excluded financially often live on the margins of society, reinforcing their broader social exclusion. Over time, discrimination as well as financial exclusion deepens inequalities between those who can participate fully in the economy and those who cannot. Morgan et al. (2007) argue that such exclusion is both a cause and consequence of mental illness, showing how mental health issues are deeply rooted in social disadvantage. A decrease in mental health is linked to lower labor participation (Vecchio et al., 2014) which indicates a decreased participation in the economy.

Surveillance Linked to Wellbeing and Inequality

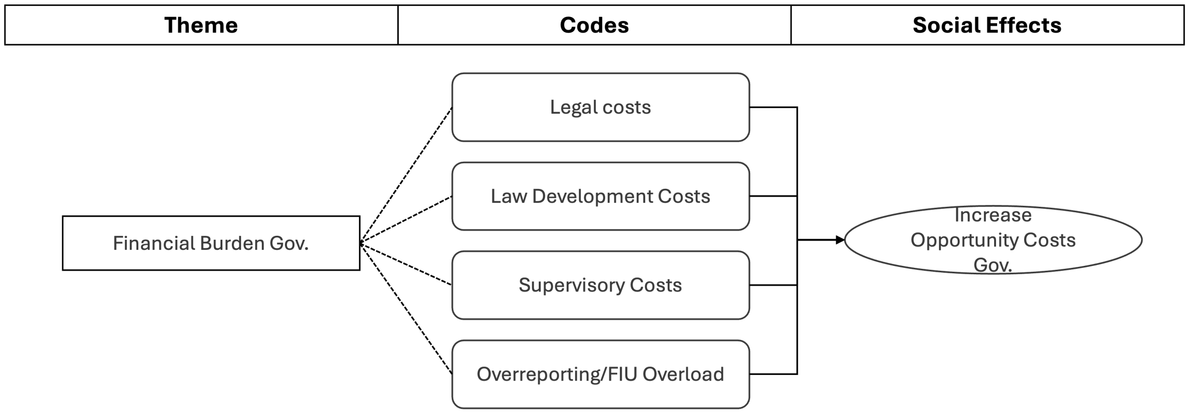
Privacy concerns also shape consumer behavior. Acquisti et al. (2016) explain that when individuals feel vulnerable to data misuse, their trust declines, reducing both satisfaction and overall welfare. Disproportionality indicates that the means used for the KYC process could be excessive compared to the objective. The means being the over-compliance or surveillance by banks. Excessive data scrutiny may lower client benefits by making users feel overexposed or can be seen as unfair action (Malakoutikhah, 2020). Monahan (2008) argues, surveillance systems often operate as mechanisms of social sorting, disproportionately targeting and regulating marginalized groups while giving more favorable treatment to privileged populations. This is a clear indication of how privacy risks can in turn aggravate inequality. Additionally, perceived financial discrimination can trigger stress, leading to lower wellbeing (Bridson et al., 2024). In the context of AML, enhanced monitoring and profiling through KYC processes and transaction surveillance may systematically affect those with atypical financial behaviors, limited access to formal identification, or connections to sanctioned countries. Rather than providing neutral security, AML surveillance practices can reproduce patterns of exclusion and contribute to inequality.

Effects on Economy and Consumer Time Efficiency

A lack of trust in institutions further undermines economic stability (Perry, 2021). Dhrifi et al. (2020) suggest that in high-income countries economic stability and growth contributes to improved health through better housing, nutrition, and access to healthcare. The author also states that the effect does not go both ways. This indicates that the decrease of economic stability due to the loss of trust in institutions can in turn negatively affect the health of society. Based on the authors' own analytical thinking, economic participation supports overall economic stability. When people can access financial services, work, and pay taxes, they contribute to demand, production, and public revenue. In contrast, exclusion, such as not having a bank account, limits spending in the real economy, which can reduce growth and employment. Lastly, KYC procedures can lead to lost time due to repeated documentation requests, onboarding delays, and manual checks. For low-risk consumers especially, this time has little added value and represents a loss of welfare through lost opportunities for productive or leisure activities.

4.3.3. Financial Burden Government

Figure 4.5: Data Visual of Financial Burden Government



The theme Financial Burden Government captures the various ways in which current KYC processes generate costs for the government. These burdens, as seen in Figure 4.5 span legal obligations, supervisory responsibilities, and the implications of over-reporting to FIUs. Several respondents from different professional backgrounds noted the financial burden of the government.

Legal Challenges and Ongoing Costs

A cost category that was mentioned by respondent 8 (human rights advocate) is the legal burden the government faces in maintaining and defending its AML framework. Respondent 8 highlighted the legal challenges initiated by actors such as customer advocacy groups. Lawsuits and complaints, often tied to perceived injustices or overreach within the system, result not only in legal defense costs but also in substantial recovery expenses, such as revising policy frameworks after judicial intervention. This observation underlines that legal costs are not one-time expenditures but ongoing liabilities tied to potential changes to the policy itself. This specific legal cost to the government was not mentioned in the literature however is a valid and insightful. Legal costs can be categorized as aministrative and staff costs, which does align with literature (Unger et al., 2013, New Zealand Ministry of Justice, 2017, Harvey, 2004, Ferwerda, 2018). From this code it can be derived that there are a significant amount citizens that do not agree with the governments' initiatives against money laundering.

Costs of Legislative and Supervisory Infrastructure

Legislative and supervisory responsibilities are also suggested dimensions of this theme. As Respondent 8 (human rights advocate) noted, the bureaucratic infrastructure required to uphold current AML policy is resource-intensive in itself. Respondent 7 (a corporate employee) also remarked, "Legislation needs to be made and supervised, and that obviously costs money." This quote reflects a shared understanding that developing and maintaining AML legislation is not a static task but an evolving process that demands continuous high investments. The ongoing policy making and supervisory cost of the government resonates with Unger et al. (2013) who included it into a cost-benefit analysis.

Over-Reporting

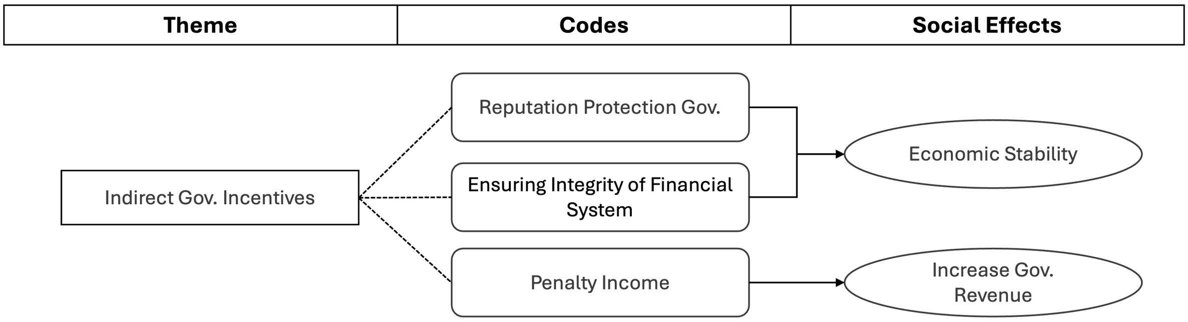
An identified cost driver is the act of over-reporting, where financial institutions err on the side of caution and report excessively to avoid non-compliance. This practice, suggested by multiple respondents, leads to a significant overload of FIUs. An academic respondent highlighted that "too many transactions are being flagged," creating bottlenecks in the investigative process. Respondent 3, an employee at a corporate, added that this dynamic creates "enormous additional costs for the government, the AFM, and other regulators," emphasizing that compliance incentives have shifted the reporting burden from private actors to public oversight bodies. This is supported in the literature by, Unger et al. (2013), Ferwerda (2018), who recognize the costs of FIUs to be a criteria in a cost benefit analysis.

Government Opportunity Costs

In the base case of the current KYC-process a high opportunity cost was identified as the social effect which leads from the identified codes within this theme. It is the government's role to enforce the AML policies and therefore also the KYC-process. The government determines the allocation of their financial resources to this incentive and/or other areas. Choice can be seen as involving both rejected and selected alternatives (Buchanan, 1991). Opportunity cost is defined as the value placed on the rejected alternatives or opportunities (Buchanan, 1991). The government's decision to allocate its budget to the costs in the codes stated in Figure 4.5 hinders the possibility of utilizing those funds for other areas, such as e.g. healthcare and education. This results in opportunity costs for the government, ultimately disadvantaging society. Therefore, opportunity costs for the government are a criteria in the SCBA.

4.3.4. Indirect Government Incentives

Figure 4.6: Data Visual of Indirect Government Incentives



This theme as seen in 4.6 captures the perceived indirect motivations and benefits for governments to uphold and promote the current KYC-processes in financial institutions. These incentives are not necessarily a direct policy goal or financial crime prevention but emerge from secondary effects of regulation. Three codes, reputation protection, integrity of financial system and penalty income, emerged from the interview codes and offer insight into the social effects of the government indirectly benefiting from KYC-processes. Respondents from different professional backgrounds identified these codes.

International Reputation Management

A point mentioned in the interviews was the reputational interest of governments. As noted by a representative of a human rights initiative, one of the benefits of the KYC-process is that it supports international government reputation management. Several authors in literature support this view. New Zealand Ministry of Justice (2017) and Harvey (2004) note the reputational benefit the government receive from demonstrating compliance with international requirements for money laundering.

Integrity of Fin. System as one of the Core Incentives for KYC Processes

Three respondents addressed the importance of maintaining the integrity of the financial system. They emphasized that the KYC process plays a crucial role in excluding unethical and illegal actors, thereby preserving the system's functionality for legitimate use. A corporate respondent elaborated on this point, noting that screening out undesirable customers contributes to making the financial system safer. This perception aligns with academic literature that frames money laundering as a threat to the integrity and stability of financial systems. For example, Unger et al. (2013) highlight that money laundering undermines trust in financial institutions and distorts legitimate financial flows, thereby negatively affecting both the financial sector and the real economy. This article points to AML positively impacting trust in institutions. At the same time, other studies warn for over surveillance causing lower trust in the financial system (Amicelle and Favarel-Garrigues, 2012; Ampudia and Palligkinis, 2018). This suggest that there is a trade-off to be made: while KYC helps protect the financial system from abuse, it's design must avoid the decrease of trust. Another corporate sector respondent, stated their view that the KYC-process ultimately contributes to the broader public good by fostering a clean and lawful financial system. Unger et al. (2013) supports this code with their view on money laundering having a negative effect on the integrity of the financial system.

Government Income through Fines

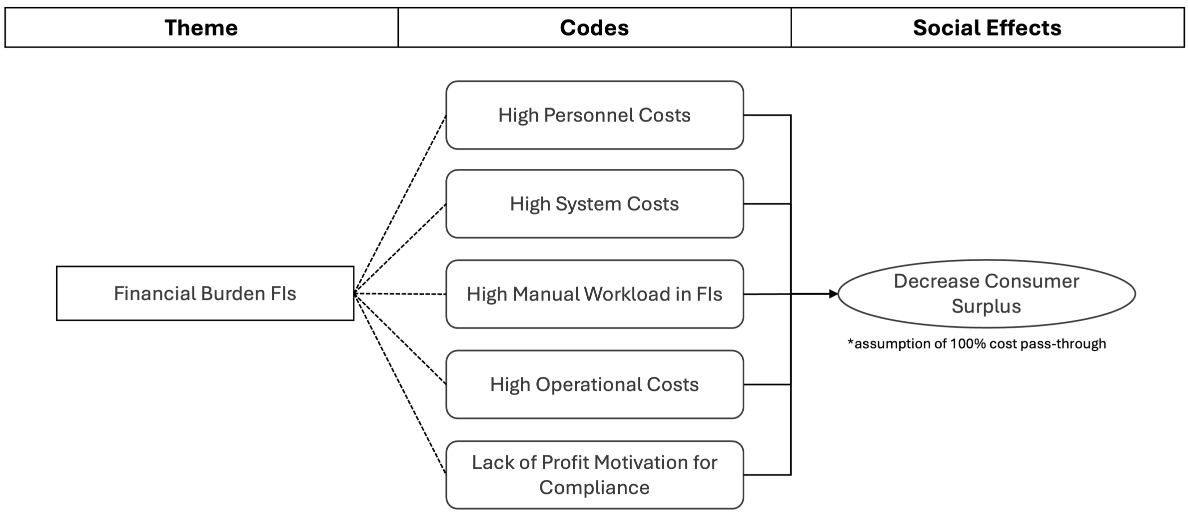
A second, more material incentive surfaced in the reflections of a manager in a corporate, who speculated that government income from penalties could be enough to pay for the AML expenses: "...I think it also generates quite a lot of money, because huge fines are issued. I'm not sure, but I can imagine that the cost of supervision might actually be offset by the fines that are imposed". Though the respondent acknowledged uncertainty about the net balance, the idea that supervision costs could be partially recouped through penalties presents a practical incentive. Unger et al. (2013) also recognized this code and categorized the government income through preventive and repressive fines as a benefit of AML policy.

Trust Building and Potentially Misaligned Policy Incentive

The implication is that by enforcing strict AML controls through KYC, a government can demonstrate commitment to international standards, such as those set by the FATF. By promoting the integrity of the financial system, trust in institutions can also increase. This trust gives confidence to consumers and investors alike. This aligns with broader observations that public trust in institutions fosters economic security (Perry, 2021). High penalties imposed on FIs due to non-compliance with AML policies increases government revenue. The social benefit of such government revenue lies in its potential to fund public goods and services e.g. healthcare, infrastructure, and education. However, while these revenues can potentially fund public goods, it is important to acknowledge the risk that enforcement mechanisms driven by financial incentives (e.g., fines) could distort policy goals, especially when social harms are considered, as seen in subsection 4.3.2. This raises the concern that the government's priorities may be off balance, with earning money from fines becoming more important than paying attention to the social costs the policy may cause.

4.3.5. Financial Burden FIs

Figure 4.7: Data Visual of Financial Burden FIs



A very prevalent finding, mentioned by almost all respondents, was the substantial financial burden current KYC-processes impose on FIs. While designed to detect financial crime, these procedures are widely perceived as operationally inefficient, marked by high personnel costs, manual workloads, costly infrastructure, and unclear regulatory expectations, especially challenging for smaller banks (see Figure 4.7).

High Staffing and Technology Investments

Over half of respondents mentioned high staffing costs. A corporate sector respondent estimated that 8–10% of a bank's change-related spending is devoted to compliance. A manager at a professional services firm claimed that up to 20% of bank employees work on AML-related tasks. This is largely due to minimal automation: Respondents from corporate and academic backgrounds described time-consuming manual reviews of alerts, ownership structures, and transaction patterns. Even though monitoring is mostly done manually, the technology is done on, is also a cost for FIs. A corporate respondent emphasized the need for constant investment in systems and models. This cost aligns with Harvey (2004) who observe that the private costs of compliance mainly include staff and system spending.

Labor-Intensive Processes

Respondents pointed out that KYC-processes are largely manual and labor-intensive. Due to limited automation, banks must dedicate significant staff resources to review complex ownership structures, analyze alerts, and comply with rigid internal rules. This manual approach leads to inefficiencies, high costs, and limited added value. An independent consultant mentioned that tasks, such as event-driven reviews, can take up to 30 hours per case. The high manual workload is not specifically addressed in academic literature however, consulting and government reports do support this claim. De Nederlandsche Bank (2023) and McKinsey & Company (2021) stated that the KYC process is often highly manual.

Administrative and Reporting Burdens on Institutions

Several respondents emphasized that the KYC process generates substantial administrative and reporting burdens for financial institutions. These tasks lead to significant operational costs, particularly for smaller institutions. Respondents highlighted that a large share of banks' expenditures is allocated to compliance, with limited return, and that resources are diverted away from core activities such as relationship management and financial services. Respondent 9, who is an independent consultant, estimated that handling a single dossier can cost €80,000. The high reporting and compliance costs can also be found in literature. There are high compliance costs and reporting costs for FIs according to Pol (2020), Deloitte (2016), New Zealand Ministry of Justice (2017), Harvey (2004) and Unger et al. (2013). This perspective is extracted from a mix of academic literature and government and consultancy reports.

Misalignment Between Compliance Duties and Commercial Interests FIs

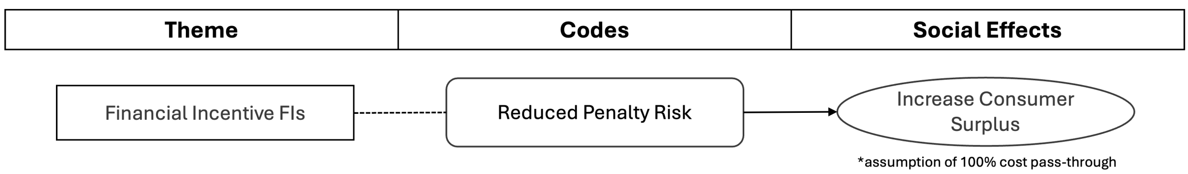
In the interviews, there was a fundamental misalignment identified between the KYC-process and the banks' commercial interests. While banks have a social responsibility to prevent financial crime, the activities most associated with money laundering, such as cash and foreign transactions, are also key sources of revenue. As a result, there is little financial incentive for banks to invest in rigorous compliance beyond what is required, which limits the business case for proactive enforcement. Harvey (2004) underscores this claim stating the FIs do not view themselves as upholding the integrity of the financial system but as "unpaid policemen".

Compliance Cost Pass-Through to Consumer Surplus

These financial pressures often spill over to consumers. As noted by Pol (2020), FIs typically pass compliance costs to clients and shareholders via higher fees, reduced interest rates, and lower dividends. In this research the assumption is made that these fees and rates are fully transferred onto the customers, as can be seen in Figure 4.7. The increase of the price of financial services reduces consumer surplus, which is the difference between a customer's willingness to pay and the actual price.

4.3.6. Reduced Penalty Risk FIs

Figure 4.8: Data Visual of Reduced Penalty Risk FIs



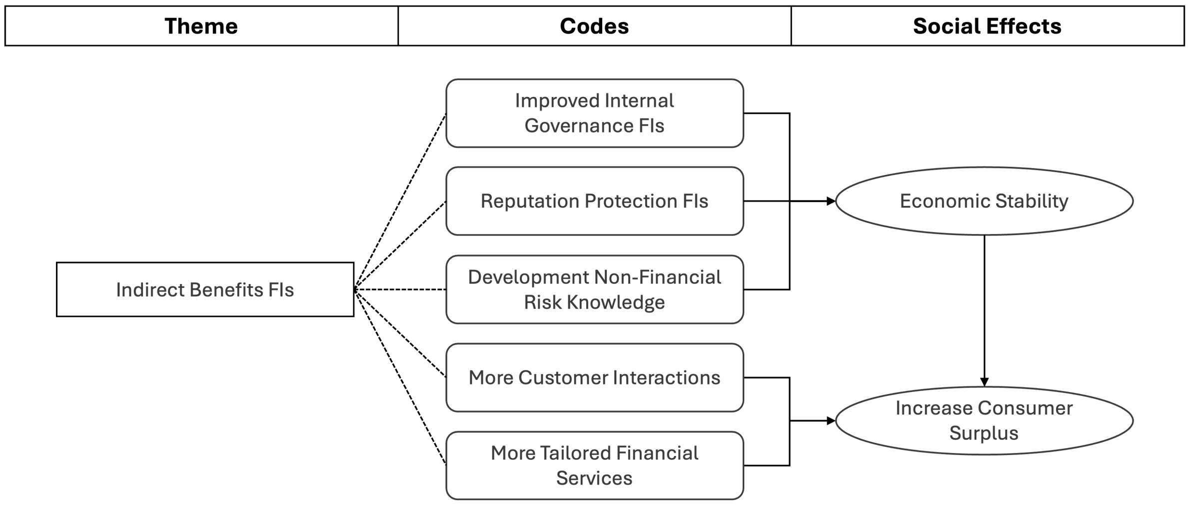
Two respondents explained the financial incentive for banks to employ KYC-processes, that is the reduced penalty risk for banks (see Figure 4.8). The reduced penalty risk is obtained through effective adherence to AML regulations.

Reduced Risk of Fines for FIs Linked to Fin. Banefit Customers

Respondent 1 and 3, both coming from a corporate background, highlighted that the main driver for compliance is avoiding regulatory fines, such as ING's €775 million penalty. One respondent mentioned that that is what banks are afraid of. The high penalties FIs are risking was also mentioned by Pol (2020). The reduced risk of the penalty is linked to a reduced cost risk for FIs. When the bank make less costs these cost reductions can be translated into lower fees for customers, assuming FI costs are 100% passed through to the customer. A higher consumer surplus is the result of the lower cost of financial services, the consumer pays less compared to their willingness to pay.

4.3.7. Indirect Benefits FIs

Figure 4.9: Data Visual of Indirect Benefits FIs



In the current KYC landscape, several indirect benefits accumulate for FIs as a result of compliance activities. These indirect benefits refer to advantageous outcomes that are not the primary aim of KYC regulation, namely, crime prevention, but which also improve institutions trough client relationships, and internal governance as seen in Figure 4.9. These codes were mentioned by 4 different respondents coming from a corporate and advocacy group background.

Improved Internal Governance

By implementing the KYC-process the FIs can experience an "Improved Internal Governance". Here, Respondent 8 remarked that KYC processes can improve "operational hygiene" within banks, enhancing internal control mechanisms. Although these improvements are not mandated outcomes of compliance procedures, they contribute to better institutional risk management. This code is also recognized in a consultancy report (Deloitte, 2016) highlighting the more streamlined internal governance due to AML.

Reputational Protection FIs

A theme in the interviews is the reputational benefit of KYC practices. Respondent 8 noted that a structured KYC process enables banks to safeguard their reputation. This topic resonates with the following quote from Harvey (2004): "It is generally accepted that the integrity of the banking and financial services sector and hence the effective functioning of financial markets is highly dependent upon its reputation.". This quote already points at the social impact of the reputational benefit of the effective functioning of the economy due to the trusted FIs.

Transferability of KYC Knowledge to Other Non-Financial Risks

Another important insight is provided by respondent 7 as they framed KYC as an early large-scale attempt by the financial sector to manage non-financial risks, which are risks not associated with products and services sold like loans and bank accounts. The non-financial risks refer to the risks that do not stem from financial markets or credit exposure, but from factors as non-compliance with laws and regulations. The respondent added that knowledge and infrastructure developed through KYC are transferable to other non-financial domains such as ESG compliance and privacy. Although this point is not yet substantiated in academic literature, it offers a valuable new perspective. It suggests that the systems and expertise developed through KYC (e.g. data infrastructure and compliance routines) may be repurposed to manage other non-financial risks, like those related to ESG and data privacy.

Customer Engagements and Their Impact on Clients

Furthermore, the KYC process alters the nature of customer engagement. The code more customer interactions highlights that while frequent contact with clients can lead to friction, as noted by respondent 7 (private sector), it also creates an opportunity for communication for services. Respondent 6, a corporate stakeholder, emphasized that customer profile updates, offer a chance for banks to initiate financial well-being conversations. These interactions can thus move beyond compliance to customer relationship management.

Both respondents 1 and 6, from the private sector, observed that deeper knowledge of client structures allows banks to offer more precise financial advice and products. For example, understanding a client's broader corporate structure or investment profile enables tailored recommendations, improving the relevance and quality of financial services. This customization, while a byproduct of compliance data, ultimately enhances consumer experience and satisfaction. Although improved customer engagement and more tailored financial services is not supported by existing literature, it introduces a possible hypothesis: interactions initiated through KYC processes may open the door to more personalized services and better client relationships, potentially increasing customer satisfaction and trust. However, this positive effect contrasts with the concerns raised under the code "Compliance Burden Legitimate Customers" (Figure 4.4), which highlights that the same data demands may place a time and privacy burden on clients. Thus, while financial institutions gain in service precision, customers may experience increased costs through more information sharing.

Contribution to Economic Stability and Consumer Surplus

The five indirect benefits seen in Figure 4.9 enhance the functioning of financial institutions, indirectly fostering economic stability by increasing institutional resilience and trust in the financial system. Enhanced governance practices create a more disciplined internal environment, which is likely to be more resilient in the face of regulatory changes or emerging risks. As public trust in banks rises due to visible adherence to regulatory standards and proactive governance, so does economic stability (Perry, 2021). The codes concerning FI business opportunities increase consumer surplus. Clients receive higher-quality, better-targeted financial services without additional cost. This surplus is generated through improved personalization, greater accessibility to financial advice, and a more secure financial ecosystem. Economic stability contributes to higher consumer surplus by creating conditions that increase individuals' ability to purchase goods and services at favorable prices. As stable economies promote higher wages and lower unemployment, people have more disposable income to spend.

4.4. Exploration of the Social Costs and Benefits of ML Implementation in the KYC- process

Having identified the key social costs and benefits of existing AML regulation, the next step is to analyze how the use of ML in the KYC process may influence these outcomes. This section evaluates the potential impact of ML on the identified effects. By doing so, the analysis provides insight into the overall contribution of ML to the social cost–benefit balance of AML compliance, answering sub-question 4. The themes influencing the social effect are the following: inherent model risks, operational costs FIs, operational beneftis FIs, better model effectiveness, legal uncertainty government, and structural improvements government.

4.5. Summary of Social Costs and Benefits of ML in KYC

Figure 4.10: Visual of interview themes indicating a positive or negative impact of ML in KYC processes on social effects

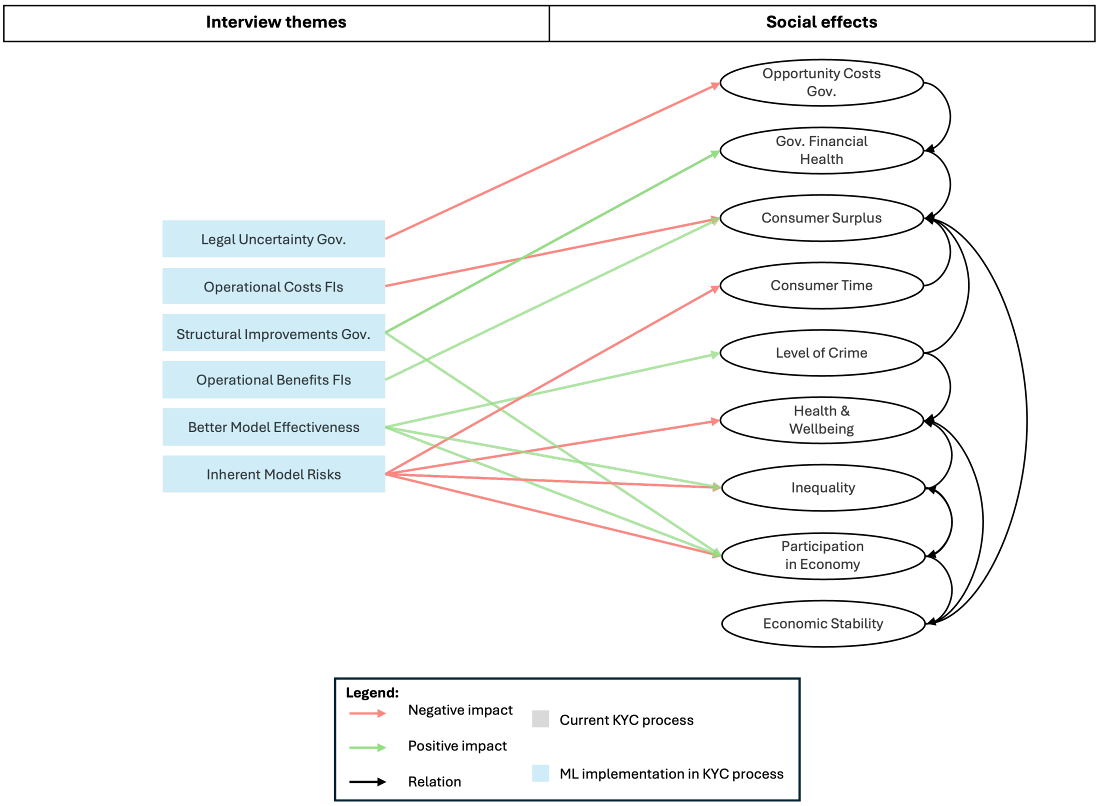
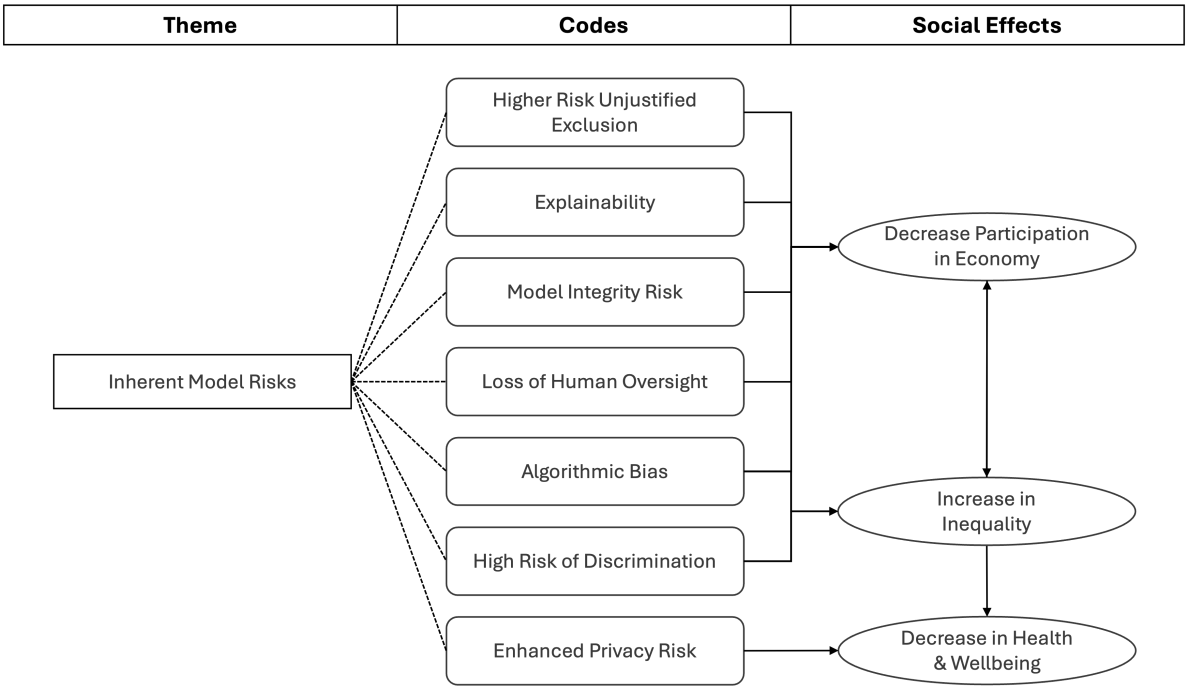


Figure 4.10 provides a summary of the expected social costs and benefits resulting from the implementation of ML in the KYC process under AML regulation. The blue boxes on the left represent overarching themes derived from the interview codes, capturing key changes introduced by ML, such as improved model effectiveness or increased legal uncertainty. These themes are linked to broader social effects on the right, with green arrows indicating a positive impact and red arrows a negative one. Black arrows show relationships between social effects, where one effect may influence another. Further explanation of these effects and their relations is provided in section 5.2. Figure 4.10 offers a visual overview of how the introduction of ML may shift the distribution of social costs and benefits in AML compliance. A full conceptualization of the results will be discussed in chapter 5.

4.5.1. Inherent Model Risks

Figure 4.11: Data Visual of Inherent Model Risks in ML in the KYC-Process



The theme of Inherent Model Risks encompasses the various uncertainties and potential hazards associated with deploying ML systems in KYC-processes. These risks are often intrinsic to the nature of the technology itself, as discussed in chapter 2, stemming from the data used to train models, the lack of transparency of the decision-making processes, and the absence of human oversight in critical decision points. Such risks can compromise the effectiveness of the model and introduce unintended negative consequences for the customers and broader society. The interview results as shown in Figure 4.11 reveals several recurring concerns that reinforce the theme of Inherent Model Risks, particularly the lack of explainability, risks to model integrity, loss of human oversight, algorithmic bias, and enhanced privacy risks. This theme was mentioned by a mix of respondents form a corporate, academic and human rights background.

Risk of Unjustified Exclusion

A key concern raised by respondents is the higher risk of unjustified exclusion due to biases in machine learning models. Respondent 8, with a human rights background, pointed out the increased risk of financial exclusion driven by algorithmic biases. The respondent emphasized that such exclusion could be without clear justification. Respondent 1, with a corporate background, shared this concern, noting the risks associated with both false positives and false negatives. These issues are particularly concerning because they can lead to financial institutions inadvertently discriminating against certain groups or individuals. A higher risk of exclusion due to false positives was not explicitely found in literature. However a report by the FATF highlights the increasing risk of financial exclusion due to digitalisation (FATF, 2021). Additionally, the codes after this claiming the bias and higher risk of discrimination also contribute to the higher risk of unjustified exclusion.

"Black Box" Nature of ML Algorithms

The lack of explainability is a significant issue in ML applications, particularly in critical sectors such as finance. Respondents frequently noted that ML models often operate as "black boxes," obscuring the reasoning behind their decisions. This was articulated by Respondent 4, who expressed concerns about compliance officers being unable to assess or challenge outcomes due to the opacity of the process. Respondent 2, from an academic background, emphasized that the inability to explain deep learning models creates significant risks, particularly when high-stakes decisions, such as labeling individuals as suspicious, are made. Respondent 3 noted that there is a need for self-explaining AI, a feature that is still being researched. The concept of explainability is also viewed more positively, with respondent 5 saying: 'The problem is that when the model flags someone as suspicious, it's often impossible to trace the reason why.' That's the explainability issue. However, work is being done on it. For example, Google has partnered with HSBC (May, 2023) to create a system that shows you why a particular score was given. It's called 'explainable AI'. They are making real progress there." The progress being made towards explainable AI is clear in this quote, although it is still in its early stages. These findings implicate that without explainability, institutions face difficulties in defending automated decisions to regulators, and customers may lose trust in systems that cannot clarify why they have been flagged as high-risk. Literature substantiates that explainability of ML or AI in AML practices is a reocurring issue (Turksen et al., 2024, Maxwell et al., 2020, Yi et al., 2023).

Data Integrity and Human Oversight Risks

Model integrity risk, closely related to the concept of "garbage in, garbage out," is highlighted in several responses. Respondent 3 pointed out that when ML models are trained on poor-quality data, their outputs become unreliable. Inaccurate or incomplete data from the past, due to improper handling by analysts or a lack of feedback loops, can result in errors in future model outputs. The poor data quality is also highlighted as a risk in ML in AML practices by Lyeonov et al. (2024).

Respondent 4's concern about the loss of human oversight further elaborates on the risks inherent in relying on ML to make final decisions in KYC-processes. While ML may be used effectively for tasks such as flagging suspicious behavior during CDD, the moment these systems are allowed to determine outcomes, such as offboarding clients or filing STRs, the risks become more profound. This loss of human judgment can lead to potentially catastrophic mistakes, such as wrongful accusations or denial of services to legitimate customers. In complex decision-making environments like KYC, human intuition and expertise are often essential for providing context and understanding that an algorithm might overlook. The findings suggest that while automation can streamline many aspects of the KYC process, it should not replace human decision-making in high-stakes outcomes. The report by FATF (2021) also underline the importance of human input in AML technology.

Risk of Algorithmic Bias and Discrimination

A critical risk associated with ML in KYC-processes is algorithmic bias. Respondent 5 discussed the issue of biases in ML models, particularly in the context of sanction lists that are disproportionately based on Arabic names. The ML system may learn to make decisions based on these biases, flagging individuals erroneously based on name recognition rather than the actual risk profile. This risk is not only a technological failure but also a social justice issue, as it can lead to discrimination against certain groups, particularly in financial services. The potential for bias in the model further complicates its ethical implications, making it crucial to ensure fairness and equity in its design. Several sources echo this code stating that AI, which encompasses ML, can amplify biases in AML processes (Pavlidis, 2023b, Turksen et al., 2024).

Discrimination in ML-based KYC processes, particularly relating to ethnicity, geography, or religion, poses significant ethical challenges. Respondent 4 pointed out that ML systems often make risk assessments based on assumptions about organizations or customers, introducing biases based on location, ethnicity, or religion. This could lead to wrongful identification of individuals as suspicious, disproportionately affecting certain demographics. Respondent 2 emphasized that the risk of algorithmic misinterpretation further reinforces potential discriminatory outcomes. Such biases in financial crime detection can lead to unfair treatment, disproportionately flagging individuals for scrutiny due to characteristics unrelated to actual risk Pavlidis (2023b) also highlight the fact that discrimination can be enlarged with the use of AI technologies in AML.

Privacy Risks Through ML

Respondent 4, coming from an academic background, raised concerns about privacy in the context of ML-based KYC systems. The need for large amounts of personal data to train these models can result in privacy risks. Moreover, when the criteria for data collection and pattern recognition are predefined, they may become discriminatory. The privacy risk that occurs due to AI or ML use is widely supported in the literature (Pavlidis, 2023b, Yi et al., 2023, Lyeonov et al., 2024, Maxwell et al., 2020).

One respondent mentioned the privacy risks of centralized data sharing, which is notable given how extensively this issue is addressed in academic literature. This gap highlights a disconnect between real-world perceptions and the broader research consensus, suggesting that privacy concerns may be underappreciated in day-to-day operations.

Exclusion Linked to Participation in Economy

The inherent risks of deploying machine learning models in KYC processes, such as algorithmic bias, loss of human oversight, and weak model explainability, contribute to negative societal effects. Algorithmic bias and discrimination risks can result in unjustified exclusion of individuals based on flawed or opaque risk assessments, disproportionately affecting marginalized groups. As Koku (2015) points out, financial exclusion often pushes people to the margins of society, limiting their economic participation and reinforcing broader social exclusion, therefore enhancing inequality.

Structural Inequality and Mental Health Impacts

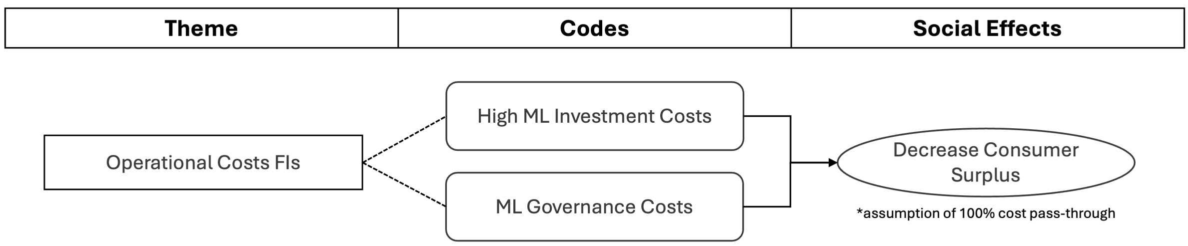
When ML models embed or amplify bias, they can deepen structural inequalities. Monahan (2008) explains that surveillance systems often disproportionately target marginalized groups, which can be enhanced by bias embedded in ML. Morgan et al. (2007) show that such exclusion contributes to mental health issues.

Machine learning systems require large volumes of personal data. Acquisti et al. (2016) show that when people feel overexposed or vulnerable to data misuse, their trust and wellbeing decline. Malakoutikhah (2020) emphasizes that excessive data scrutiny can feel unfair, fueling perceptions of surveillance.

Without human judgment, ML-based decisions may seem arbitrary or unchallengeable. This loss of control can foster feelings of injustice. Bridson et al. (2024) argues how perceived financial-related discrimination can act as a direct source of stress, which may in turn negatively affect individuals' overall wellbeing. Lack of transparency in ML models makes it difficult for individuals to understand or contest decisions, especially when wrongly excluded. As trust in institutions erodes (Perry, 2021, economic participation declines, ultimately weakening economic stability and wellbeing (Dhrifi et al., 2020).

4.5.2. Operational Costs FIs

Figure 4.12: Data Visual of Operational Effects FIs of ML in the KYC-Process



The theme of Operational Costs for FIs addresses the various practical implications of ML implementation in the KYC-process within FIs. While some effects highlight challenges related to costs, and compliance others point to efficiencies, cost reductions, and growth opportunities for institutions that adopt ML systems as can be seen in Figure 4.12. This theme is based on the quotes of respondent 8, a representative of a human rights initiative, alone.

Initial and Ongoing Investments ML

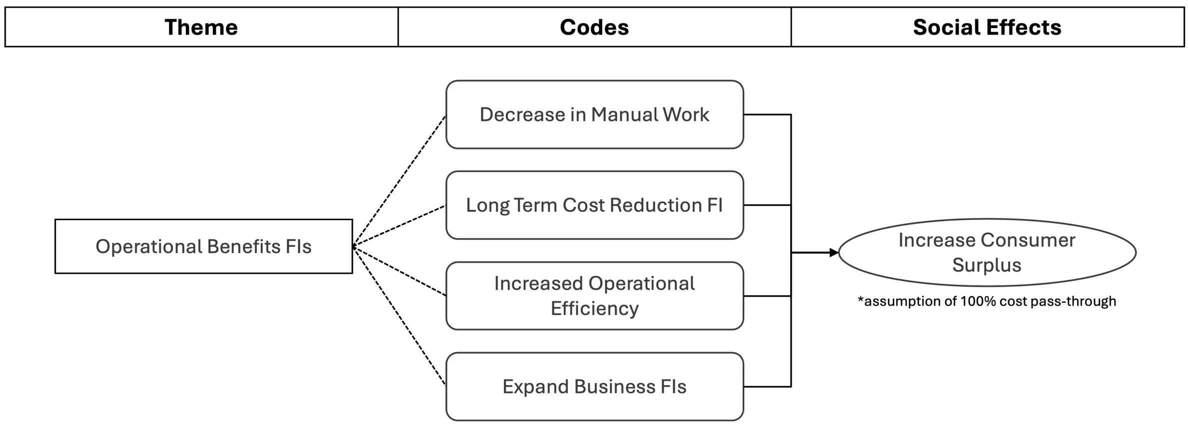
The high initial investment of ML was discussed in the interviews. Respondent 8 highlighted the high initial costs, including investments in technology and reliance on tech partners, which are both costly. Respondent 8 adds that while automation reduces the need for human intervention in routine tasks, it simultaneously introduces the need for increased oversight in areas like ethics, legal considerations, and model validation. This shows that ML is not just a means to decrease the amount of work, it merely changes the point of focus of the work. This is presented by the ML Governance Costs code.

Investments FI Linked to Consumer Welfare

These findings suggest that using ML in KYC processes may help reduce some types of manual work, but it also brings new and ongoing financial costs for FIs. If these costs are fully passed on to customers, through higher fees, it leads to a decrease in consumer surplus. This means that customers get less value for the money they spend. Even if the costs balance out internally by shifting work from one area to another, there is still a real risk that these extra expenses will end up being paid by the consumer.

4.5.3. Operational Benefits FIs

Figure 4.13: Data Visual of Operational Benefits FIs of ML in the KYC-Process



The theme Operational Benefits for FIs emerged across seven interviews, reflecting a shared expectation that ML systems can yield substantial long-term gains for institutions. It includes perceived gains in efficiency, cost reduction, and potential business expansion. This cluster of insights emphasizes that, beyond regulatory compliance, ML adoption in KYC processes can be leveraged as a strategic investment for performance enhancement.

Manual Workload Reduction

The first benefit noted was a decrease in manual work, which respondents linked to automation of repetitive tasks and improved filtering of low-risk customers. Respondents 1 and 2, with an corporate and academic background, described how ML reduces false positives and irrelevant alerts, allowing staff to focus on meaningful risks. This shift was seen to free up resources for more valuable tasks and reduce the strain on compliance teams. The lowering of manual workload is also a benefit found in literature (Yi et al., 2023, Pavlidis, 2023b, Turksen et al., 2024).

Long-Term Cost Savings FIs

Building on this, multiple respondents suggested that these efficiency gains translate into a long-term cost reduction for FIs. Respondent 1 with a corporate background emphasized that the upfront costs of ML are offset over time through lower staffing requirements, particularly in labor-intensive areas like KYC reviews. Respondent 3, also coming from a corporate, supported this view, suggesting that even accounting for ongoing governance and oversight, the net effect on operational costs could be positive. The FATF (2021) report also states that the use of ML in AML contributes to cost savings.

Improved Operational Efficiency

A related code, increased operational efficiency, refers to the improved allocation of resources and streamlining of internal processes. Respondent 8, with a human rights background, explained that ML relieves procedural burdens and reduces internal friction, while a corporate employee (Respondent 3) highlighted the added value of being able to quickly and accurately sort customers by risk profile. These gains help financial institutions focus their attention on the most relevant compliance tasks. Efficiency gains by ML in financial crime prevention is also substantiated by Dzingirai (2024) and Lyeonov et al. (2024).

Opportunities to Serve High-Risk Clients

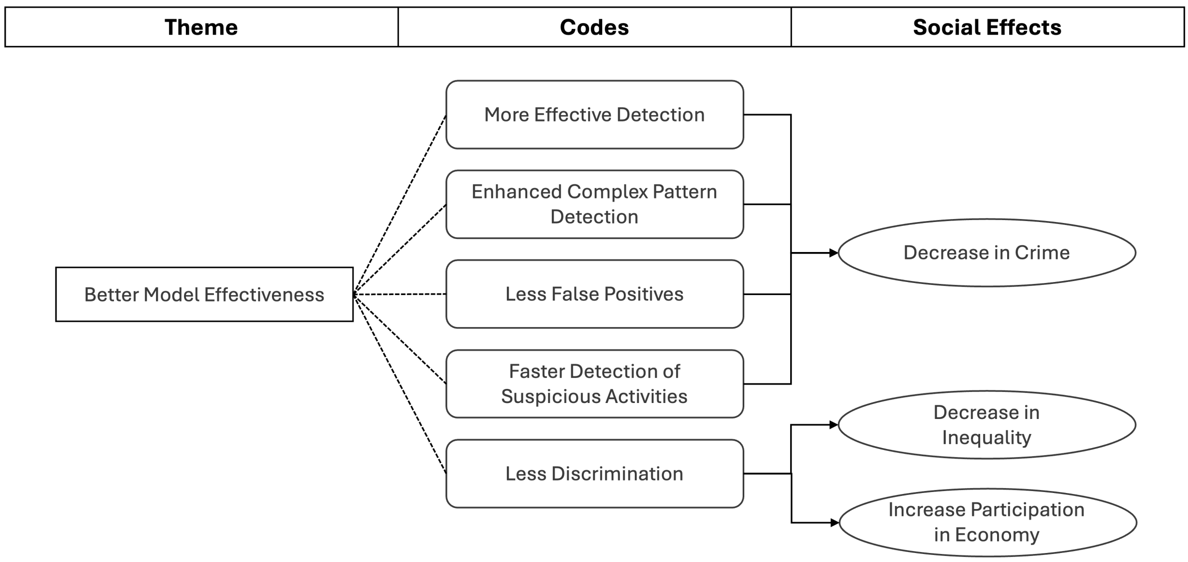
Finally, business expansion opportunities were cited by an employee at a professional services firm (Respondent 6), who noted that more accurate and reliable risk models could allow institutions to responsibly engage with client segments previously seen as too risky. The ability to take on higher-risk customers without compromising regulatory compliance opens up new revenue streams and service offerings, particularly for firms willing to innovate on the margins of current AML practices. Dzingirai (2024) found something similar, namely that ML in AML contributes to an enhanced customer insight.

Potential Benefits for Customers Through Cost Pass-Through

These operational benefits suggest that ML integration may ultimately lead to increased consumer surplus, under the assumption that lower costs and expanded services are passed through to end users. As institutions streamline operations and reduce their cost base, they may be able to offer better pricing, faster services, or broader access to financial products. However, this positive outcome hinges on full or partial cost pass-through, a condition not guaranteed, but assumed in this research.

4.5.4. Better Model Effectiveness

Figure 4.14: Data Visual of Better Model Effectiveness of ML in the KYC-Process



The theme Better Model Effectiveness captures how interviewees view ML as improving the quality and precision of transaction monitoring in KYC-processes. This theme encompasses the belief that ML systems can identify illicit financial behavior faster, more accurately, and efficiently than traditional rule-based systems. It reflects an overall improvement in both the detection capabilities and operational efficiency of KYC systems. These effects can be framed as increases in consumer surplus, as they reduce costs associated with false positives, speed up legitimate transactions, and improve protection against fraud.

Improved Detection Rates of Suspicious Activity

An observation was made that ML systems significantly improve detection rates. Respondent 5, a firm employee, cited the HSBC-Google collaboration (May, 2023), where machine learning led to two to four times more suspicious transactions being identified than in legacy systems. The implication is a substantial reduction in undetected fraud and money laundering cases. It is worth noting that this statement was based on information from a Google-affiliated promotional source, which may present the technology in a more favorable light and lacks independent verification.

Ability to Uncover Complex Fraud Patterns

The code ”Enhanced Complex Pattern Detection” reflects the advanced capabilities of ML to uncover non-obvious and evolving fraud schemes. Respondents stressed that rule-based systems struggle with cross-border, or complex patterns, e.g., romance scams or misuse of child accounts. A corporate sector interviewee (Respondent 1),noted the ability of ML to identify fraud that only becomes apparent when viewing a broader behavioral pattern. This “360-degree view” allows the system to flag relationships or transactions that, in isolation, seem benign. Another corporate interviewee (Respondent 5) shared their view, emphasizing that machine learning can contextualize anomalies, such as many individuals at one address or account usage mismatched to customer profiles. The identification of complex patterns by ML in transactions can be found in literature by Maxwell et al. (2020) and Dzingirai (2024).

Reduction in False Positives with Human Oversight

Reducing false positives, where legitimate activity is incorrectly flagged as suspicious, was frequently cited as a benefit. Interviewees form a corporate, academic and human rights background (Respondents 1, 2, 6, and 8) independently mentioned this. Respondent 2 summarized it: ”There’s always going to be false positives... will they (ML models) make fewer mistakes than something not learned? Yes, probably yes.” This indicates an expectation that ML, when supervised and tuned correctly, outperforms rule-based systems in avoiding false positives. Fewer false positives reduce unnecessary customer friction (e.g., blocked accounts, delayed transactions, intrusive questions), directly enhancing user experience. This is a clear gain in consumer surplus: customers face fewer disruptions, and banks reduce unnecessary investigation costs. However, Respondent 8 emphasized the importance of proper model oversight, implying that this benefit is reliant upon ongoing human-in-the-loop practices. The reduction in false positives is prevalent in literature, where several authors state that ML models can potentially reduce false positives (Pavlidis, 2023b, Yi et al., 2023, Lyeonov et al., 2024).

Faster Detection and Potential for more Individualized Risk Assessment

Respondent 8, employed at a large professional services firm, mentioned that ML systems enable faster detection of suspicious activities. This matters because financial fraud and money laundering often rely on speed and transaction layering to avoid detection. Early identification can prevent the escalation or completion of illicit financial behavior. Similarly, Pavlidis (2023b) argues that the use of ML models helps banks detect suspicious activity more quickly than while using more manual based procedures.

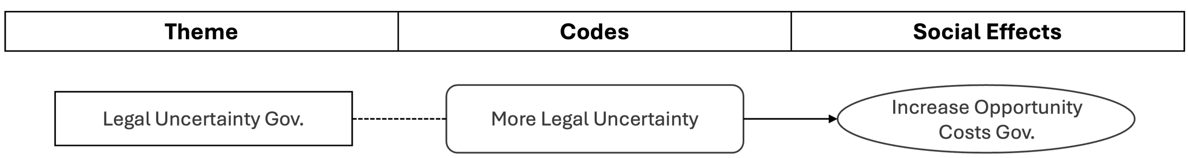
Lastly, Respondent 1 (corporate background) believed that machine learning could reduce discrimination if used correctly. They explained that ML might move away from biased rules based on things like nationality or surname, and instead allow for more personalized, data-driven risk assessments. This, in their view, could make the process fairer. However, this view was not shared by all respondents. Others expressed concerns about bias in ML models, which reflects common worries in the literature about unfair outcomes caused by data or design choices (see Section subsection 4.5.1). While the idea of tailoring assessments to individuals sounds fairer in theory, academic research does not clearly support this. In fact, many studies warn that ML can also reinforce existing inequalities.

Effects on Crime, Inequality and Economic Participation

The codes under this theme suggest that ML improves both the effectiveness and fairness of the KYC process. These capabilities translate into broader social benefits. More effective detection, faster intervention, and fewer false positives all support the reduction of financial crime, while the potential for fairer assessments may help marginalized groups gain more equitable access to financial services. Which can in turn decrease inequality and increase their participation in economy. Collectively, these outcomes contribute to both a decrease in crime and an increase in economic participation. However, realizing these benefits depends partially on continuous human oversight.

4.5.5. Legal Uncertainty Government

Figure 4.15: Data Visual of Legal Uncertainty Government through ML in the KYC



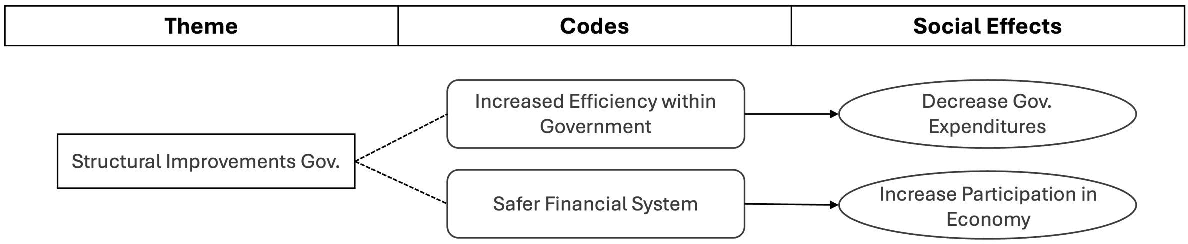
The theme Legal Uncertainty Government captures the regulatory ambiguity faced by government institutions when responding to ML-based KYC innovations. This theme emerged from interviews with people with a corporate and human rights background and reflects the challenges involved in adapting existing legal frameworks to accommodate advanced technologies.

Supervisory Capacity and Public Resource Shifts

The associated code, More Legal Uncertainty, highlights concerns about the lack of clear regulatory guidance and oversight mechanisms. Respondent 8 (corporate background) pointed out that governments and supervisors are expected to assess ML systems without sufficient legal infrastructure or expertise. Respondent 6 (corporate background) stated that it is very challenging to demonstrate compliance of ML models. A report by the FATF (2021) also expresses the same view in saying supervisors lack expertise and resources to understand the models to adequately supervise them. This creates an institutional strain, requiring legal and human capital to be reallocated toward the development of new competencies in the government. In doing so, governments accrue opportunity costs, as attention and resources are diverted from other policy domains.

4.5.6. Structural Improvements Government

Figure 4.16: Data Visual of Structural Improvements Government through ML in the KYC-Process



The theme Structural Improvements Government reflects the ways in which ML-enhanced KYC can contribute to better functioning governmental processes and outcomes. It emerged in interviews with corporate and academic respondents.

Efficiency Gains and Financial Health Gov.

The code Increased Efficiency within Government was supported by a corporate interviewee (Respondent 3), who noted that ML offers clearer insights into financial risks, shifting the emphasis from the sheer volume of reports to the quality and relevance of the information provided. This transition enables supervisory bodies to allocate their resources more efficiently, which, over time, can reduce government expenditures either through staffing reductions or improved use of personnel. A report by the FATF (2021) supports this argument by saying that ML can provide more detail on suspicious transactions to the FIU.

Safer Fin. System and Fin. Participation in Economy

The second code, Safer Financial System, was emphasized by an academic interviewee (Respondent 2), who argued that ML brings KYC back to its core purpose, which is detecting genuine risk and preventing financial crime. This view is supported in several articles that mentioned the enhanced detection of money laundering due to ML (Maxwell et al., 2020, Yi et al., 2023, Dzingirai, 2024). Enhanced model precision supports systemic integrity and contributes to restoring public confidence in financial institutions. This, in turn, can foster greater economic engagement, as both consumers and businesses are more likely to trust and participate in a stable financial system.

5

Conceptualization

This chapter defines and structures the social effects that form the basis of the SCBA of the KYC process and its potential transformation through machine learning. The chapter first identifies and explains each selected social effect, then examines their interrelations and the ways they are influenced by both the current KYC process and the introduction of machine learning. This provides a structured foundation for later valuation and highlights the systemic and interconnected nature of the social costs and benefits.

5.1. Identification and Definition of Social Effects for SCBA

The codes found in section 4.3 and section 4.4 resulted in several social effects. This section provides an overview of the social effects that must be taken into account in a SCBA. According to SCBA methodology, it is essential to identify all relevant effects a policy measure may have. All effects are listed and explained in Table 5.1. The social effects in Table 5.1 are the criteria for a full SCBA.

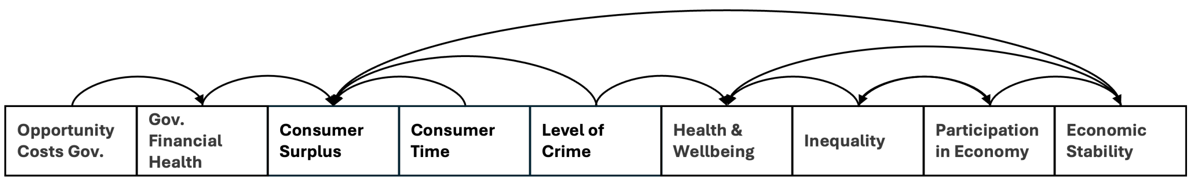
Table 5.1: Overview of social effects and corresponding explanations

Social Effect	Explanation
Level of Crime	This effect indicates the reduction of illegal activities such as money laundering, fraud, or terrorist financing. In the context of AML, the disrupting of money laundering is connected to disrupting the underlying criminal activities.
Health & Wellbeing	In the context of this thesis this effect refers to stress levels and mental health. Stress and anxiety can arise when individuals are wrongly flagged, face account closures, or struggle to resolve issues with little explanation.
Inequality	This points to unequal distribution of opportunities and resources between different groups in society. In the context of AML, inequality can arise when risk-based controls disproportionately target certain groups, making it harder for them to access or keep financial services, worsening the divide.
Participation in Economy	This effect refers to the act of having access to financial services and being able to spend income in the legal, real economy. In the context of KYC processes, when individuals are wrongly flagged, profiled, or excluded from financial services, they may be pushed to the margins of the formal economy. This limits their ability to save, invest, or participate in buying an selling.
Economic Stability	In this thesis it pertains to a state where the economy experiences minimal fluctuations. It is characterized by trust in institutions, consistent access to financial services, and confidence in the security and fairness of economic transactions.
Consumer Surplus	This is related to the benefit people receive when the price to access financial services is lower than their willingness to pay. Complex or restrictive compliance processes can reduce this surplus by making services cost more for consumers.
Consumer Time	This is the time individuals spend fulfilling identity and compliance requirements imposed by financial institutions as part of AML measures.
Gov. Financial Health	This effect refers to the balance between government revenue (such as taxes and fines) and government expenditures (such as supervision, enforcement, and administrative costs). In the context of this thesis, it reflects how AML policies affect public finances.
Increase Opportunity Costs Gov.	This specifies the resources governments spend on AML supervision and enforcement that could have been used elsewhere. This includes time, money, and personnel dedicated to monitoring compliance. These funds could potentially could have been used for education, healthcare, or social programs.

5.2. Interrelation Between Identified Social Effects

In this part of the chapter the interrelation of all social effects is explored. A social effect can rarely be seen in isolation. It is usually influenced or impacts other factors in society. For this reason the interaction between the found effects of the KYC process needs to be elaborated upon. The relations between the social effects are found in literature or by the researchers' own analytical thinking. A visual of the relations can be seen in Figure 5.1, represented by the top row and arrows from one effect to the other.

Figure 5.1: Overview of all social effects with their interrelations



Systemic Dependencies Between Social Effects

This section shows that the identified social effects are closely interlinked, often reinforcing or influencing one another. A decline in one area, such as participation in the economy or financial health, can trigger chain reaction, negatively impacting other outcomes like consumer surplus, inequality, or health and wellbeing. These connections highlight that social costs or benefits should not be assessed in isolation. Instead, their broader impact across the system must be considered. This underlines the importance of a comprehensive system view.

Key Interactions: Consumer Surplus and Health & Wellbeing

Something notable about the connections between the effects is some effects have a higher interconnectedness than others. This could point to a higher importance tied to the effects in literature. This is the case with consumer surplus, health and wellbeing, which have multiple incoming and outgoing arrows. Economic stability and level of crime also send out a few arrows, showing their significance in influencing the rest of the effects.

Feedback Loop between Inequality and Economic Participation

One causal loop is found in the figure: inequality and participation in the economy. Not participating in the economy increases social exclusion as seen in subsection 4.3.2. When people do not have access to financial services there can be impact on their reputation and mental health (Amicelle and Favarel-Garrigues, 2012, Morgan et al., 2007). Social exclusion of the individuals has repercussions on inequality through marginalizing them even more. The reverse is also true, when there is inequality in society, marginalized groups struggle to participate in economy. They can have limited access to resources like a stable income which could be a requirement for certain financial services. Additionally, certain groups may be more likely to be flagged as high-risk based on nationality, income level, or place of birth. These marginalized individuals may face more checks, delays, or exclusion from financial services. This creates barriers to participation in the economy. This shows the risk of it becoming a vicious circle, for better or worse, and that if one improves, the other will eventually follow.

Government Spending Efficiency and Consumer Impact

A high opportunity cost means that the government is not making the most of its limited resources, which can impair its ability to finance debt or public services. This is linked to the governments' financial health. When the government is not allocating its resources optimally, it may end up spending more than necessary or be forced to cut spending in other important areas. The financial health of a government influences consumer surplus because tax policies used to raise revenue often lead to higher prices for consumers. As Kang and Vasserman (2022) show, higher taxes increase government income but reduce consumer surplus, even though the size of this loss is hard to measure directly.

Consumer Time and Surplus

As Jara-Diaz (1990) shows in the context of transportation, reductions in travel time lead to measurable gains in consumer surplus, as individuals value time as a component of utility. Therefore it can be derived that when time costs decrease, for example through faster or more efficient service, consumers experience higher utility, which translates into economic benefit. Applying this reasoning to the KYC process, it can be expected that increased time burdens, such as lengthy identification procedures or repeated document requests, may reduce consumer surplus by lowering perceived service quality and utility.

The Interplay of Crime, Economic Stability, and Health

The decrease in crime can have the effect of enhancing health and wellbeing of society. As stated in subsection 4.3.1, crime can have emotional and physical consequences on it's victims. Lowering crime through the reduction of money laundering can have the effect of increasing the health and wellbeing of society. Economic stability influences the health and wellbeing of society. When the economy is running smoothly, there is improved health through better housing, nutrition and healthcare (see subsection 4.3.2). Crime prevention increases consumer surplus through lower costs that are associated to crime like theft prevention, insurance, and security.

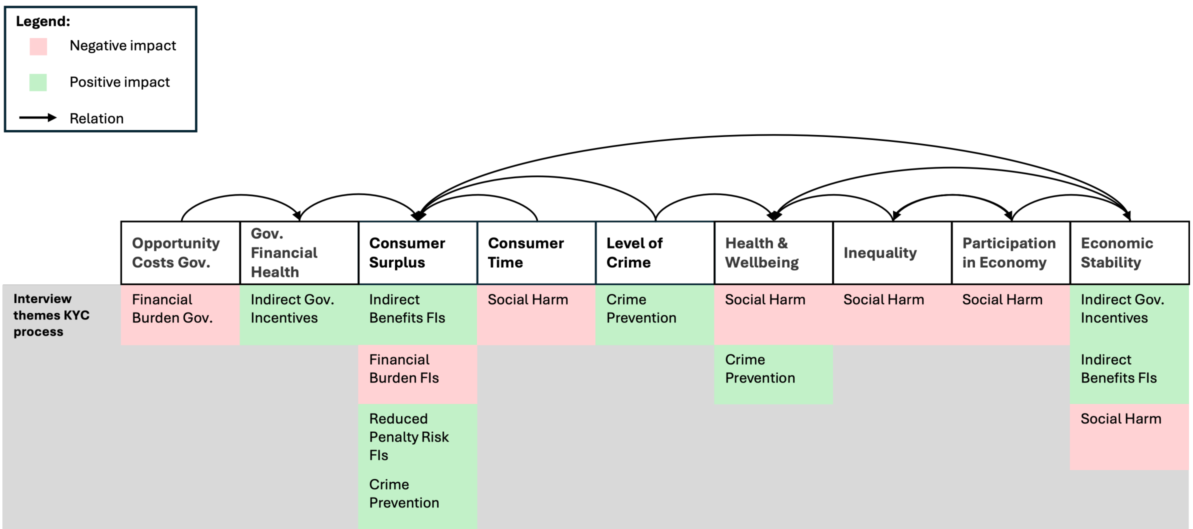
Economic Participation as a Driver of Economic Stability

Derived from the authors' own analytical thinking, participation in economy influences the stability of the economy. Being able to participate means the individual can e.g. open a bank account, participate to the labor market, and pay taxes. These are all things that contribute to economic growth or stability. When one does not have a bank account with money to spend in the real economy, the economy experiences a decreased demand, lower production, and in turn maybe lower employment.

5.3. Influence of current KYC process on social effects

This section creates an overview of the candidate effects including their direction (positive or negative). The findings are summarized in Figure 5.2, which visualizes how the current KYC process impacts broader social effects based on themes identified in the interviews (section 4.3). The figure shows whether each theme contributes positively (green) or negatively (red) to a specific social effect. The arrows indicate how these effects influence one another, as elaborated in section 5.2. Together, the figure and underlying analysis offer a structured basis for evaluating the societal costs and benefits within a SCBA. The identified social effects are from left to right: opportunity costs for the government, government financial health, consumer surplus, consumer time, level of crime, health and wellbeing, inequality, economic participation, and economic stability. The current KYC process generates both social benefits and costs, which are distributed unevenly across key stakeholders.

Figure 5.2: Overview of how interview themes indicate positive (green) or negative (red) impacts of the current KYC process on social effects. Arrows show relationships between the effects.



Financial Health Government and Crime Level Positively Influenced

In the column Government Financial Health, an interview theme indicates a positive effect of the KYC process. High AML fines on financial institutions also generate government revenue. This income can be used to fund public goods such as healthcare, infrastructure, and education, thereby strengthening government financial health. The column titled Level of Crime shows one interview theme indicating a positive effect of the KYC process under AML regulation. This is linked to its preventive role, which helps reduce crime, as supported by the interviews and discussed in subsection 4.3.1.

Negative Societal Consequences of the KYC Process

The interviews revealed that certain aspects of the KYC process contribute to negative consequences, affecting several societal effects. For the social effect Opportunity Costs Government, one interview theme indicates a negative impact resulting from the current KYC process. High costs related to supervision, legal processes, and the operation of the FIU take resources away from other public services. This creates opportunity costs, as funds spent on KYC enforcement cannot be used for alternative priorities like education or healthcare. The column containing Consumer Time shows one interview theme indicating a negative impact of the KYC process under AML regulation. This effect is linked to the additional identification and verification steps, which increase the time burden for consumers. Inequality increases when vulnerable groups, like migrants or self-employed people, are excluded from financial services. This negative influence of the KYC process is represented by the interview theme Social Harm. Social harm was identified as a interview theme indicating a negative effect on Participation in the Economy. Economic participation is reduced when people are unable to open accounts, access benefits, or start businesses.

Mixed Effects of KYC on Consumer Surplus and Economic Stability

Some interview themes related to the KYC process show a mixed influence on certain social effects, with both positive and negative impacts appearing in the responses. On the positive side of Consumer Surplus, crime prevention lowers costs related to theft prevention, insurance, and fraud protection. Indirect benefits to financial institutions, e.g. improved operations and reputational gains, also enhance consumer surplus by enabling better services. Moreover, reduced penalty risk through compliance lowers the likelihood that large fines will be passed on to customers as increased fees. However, the financial burden that KYC imposes on banks negatively affects consumer surplus. Interviewees noted that banks employ large teams and invest heavily in systems to maintain compliance. As this research assumes that these costs are fully passed on to the customer, the result is a decrease in consumer surplus. The social effect Health & Wellbeing is influenced by both positive and negative aspects of the KYC process, as reflected in the interview themes. On the negative side, the theme Social Harm contributes to exclusion, discrimination, privacy violations, and a loss of trust in institutions, all of which are linked to mental health challenges. Conversely, the theme Crime Prevention is expected to have a positive influence by reducing the number of crime victims and enhancing public safety, which in turn supports overall health and wellbeing. Based on interview themes, Economic Stability is both positively and negatively affected by the KYC process. Social Harm through the loss of trust in institutions undermines Economic Stability (see subsection 4.3.2). The themes Indirect Government Incentives and Indirect Benefits for Financial Institutions suggest that the KYC process could improve economic stability by strengthening trust in both government and FIs, and by improving internal knowledge and governance in FIs.

Stakeholder Roles and Redistribution of Costs

As discussed in this section, the interview themes indicate negative, positive and dual effects. Within the interview themes it becomes clear that there are three main stakeholders impacted by the effects. These are society as a whole, FIs and the government. It can be seen in Figure 5.2 that the government experiences costs as well as benefits in through the KYC process. Through the relations displayed at the top of the figure, these costs and benefits in turn are passed onto the consumer surplus. This shows how government expenditures are passed onto the financial wellbeing of individuals. The KYC process was also found to have positive and negative effects on FIs. While it reduces the risk of fines, it requires significant resources. This research assumes these costs and benefits are fully passed on to customers, meaning society ultimately bears the financial burden. At the societal level, a trade-off exists between crime prevention and social harm. These two themes represent the core tension of AML regulation: improved safety versus exclusion, reduced wellbeing, and increased inequality. Although the government and FIs pay the direct costs, the public carries the indirect impact. The extent to which each stakeholder benefits or suffers cannot be determined from this qualitative analysis.

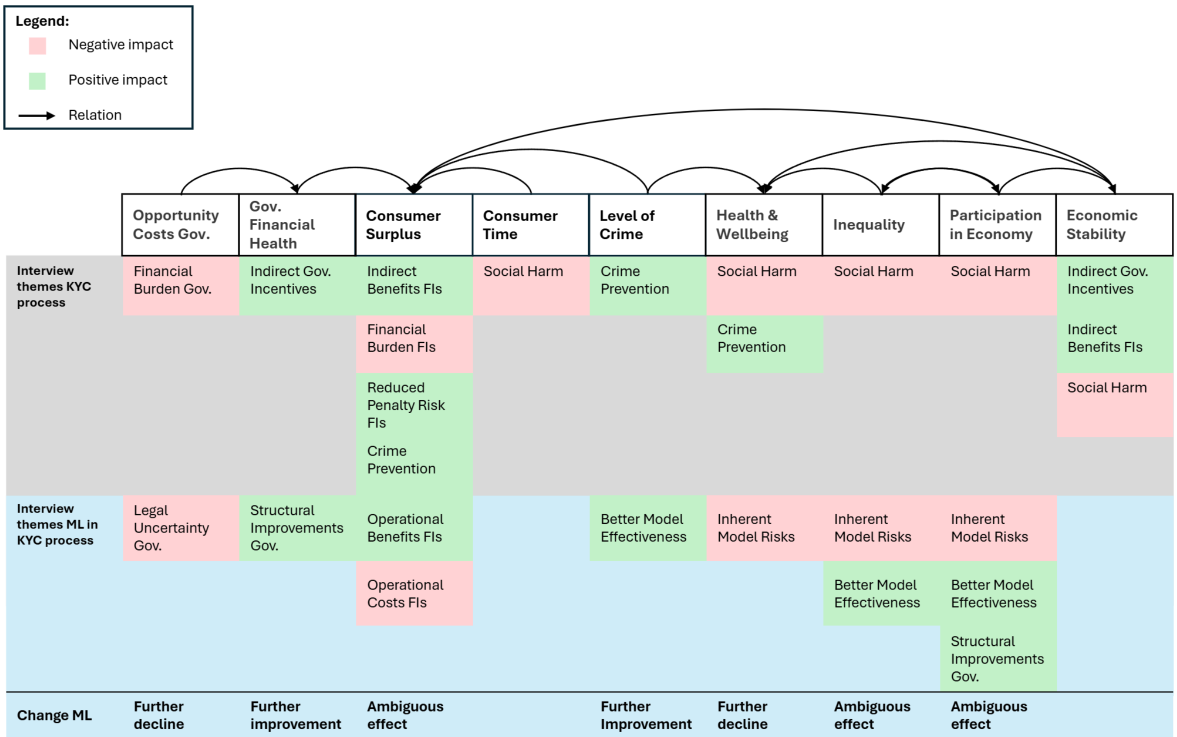
The Central Trade-Off in AML Regulation

In sum, the current KYC process creates a clear trade-off: while it helps reduce crime, it also leads to exclusion, inequality, and opportunity costs that ultimately fall on society. Financial institutions and the government may absorb the direct costs, but these are largely passed on to the public. This uneven distribution highlights a core tension in AML enforcement, between public security and harm.

5.4. Influence ML on social effect KYC process

This section elaborates on the influence ML has on the social costs and benefits of the KYC process. There are three categories of change ML creates in this context. ML can cause a further decline, improvement or a dual effect in the social effects identified in section 4.4. These results answer the subquestion: "How does the introduction of machine learning alter the identified social costs and benefits of the KYC process?". The overview of the social effects and the interview themes that influence them positively or negatively can be seen in Figure 5.3. These themes give an indication of direction, whether ML amplifies or reduces an effect, but they do not show how large that effect is. A full social cost-benefit analysis would require monetizing each effect. The ultimate change that ML brings to the social effect is summarized in the last row, with a further decline, improvement or a dual effect. These themes give an indication of direction, whether ML amplifies or reduces an effect, but they do not show how large that effect is. A full social cost-benefit analysis would require monetizing each effect. The codes from the interviews can serve as a guide in that process, offering a foundation for future valuation work.

Figure 5.3: Overview effects of current and ML KYC process



Strengthening Crime Detection and Government Capacity Through ML

The introduction of machine learning further improves the social benefits of the KYC process for the social effects: Government Financial Health and Level of Crime. Interviews indicated that ML enables the FIU to receive higher-quality, more relevant suspicious activity reports, reducing unnecessary workload and spending. This improves the financial health of the government (see subsection 4.5.6). ML models are expected to be more effective at detecting unusual transactions and complex patterns, enhancing the detection of money laundering. As a result, ML supports a further decrease in crime (see subsection 4.3.1).

Legal Government and Mental Health Costs

The Opportunity Costs of the Government and Health & Wellbeing of society are expected to further decline due to the introduction of ML in KYC processes. Legal uncertainty for the government was found to increase the opportunity costs of implementing ML (subsection 4.5.5). Because ML is still new and complex, existing legislation has not yet fully adapted. Developing suitable regulation and supervisory capacity requires resources that could otherwise be used for other public services, increasing the opportunity cost to the government. Privacy risks tied to ML may make individuals feel unsafe about how their data is used, increasing stress (see subsection 4.5.1).

Ambiguous Impacts of ML on Inequality, Participation, and Consumer Surplus

Three social effects were found to be ambiguously effected by the introduction of ML. Consumer surplus may be improved by lowering operational costs and improving services, if banks pass those savings on to customers. However, ML also introduces new costs, such as model governance and legal oversight. If banks pass these costs to customers through higher fees, consumer surplus may decline. These themes identified in the interviews suggest that ML can either amplify or reduce the consumer surplus impacts caused by the KYC process. The theme Better Model Effectiveness was tied to less discrimination (see subsection 4.5.1). When fewer people are wrongly excluded from the financial system, the social effect of Participation in the Economy can increase. The interview theme Inherent Model

Risks indicates that ML can negatively impact inequality. Biased or ”black box” ML decisions can unfairly exclude marginalized groups, increasing inequality. Excluded individuals cannot access accounts or services, limiting their ability to participate in the economy. This indicates the negative impact Inherent Model Risks can have on the Participtaion in Economy. Based on the interviews, Structural Improvements by the Government influence both economic participation. Another improvement is a safer financial system due to more accurate detection of financial crime. This can increase public trust in institutions and, in turn, raise participation in the economy. These interview themes that indicate positive and negative effects in Inequality and the Participation in the Economy highlight the ambiguous effect ML has on the aforementioned social effects.

The Amplification of Social Harm Through Model Risks

The KYC process interview theme social harm is shown to be aggrevated by the inherent model risks in the ML interview themes. This shows how privacy, discrimination and exclusion in the current system could potentially by amplified by biases, opacity and lack of human oversight. The counterpart to these model risks are the promised better model effectiveness, the desired higher accuracy of the system. The better model effectiveness would directly benefit society through crime reduction.

Indirect Burden Transfer from Institutions to Society

Stakeholder-specific effects also vary. The government faces both rising legal uncertainty and fewer low-quality alerts. These effects could balance each other out, but their actual value needs further research. For FIs, ML brings both burdens and benefits. It may improve efficiency but also requires investments in oversight and compliance. Whether the costs or benefits dominate cannot be concluded from this study. What can be concluded from Figure 5.3 is how the effects that influence the government and FIs in a direct way, indirectly carry onto society as a whole. This reveals a deeper truth: society bears the consequences of how ML is implemented, even when it is not the direct decision-maker.

Balancing Social Benefits and Harms of ML in KYC

To conclude, this section answered sub-question 4: ”How does the introduction of machine learning alter the identified social costs and benefits of the KYC process?”. The introduction of ML shifts and intensifies the social impacts of KYC. It strengthens benefits like crime reduction and government efficiency. It also deepens some costs, especially around legal uncertainty and wellbeing. Some effects, like inequality, participation, and consumer surplus, are shaped by both risks and opportunities. The net impact depends on how ML is implemented and governed, and should be analyzed in future research. Importantly, the distribution of these costs and benefits is uneven. While financial institutions and governments may carry some of the burden, society, often absorbs the harms indirectly. This section highlights that many of the negative effects ultimately fall on the public, not on the institutions responsible for implementation. This underscores the need for greater accountability and a more balanced approach to ensure that the benefits of ML in KYC do not come at society’s expense. The challenge going forward is not just to use ML, but to use it in a way that distributes its impact fairly and benefits society as a whole.

5.5. Complex Nature of the Social Costs and Benefits

To convey the complexity of the social costs and benefits caused by the KYC process and the implementation of ML in it, Figure 5.4 was developed.

Figure 5.4: Overview effects of current and ML KYC process with connections

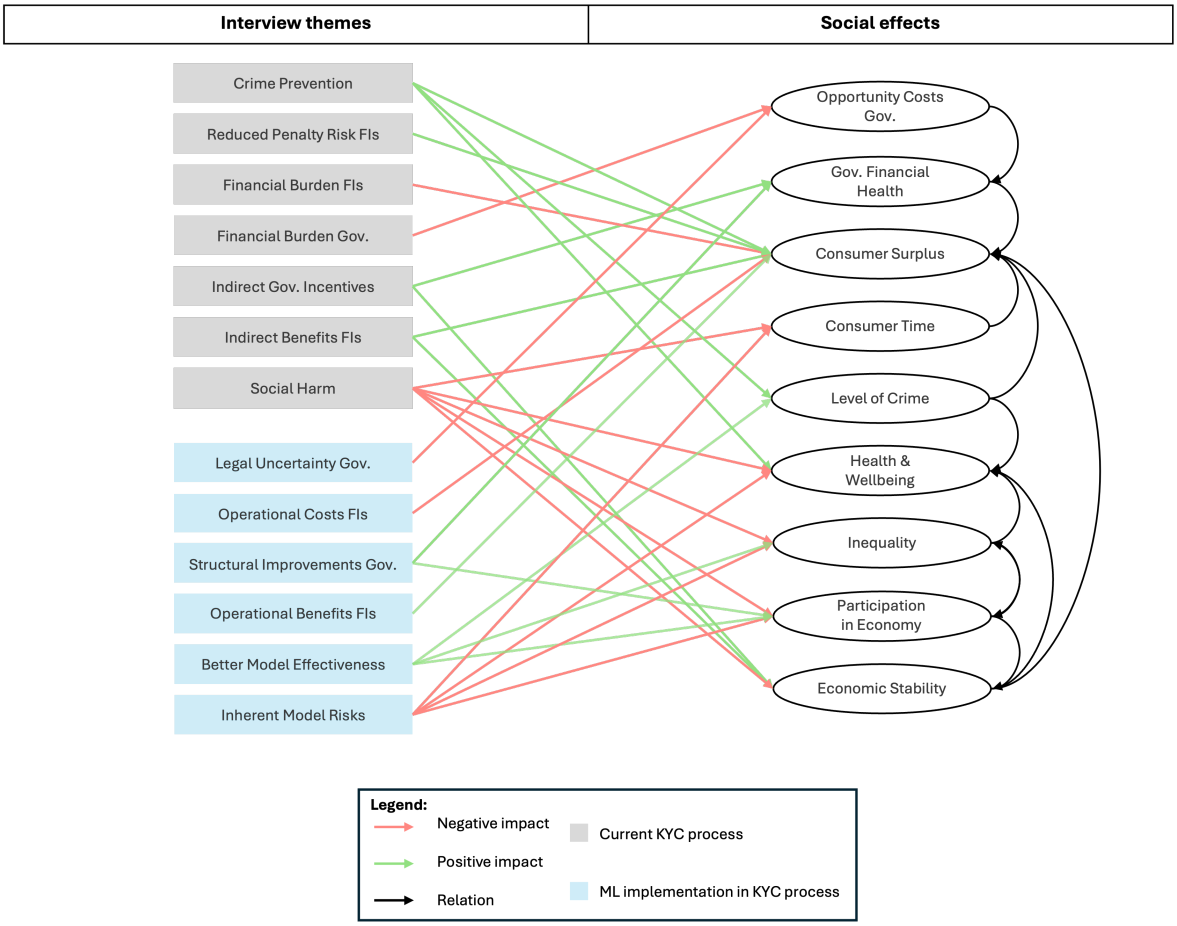


Figure 5.4 presents a visualization that connects interview themes, KYC process with and without ML, and their resulting social effects. The left side of the figure outlines the key themes that emerged from the interviews, with the themes connected to the current KYC process in grey and the themes linked to ML implementation in blue. The themes are connected with red or green arrows respectively indicating a negative or positive impact on the social effects on the right.

The visualization highlights how different aspects of KYC implementation, particularly the use of machine learning, shape the distribution and intensity of social impacts across stakeholders. First, it illustrates that machine learning amplifies both the positive and negative effects of the KYC process. Second, the figure shows how the different ways of implementing the KYC process (manual and rule-based vs ML) affects the social effects differently. Consumer surplus being the most linked to interview themes, indicating its strong relevance in interviewee concerns. Third, social harm within the KYC interview themes and inherent model risks coming from the ML themes influence various social effects. Their broad impact underscores their social relevance, as both are linked to a wide range of negative effects. Other harms in both interview theme categories appear less significant, as they are linked to fewer social effects. As a result, it becomes clear that social harm and model risks place a greater burden on society. The government and FIs do not seem to face these widespread negative consequences. This points to a possible imbalance in how the costs of KYC are distributed, with society carrying the largest share.

The visualization shows many arrows connecting interview themes to social effects, as well as interdependencies between the effects themselves. This illustrates the complexity of the topic: the social impact of KYC and ML is not driven by isolated factors but shaped by interconnected effects. These interconnections highlight that changes in one area, such as crime detection, can produce ripple effects elsewhere, including consumer surplus. Recognizing this complexity is essential for policymakers and financial institutions, as it underscores the need for a systems-thinking approach when implementing ML in KYC: targeted improvements in one part of the process may unintentionally worsen outcomes in another.

Finally, the figure shows how interview themes shape social effects through both traditional and ML-enhanced KYC processes. It reinforces a key conclusion: machine learning is not a neutral tool. It can either improve or worsen the social outcomes of existing policies. The issue is not simply whether to adopt ML in KYC, but how to ensure it is used responsibly. If poorly implemented, it risks amplifying harm rather than reducing it. The visualization makes clear that these effects are deeply interconnected. A change in one area can trigger unintended consequences elsewhere. This highlights the need for a critical and systems-based approach to implementation. Policymakers and institutions must weigh not just efficiency gains, but also society who ultimately bears the cost.

6
Discussion

This chapter reflects on the study's main results and what they mean for policy, practice, and research. It interprets the mapped social costs and benefits of KYC, both in its current form and with ML, and explains how these effects interact and are distributed across stakeholders. The discussion then positions the findings within the wider AML/ML and surveillance literature, outlines the thesis's contributions, and acknowledges key limitations. Finally, it draws practical implications for regulators and financial institutions and sketches directions for future work.

6.1. Key Findings and Implications

6.1.1. Dual Social Effects of the KYC Process

The results indicate that the current KYC process generates both social benefits and significant costs, which are unevenly distributed and interconnected across society, financial institutions, and the state. The key social benefit lies in crime prevention, as KYC processes reduce opportunities for financial crime such as money laundering, which in turn supports public safety and trust. However, this benefit comes with a societal price: exclusion from financial services, increased inequality, and reduced economic participation. Vulnerable groups, such as migrants and the self-employed, bear the burden of these harms, facing disproportionate scrutiny and reduced access to financial products. The results reveal that AML policies can unintentionally harm vulnerable groups while aiming to protect the public. Understanding these trade-offs is essential for designing fairer and more effective regulation.

6.1.2. Interrelation and Distribution of Effects

The study demonstrates that the social effects of KYC processes are highly interrelated, an forming a feedback loop with systemic consequences. For example, reduced participation in the economy leads to social exclusion, which in turn deepens inequality, a dynamic that could be self-reinforcing. A systems-thinking approach is needed to evaluate how changes in one effect, such as consumer time burden or government spending, can eventually affect consumer surplus. The effects that are initially borne by the government and FIs, can eventually influence broader society indirectly. This indicates that society as a whole is paying for and/or benefiting from AML practices. An issue with the bank account holder being the ones experiencing these social harms is that if they do not agree with data scrutiny and privacy risks, they aren't able have a bank account. Also individual bank customers do not have access to the huge legal teams that are built-into these institutions. These interpretations challenge narrow cost-benefit studies which only consider one stakeholder and highlight the need for broader evaluation approaches like the SCBA.

6.1.3. MLs Amplifying and Ambiguous Impact on Social Effects KYC

This research reveals that ML alters, but does not eliminate, the social tensions inherent in KYC processes. ML improves certain outcomes, such as the quality of suspicious transaction reports and crime detection accuracy, enhancing both government efficiency and financial stability. However, it also introduces new risks and worsens existing harms. Model opacity, legal uncertainty, and potential bias increase privacy risks and can sustain discrimination. With the introduction of ML, the dual nature of the social effects of the KYC process becomes even clearer. ML's implementation must be carefully governed, as the same technology that enhances efficiency can undermine legitimacy and social trust. Contrary to ML optimistic claims, the findings show that ML's societal impact can be very significant and demand to be controlled with caution.

6.2. Structural Social Effects

An underlying but important theme, raised by two respondents (from academia and human rights), concerns the erosion of consumer trust in financial institutions. They warned that as banks take on enforcement roles traditionally held by the state, monitoring, screening, and reporting customers, this may undermine their identity as service providers and blur the line between public and private actors. This concern is echoed in Amicelle and Favarel-Garrigues (2012) work on financial surveillance, which highlights how such practices, though often invisible to customers, can erode trust and democratic accountability. Their article emphasizes that AML measures often lack transparency, leaving individuals unaware of why they are flagged or how to respond, an issue amplified in ML-based KYC systems. Furthermore, they argue that financial surveillance expands under the banner of security without strong evidence of effectiveness, mirroring this thesis's critique of the current AML regime. Despite being over a decade old, their analysis remains highly relevant today as surveillance practices intensify with new technologies. This perspective underscores that ML in KYC is not just a technical matter but part of a broader political and societal shift that warrants critical attention.

Monahan (2008) argue that surveillance systems often reinforce existing social inequalities, especially along lines of race, class, and gender. Instead of being neutral tools, these technologies reflect and reproduce inequalities in society. The authors highlight how shifting responsibilities from the government to the private sector can increase surveillance to control and exclude marginalized groups. Concepts like social sorting and marginalizing surveillance show how these systems treat people differently, often without them noticing (Monahan, 2008). Social sorting is categorizing and treating people differently based on surveillance data and marginalizing surveillance is applying stricter, more invasive systems to already disadvantaged groups, deepening their marginal status. These insights on surveillance and inequality offer a critical lens through which to view KYC processes in the financial sector. As ML could potentially be used to automate transaction monitoring and risk profiling, similar dynamics of social sorting and marginalizing surveillance may emerge. This situates ML-based KYC not just as a compliance tool, but as part of a broader surveillance infrastructure with social consequences. By linking it to theories of inequality and control, this study adds a critical perspective on how such technologies may unintentionally reinforce inequality.

6.3. Policy Effectiveness Discourse

While the interviews focused on assessing the potentially relevant social costs and benefits in KYC processes and the change that ML could bring, interviewees also elaborated on the score of costs vs benefits in KYC processes. This section explores expert concerns about the effectiveness of the current KYC system, including views on compliance as a formal exercise, the global displacement of crime, systemic inefficiencies, and the possibility of hidden preventive benefits, all of which shape the overall assessment of costs and benefits in a SCBA.

Several respondents questioned whether current KYC practices meet their policy objectives efficiently. There were doubts expressed by respondents about the actual effectiveness of AML regulation, where compliance often appears symbolic, inefficient, and fragmented. While this theme does not lead to a defined social cost or benefit, it shapes how all other effects should be interpreted within the SCBA. Three corporate respondents raised concerns about the performative nature of compliance. They described KYC as a “box-ticking” exercise, where institutions follow formal steps without considering their actual impact. This reduces the value of compliance, as effort is focused on form rather than substance. Two respondents from corporate and human rights backgrounds mentioned the displacement of criminal activity. Stricter AML enforcement in one country may push illicit activity to jurisdictions with weaker controls. This questions the global effectiveness of national AML compliance. Six respondents, including academics and consultants, highlighted systemic inefficiency. Banks work in isolation, leading to duplication and missed opportunities to detect crime more effectively. Some suggested centralizing data, though privacy concerns remain. Others criticized the Dutch system for requiring the reporting of unusual rather than suspicious transactions, resulting in large volumes of unprocessable reports. One corporate respondent mentioned a more positive view of the KYC process through preventive filtering. This refers to excluding high-risk clients before onboarding. It suggests that low numbers of confirmed cases may reflect successful deterrence, not system failure. These benefits may be real but hard to measure.

This section reflects expert critique on the balance of costs and benefits in the current AML system. Eight out of nine interviewees believed the costs likely outweigh the benefits. One respondent offered a more nuanced view, suggesting the appearance of inefficiency may reflect unobserved preventive effects. Overall, the majority perspective points to a negative net balance, which should be seriously considered in a future SCBA.

6.4. Contributions and Limitations

6.4.1. EPA Relevance

The research conducted aligns with the values of the Engineering and Policy Analysis (EPA) program. It addresses a grand challenge at the intersection of financial integrity, digitalization, and social justice. The research identifies the social costs and benefits of the KYC process and the change ML brings upon the social effects. The work is analytical in nature, combining a qualitative SCBA with thematic analysis of semi-structured interviews to explore the broader societal impacts of implementing machine learning in financial institutions. It takes a clear systems perspective by considering how technological tools, regulatory frameworks, and society interact around the KYC process. Moreover, the study includes a multi-actor dimension by incorporating insights from corporate, academic, and human rights backgrounds. The interviews revealed that the KYC process affects three main stakeholder groups: the government, financial institutions, and society. This broad impact highlights the Grand Challenge nature of the topic. It also reflects systems thinking, as the study considers how changes in one part, like the use of machine learning, affect the wider financial and regulatory ecosystem. The study also sits between public and private sectors, as banks increasingly take on surveillance-like roles traditionally held by the state. By addressing both policy and practical challenges, the research supports AML governance that balances effective risk detection with reduced social harm.

6.4.2. Societal & Managerial Relevance

This thesis is relevant to society and because it creates awareness on potential social costs and benefits of KYC processes and ML. While ML can potentially help banks detect suspicious behavior more efficiently, the research also shows that it can lead to problems, like customers being flagged without knowing why, or certain groups being treated unfairly. For example, interviews in this study revealed concerns about how automated systems might exclude people with irregular incomes or foreign-sounding names, even if they've done nothing wrong. These findings matter because they show that fighting financial crime using technology isn't just a technical issue, it affects trust in banks, access to financial services, and the fairness of the system. The research promotes policy makers, banks, and the public think more critically about the social risks tied to the use ML.

This study also offers valuable insights for managers and decision-makers in the financial sector, particularly those involved in compliance, risk, and innovation. As Dutch banks adopt machine learning in KYC processes, they face important choices about how to balance efficiency with fairness, transparency, and customer trust. The findings highlight concrete challenges, such as unclear flagging criteria, limited feedback loops, and risk of bias, that managers need to consider when implementing or scaling up ML systems. For example, the study shows that a lack of explainability can lead to internal confusion or reputational damage if customers are wrongly classified.

6.4.3. Academic Contribution

This research makes a novel contribution by conceptualizing the KYC process not only as a compliance tool, but as a socio-technical system with broad and interconnected societal impacts. It extends the existing literature in several ways: by mapping thematic insights based on interviews onto a framework of social costs and benefits, and by including ML in the analysis. Hereby, the thesis shows how technology could change the balance between the social costs and benefits. Prior AML/ML studies rarely connect the social outcomes or they tend to cover them in isolation. This thesis maps a wide overview of social effects and those links. In doing so, the thesis brings societal well-being into how compliance tools and financial technologies should be judged.

This thesis applies the first five SCBA steps qualitatively and turns them into a codebook of criteria and each built upon sub-codes. Using one coherent framework with visualisations, it maps the KYC social costs and benefits and shows how the effects connect. Expert interviews ground the analysis in real practice, and in literature side-by-side comparison of today's KYC and ML-enhanced KYC reveals where technology shifts that balance. Beyond KYC, the qualitative-SCBA template is portable to other AML/CFT tools, and algorithmic screening processes. By clearly mapping themes to social outcomes, it pinpoints which effects merit monetisation in future full SCBAs and enables cumulative, comparative research that links technological change to societal impact.

This study offers practical guidance for socially sustainable AML. Crime prevention must be balanced against the risks of overreach, exclusion, and inefficiency. ML shouldn't be adopted just to cut costs or speed things up; it should be judged against accountability, fairness, and transparency. Unchecked, it can reproduce the very harms AML aims to prevent. The thesis also sets a roadmap for future work by pinpointing which social effects should be monetized in full SCBAs—its clear mapping enables sharper valuations and evidence-based policy trade-offs. It also shows how KYC and ML shape people's lives, not only financial systems. The clear mapping of themes to social outcomes enables more precise valuations and opens the door to evidence-based policy trade-offs. Moreover, the study complements quantitative research by providing a qualitative map of the ripple effects caused by both traditional and ML-based KYC. This insight challenges narrow interpretations of AML success and calls for broader metrics that include social justice.

6.4.4. Research Limitations

The research may have benefited from different adjustments. The diversity of respondents could have been expanded to bank employees and directive staff. This would have expanded the points of views which the interviews contained.

The method of thematic analysis relies on researcher interpretation, which introduces a degree of subjectivity into the coding and theme development process. While efforts were made to ensure rigor through transparent coding and the use of predefined categories, the analysis is shaped by the researcher's perspective and prior assumptions. This may influence which themes are prioritized or how certain responses are interpreted, potentially affecting the consistency or replicability of findings.

The findings of this study are specific to the Dutch financial context, where KYC processes and AML compliance operate under particular regulatory, institutional, and cultural conditions. While some insights may be relevant to other jurisdictions or financial systems, it is important to note that the research is based solely on experiences within the Netherlands. Therefore, any generalization should be made with caution, taking into account the country-specific nature of the KYC framework and the early-stage adoption of machine learning in this domain

This study adopted welfare economics as its theoretical focus to assess the social costs and benefits of KYC processes. Concepts such as consumer surplus frame individuals as rational, utility-maximizing consumers. While useful for quantification, this perspective risks reducing complex social identities to simplified economic behavior. An example from this research is that risks such as privacy, and over-surveillance are simplified into a decrease in consumer health & wellbeing. Moreover, concepts like public safety or trust in institutions are central to the legitimacy and effectiveness of AML policies, they aren't easily valued. As a result, the SCBA framework may unintentionally downplay or overlook these essential dimensions. This may have limited the study's ability to fully capture the societal implications of KYC beyond economic terms. Additionally, the analysis could have been strengthened by a more detailed breakdown of stakeholder groups. In particular, identifying different societal groups would have made it clearer who actually bears the costs. Moreover, SCBA can be less suitable when efficiency is not the main policy criterion, such as in matters involving privacy, discrimination, or other fundamental rights, because these values resist monetisation. Squeezing all that into one number hides what values are at stake, showing how AML policy doesn't fit neatly into an SCBA. Some welfare effects cannot be included simply due to insufficient information to quantify or monetise them, which can result in blind spots for socially important, but less measurable, effects. However, this thesis made an attempt at incorporating all relevant social effects in the first five SCBA steps qualitatively. The finer-grained sub-criteria behind each social cost or benefit are mapped in the qualitative codes and examined in depth, which helps avoid the “flattening” of complex values that a standard, purely monetary SCBA could produce.

Framing choices lead to a technology-centered approach taken to analyze the KYC process and the implementation of ML into KYC systems. This study is primarily focused on how ML can alter social costs and benefits in KYC processes, rather than on the power relations and institutional structures that shape ML’s use. It could have been useful to start off the study with an analysis of social dynamics which could function as a basis to build the study upon. As a result, this thesis may underemphasize how structural inequalities are embedded and reproduced through KYC technologies.

In the analysis on how the criteria for a SCBA on the KYC processes change when ML is introduced, this study did not focus on one specific type of ML technology. This is because the exact stage where ML was applied only emerged during the analysis of the interview data, rather than being explicitly targeted in the interview design. For example, the interview questions did not directly ask about the costs or benefits of implementing ML in specific components such as transaction monitoring. As a result, the findings presented in Chapter 4 are not tailored to particular ML applications or sub-processes within KYC.

6.5. Future Research Recommendations

Building on the findings and limitations of this study, several promising directions emerge for future research. These can help further develop, test, and refine both the conceptual and practical understanding of ML in KYC processes and its broader societal impact.

6.5.1. Full Quantified SCBA

This thesis has laid the groundwork of a qualitative SCBA of KYC-processes through AML regulation, identifying key social effects as Consumer Surplus, Health & Wellbeing, and Participation in Economy through literature and interviews with stakeholders. However, the actual magnitude and balance of these effects remain unknown. Future research should build on the thematic base laid out in this thesis. The underlying codes of each theme and the directions of the social effects that the themes indicate can serve as a guide in the valuation process. Monetizing the codes and themes that contribute to a social effect could potentially be done using stated preference surveys. There is also literature to be found on the willingness to pay for more intangible factors, this could also be used in quantifying the results of this thesis. A future SCBA could also benefit from a more detailed examination of the distributional effects by differentiating society.

While the next step of the SCBA would be to express all effects in monetary terms, this approach has inherent limitations. The monetary weighting treats one euro as equal regardless of who gains or loses, without addressing issues of income inequality or the lack of actual compensation for ”losers” (Bos et al., 2022). Distributional impacts remain invisible in the final balance, which masks how many people are adversely affected and to what extent (Bos et al., 2022).

6.5.2. Comparative Study of ML Techniques

This thesis has considered ML in general terms, rather than focusing on specific algorithms or model types. Future research could compare different ML techniques, for instance, supervised learning models, and deep learning algorithms, in terms of their explainability, bias mitigation potential, and real-world performance in KYC. This would allow for more actionable implementation choices for banks and regulators and link technical model design to societal outcomes more directly. Next to this, it could also be valuable to examine how the effects of ML vary between different steps of the KYC process, e.g. customer onboarding, transaction monitoring, or ongoing due diligence. Focusing on stage-specific impacts would reveal where ML delivers the greatest benefits or risks, enabling more targeted policy and design interventions.

6.5.3. Longitudinal Study of Social Effects

Many of the social costs identified in this study, such as exclusion from financial services or declining trust, may accumulate or shift over time. A longitudinal study could track the long-term effects of ML-based KYC implementations on financial inclusion, institutional trust, and consumer behavior. This would be particularly valuable as these technologies become more used and normalized within FIs.

6.5.4. Cross-Country Comparative Research

This study focuses on the Dutch financial and regulatory context, which is known for its strong institutional oversight. Future research could explore how similar technologies are implemented and experienced in other jurisdictions, especially those with different regulatory frameworks, financial infrastructures, or social norms. A comparative case study could shed light on how contextual factors shape the outcomes of KYC automation, offering insights for international policy harmonization or differentiation.

6.5.5. Client-Centered Perspective and Lived Experience

Given the theoretical and analytical limitations of this study, future research should move beyond a welfare economics framework to incorporate perspectives that account for structural societal issues like inequality. Frameworks from surveillance studies, critical data studies, or political economy could help to analyze how KYC technologies shape and reflect broader social hierarchies, particularly around race, migration status, class, or digital exclusion. Such studies could begin not with technology or quantified outcomes, but with the lived experiences of those most impacted by KYC decisions, such as individuals excluded from banking services.

6.5.6. Explainability in Practice

This study has identified explainability as a very important part for addressing bias and ensuring fairness in ML systems. However, what explainability means in practice, and how different stakeholders (e.g., compliance officers, regulators, customers) interpret and apply it, remains underexplored. Future research could investigate how explainability tools are used and understood in real banking environments, and whether they actually support better decision-making or merely serve as technical justifications.

6.5.7. Regulatory Readiness and Supervisory Capacity

As the use of ML in the KYC process evolves, AML regulations will need to adapt accordingly. Future research could take very practical steps to explore this readiness. First, it could map the current tools, skills, and resources supervisors have for assessing whether ML models treat different groups fairly and can clearly explain their decisions. Second, researchers could look at how new ML systems for KYC are tested in controlled, small-scale settings before full use. This would help assess whether these trials reflect real-world conditions, how often they are used, and what kind of useful feedback they provide to both regulators and banks. Finally, future work could review and compare guidelines from different countries to identify the most effective ways to check fairness, transparency, and performance of ML models.

7 Conclusion

This chapter addresses the research sub-questions and central research question by drawing on the key findings from the previous chapters. It also highlights the practical implications of the study and concludes with suggestions for future research directions.

7.1. Answers to Sub-Questions

This section consolidates the findings from each of the four sub-questions in this research. It begins with the two preliminary questions covering: the steps of the current KYC process and the ML used within it. After, the criteria for a SCBA are described in the answer of sub-question 3 and the change ML brings upon those social effects is detailed in the answer to sub-question 4.

1) What are the current KYC operations and compliance practices used by banks under AML regulation?

The findings presented in section 4.1 are the result of an iterative process combining academic literature with expert guided conceptualization. By validating a preliminary process diagram during interviews with respondents, the research ensured that the KYC model reflects both formal regulatory expectations and real-world implementation practices. This dual grounding in literature and empirical insights strengthens the relevance of the diagram as a baseline for analyzing the social costs and benefits of AML compliance.

As seen in section 4.1, this study identified how banks implement AML regulation through the operations in the KYC process. The KYC process is made up of three main stages: Onboarding, Ongoing Due Diligence/Enhanced Due Diligence, and Exit. Onboarding begins with Customer Identification and Verification, where identity documents are collected and authenticated. This is followed by a Client Risk Assessment, classifying customers based on factors like geography, sector, and ownership structure. The assigned risk rating, low, medium, high, or unacceptable, determines the intensity and frequency of monitoring throughout the client relationship. Ongoing Due Diligence involves continuous monitoring through: Client Monitoring of structural and behavioral risk indicators, Sanctions Screening against watchlists, Transaction Filtering to block sanctioned transactions pre-execution, and Transaction Monitoring to flag behavior that deviates from expected patterns. When these mechanisms detect anomalies, they trigger an Event-Driven Review, which may lead to a risk reassessment or the filing of an Unusual Activity Report to the Financial Intelligence Unit. Additionally, Periodic Reviews are conducted at intervals aligned with the client's risk classification. Exit refers to Client Offboarding, which occurs when a customer is considered to pose an unacceptable AML/CTF risk. These practices are informed by internal policies, and legal frameworks.

2) How is machine learning currently applied in the identified KYC process?

To investigate how machine learning is currently applied in the KYC process, this study adopted a qualitative approach grounded in expert interviews with professionals from corporate, academic, and human rights backgrounds. This methodology was chosen to complement academic literature with practical insights. The interviews found that ML is currently applied in the KYC process in a selective and largely cautious manner. It was found that ML is most often used in transaction monitoring, where ML models assist in detecting suspicious patterns, an application well-suited to high-volume, repetitive tasks. In contrast, its adoption in other areas such as client onboarding or risk assessment remains limited and exploratory. While some financial institutions are experimenting with pre-assessment tools to filter out low-risk clients, such practices are not widespread. A recurring theme in both literature and interviews is the significant gap between ML's theoretical promise and its real-world implementation. This is driven not only by technical and operational challenges, but also by trust, explainability, and regulatory uncertainty. These findings underscore that while ML holds considerable potential to reshape how KYC processes are carried out, its current role is narrow. Machine learning is being implemented in practice, yet academic literature still frames FIs as hesitant. This gap suggests that real-world use may be outpacing academic literature, or that academic concerns remain under-addressed in practice.

3) What candidate social effects need to be considered in a SCBA of the current KYC process under AML regulation?

This research used a qualitative social cost-benefit analysis (SCBA) to evaluate the societal impact of the current KYC process under AML regulation. The method was chosen because it allowed for the structured identification of social effects that are difficult to quantify. Semi-structured interviews provided expert insights, which were analyzed thematically and translated into social effects. A conceptual summary was developed to show how these effects are interrelated. The analysis identified nine key social effects: crime level, health and wellbeing, inequality, economic participation, economic stability, consumer surplus, consumer time, government financial health, and government opportunity costs. These effects were based on interview themes such as exclusion, deterrence, and administrative burdens. Importantly, these effects are interconnected. For instance, exclusion from financial services reduces economic participation, which can increase inequality, reduce economic stability, and harm wellbeing. Similarly, government spending on AML enforcement can improve financial health but also limits investments in other public services.

The research also found that the social costs and benefits are not evenly distributed. While governments and financial institutions bear direct costs, these are often passed on to consumers. Society experiences both the benefits of crime reduction and the harms of exclusion, loss of trust, and stress, particularly among vulnerable groups.

Overall, the findings show that evaluating KYC's societal impact requires looking beyond compliance outcomes. The process creates complex trade-offs between security and social harm, trust and exclusion, and efficiency and administrative burden. This qualitative SCBA highlights the importance of viewing these outcomes as part of an interconnected system and underlines the need for more holistic thinking in policy development. The first five qualitative steps of the SCBA were not intended to provide definitive policy recommendations, but rather to establish a clear framework for assessing the societal consequences of AML regulation and to contribute to an informed policy discussion.

4) How does the introduction of machine learning alter the identified candidate social costs and benefits of the current KYC process?

In section 5.4 it was explored how ML alters the social costs and benefits of the KYC process, using expert interviews to gain insight into impacts that are not easily quantifiable. The results show that ML intensifies both benefits and costs. Benefits such as crime reduction and government efficiency are strengthened through perceived better detection and higher-quality reports. However, ML can also increases legal uncertainty and privacy risks, raising opportunity costs and potentially affecting public wellbeing.

Some effects, like consumer surplus, economic participation, and inequality are ambiguously impacted through ML use. ML can reduce exclusion and improve services, but also introduces new risks like algorithmic bias and increased oversight costs.

While governments and financial institutions experience direct effects, it is society that ultimately absorbs many of the consequences, without having control over ML implementation. This highlights the need for fairer distribution of both benefits and burdens to ensure ML in KYC serves the public good.

7.2. Answer Main Research Question

"How does the implementation of machine learning in the KYC process alter the relevant social costs and benefits of the current KYC process under AML regulation?"

Based on a thematic analysis of expert interviews, the research shows that machine learning reshapes the societal impact of KYC processes by amplifying both their benefits and their risks. ML strengthens existing benefits by potentially improving the accuracy and efficiency of financial crime detection. This enhances government financial health and public safety, contributing to crime reduction and more effective allocation of resources. At the same time, it introduces new complexities and intensifies existing concerns. Inherent model risks e.g. bias, opacity, and exclusion threaten to deepen inequality and undermine trust in financial institutions. Effects like consumer surplus, economic participation, and wellbeing are no longer static but are reliant on how ML is designed, governed, and implemented.

The findings highlight that the social costs and benefits of KYC are interconnected, with changes in one area, such as increased efficiency or new forms of exclusion, rippling across others. Importantly, while financial institutions and governments carry some direct effects, the broader social consequences often fall disproportionately on the public. This reveals a structural imbalance in who benefits from innovation and who bears the harm.

By using qualitative methods, this research captured the nuanced and often ambiguous nature of these impacts, something that cannot be fully measured. The interview insights provide a foundation for future valuation. They also underscore that ML is not a neutral upgrade to the compliance process.

Ultimately, the introduction of machine learning into the KYC process presents both an opportunity and a responsibility. The challenge is not simply whether to use ML, but how to ensure its benefits are fairly distributed, and its harms mitigated.

7.3. Theoretical Implications

This thesis fills a gap in the literature by showing how ML in the KYC process affects not only efficiency and detection, but also broader social outcomes. It applies a qualitative Social Cost-Benefit Analysis (SCBA) to conceptualize effects like exclusion, inequality, and health & wellbeing, which are often overlooked in AML evaluations. This thesis also adds to the existing body of literature by presenting the whole system as a socio-technical system with significant social implications.

Theoretically, this thesis contributes to the literature by applying the SCBA framework to the domain of AML compliance, which is an approach that is rarely used for financial regulation. By adapting SCBA to assess non-monetized societal effects such as exclusion, inequality, and wellbeing, it offers a new method for evaluating policies that are typically judged by technical or legal criteria. The thesis also addresses a gap in the literature by uncovering real-world, expert-based insights into the social consequences of the KYC process, which are often overlooked in existing academic and policy discussions.

7.4. Practical Implications

7.4.1. For Policymakers

Policymakers should recognize that the societal impact of AML compliance extends beyond crime prevention and financial integrity. The introduction of machine learning (ML) in the KYC process may improve efficiency and detection, but it also raises risks of exclusion, inequality, and declining trust in institutions. A narrow focus on enforcement outcomes ignores these broader effects. Policymakers should therefore embed social impact assessments into AML policy design, support the development of explainability standards for ML models, and ensure that regulation balances technological innovation with safeguards for fundamental rights. They should also invest in stronger regulatory capacity to monitor machine learning systems. This includes not only checking for legal compliance, but also assessing how these systems impact different groups in society. To do this effectively, regulators should collaborate closely with academic researchers, involve them early in the policy process, and give them a meaningful say in shaping regulations.

7.4.2. For Financial Institutions

Based on the findings of this study, FIs should approach the implementation of ML in KYC processes cautiously, with close attention to explainability and potential biases. While ML holds promise for improving efficiency in both sanctions screening and transaction monitoring, its current use remains limited and fragmented. A key barrier identified is the lack of explainability: before banks can meaningfully address issues such as bias, false positives, or customer exclusion, they must first be able to understand and justify model outputs. Banks are responsible for explaining these decisions clearly to internal risk teams, regulators, and the customers affected. This is particularly important in cases where ML solutions are outsourced to external vendors, introducing additional governance and compliance risks. In-house development may offer more control, but it requires sufficient technical expertise and internal oversight. Respondents in this study emphasized that ML is most suitable for high-volume stages of the KYC process, such as transaction monitoring. FI boards could therefore invest in identifying what kind of ML is best implemented in the KYC process. With the main selection criteria being ML's explainability.

To implement ML responsibly, banks should take several concrete steps. First, they must embed explainability from the outset. Second, they should implement bias and fairness audits to evaluate whether models perform equally across customer groups, particularly in relation to exclusion or risk categorization. Third, vendor relationships must be governed by clear criteria around explainability and oversight, with regular audits to maintain control over outsourced models. Finally, banks should actively engage with academia and regulators through joint pilots, and working groups, to help shape emerging standards around explainable and fair ML in financial compliance.

7.4.3. For Society

Society, while not a decision-maker in KYC implementation, bears many of the indirect costs, such as exclusion, reduced privacy, and stress, especially among vulnerable groups. Society has out of the three key stakeholder groups the least amount of power to change the ways of the KYC process. Public awareness and engagement are therefore essential. Citizens and advocacy groups should demand greater transparency and accountability in how financial institutions and regulators apply ML in compliance processes. This includes pushing for, stronger data protection, and active participation in shaping fair digital finance policies. Society should not passively absorb the unintended effects of regulatory technology, but instead claim a stronger voice in debates about fairness, access, and rights in the financial system.

8
Reflection

I expected that ML would reduce costs and prevent many of the mistakes made when innocent customers are wrongly flagged. This view is quite common: many people see ML as a tool that can solve everything. Looking back, I realize that this belief influenced how I approached the topic at first. It was only after reading more of the academic literature that I saw how carefully researchers discuss ML, especially because of its possible risks and unintended effects. During the interviews, I was surprised by how little attention some corporate respondents gave to issues like privacy in the KYC process and ML's role in it. Instead, many focused on how difficult and expensive it is for financial institutions to meet all the requirements of anti-money laundering (AML) regulation. It seemed that banks often feel overwhelmed by these rules and struggle to keep up. When I brought up concerns like surveillance or exclusion, these were often reframed. For example, respondents talked about how surveillance protects customers from fraud, or how the data is already collected, so it makes sense to use it.

Two quotes from the interviews stood out. One respondent added how 15 years ago a general news outlet in the Netherlands framed money laundering as something that greased the economy. Nowadays that would be unheard of and shows how the perspective has changed greatly. Additionally, another respondent stated that the topic of whether the benefits outweigh the costs is a highly political and subjective topic. People who hold a postion on either side of the topic will also find arguments that support it.

The method I first planned to use was a full SCBA, comparing ML-based KYC with the current process. But I learned that SCBA needs a policy change to compare to. ML is not a required policy from the government, so I could not use it as a policy alternative. I pivoted by using the SCBA framework to compare a situation without KYC to the current KYC process, since AML regulation requires KYC. I also realized that doing a full SCBA, with steps like monetizing the effects, was too large for one thesis. Just identifying the social effects already took the full research time. A full SCBA would need to be a separate project.

Another challenge was finding interviewees. I contacted many banks and professionals, but often got no reply or was turned down. I think this was partly because of the KYC topic's sensitivity. Especially now that some banks are being fined for doing it poorly. This made it hard to get input from the people most directly involved.

Finally, I believe this research adds useful insights. It gives a new way to look at KYC and ML, not only from a legal or technical side, but from a social and economic one. It applies the SCBA method and therefore a welfare economics lens to a topic where it is rarely used. Also, it provides real-life insights from people working in the field, showing how the process actually affects people, and companies. Most of all, I hope this research helps policymakers reflect on the social effects of the policies they create. If the KYC process can be improved at the policy level, then the overall impact of AML regulation on society could also improve.

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A

Interview Protocol and Artifacts

Interview questions master thesis AML & ML

MSc Engineering & Policy Analysis, TU Delft

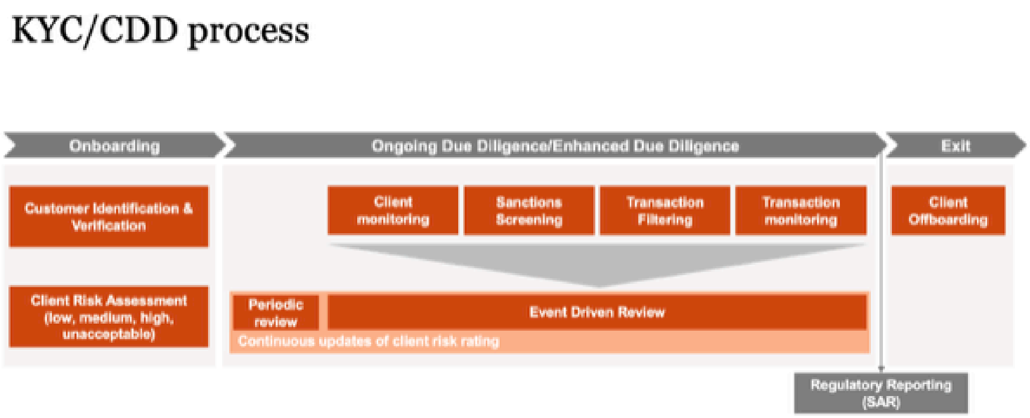
Part 1: Current AML Practices in Banks

Look at the following KYC process:

0. What are your thoughts on how this process reflects your experience?
Follow-up:

- Are there any steps you would add, remove, or adjust?
- How do you experience this process in practice?

Figure 1: summary of the KYC/CDD process within banks



1. What do you see as the main costs associated with conducting the KYC process today?
(*Costs for banks, government, society*)
Follow-up:

- How would you describe the magnitude of these costs?
- How many employees are typically involved?
- How significant are penalties in your view?
- What broader impacts do you observe on society or on government institutions?

- Could you describe benefits for different groups (society, government, obliged entities)?
- In your opinion, do these benefits outweigh the costs and efforts? Why or why not?

Part 2: Implementation of Machine Learning in AML

3. Where, if at all, do you currently see machine learning being used in the KYC process?
Follow-up:

- In which parts of the process?
- How is machine learning applied in practice?
- If not yet used: where do you think it could add value?

4. What costs or risks do you associate with implementing machine learning in the KYC process?
(*Think explainability, data quality, regulatory uncertainty, bias, initial investments, training*)
Follow-up:

- Which of these costs or risks do you think are most significant?
- How would you describe the magnitude of these costs compared to the traditional KYC process?
- How does the need for personnel change with machine learning?

5. What benefits do you foresee from implementing machine learning in the KYC process?
(*Think detection accuracy, efficiency, fewer false positives, reduced manual workload*)
Follow-up:

- Which two benefits do you personally find most important? Why?
- What long-term effects do you expect for banks, society, and regulatory bodies?

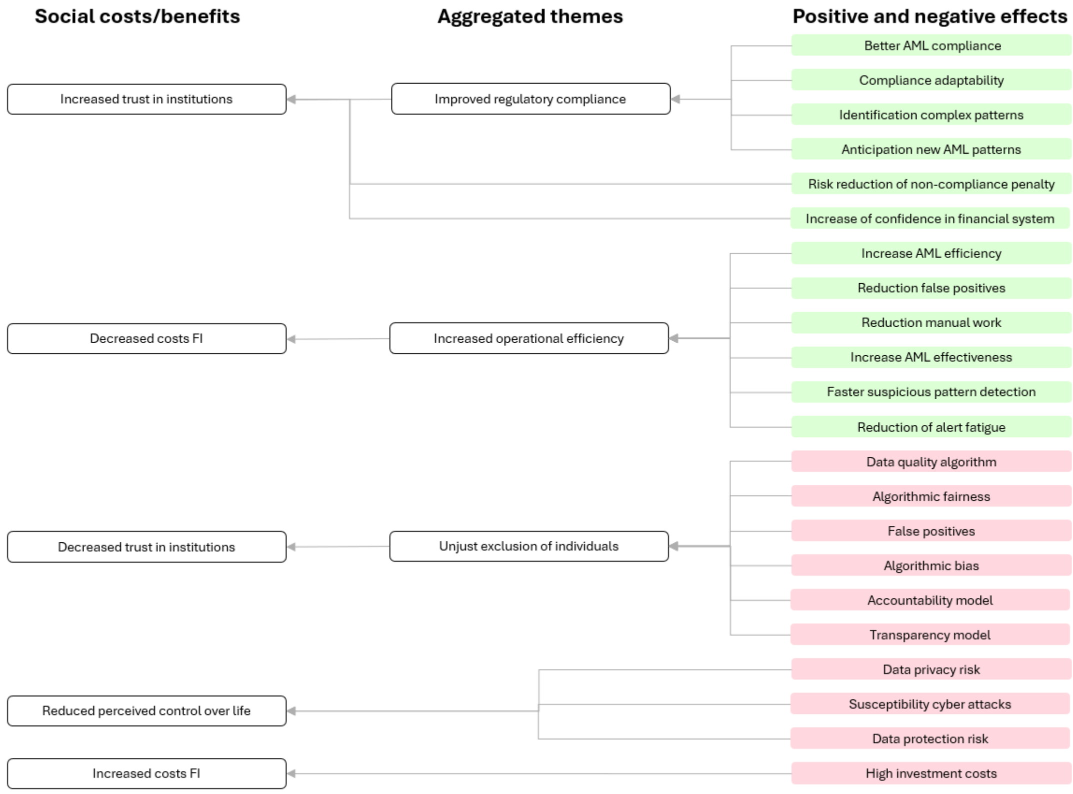
Part 3: Validation of costs and benefits found in literature

Look at the following chart of the positive (green) and negative (red) effects found in literature of implementing machine learning in KYC processes. On the left, you can see the different social costs and benefits that group the effects found in literature.

6. What in this diagram (figure 2) about the costs and benefits of the current KYC process stands out as most important? (Choose a few effects/costs/benefits)

7. Which parts of the following diagram (figure 2) have a lesser priority/ are less relevant in your view? (Choose a few effects/costs/benefits)

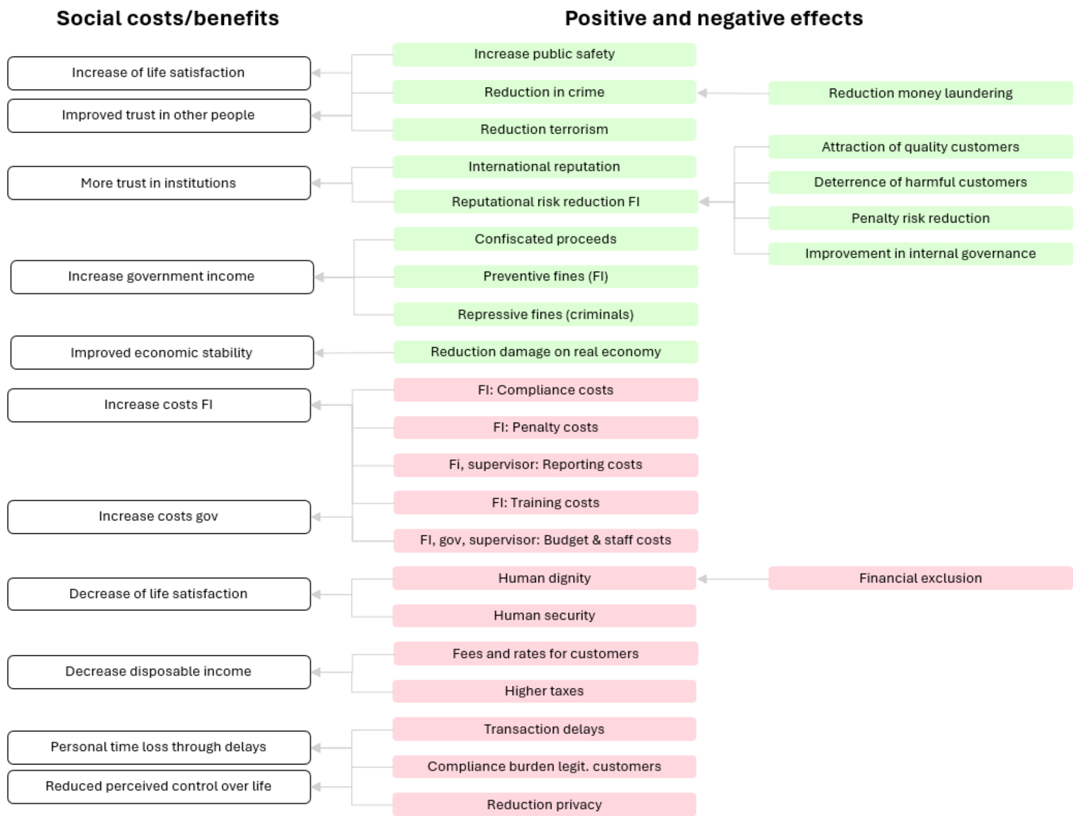
Figure 2: Aggregated Costs and Benefits of Current KYC Processes in Banks



8. What in this diagram (figure 3) about the costs and benefits of the implementation of machine learning in the KYC process stands out as most important? (Choose a few effects/costs/benefits)

9. Which parts of the following diagram (figure 3) have a lesser priority/ are less relevant in your view? (Choose a few effects/costs/benefits)

Figure 3: Aggregated Costs and Benefits of the implementation of machine learning in KYC Processes in Banks



10. Which stakeholders are most impacted by the costs and benefits of using machine learning?

Interviewvragen Nederlands:

Deel 1: Huidige AML-praktijken in Banken

0. Ben je bekend met dit process, en in hoeverre weerspiegelt dit jouw ervaring?
Follow-up:

- Welke stappen zou je willen toevoegen, weghalen of veranderen?
- Hoe ervaar jij dit proces in de praktijk?

1. **Wat zie jij als de belangrijkste kosten en risico's die gepaard gaan met het uitvoeren van het KYC-proces vandaag de dag?**
(Kosten voor banken, overheid, samenleving)

Follow-up:

- Hoe zou je de omvang van deze kosten omschrijven?
- Hoeveel medewerkers zijn er doorgaans betrokken?
- Hoe belangrijk zijn boetes naar jouw mening?
- Welke bredere impact observeer je op de samenleving of op overheidsinstellingen?

2. **Wat zijn volgens jou de voordelen of positieve uitkomsten van het huidige KYC-proces?**

Follow-up:

- Kun je voordelen beschrijven voor verschillende groepen (samenleving, overheid, verplichte entiteiten)?
- Vind je dat deze voordelen opwegen tegen de kosten en inspanningen? Waarom wel of niet?

Deel 2: Implementatie van Machine Learning in AML

3. **Waar zie je momenteel Machine Learning worden gebruikt in het KYC-proces, indien überhaupt?**

Follow-up:

- In welke delen van het proces?
- Hoe wordt Machine Learning in de praktijk toegepast?

- Indien nog niet gebruikt: waar denk je dat het waarde zou kunnen toevoegen?

4. **Welke kosten of risico's associeer je met de implementatie van Machine Learning in het KYC-proces?**
(Denk aan initiële investeringen, training, uitlegbaarheid, datakwaliteit, regelgevingsonzekerheid, bias)

Follow-up:

- Welke van deze kosten of risico's zijn volgens jou het meest significant?
- Hoe zou je de omvang van deze kosten omschrijven in vergelijking met het traditionele KYC-proces?
- Hoe verandert de behoefte aan personeel met Machine Learning?

5. **Welke voordelen voorzie je bij het implementeren van Machine Learning in het KYC-proces?**
(Denk aan detectienauwkeurigheid, efficiëntie, minder valse positieven, vermindering van handmatige werkdruk)

Follow-up:

- Welke twee voordelen vind je persoonlijk het belangrijkst? Waarom?
- Welke langetermijneffecten verwacht je voor banken, samenleving en regelgevende instanties?

Deel 3: Validatie van kosten en voordelen gevonden in de literatuur

6. **Wat valt in dit figuur over de kosten en voordelen van het huidige KYC-proces op als het belangrijkst?**
(Kies een paar effecten/kosten/voordelen)

7. **Welke delen van de volgende figuur hebben een lagere prioriteit / zijn minder relevant volgens jou?**
(Kies een paar effecten/kosten/voordelen)

8. **Welke onderdelen in dit figuur over de kosten en voordelen van de implementatie van Machine Learning in het KYC-proces vallen op als het belangrijkst?**
(Kies een paar effecten/kosten/voordelen)

9. **Welke delen van de volgende figuur hebben een lagere prioriteit / zijn minder relevant volgens jou?**
(Kies een paar effecten/kosten/voordelen)

10. **Welke belanghebbenden worden het meest beïnvloed door de kosten en voordelen van het gebruik van Machine Learning?**

B

Informed Consent Form

Figure B.1: Informed consent form for interview thesis

Delft University of Technology
HUMAN RESEARCH ETHICS
INFORMED CONSENT FORM

PLEASE TICK THE APPROPRIATE BOXES	**Yes**	**No**
A: GENERAL AGREEMENT – RESEARCH GOALS, PARTICPANT TASKS AND VOLUNTARY PARTICIPATION		
1. I have read and understood the study information dated [*DD/MM/YYYY*], or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	☐	☐
2. I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	☐	☐
3. I understand that taking part in the study involves: Participating in a semi-structured interview of approximately 45-60 minutes. The interview will be audio-recorded (with my explicit consent) and subsequently transcribed. All recordings will be securely stored, fully anonymized, and permanently deleted after transcription and analysis. Only anonymized transcripts will be retained for analysis, and no personally identifiable information will be shared or published.	☐	☐
4. I understand that there is no financial remuneration or compensation provided for participation in this study.	☐	☐
5. I understand that the study will end upon completion of the master's thesis, anticipated by July 2025.		

B: POTENTIAL RISKS OF PARTICIPATING (INCLUDING DATA PROTECTION)		
6. I understand that taking part in the study involves the risks such as discomfort discussing sensitive professional topics, mitigated by the option to skip questions or withdraw anytime.	☐	☐
7. I understand that taking part in the study also involves collecting specific personally identifiable information (PII) including my name and email address for administrative purposes only and associated personally identifiable research data (PIRD) in the form of audio recording.	☐	☐
8. I understand that none of the personally identifiable research data collected in this study is classified as "sensitive" under GDPR legislation (e.g., religion, political views, criminal records).	☐	☐
9. I understand that the following steps will be taken to minimise the threat of a data breach, and protect my identity in the event of such a breach: • Interviews transcribed and anonymized immediately after recording; original audio deleted post-transcription • Data securely stored and encrypted on TU Delft's SharePoint, access limited strictly to researcher • Personal data stored separately from anonymized research data	☐	☐
10. I understand that personal information collected about me that can identify me (such as my name and email) will remain confidential and will not be shared beyond the research team.	☐	☐
11. I understand that the personally identifiable data collected for administrative purposes (names, emails, consent forms) will be securely destroyed within six months after thesis completion.	☐	☐
C: RESEARCH PUBLICATION, DISSEMINATION AND APPLICATION		

PLEASE TICK THE APPROPRIATE BOXES	Yes	No
12. I understand that after the research study the de-identified information I provide may be used in outputs such as a master's thesis.	☐	☐
13. I agree that my responses, views or other input can be quoted anonymously in research outputs	☐	☐
D: (LONGTERM) DATA STORAGE, ACCESS AND REUSE		
16. I give permission for anonymized interview transcripts and analysis scripts to be archived securely on TU Delft's Project Data Storage after completion of the research for potential future research and educational purposes.	☐	☐
17. I understand that access to archived anonymized data will be restricted to TU Delft researchers or students with explicit permission from the researcher or supervisor.	☐	☐

Signatures

_________________________ _________________________ ________

Name of participant [printed] Signature Date

[Add legal representative, and/or amend text for assent where participants cannot give consent as applicable]

I, as legal representative, have witnessed the accurate reading of the consent form with the potential participant and the individual has had the opportunity to ask questions. I confirm that the individual has given consent freely.

_________________________ _________________________ ________

Name of witness [printed] Signature Date

I, as researcher, have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

Annette Kerkhoven 29 april 2025

_________________________ _________________________

Researcher name [printed] Signature Date

C

Interview Codes

C.1. Interview Findings

The different codes found in the interviews are listed in this section. The explanation of the costs are explained per respondent per code.

C.1.1. Costs of current KYC processes

1 - Legal Costs Government

Respondent 8 explained that governments have costs through upholding the bureaucratic system of the AML policy. Customer advocacy groups also file complaints and initiate lawsuits, which also incur costs for the government. They also noted the recovery costs needed to revise the policy after such lawsuits have taken place.

2 - Overreporting/FIU Overlaod

Respondent 4: "Overreporting. Too many transactions are being flagged, which overloads Financial Intelligence Units (FIUs)."

Respondent 3:"Because, much more is reported, because people think: the more we report, the better, you also get enormous additional costs for the government, the AFM, and other regulators. So, those two cost items are really important societal burdens."

3 - Investments by FI's

Respondent 8 stated that the KYC process entails substantial administrative and reporting tasks for financial institutions. These duties impose significant costs on financial institutions especially smaller parties. This respondent also mentioned the opportunity cost of focusing on administrative duties rather than relationship management and financial services.

Respondent 1: "I think around 8 to 10% of the bank's total change-related expenditures go toward this area. Possibly even more, since all product lines must comply with financial crime regulations. "

Respondent 3: "They report a lot or, at the very least, review a lot. And this results in a lot of operational costs."

Respondent 9: "That at ABN it costs about €60,000 to €70,000 per SE dossier. And I think it might even be a bit more expensive here, maybe €80,000 per dossier." This highlights the high costs of handling each suspicious entity dossier insinuating a high financial burden.

4 - Lack of Profit Motivation for Compliance

Respondent 3 noted that there is no profit motivation for banks to comply with AML. They stated: "Where do banks make money? From transactions. Cash transactions, foreign transactions, business accounts, basically everything that is traditionally linked to money laundering, are also transactions from which banks earn money. So, they do have a social responsibility, but from a business perspective, they don't have much interest in it."

5 - High Personnel Costs FIs
Respondent 7: ”And they just have really high costs, actual financial costs, to make that happen. And that’s in… well, I think at some Dutch banks, 20% of all employees are working on this. So that’s obviously a huge cost item.”

Respondent 6 in context of the most important costs of the current compliance process: ”Just the operational costs. So essentially, running these processes, paying the people who work in them.”

6 - High System Costs FIs
Respondent 7: “The second thing is that, in addition to personnel costs, you also have all sorts of systems, tools, models, rules, all those kinds of things. Those obviously cost money too. So on the one hand, you have the actual financial cost burden for the banks or other parties involved.”

7 - Financial Exclusion
Respondent 8 expressed the view that the social harm caused by exclusion is often not given the full attention it deserves, and that it is a significant issue that is being overlooked. They also stated that it is important to note that there are unintended consequences for both citizens and businesses, such as not being able to open a bank account, delays in transactions which causes certain groups to be excluded from the financial system.

According to *respondent 8*, the KYC process excludes vulnerable groups such as migrants, self-employed persons, and activists through excessive or discriminatory risk assessments.

Respondent 4: ”Then, there’s financial exclusion, not a fundamental right in itself, but definitely linked to discrimination. For example, there was a case in the UK where Chinese students were being denied bank accounts. There had been indications that some were involved in money laundering schemes, and so simply having a Chinese passport and being a student in London became a reason to deny someone an account.”

Respondent 6 mentioned that the compliance process is related to people not being able to get access to the payment system while they are legitimate customers. The respondent also mentioned that, in a sense, the entire system is discriminatory. They explained that certain groups have been excluded, as seen in cases in recent years. While the judiciary has corrected this on multiple occasions, the respondent believes that such exclusion is still structurally embedded in the system. The respondent provided a concrete example from the Ukraine war, where a significant influx of refugees to the Netherlands raised concerns. It became clear that many of these refugees likely did not have passports, presenting a challenge for banks to fulfill their legal obligation to identify and verify customers. The respondent noted that denying these individuals access to bank accounts would create significant costs, as it would also prevent them from accessing the financial system, working, or receiving benefits. This case illustrated how vulnerable groups could be excluded from the system, even though such exclusion may not always be visible or intentional. The respondent suggested that, in some cases, we might be unintentionally excluding people who should be included.

Respondent 6 pointed out that, from a holistic perspective, this process also affects society. They explained that someone who cannot start their business because they can’t open a bank account also doesn’t pay taxes.

Respondent 5 noted that just recently, new legislation was passed in the Netherlands that cash transactions can be no more than 3,000 euros. The respondent pointed out that this policy, is significant as it has a big impact on all cash-based businesses. For example car businesses which are mainly cash based could need to stop due to this new policy.

8 - Discrimination
Respondent 4, in context of transaction flagging criteria: ”As soon as you make it more customer-specific, the risk of discrimination grows.”

9 - Disroportionality
Respondent 8 specifies that the question of proportionality, which is the idea that restrictions on an individual’s rights should be in proportion to the severity of the threat, is often raised, especially when the benefits are uncertain.

Respondent 7: ”And more broadly, it also affects privacy. You’re just being investigated much more, and the question is whether that’s always really necessary.”

10 - Loss of Trust in Institutions
Respondent 8 explained that the enforcement of the KYC-process damages the trust in financial institutions and rule of law.

Respondent 4: ”Am I just like making a contract with them to manage my money and transactions, or are they suspecting me of being a criminal? Are they reporting me? Are they working for me or for the government? You have to remember: AML is not only implemented in democratic countries. In countries where governments themselves are not trustworthy, the risks multiply. So ultimately, I think this shift is a huge cost to democracy. The repositioning of banks, where they act as agents of the state, undermines democratic principles. They are not elected. They are not accountable in the same way. That creates serious issues.”

Respondent 4: ”Banks used to be trusted, we created them because we didn’t want to store money under our mattresses. Now, with all this data collection and reporting, which is, of course, mandated, banks risk becoming extensions of the state’s policing apparatus. That erodes the trust relationship.” ”In the classic social contract, citizens give up freedoms for state protection. That’s fine, we elect and hold our governments accountable. But if banks, private actors, take over these policing roles, where’s the accountability? Where’s the trust?”

11 - Inefectiveness of policy
Respondent 8 stated that there is very little verifiable effect in the prevention of money laundering and terrorism financing, noting that the detection yield is low, as only a small amount of money laundering is actually uncovered through KYC processes.

Respondent 3 highlights the lack of clear feedback loops in the regulatory process.

Respondent 3: ”And I think that this whole process leads to a lot of operational costs, but not necessarily added value for society. I don’t believe that financial crime is really being effectively tackled by this.”

Respondent 9:”And then the question is: what does the entire AML system cost, but also: what does it cost to not have it? In 2008, De Telegraaf still thought it was good that black money greased the economy. Now, that is unthinkable: black money must be fought. So the thinking has changed. The question then is: what does it yield? Hopefully, less crime. But it’s all so severe: it costs a lot, and you don’t really know how much crime is being prevented by it. That’s kind of the issue.”

Respondent 5: ”Even though it’s difficult to estimate, you don’t know how big the tip of the iceberg is, but you also don’t know how big the iceberg beneath the water is. Estimating that is challenging, but even the government acknowledges that it cannot be ignored.”

12 - Performative Compliance
Respondent 1 expressed that the compliance within banks is like a box ticking excersice. The process is described as a scriptprocedure, highlighting how KYC has become a ritualized formality, a sequence of steps followed for appearance rather than actual risk identification.

Respondent 3 explains that FI’s may not necessarily understand what they need to do to fully comply with regulations, but they act in a way that demonstrates they are meeting the expectations, by not underperforming other banks.

Respondent 7: ”I think that if you perceive AML compliance as just ticking boxes, we’ve done this, without actually mitigating the risk, then you’re interpreting AML compliance too narrowly. Because you can comply with the letter of the law, but also with the spirit of the law. And the spirit of the law is: effectively tackling criminals.” ”So I wouldn’t separate that. I really recognize what you’re saying, we call that ’regulatory compliance.’ So that’s really ticking boxes: we requested this document, and that’s it. But that’s not actually what the spirit of the law is.”

13 - Systemic Inefficiency
Respondent 1: “Because if the societal benefits are so large, and the costs too, then why are banks all doing this individually? There really is a strong business case for collaboration. With four major banks and a few smaller ones, you could save at least 75% of the costs.”

Respondent 2: "Maybe it's not so efficient in terms of its purpose. It might not be the most efficient system. So maybe it doesn't serve the purpose that it should, also for the clients."

Respondent 3 : "So on one hand, banks don't really know what they need to do to comply with the regulations, but they at least know they must not do too little. So they end up reporting a lot or, at the very least, reviewing a lot."

Respondent 5: "You also see that banks often don't know what's happening at other banks. So, a criminal can easily open accounts at multiple banks. A joint approach would be better."

Respondent 6 highlights a major cost: the inefficiency of the current detection process. While the goal is to identify serious financial crimes like money laundering, terrorist financing, and sanctions violations, the system generates overwhelming numbers of false positives. According to the respondent, financial institutions typically estimate that between 95% and 99% of all flagged cases turn out to be false alarms, indicating a highly inefficient allocation of resources in AML enforcement.

Respondent 9: "A second issue is the difference between unusual and suspicious transactions. The Netherlands, along with the Czech Republic, is the only country that also reports unusual transactions. You get a huge number of reports, but not everything can be acted upon because the FIU is heavily overloaded."

Respondent 5 explained that accountants and tax advisors are also key actors in this process, acting as gatekeepers who are given a public responsibility by the government. The Financial Intelligence Unit (FIU) then investigates the reports submitted. Notably, the Netherlands is almost the only country that investigates unusual transactions instead of only suspicious ones. This stems from the country's legal history: originally, the Netherlands believed that gatekeepers should not look at suspicious transactions as it was considered a task for the government, whereas the rest of Europe allows banks to flag suspicious transactions.

For example, if someone living in Rotterdam suddenly makes a large purchase of 1,000 euros in Amsterdam, it would be seen as an unusual transaction. However, is it suspicious? No. The process is far more costly in the Netherlands compared to other countries. This is a crucial nuance: unusual versus suspicious. The FIU lacks the capacity to review all the reports, so it combines multiple sources, including registers from the tax authorities and the police.

14 - Displacement criminal activity
Respondent 8 stated that by having KYC-processes makes it so ML moves to other coutries or sectors, where it is less strict. *Respondent 1* : "Criminals have free rein by making use of countries like Mauritius, where there is less oversight."

15 - False sense of security
Respondent 8 mentioned that the current KYC system causes a false sense of security all the while real supervision and legal protection are neglected.

16 - High Manual Workload for FI
Respondent 1: "Banks often have large operational centers for this. It is also only partially automated, so a lot still has to be investigated manually. For example, you have to unravel a network of companies with various shareholdings and ownership structures. There might be a subsidiary in a high-risk country, and that then has implications all the way up to the UBO."

Respondent 2: "All the monitoring is essentially done manually. That's pretty much how it's handled, and that's significantly costly for institutions. If you don't have a way of automatically raising alerts and you have to do this by hand, with a rule-based system, it becomes really expensive. It's significantly costly because you have to analyse everything by hand, and that means you need to hire people to do that."

Respondent 3 explains that the FI's monitoring rules are implemented without fully considering their outcomes. Often, these rules are introduced because they are deemed important in the risk assessment process. However, once the rules are live, the policy dictates that everything resulting from them must be reviewed. If not, the institution would fail to meet its own policy requirements and it's role as gatekeeper. As a result, a massive flow of reports is generated, and everything related to certain types of risks must be examined.

Respondent 3 stated that it's not an enjoyable job. They've had many conversations with these individuals, and there are thousands of them in the Netherlands.

Respondent 6 noted that event-driven or periodic reviews for some parties can take up to 20 to 30 hours of work. These time-intensive processes, the respondent noted, are inefficient and do not provide benefits that justify such high costs.

Respondent 9: "But much is still handled manually, and machine learning is not used."

17 - Compliance Burden Legitimate Customers
Respondent 1 pointed out that the KYC process also imposes costs on clients, who are often required to provide detailed information for all their entities. They highlight the practical inconvenience of threshold-based rules, such as the €10,000 limit, noting that transactions above this amount are frequently delayed. Drawing from personal experience, they describe this as frustrating, when legitimate cross-border payments are unnecessarily flagged.

Respondent 6 pointed out that for certain groups, it can take months to open an account.

18 - False Positives
Respondent 2 stated that the biggest issue with the traditional KYC process is the high amount of false positives.

19 - Law Development & Supervisory Costs
Respondent 7: "Legislation needs to be made and supervised, and that obviously costs money."

20 - Privacy Concerns
Respondent 9 explained that AML processes can raise significant privacy concerns when individuals are scrutinized for transactions linked to people on watchlists, as illustrated by the example of a €10 Tikkie payment. Even small payments can trigger investigations if the sender is connected to someone with a suspicious background. This scrutiny highlights the tension between compliance requirements and the privacy rights of individuals, leading to false positives and unnecessary investigations.

C.1.2. Benefits of current KYC processes

21 - Improved internal governance
Respondent 8 explained that internal control mechanisms sometimes enhance operational hygiene.

22 - Reputation Protection Financial Institutions
Respondent 8 stated that a benefit of the KYC-process for banks is the protection of their reputation.

23 - Preventive Filtering
Respondent 6 highlighted that an important function of the system is to screen out and exclude high-risk parties or groups, even before they become part of the institution. The absence of high-risk cases in the institution's records doesn't necessarily indicate that the system isn't working; it could simply mean that these individuals were prevented from entering the system at the onboarding stage or were removed through an exit process.

24 - Reputation Protection Government
Respondent 8 expressed that the international relations and reputation management are a positive effect due to the KYC-process for the government.

25 - Deterrence of Money Laundering
Respondent 8 specified that an indirect positive effect is the prevention of money laundering through deterrence.

Respondent 3: "Of course, you also want to deter, whether that really works, I'm not sure, but you can assume that if you set certain requirements in the onboarding process for who can become a customer, that it will deter some people. Especially criminal entities. You might miss out on some profit, but you're also making a social contribution. Of course, it helps if the entire market does this."

26 - More Tailored Financial Services
Respondent 1: "It's nice that we have a clear understanding of a client's structure. That also helps in offering the right financial products. For example, you don't just look at the individual entity but at the entire group and say: you have seven operating companies, three holdings, a cash pool here, a joint venture there and then specific products match that setup."

Respondent 6 explained that banks can better understand their customers by having detailed insights into their financial activities. This enables banks, especially frontrunners in the field, to provide more tailored financial advice. Although not the primary goal of AML legislation, having a clear picture of a customer's income and sources can be used to assist with wealth management advice, such as savings or investment strategies. This, the respondent suggested, is a significant advantage.

27 - More Customer Interactions
Respondent 7: "Now, you could take a positive view and say: you have more contact with your customer, but in practice that's often negative. That you still have to request information from the customer for these processes, which the customer is not waiting for. So it can also result in a negative customer experience."

Respondent 6 also discussed that updating customer profiles, banks can use these interactions as opportunities to offer tailored financial advice, such as discussing financial well-being when a profile is updated. While not widely practiced, this approach could serve as a valuable way for banks to engage with customers and provide more personalized service.

28 - Government Penalty Income
Respondent 7: "But to be honest, I think it also generates quite a lot of money, because huge fines are issued. So I'm not sure, but I can imagine that the cost of supervision might actually be offset by the fines that are imposed. But I don't know for sure. "

29 - Reduced penalty risk
Respondent 1: "For example, you prevent the bank from receiving a massive fine. ING, for instance, received a large fine, so there is a clear economic incentive."

Respondent 3 in the context of why FI's carry out the AML processes: "The only motivation is that they don't want to get fined." "It's especially costly when you get fined again, that's what everyone is afraid of."

30 - Enhanced Trust in Institutions
Respondent 1: "From a societal perspective, there is greater trust in the financial system. Citizens entrust their savings to a bank that has no ties to criminals."

31 - Reduced Crime
Respondent 1:"These money flows inevitably end up at a bank at some point. So if you regulate AML very strictly within banks, you can indirectly reduce both terrorism and drug trafficking. The costs of crime: drugs and terrorism are enormous. Think of violence, medical expenses, societal harm. So the benefits also lie in creating a safer society."

Respondent 3: "It goes beyond just criminals: it's also tax evasion. Then you have sanctions screening, that's essential to do properly. You don't want to support war criminals or terrorist organizations. If all banks do this properly then it becomes much harder for Al Qaeda, ISIS, or any group to receive money. So, that's really important for society. Financial institutions play a crucial role in this."

Respondent 5: "The reason we do this is because we are against crime. Money laundering is linked to drugs and human trafficking. This is what we are preventing with this."

32 - Ensuring the Integrity of Financial System
Respondent 2 stated that the gatekeeping function of the FI's through the KYC-process keeps the financial system operating for normal use. It's the first line of enforcing unethical and illegal violations.

Respondent 6: "Another benefit is, although it's hard to measure, that you also screen out many customers at the door who you wouldn't want to have in the first place. It might be a big statement, but the entire system does become safer as a result."

Respondent 7: "I think it's actually good to have a clean and legal financial system. I really believe that it results in that."

33 - Development Non-Financial Risk Knowledge
Respondent 7: "So this is one of the first non-financial risks that is being tackled on such a large scale. So as a side effect, you learn how to deal with such a risk, what works and what doesn't. And then you can use that knowledge for other compliance risks as well. So for example, for ESG, privacy, that kind of thing. You build a kind of knowledge and skills for non-financial risks in the financial sector."

"Instead of managing risks on credit and the market, the risk here lies in the non-compliance with laws and regulations."

34 - Fraud Detection
Respondent 2 noted that the KYC-process aids in fraud detection. They mentioned that bank customers are being protected from fraud because of the banks efforts in trying to uncover fraudulent accounts taking money from other accounts, within or outside the bank.

C.1.3. Costs of ML implementation in KYC processes

35 - Higher ML Investment Costs FI
Respondent 8 mentioned the high initial implementation cost of ML in the KYC-process. Next to that the respondent stated the reliance on tech partners, which are also costly.

36 - Creation False Sense of Security FI
Respondent 4: "Also, I worry that the wider deployment of technology might create a false sense of security. Financial institutions might think, "We use the latest tech, so we must be compliant," when compliance should be an ongoing, critical process."

37 - *Respondent 6* pointed out that the biggest challenge for FIs, particularly in transaction monitoring, is the complexity and high cost of demonstrating compliance with their models.

38 - More Legal Uncertainty
Respondent 8 highlighted the uncertain legal framework that can contain ML. The supervisors have new tasks of checking AI applications for which they are often not yet equipped.

39 - Enhanced Privacy Risk
Respondent 4: "Machine learning, because such systems have to learn from patterns, and those patterns are predefined using criteria, which may be discriminatory or privacy-intrusive." This respondent also noted that customers of FIs are required to share more and more personal data each time there is a new policy.

40 - Higher Risk of Unjustified Exclusion
Respondent 8 describes a higher risk of financial exclusion due to bias and discrimination. The respondent emphasizes the risk increase of invisible exclusion without democratic control.

Respondent 1 noted that the risks lie in both false positives and false negatives, either missing suspicious activity because the algorithm lacks sophistication, or wrongly investigating individuals who are not actually involved in illicit behavior.

41 - Higher Risk of Discrimination
Respondent 4 :"I don't see how AI or machine learning can help us predict which transactions may lead to the financing of terrorism. Assessing that kind of risk inevitably involves assumptions about what kind of organizations or customers might be linked to terrorism. That introduces a high risk of discrimination, based on ethnicity, geography, religion, etc. " They also mentioned the risk of discrimination inherent to machine learning when setting pre-defined criteria to learn from patterns.

Respondent 2: "The risk of mistakenly identifying someone as doing something anomalous is high."

Respondent 8 stated that by using ML there is a higher risk of discrimination.

42 - Algorithmic Bias
Respondent 5: "And sometimes machine learning comes into play to do this more quickly. But there is a greater risk of bias. The sanction lists are made up of more than 80% Arabic names. And the model learns from that. This leads to alerts based on name recognition, which could potentially result in incorrect conclusions. This is an inherent risk."

43 - Loss of human oversight
Respondent 4: "The risk isn't necessarily in using machine learning for individual tasks, it's in using it to determine outcomes. For example, if machine learning is used for red-flagging internally during CDD, that's one thing. But if it's used to make the final decision, offboarding a client, denying service, or submitting an STR, that's a huge risk."

44 - Explainability
Respondent 4 highlighted that machine learning models function as a "black box," making it unclear

how decisions are reached. Unlike complex rule-based systems, which still allow visibility into which rules were applied, ML models obscure the steps behind an assessment. This lack of explainability may leave compliance officers unable or unwilling to question or override outcomes, even if they disagree or don't understand them.

Respondent 2 : "The biggest issue of deep learning is that it's not explainable by design. And in this application, it is complex. The risk of mistakenly identifying someone as doing something anomalous is high. So you really need systems that are self-explanatory, that can make a decision and explain why they made that decision. This is an ongoing area of research in computer science. It's far from being solved. That's why I'd say it's the biggest issue preventing these systems from being implemented in practice."

Respondent 3: "And then you also have the aspect of 'responsible' and 'explainable AI'. You never want people to be flagged as high risk just because a model says so. Because, well, why is that? People have the right to know."

Respondent 6: "Okay, I have money laundering risks, to put it simply, my model does magic and then this comes out."

Respondent 7: "What's less well done is that in this field, you need to be able to prove that with such a model, you're actually mitigating the risk. So the explainability of the model, that's what many institutions are struggling with right now."

Respondent 5: "The problem is that when the model says "this person is suspicious," you often can't trace why. That's the explainability issue. But work is being done on it. For example, Google has partnered with HSBC to set up a system where you can see why a particular score was given. It's called "explainable AI." And there, you can see that they are making real progress."

45 - Model integrity Risk
Respondent 3:"Risks are always present. Garbage in, garbage out, that's always a risk. You train your models based on what you've found in the past. Especially when there is no feedback loop: if you've consistently submitted poor data, like bad files to the AFM, because your analysts aren't well-trained or lack proper instructions, and the AFM gives no feedback, then you'll also train your models on that poor input. And no one benefits from that. Not society, not the bank."

46 - ML Governance Costs
Respondent 8 emphasized that while automation reduces manual and repetitive work, it also increases the need for tech ethics, legal oversight, and human supervision which are areas that are still underdeveloped. They compared the early years of this shift to a kind of digital Wild West, noting that the Netherlands has already experienced this phase with TMNL.

C.1.4. Benefits of ML implementation in KYC processes

47 - Faster Detection of Suspicious Activities
Respondent 8 mentioned a the benefit of faster signaling of anomalous transactions.

48 - Increased Efficiency within Government
Respondent 3 highlighted that the benefit of increased efficiency extends beyond banks, as regulators also gain from it. Ultimately, the government seeks better insight into risks and more meaningful reporting. While the immediate result may not be lower costs, there will certainly be a more efficient use of resources. This could potentially mean fewer staff, but more importantly, it leads to the identification of more relevant signals.

49 - Safer Financial System
Respondent 2: "You really make the KYC-process more aligned with achieving your goal, right? So, if the goal is to make the financial system, let's say, safer in general. Then you do bring that more into reality. So I think yes, when you apply machine learning (again, what type of machine learning you apply is another question), but yes, it brings it closer to its purpose."

50 - Less False Positives
Respondent 8 explained that there are potentially less false positives. They said this with a strong sidenote that this is only true with the right model settings and supervision.

Respondent 1: acknowledges that the use of ML can enhance anomaly detection by enabling more nuanced, targeted decision-making, avoiding broad profiling and better handling of complex cases.

Respondent 2: ”To me, the most obvious benefit is the reduction in false positives.” ”There’s always going to be false positives. These are machine learning systems that, by design, will have mistakes. The thing is: will they be able to make fewer mistakes than something that is not learned? Yes, probably yes.”

Respondent 6: ”You would hope that a model will ultimately work more efficiently, resulting in fewer false positives.”

51 - Less discrimination

Respondent 1 recalled sending humanitarian support to someone in the Philippines, a transaction that today might be flagged as potential terrorism financing simply because of the region involved. However, they argued that if applied correctly, machine learning could actually reduce discriminatory outcomes. By analyzing more complex patterns, these systems can move beyond blunt categories like nationality or surname, allowing for more nuanced, individualized assessments.

52 - Decrease in Manual Work

Respondent 1: ”That means investing in data analysts and proper tools. But in the long run, it saves costs, because otherwise you need a team of people to manually check everything.”

Respondent 2: ”With traditional approaches, you get swamped with things to review. You don’t have the time or people for that. But if a system helps you reduce false positives, you’re no longer overwhelmed. That’s the biggest benefit. You still need someone reviewing the model’s decisions, but if you reduce the number of such decisions, the workload becomes significantly less. That’s a big deal for institutions.”

Respondent 6 explained that the third point, while not the most important, is still relevant: there is a significant amount of manual, repetitive, and tedious work involved in both transaction monitoring and client risk assessments. They hope that all these highly educated individuals can use their talents in a better way, rather than focusing on repetitive and, frankly speaking, quite boring tasks. They believe there is a social benefit in this, not in reducing the workload, but in better utilizing the capacity.

Respondent 7: ”The promise of these models is, of course, that they can eliminate the disadvantages we discussed earlier. So that you don’t need a huge number of people to manually do all of this that’s the big promise. And why everyone wants this.”

53 - Long Term Cost Reduction FI

Respondent 1: ”That means investing in data analysts and proper tools. But in the long run, it saves costs, because otherwise you need a team of people to manually check everything.”

Respondent 3 about the costs related to KYC-analysts: ”If you can eliminate 20 or 30 percent of that, it’s already worth it. You never need twenty million a year to build, run, and update a model. So, I think the societal and reputational risks are greater, but financially, the cost picture definitely adds up.”

54 - Enhanced Complex Pattern Detection

Pattern recognition in transaction monitoring goes beyond simple rule-based checks. *Respondent 1* explained that while initial transactions may pass unnoticed, a third one, especially involving large sums or cross-border transfers, can trigger a block pending review. They also reference fraud types like romance scams, where individuals are deceived into sending money abroad under false pretenses. To detect such cases, banks use both predefined rules and machine learning models that identify new and complex transaction patterns.

Respondent 5 argues that machine learning can aid in complex pattern detection. For instance, if a bank sees an address where twenty people are registered, that’s unusual. Or, if a child’s account is being used by individuals with no connection to the child, that could raise a red flag. Banks want a 360-degree view of their customers: what do they do, where do they live, and who is connected to their account? This helps in spotting suspicious patterns.

55 - Reduced Crime

Respondent 5: ”Yes. You spot the right cases better, and you do it with less work. Hopefully, this will actually lead to less crime. Ultimately, that is the goal of this AML process.”

56 - Increased Operational Efficiency
Respondent 8 noted that efficiency gains are possible if applied correctly, as they can ease the procedural burden on employees. For banks specifically, this means a reduction in operational pressure, although it comes with increased accountability. At the same time, they stressed that improved efficiency should not be used as an excuse to diminish human oversight.

Respondent 8 also noted that more precise risk assessments could be achieved through carefully designed models, but this would require explicit oversight to prevent bias and protect fundamental rights.

Respondent 3: "So you want to triage upfront: which customers are so predictable or straightforward that you can say with high certainty: there is no risk there. You can filter them out with an algorithm. This significantly reduces your operational pressure."

Respondent 3: "If you work with one-dimensional rules, you either set them too strict, and miss things, or too broad, and get too much output. Machine learning can help make that multidimensional and find the right balance."

Respondent 6: "You would hope that a model will ultimately work more efficiently, resulting in fewer false positives."

Respondent 5 in context of the HSEC Google collaboration: "Yes, because they claim: look, in the previous system, we found a certain number of suspicious transactions. Now, we find two to four times as many, with a 60% reduction in the number of alerts. So, that's fantastic in terms of effectiveness."

57 - More effective detection
Respondent 5 in context of the HSEC Google collaboration: "Yes, because they claim: look, in the previous system, we found a certain number of suspicious transactions. Now, we find two to four times as many"

58 - Expand business FIs
Respondent 6 explained that the goal is for the model to become more efficient, reducing false positives. They also hope it will enable institutions to engage in more high-risk activities, as certain transactions and business models are currently deemed too risky. If the model can better monitor transaction behavior than customer profiles, it should allow for an expansion of services.

C.2. Use of ML in KYC process

59 - ML in transaction monitoring
Respondent 1: "This is namely in the transaction part, transaction monitoring and filtering. You use pattern recognition there: when is a transaction suspicious?"

Respondent 2: "Client monitoring, transaction screening, sanctions screening, and transaction filtering and monitoring. All of those allow for deep learning solutions."

Respondent 3: "We used machine learning to reduce up to five thousand alerts per month to low-risk classification, we called it 'alert filtering' or 'transaction reduction.'"

Respondent 6: "I mostly see it with my clients in transaction monitoring. There is a shift from rule-based scenarios to what we call 'model-based.'"

Respondent 7: "Especially in transaction monitoring, there's real development. Some banks use machine learning in parts of the process."

Respondent 8: "Not yet applied in risk decisions without human review. But could be useful for transaction analysis."

60 - Types of models and techniques
Respondent 1: "You no longer use simple Excel models, but algorithms running on graphs and vector databases that assess transaction linkage to money laundering." "Neural networks, combined with statistics, like Bayesian statistics. They search for correlations across multiple variables indicating suspicious behavior."

Respondent 3: ”We used supervised learning models like gradient boosting and random forest. We also applied SHAP value analysis and autoencoders for anomaly detection.”

Respondent 7: ”You see both supervised and unsupervised models across different parties.”

61 - LLMs & no ML in onboarding
Respondent 2: ”In onboarding, for identification, verification, and risk assessment, you could use LLMs for part of the process. But not that common in practice.”
”Onboarding doesn’t have the volume to justify deep learning, unlike transaction monitoring.”

Respondent 3: ”For onboarding, you need to collect documents like passports and UBOs. LLMs can speed up the process, but you still have to compile the file manually.”

Respondent 6: ”I’ve not seen machine learning used in client onboarding.”

62 - Client segmentation and low-risk triage
Respondent 3: ”You want to pre-assess which clients are so predictable that there’s almost no risk? You can catch those with an algorithm and reduce operational burden.” ”We did a pre-assessment of client risk ratings. If the data suggested low risk again, we could skip the manual review.”

63 - Assisted writing and risk scoring
Respondent 6: ”In risk assessments, machine learning is used to generate suggested classifications and risk narratives, a form of ‘assisted writing’.”

Respondent 8: ”Used in risk scoring during onboarding and monitoring.”

64 - Sanctions screening and name matching
Respondent 4: ”Sanction screening has challenges like name matching. Pattern recognition might help there.”

Respondent 7: ”There are some ML models running for sanction and transaction filtering, those processes are simpler and easier to implement.” ”What works well is generating alerts. What works less well is proving to supervisors that these models truly mitigate risk, explainability is a challenge.”

65 - Data cleaning and deduplication
Respondent 8: ”ML could be useful for data cleaning and duplicate detection, but not for risk decisions without human involvement.”

66 - Explainability and compliance
Respondent 2: ”ML grew in domains where explainability wasn’t crucial. In KYC, explainability is key, so self-explaining methods are being developed, mostly in research.”

Respondent 7: ”What works well is generating alerts. What works less well is proving to supervisors that these models truly mitigate risk, explainability is a challenge.”

67 - Early-stage implementation and maturity
Respondent 7: ”Everyone sees the potential, but true implementation is just beginning.” ”We’re still in early stages, but both supervised and unsupervised learning are being explored.” ”HSBC and Google implemented a fully ML-based transaction monitoring system, that’s rare and worth investigating.”