ADOPTION FACTORS OF AI-POWERED TOOLS IN SAAS-BASED FINANCIAL SOLUTIONS: A BUSINESS MODEL INNOVATION PERSPECTIVE

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Executive Summary

This thesis explores a central tension within digital financial innovation: while tools powered by artificial intelligence (AI) delivered through financial technology (fintech) Software-as-a-Service (SaaS) platforms hold significant promise, their adoption by financial institutions remains partial and inconsistent. Although the sector widely acknowledges the potential for AI to improve efficiency, compliance, and client servicing, the gap between interest and sustained implementation reveals deeper structural misalignments. Crucially, this study shows that adoption inertia is not the responsibility of one party alone. Instead, it emerges from a mutual disconnect between SaaS providers and financial institutions in how risk, value, and operational feasibility are framed and negotiated.

Ownership of the problem is shared. Financial institutions often lack the internal agility to trial or integrate AI tools, constrained by legacy infrastructure, regulatory ambiguity, and risk-averse procurement structures. At the same time, many SaaS providers fall short in translating technological novelty into contextualised, use-case-driven solutions that reflect the operational and governance realities of their clients. Adoption, then, is less a matter of technical readiness than one of institutional fit, trust-building, and mutual learning.

This study offers concrete strategies to move from exploratory interest to operational adoption. For SaaS providers, success lies in shifting from a transactional to a relational approach. Rather than leading with abstract AI potential, providers should anchor their offerings in concrete institutional pain points and communicate expected outputs in operational terms. Framing AI tools around measurable gains in efficiency or compliance, for example, by co-developing a model that predicts transaction spikes or automates clause extraction for regulatory reporting, can help bridge the adoption gap. Providers should also proactively guide onboarding, reduce friction through modular service delivery, and ensure that tools are not only explainable but demonstrably low-risk. Initiatives such as internal AI usage, client-specific self-assessments, and certification regimes can serve to enhance credibility and lower perceived onboarding costs.

Furthermore, providers that embrace co-ownership of the implementation challenge are more likely to build lasting partnerships. This means engaging client teams in iterative development, clearly defining shared responsibilities, and offering support tailored to user roles. By positioning themselves as strategic enablers rather than passive vendors, providers can help institutions move from proof-of-concept fatigue to actual institutional integration. The resulting dynamic is one of mutual value creation, a principle that must underpin any successful AI deployment in this space.

For financial institutions, realising the promised output gains of AI, whether in speed, compliance, or resource allocation, requires internal transformation. This begins with cross-functional governance models that allow technology sourcing, evaluation, and experimentation to proceed without procedural gridlock. Institutions benefit most when they participate as active co-creators in the development of AI solutions, bringing domain knowledge, regulatory nuance, and implementation constraints into early conversations. Clearer ownership over innovation pipelines, investment in internal AI literacy, and an honest appraisal of cloud and data readiness are all preconditions for value capture. Starting with non-core use cases, such as onboarding automation or analytics dashboards, can offer a lower-risk path to building trust in external solutions.

What this research ultimately reveals is that AI adoption is not a single decision, but a phased and co-constructed journey shaped by institutional politics, strategic fit, and the capacity for mutual adaptation. The path to improved outcomes lies in recognising that both sides, the AI SaaS provider and the financial institution, are custodians of the adoption process. When providers tailor their approach to institutional rhythms and institutions open up to collaborative, iterative partnerships, AI moves from potential to practice. And in doing so, it fulfils its promise not as a technological differentiator alone, but as a driver of resilient, data-driven, and future-oriented financial services.

Contents

List of Abbreviations

AaaS	Analytics-as-a-Service
AI	artificial intelligence
AML	anti-money laundering
ASPs	application service providers
AWS	Amazon Web Services
BO	back office
B2B	business-to-business
B2C	business-to-customer
BMC	Business Model Canvas
CC	cloud computing
core	centralised online real-time environment
COTS	commercial off-the-shelf
CRM	customer relationship management
CyberSec	cyber security
DGF	Digital Governance Framework
DL	Deep Learning
DNB	De Nederlandsche Bank
EBITDA	earnings before interest, taxes, depreciation and amortisation
ECB	European Central Bank
ESCB	European System of Central Banks
ESG	environmental, social, and governance
EU	European Union
fintech	financial technology
FO	front office
FOMO	fear of missing out
FTEs	full-time employees
GenAI	generative artificial intelligence
GCP	Google Cloud Platform
GTM	go-to-market
IaaS	Infrastructure-as-a-Service
IAM	identity and access management
InsurTech	insurance technology
IoT	Internet of Things
KYC	Know Your Customer
LLMs	Large Language Models
ML	machine learning
MO	middle office
MSMEs	micro, small, and medium enterprises
NLP	natural language processing

OECD	Organisation for Economic Co-operation and Development
PaaS	Platform-as-a-Service
P2P	peer-to-peer
RegTech	regulatory technology
RFI	request for information
RFP	request for proposal
ROAS	return on ad spend
ROI	return on investment
SaaS	Software-as-a-Service
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
ELM	Elaboration Likelihood Model
VAM	Value-based Adoption Model

Definitions of key concepts can be found in Appendix A.

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1 Introduction

1.1 Background

The financial technology (fintech) sector has experienced rapid expansion over the past two decades, driven by increasing demand and accelerated digital innovation, particularly following the 2008 financial crisis, which eroded trust in traditional banking institutions (Challoumis, 2024; Giglio, 2021). The rise of technology-enabled financial services has been transformative for both developed and developing economies (Torkington, 2024). More recently, the adoption of emerging technologies, particularly artificial intelligence (AI), has been recognised for its potential to further revolutionise digital financial services, making transactions more cost-effective, convenient, and secure (Chen et al., 2018; Deloitte, 2024; Lazo & Ebardo, 2023). AI applications in finance extend across multiple functions, including automating risk assessment, enhancing trading strategies, improving credit evaluation, and optimising customer interactions. By surpassing human capabilities in terms of speed and precision, AI is reshaping the landscape of digital financial services (Challoumis, 2024; Deloitte, 2024; Fong et al., 2021; Ionescu & Diaconita, 2023).

At the core of this digital transformation is cloud computing, where Software-as-a-Service (SaaS) plays a central role. The global SaaS market is projected to reach approximately $299 billion by 2025 (Vailshery, 2025) and is expected to generate over $1 trillion in earnings before interest, taxes, depreciation and amortisation (EBITDA) for Fortune 500 companies by 2030 (Forrest et al., 2021). SaaS now accounts for over 75% of global enterprise software spending, increasingly replacing traditional software vendors (Roche et al., 2020). Unlike conventional software providers that offer predefined functionality with upfront purchases, SaaS firms often leverage Platform-as-a-Service (PaaS) infrastructures to deliver dynamic, on-demand IT solutions (Rosati & Lynn, 2020). The rise of cloud-based financial platforms has enabled financial institutions to improve revenue generation by leveraging customer insights to develop more scalable, market-relevant solutions with shorter time-to-market while optimising the monetisation of data assets (Deloitte, 2024; Nutalapati, 2024; Sabbani, 2023). SaaS fintech solutions allow companies to access software as needed without the burden of owning or maintaining infrastructure, eliminating the need to facilitate transactional data on their own servers and freeing up significant upfront resources (Dan & Guo, 2018; Fong et al., 2021; Sabbani, 2023).

For SaaS providers specialising in online banking platforms, AI-powered tools have become key drivers of value creation across the financial services value chain (Deloitte, 2024; Fong et al., 2021; Seremet & Rakic, 2024). Seremet and Rakic (2024) highlight how AI can enhance middle office (MO) and back office (BO) functions by automating processes such as fund allocation based on demand forecasts for financial products. Additionally, AI's ability to analyse large datasets enables real-time analytics, helping financial institutions optimise resource allocation while maintaining service quality in the front office (FO). Lazo and Ebardo (2023) emphasises that leveraging AI-powered tools is no longer just an option for financial institutions. It has become a necessity. Traditional banks face mounting pressure from digital-first competitors that are unencumbered by the legacy systems and structural challenges associated with digital transformation, a sentiment echoed by Dan and Guo (2018) and Seremet and Rakic (2024). Some experts argue that in the highly competitive SaaS fintech industry, where McKinsey characterises market dynamics as "winner-takes-all" (Fong et al., 2021, p. 8), harnessing AI effectively can provide firms with a decisive competitive edge. By leveraging AI, SaaS providers can offer highly adaptable, always-available, and cost-efficient services that meet the growing demand for seamless, personalised banking experiences (Lazo & Ebardo, 2023).

Despite AI's transformative potential, both SaaS providers and financial institutions struggle to fully capitalise on its benefits (Seremet & Rakic, 2024). Lazo and Ebardo (2023) note that while AI has broad applicability across industries, the banking sector faces unique regulatory challenges. Financial institutions play a critical role in maintaining economic stability, resulting in stringent oversight from central banks and a generally conservative approach to risk management and innovation adoption, particularly within the EU. This complex regulatory environment heightens concerns about risk perception and presents challenges in managing the intricate relationships between SaaS providers and their clients (Lazo & Ebardo, 2023; Sabbani, 2023).

The intersection of AI and finance remains an evolving field of research, especially as rapid advancements in AI technology continuously redefine its applications and associated risks. The EU's regulatory stance, marked by its proactive approach to governing technologies with significant societal implications (Sukharevsky et al., 2024), further complicates adoption decisions for European financial institutions. These institutions must navigate a shifting regulatory landscape while ensuring compliance with evolving data protection laws and guidelines. However, existing literature lacks robust theoretical foundations and comprehensive empirical research on the forefront of modern financial services, particularly regarding the increasing dominance of SaaS providers over traditional financial software vendors. SaaS firms must balance delivering AI-driven solutions that meet evolving customer needs with ensuring cost-effective platform deployment (García-Fernández et al., 2024). A key practical challenge in this landscape is the persistent reluctance among financial institutions to adopt AI-powered tools, despite their potential to enhance competitive positioning and customer experience, due to regulatory uncertainty, risk concerns, and the complexities of provider-client relationships (Lazo & Ebardo, 2023; Sabbani, 2023).

1.2 Problem Exploration

The reluctance of financial institutions to adopt AI-powered tools in fintech SaaS platforms stems from industry-specific challenges. Banks, lenders, financial groups, and government-funded initiatives perceive AI-related risks differently than other sectors embracing AI and cloud-based platforms. In traditional finance, concerns range from the opacity of AI decision-making due to black-box phenomena to the complexities of integrating AI within existing legacy infrastructure. While cloud-based fintech solutions offer improved AI integration capabilities, they also introduce new challenges, particularly regarding security and data privacy (Ionescu & Diaconita, 2023).

Beyond technical concerns, financial institutions must also navigate economic and strategic challenges when adopting AI-powered tools. The licensing-based pricing models commonly used by SaaS providers create difficulties in monetising AI innovations, requiring a balance between standardisation and customisation (García-Fernández et al., 2024). Additionally, AI adoption extends beyond product innovation. SaaS firms must rethink client relationships, pricing and revenue models, operational frameworks, and go-to-market (GTM) strategies to remain competitive (Fong et al., 2021; Ravid, 2024). Despite AI's potential to optimise financial services, from automating routine processes to enhancing customer interactions, current research provides limited insight into the real-world considerations when deciding to implement these technological advancements.

Many firms focus on technological possibilities rather than aligning AI solutions with client needs. However, this technology-driven approach often proves ineffective, especially in the European Union (EU), where financial institutions lag behind their U.S. counterparts in leveraging AI (Choudhary & Thenmozhi, 2024; Sukharevsky et al., 2024). This slower adoption rate presents a challenge for SaaS providers seeking to capitalise on AI-driven R&D investments within European markets. Moreover, the lack of mutual value exchange in the development of AI-powered tools, such as co-creation and data contribution collaborations, makes effective development efforts strenuous due to the lack of real-world testing and available end-user data.

Addressing AI adoption barriers in fintech SaaS requires a deeper understanding of the decision-making criteria and practical obstacles that contribute to the reluctance. Insights into these challenges are essential for both fintech providers and financial institutions, as they shape the evolving landscape of AI-driven finance. Collaboration between these two sectors is critical, given that the intersection of fintech SaaS and AI represents a rapidly growing market segment that will influence the industry's future trajectory.

To develop a holistic understanding of challenges in AI adoption decisions, it is crucial to consider not only technological factors but also organisational dynamics, regulatory constraints, and broader market forces. Current literature inadequately addresses the specific challenges financial institutions face when deciding whether to integrate AI-powered tools into fintech SaaS platforms. Literature commonly focuses on the technological reasons for adoption (Chen et al. (2018), García-Fernández et al. (2024), and Ionescu and Diaconita (2023) among others) but fails to provide an overview of actual decision-making aspects that influence real-world adoption decisions by financial institutions. Furthermore, existing studies often overlook the practical considerations SaaS providers must account for when developing AI-driven financial solutions.

This study aims to bridge these gaps by exploring the key drivers behind the decision-making leading to either the adoption or rejection of AI-powered tools in fintech SaaS. By uncovering the underlying factors influencing adoption decisions, this research will provide actionable insights for SaaS providers seeking to optimise their AI strategies. A better understanding of these dynamics will allow providers to allocate resources more effectively, reducing development costs while maximising the commercial viability of their AI offerings. For financial institutions, aligning AI solutions with internal systems and workflows will lead to greater efficiency and streamlined integration processes. Ultimately, a clearer understanding of how core banking platforms and their clients interact will facilitate the development of AI-driven solutions that balance innovation with regulatory compliance, fostering sustainable adoption in the fintech SaaS sector.

1.3 Research Objective and Questions

This study aims to deepen the understanding of AI adoption in fintech SaaS by identifying and addressing the factors that influence the decisions of financial institutions, which often lead to rejection rather than acceptance and, therefore, adoption of AI-powered tools. Specifically, it seeks to determine the key factors influencing financial institutions' willingness to adopt AI-powered tools in terms of both factors enabling adoption and factors hindering it. Moreover, the practical challenges these factors present and strategies to overcome these obstacles will be addressed. By doing so, this research will provide actionable insights for more effective AI tool development and implementation within fintech SaaS platforms. By focusing on both enablers and barriers of effective adoption, the insights this study aims to provide can be used for formulating, improving, and/or maintaining operational strategies by companies of all sizes active in the digital financial services industry.

Additionally, this study aims to bridge the gap in existing research by examining the intersection of two critical forces shaping the financial industry: fintech SaaS and AI-driven innovation. By taking a practical perspective, the research will offer SaaS providers short-term, development-focused insights while also equipping them with strategies to manage client expectations and perceptions regarding AI-powered tools. These insights will help providers refine their service models to better align with the needs of European financial institutions, ultimately enhancing the value proposition for both providers and their clients. More effective AI deployment in fintech SaaS will not only improve operational efficiency for financial institutions but also enhance the end-user experience, meeting the growing demand for seamless, reliable, and always-available financial services.

The study is guided by the following central research question:

What factors influence financial institutions' decision-making (acceptance or rejection) concerning AI-powered tools in fintech SaaS?

The research is further structured around three sub-questions:

1. *Why do financial institutions initially become interested in AI-powered tools?*
2. *What are the key challenges in financial institutions' decision-making regarding AI adoption?*
3. *How can SaaS providers address the challenges that hinder the adoption of AI-powered tools?*

To address these questions, this exploratory study will collect qualitative data by interviewing stakeholders on both sides of the fintech SaaS provider-client relationship. The interview questions will be guided by aspects from the most appropriate technology adoption model(s), which include intentions to use AI and its rationale, and actual adoption behaviour with technological, social, and facilitating constructs. Exploratory questions on the intersection of fintech SaaS and AI will be asked to identify topics of interest, both in terms of real-world concerns slowing down effective AI adoption in the sector and the effect of AI on the future of the fintech SaaS business model.

1.4 Report Structure

The structure of this paper is designed to present all pertinent information clearly and coherently. The **Introduction** has outlined the core tension between the transformative promise of AI-powered tools and their limited adoption by financial institutions, positioning this as a shared challenge for both SaaS providers and institutional clients. The **Literature Review** examines the rise of AI in finance, the characteristics of fintech SaaS platforms, and technology adoption theory, establishing a conceptual foundation and highlighting a lack of research into real-world adoption dynamics at the intersection of these technologies (Chapter 2).

The **Research Methodology** explains the qualitative research design, including data collection and analysis methods used to explore the adoption process across both sides of the provider-client relationship (Chapter 3). The **Findings** Chapter presents the empirical results structured around the study's sub-questions: motivations for adoption interest, barriers to adoption, and strategies to address those barriers (Chapter 4). The **Discussion** synthesises these insights, explores emerging adoption dynamics, and develops actionable implications and recommendations for both SaaS providers and financial institutions (Chapter 5). It also outlines the theoretical contributions of the study and identifies limitations and directions for future research. The **Conclusion** distils the central findings and reinforces their relevance to ongoing developments in the fintech SaaS landscape (Chapter 6). Supporting materials and analysis-related details are provided in the Appendices. Table 1 shows how each research question is addressed throughout the report.

Table 1: Mapping of research questions to thesis chapters

Research Questions	**Addressed in Chapter**	**Further Synthesis and Looking Ahead**
SQ1: Why do financial institutions initially become interested in AI-powered tools?	Chapter 4.1	Chapter 5.1 synthesises triggers of interest into broader adoption themes
SQ2: What are the key challenges in financial institutions' decision-making regarding AI adoption?	Chapter 4.2	Chapter 5.1 explores emerging adoption dynamics and structural barriers
SQ3: How can SaaS providers address the challenges that hinder the adoption of AI-powered tools?	Chapter 4.3	Chapters 5.3 presents actionable strategies and practical recommendations for adoption enablement

2 Literature Review

2.1 The Rise of AI in Financial Services

2.1.1 Defining AI and its Core Technologies

The term AI within the context of modern computing has been around since the early twentieth century. Alan Turing, championing some of the most impactful and transformative ideas for the field of computer science, was the first to tackle the philosophical question of whether computers could behave intelligently. To find an answer to this question, he designed the Turing Test, aimed to find out if an interrogator could distinguish a human from a computer by answering questions in text form. While his insights led to a whole branch of technological research to design machines that could, the focus was often on problems in which symbol manipulation, the mathematical approach included in early definitions of 'thinking computers', was pivotal. Not much later, in 1956, experts were brought together at a scientific workshop in the US. In the proposal for this workshop, the term artificial intelligence was first mentioned (Mucci, 2024; Oliveira & Figueiredo, 2023).

Nowadays, the latest LLMs might fool interrogators who are unfamiliar with the system's weaknesses or tells. However, the human-like nature of AI, although it still enjoys the dedication of many, is beyond the focus of the tools leveraged by businesses. That said, newly arising AI agents – AI systems with the power to make decisions without humans being involved in the process, simulate tasks, beginning-to-end, formerly performed by companies' employees (Oliveira & Figueiredo, 2023). Later in this section, agentic AI will be discussed, as well as its possible implications for the context of this research.

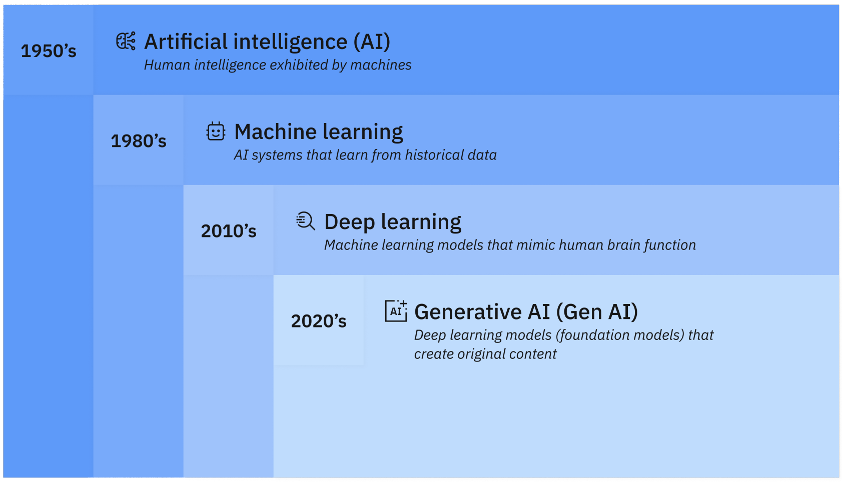

Figure 2: AI and its conceptual derivatives. From *"IBM Think"*, by Stryker and Kavlakoglu (2024) (https://www.ibm.com/think/topics/artificial-intelligence), in the public domain.

This section aims to define AI in this study's context and provide an overview of the technologies that make up the concept of AI technology as present in the finance industry. According to IBM's Stryker and Kavlakoglu (2024), AI is "technology that enables computers and machines to simulate human learning, comprehension, problem solving, decision making, creativity and autonomy" (p. 1). This definition is designed to include the technology's conceptual derivatives, displayed in Figure 2, such as machine learning (ML), Deep Learning (DL) and Large Language Models (LLMs) powered through generative artificial intelligence (GenAI) technology. To answer this study's research questions, the term AI refers to a technology that includes all of these conceptual derivatives, staying close to some of its first definitions, which were broad and somewhat easier to explain to a broader range of people (Mucci, 2024; Oliveira & Figueiredo, 2023). While AI is becoming a widely known technology, especially with OpenAI's ChatGPT reporting more than 400 million users per week (Duarte, 2025), the level of expertise necessary to participate in the technology's discussion decreases. Even with a low level of use, anyone in the connected world has some idea of the technology's usefulness and potential risks. A parallel with the business environment is undeniable: professionals burdened with technology-related decisions are often not AI-centred computer scientists, but will not have been able to have no idea what it entails. Consequently, factors influencing adoption decisions in this context do not necessarily rely on the tool-specific sub-technologies that said tool relies on. Decision makers often rely on a very high-level understanding of what a technology can offer. The focus lies on criteria that they can assess, in line with pre-(gen)AI times, such as cost-benefit analyses, potential effect on KPIs, and alignment with technology procurement goals, among others.

To possibly make more sense of findings in later stages through categorisation of AI perceptions according to the technologies that the tested concept is made up of, the working mechanisms driving the conceptual derivatives of AI are displayed in Table 2. More detailed descriptions of the working principles can be found in Appendix A. In the next section, applications of these technologies are discussed.

Table 2: Descriptions and key features of AI's main derivatives

AI Derivative	Description	Key Features
Machine Learning (ML)	A foundational AI subfield focused on statistical models that learn from data to make predictions or detect patterns. It includes regression, classification, and inference tasks.	Learns from data (training/validation/test sets); includes regression and classification; uses one-hot encoding.
Deep Learning (DL)	A subset of ML using multilayered neural networks to simulate human-like decision-making. Powers much of Industry 4.0 and NLP tasks.	Multi-layered (deep) networks; learns hierarchical data representations; supports large-scale pattern recognition.
Generative AI & LLMs	AI that creates new content based on learned patterns from existing data. LLMs are a subcategory focused on generating human-like language using probability-based NLP.	Content generation (text, images, etc.); LLMs as a subtype; increasingly multimodal.
Agentic AI	Advanced AI capable of pursuing complex, long-term goals autonomously. Goes beyond rule-based systems with dynamic, adaptable behaviours. The field is still evolving, with emphasis on ethical and regulatory considerations.	Goal-oriented autonomy; adaptive; operates with minimal oversight; degree of "agenticness" varies.

2.1.2 AI applications in finance

When discussing AI applications in finance, it is important to realise that the financial industry encompasses many activities. This study's focus is on customer-facing financial institutions such as banks, financial groups, finance-related funds, and pension providers. AI applications allow these institutions, like all other organisations and businesses, to automate tasks and processes, assist in (business) analytics, forecast and/or predict specific outcomes or circumstances, and assist customers. The different conceptual derivatives of AI have different strengths and weaknesses concerning their use in specific areas of application. Where ML and DL algorithms excel in business analytics and finding patterns in raw data, LLMs and GenAI are excellent for all customer-facing applications with their ability to comprehend written text and respond in a human-like manner.

For starters, machine learning can help institutions to predict a variety of interesting things. Financial institutions can use ML for quantitative prediction of the future sales of specific financial products and their corresponding revenue, or a customer's lifetime value. All commercial companies, including those in finance, can use ML-enabled classification of customers. Examples include the classification of likely responders to specific marketing campaigns. For financial institutions, classification can also be used to detect fraudulent behaviour from data, and to assess the credit risk of loan applicants based on the data they provided and their previous activity and loan applications. Another powerful application for e.g. investment platforms is churn modelling. This allows institutions to anticipate when users are likely to cancel their subscription to a premium investment account, enabling proactive retention efforts. Ultimately, ML enables organisations to not only make accurate predictions but also to derive actionable insights from their data, allowing more time-efficient and data-driven decision-making (Choithani et al., 2022).

Where machine learning has a statistical approach, deep learning can allow institutions to find more contextual patterns in raw data. For example, an algorithm leveraging neural networks can find patterns in subjective assessments carried out by an institution's employees. Of course, the question arises whether a subjective assessment is desirable in any case. Here, the question is whether one desires to operationalise what a human would have done, or what the data is telling statistically. The question of whether data-driven decisions are better or worse than what humans do, and what concerns arise when setting up a system's access controls, will be investigated later.

That said, deep learning has powerful applications in the financial industry. For example, DL enables what is referred to as computer vision by Durães et al. (2023), Mucci (2024), Oliveira and Figueiredo (2023), and Sarker (2021), with which DL can process images and videos. This allows for non-rule-based information extraction from documents such as pay slips, mortgage contracts, and bank statements of loan applicants, useful in automating data transfer from front to middle offices. Moreover, financial institutions can use DL, similarly to ML, for advanced predictive analytics, loan applicant risks analysis, and fraud detection, as well as portfolio management for both corporate and private investors in wealth and asset management services (Holdsworth & Scapicchio, 2025). Sarker (2021), Magrani and Da Silva (2023), and Durães et al. (2023) highlight the wide-scale use of DL for recommendation systems in entertainment and media, but also in recommending the best-fitting financial product based on a customer's financial behaviour. Another important application of DL algorithms is critically assessing transactional data to scope out suspicious patterns indicating prohibited financial (business) operations. Moreover, DL can help to detect system intrusion on all sorts of platforms (Choithani et al., 2022; Holdsworth & Scapicchio, 2025; Sarker, 2021). This cybersecurity aspect is highly relevant for financial institutions, as one's financial data is considered highly sensitive information that should be protected at all costs. Finally, Trancoso et al. (2023) state that deep learning enables the notion of a "legal AI" (p. 25), to potentially administer justice based on incident data, an application echoed by Durães et al. (2023), that can be used by central banks and other financial watchdogs in their operations.

LLMS and GenAI are rapidly transforming financial services by enabling advanced data analysis, automating workflows, enhancing customer interaction, and streamlining software development. These technologies are applied not only in explicitly financial functions but also in broader domains such as analytics, compliance, and technical infrastructure that support financial institutions. One of the core applications is in data analytics and insights generation, where LLMs are employed to process large-scale datasets, structured and unstructured, to identify trends, detect anomalies, and support strategic decision-making. In finance, this translates into more accurate macroeconomic forecasting, improved credit risk modelling, and enhanced capabilities to simulate market dynamics or stress-test financial portfolios (Joshi, 2025; Oliveira & Figueiredo, 2023). Moreover, LLMs can generate synthetic financial data, allowing for robust model training and evaluation without breaching privacy or regulatory constraints, a key consideration in sectors handling sensitive customer information (Choithani et al., 2022; Joshi, 2025).

Another major use case is automation and workflow optimisation, where LLMs reduce the manual burden of tasks such as contract review, document classification, or regulatory reporting (Joshi, 2025; Oliveira & Figueiredo, 2023). In finance, these technologies are used to extract and summarise information from financial statements or compliance documents, assist in automated monitoring of regulatory changes, and help generate compliant narratives for internal or external reporting. When integrated into analytics platforms, LLMs can offer real-time summaries, intelligent recommendations, and even personalised portfolio insights for investment professionals. Particularly in heavily regulated industries like finance, GenAI tools are proving valuable in automating compliance procedures such as anti-money laundering (AML) checks and Know Your Customer (KYC) verifications (Oliveira & Figueiredo, 2023).

Direct applications within financial services and fintech have also gained traction. LLMs support the development of quantitative trading strategies by analysing historical trading data, market news, and sentiment indicators (Choithani et al., 2022; Keller et al., 2023). In lending services, GenAI helps automate document verification, assess risk profiles, and optimise credit scoring processes.

A widely adopted use case is in the form of conversational AI and chatbots that now handle a significant share of customer service interactions. These bots are capable of providing natural and accurate responses to client queries, recommending financial products, and guiding users through onboarding or investment flows more effectively than rule-based predecessors (Choithani et al., 2022; Keller et al., 2023). Additionally, LLMs are used in regulatory reporting, where they generate structured reports and disclosures across jurisdictions, improving speed, compliance, and consistency (Joshi, 2025). Finally, software and development tools powered by GenAI play a foundational role in the fintech ecosystem. Tools like IBM's "watsonx" enable developers in financial institutions to automate code generation, assist with debugging, and build custom solutions for trading platforms, risk management systems, and client-facing applications (Mucci, 2024). This accelerates the development of tailored fintech tools while reducing technical overhead and improving system adaptability.

2.1.3 AI's transformative potential and proven role in finance

As stated before, financial institutions have a different place in society than organisations in other industries. Economic stability depends on the reliability of the financial systems in place, both on national and international levels, due to increasingly global financial markets and record-level trading between countries, spanning continents (UNCTAD, 2025). Financial institutions, such as banks, lenders, and pension funds, are burdened with ensuring stable economic continuity in the dynamic financial landscape. They ensure the availability of money through providing individuals and corporations with funds to spend and the means to execute these transactions. The demand for these fundamental financial services is increasing. Additionally, the demand for other services, such as peer-to-peer (P2P) payments, investing with savings, and paying with mobile devices, is, among others, rising (Fox & Collins, 2025; Irimia-Diéguez et al., 2023). With increasing demand and financial activity worldwide, financial institutions are responsible for processing increasingly more transactions, loan applications, mobile device-enabled payments, and different methods to do so. To deal with this, institutions are forced to become more technology-driven. While this transition promises efficiency gains, it also brings strategic challenges, as AI and other technologies introduce disruptive dynamics in the financial sector that can threaten incumbent institutions (Rahman et al., 2021).

Moreover, the transformation of third-world countries with billions of inhabitants from a cash-based system to digital payments gives the acceleration of required technological capacity an extra boost (Noreen et al., 2023; Omoge et al., 2022). Large financial institutions have always had a significant presence in emerging markets, including Asia, the Pacific region, and Africa. Although challenges to succeed in these markets prevail due to regulatory uncertainty and political instability (Ntoubia & Larissa, 2024), the potential for capturing these markets remains immense (IMF, 2012, 2014). According to Bayram et al. (2022), the stability of emerging markets' financial systems relies hugely on individual financing and loans to SMEs. The author also showcases that in countries where participatory (Islamic) finance forms a foundation for service delivery, fintech effectively enables the application of ESG principles to meet customer needs. He concludes by stating that the intersection of sustainable finance and technology-driven fintech solutions is highly relevant and important for the growing emerging markets, using Turkey as a representative case study. Similarly, Almansour (2022) notes that tech-savvy fintech start-ups are especially well-positioned to expand access and scalability in underserved regions, where their agility enables them to surpass traditional banks in both efficiency and inclusivity. In Chapter 5.4, the implications of AI-driven fintech solutions on sustainable finance practices are discussed in more detail.

Technology such as AI can allow providers of financial services to navigate this globally increasing demand for financial services, where each consumer tends to make more and more payments and transactions, partially due to the availability of mobile banking. Lee and Chen (2022) state that constant innovation is required in mobile banking that is championed by AI technology. The authors dedicate this necessity to leveraging AI to mobile-device-enabled service availability and timed transaction functionality within apps, impossible with physical banking services. This continuous innovation is demanded by the modern user, who looks for alternatives in the market when these demands are not met. Lee and Chen (2022) conclude by stating that client-facing AI tooling is pivotal in remaining competitive. This notion is echoed by Rahman et al. (2021), who note that AI facilitates dynamic and personalised offerings based on behavioural insights, and is thus essential in both attracting and retaining customers. AI applications such as behavioural finance tools help banks decode individual spending behaviour and provide customers with smarter savings strategies, thereby improving their financial health and engagement.

Moreover, increasing migration to the cloud is essential for institutions to ensure data availability wherever it is needed and allow platform-sharing for all the services that an institution provides in a streamlined way. With cloud migration, the need for sound data protection and cybersecurity is also essential. Again, a role for AI seems inevitable to empower institutions to allow for more efficient protection and data assessment at a scale that was unimaginable before the technology's wide-scale adoption. The emerging mobile-enabled banking services industry has an accelerating effect on the necessity of AI-powered solutions, which is twofold. The technology is crucial to handle the increasing number of transactions in a general sense, but also to facilitate the collection of data necessary to enable the use of AI solutions to meet the growing demand. According to Noreen et al. (2023), the emerging technology especially relies on tracking users' financial objectives and spending behaviour. Rahman et al. (2021) argue that these capabilities stretch beyond traditional notions of e-banking or consumer-facing digital services, highlighting that the boundaries between finance and fintech are increasingly porous. AI applications almost by default operate on or through digital platforms, which further embeds them in the fintech domain.

Concluding, mobile-enabled technology is pivotal to meet the modern user's demands, to facilitate the overall growing market, the growing transactions made by each user within this market, and to collect data necessary to facilitate operations that allow growing platform capacity, even more in emerging markets (Bayram et al., 2022; Boustani, 2022; Noreen et al., 2023; Omoge et al., 2022). As AI increasingly becomes embedded in both client interaction and back-end processing, its role in credit risk assessment also grows. Ramakrishnan et al. (2024) predict that AI is likely to become the de facto method for assessing creditworthiness, further consolidating its central role in financial operations.

2.2 Characteristics and Value Propositions of Fintech SaaS

2.2.1 SaaS as the Delivery Model of Cloud Computing

Providers of software as a service, formerly referred to as application service providers (ASPs), offer their customers software solutions that allow them to utilise cloud computing functionality. Cloud computing, defined by Howell-Barber et al. (2013) as a delivery method of an information system "that enables convenient, on-demand network access to a shared pool of configurable computing resources with minimal management effort or service provider interaction" (p. 4), is the underlying value offering of SaaS, a common model to deliver it. SaaS applications are hosted by their provider in the cloud and can be accessed from anywhere through an API or browser at any time. A well-known SaaS provider is Salesforce, offering a cloud-native customer relationship management (CRM) platform to track and maintain relationships with clients, and to track sales and marketing activities (van Tellingen, 2023). SaaS providers often make use of Infrastructure-as-a-Service (IaaS) to build and run virtual machines and other resources, and to access storage and network capabilities. Moreover, some SaaS firms even make use of PaaS to build advanced cloud-native tooling for a specific use case to offer to a more niche market. The biggest Western IaaS providers are Microsoft Azure, Amazon Web Services (AWS), and Google Cloud Platform (GCP). Whereas Azure and GCP solely provide IaaS, AWS also delivers PaaS and SaaS functionality, giving it a market share of 37% in the cloud services market worldwide (Clancy, 2022).

SaaS providers' primary advantage over traditional software vendors offering commercial off-the-shelf (COTS) software lies in their ability to deliver similar, or even superior, functionality at a lower total cost. Unlike COTS solutions, which do not eliminate the need for an in-house IT infrastructure, SaaS platforms fully replace much of this infrastructure by operating through the cloud. This fundamental difference in delivery model translates into cost savings that extend across the entire customer journey, as updates and maintenance are managed centrally by the provider, with minimal operational disruption. This shift in delivery model reflects broader distinctions in pricing, customizability, and service provision. As noted by Ma (2007), COTS software is typically purchased as a one-time transaction for a predefined package, often customizable by the user without vendor involvement, and managed in-house. In contrast, SaaS offerings are generally structured around licensing and/or transaction fees, involve ongoing vendor engagement for platform tailoring (often at an additional cost), and are delivered remotely, mirroring the service structure of utilities like electricity, a model often referred to as utility computing (Waters, 2005). In line with these differences, Waters (2005) highlights SaaS as a response to the shortcomings of traditional, license-based software. His analysis identifies key pain points of the pre-SaaS era: unexpected implementation costs, prolonged deployment timelines, and substantial administrative burdens. These disadvantages were often compounded by a misjudgment of implementation complexity and a continued need for significant internal IT support, even after license purchase. Both Ma (2007) and Waters (2005) thus underscore how SaaS alters the competitive landscape of software provision, not only in terms of pricing and service delivery, but also by reducing the operational and financial burdens historically associated with enterprise software adoption, a notion Misra and Doneria (2018) reports as well.

2.2.2 The Fintech SaaS Business Model

Especially in finance, SaaS can provide financial institutions with access to a cloud-native platform that can help them to monitor and analyse all transactions they desire, and gather data-driven insights for whichever use case, while constantly being able to gain functionality based on business requirements and new features made available by their provider. This, without the burden of owning or maintaining their own infrastructure, leaves them with less financial overhead from the get-go (Dan & Guo, 2018; Fong et al., 2021; Sabbani, 2023). For most firms, including financial institutions, working in the cloud brings a wide variety of advantages. According to Howell-Barber et al. (2013), cloud computing accelerates project collaboration in all departments, improves communication infrastructure, and allows for better customer relationship management in both business-to-business (B2B) and business-to-customer (B2C) contexts. The authors also note that SMEs tend to be served more effectively with SaaS than large firms due to their legacy systems, echoed by Ma (2007). However, Gapgemini reported that 91% of banks and insurers use at least one cloud platform as of November 2023 (Capgemini, 2024). Moreover, it should be mentioned that companies often have complex organisational charts. That means that some divisions act as spin-offs, with their own management in place. These entities often have the freedom to procure technology through partnerships as they see fit, to meet their technological needs. For example, car manufacturer BMW also offers financial services through their company BMW Financial Services under the BMW Group label, which offers financing and insurance options to customers and businesses (BMW Bank, n.d.; BMW Group, n.d.). Other car manufacturers such as Stellantis, Volkswagen Group, and Mercedes-Benz Group have similar financial subsidiaries. Moreover, big banks have their own spin-offs and subsidiaries, focusing on specific segments of the market, often with autonomy in technology partnerships for specific client-centric purposes. For SaaS companies offering cloud-based financial services, these subsidiaries are another customer segment, as they operate similarly to traditional lenders or other financial service providers that need a cloud infrastructure.

SaaS platforms allow financial institutions to anticipate changing financial and regulatory landscapes due to their ability to be updated constantly, keeping their cloud infrastructure capable, scalable, and compliant (Mahalle et al., 2021). Although these value-adding factors are not unique for financial institutions, the sphere in which financial institutions conduct business differs from other companies. For starters, everyone who wishes to participate in modern society is a client of the banking industry. Secondly, banks, funds and pension funds are under strict governance by central banks. In Europe, the

European System of Central Banks (ESCB), consisting of the European Central Bank (ECB) and the national central banks of the 28 member states of the EU, is responsible for supervising financial institutions and the financial system (de Ruiter, 2014). Thirdly, competition among companies that are cloud-driven fintechs by nature poses risks to customers of incumbent banks. This competitive landscape challenges companies to meet evolving customer demands, meaning better products and services that help the customer achieve financial goals.

While SaaS has numerous applications in finance and banking, it is essential to distinguish between core banking functions and other financial services. As Finn and Downie (2024) explain, the term ”core” refers to the centralised online real-time environment (core) that facilitates essential banking operations and supports all digital service functionalities. Importantly, this core system does not necessarily need to be cloud-based; it can also operate on-premise. Regardless of its deployment model, all digital transactions conducted by bank users depend on this foundational system. SaaS providers offering core banking platforms typically specialise in specific service domains such as lending, mortgages, investments, or payments. This means that a SaaS firm may provide core banking functionality tailored to just one of these areas. Moreover, the core banking platform does not have to be uniform across all departments within a financial institution.

Non-core banking SaaS providers have business models ranging from solutions with high relevance for financial institutions, such as regulatory technology (RegTech), cyber security (CyberSec), WealthTech, insurance technology (InsurTech), RiskTech and financial Analytics-as-a-Service (AaaS), to more common services also equipped by financial institutions for smoother operations, such as identity and access management (IAM) and interactive client-facing solutions (e.g., chatbots, service bots) (Eickhoff et al., 2017; Werth et al., 2023). Each of these business model archetypes is concisely described in Table 3.

Table 3: Non-core banking business model archetype descriptions and applications for financial institutions

Business Model Archetype	Description	Application for Financial Institutions
RegTech	Cloud-based tools that automate regulatory compliance using AI, machine learning, and data analytics.	Helps institutions streamline KYC/AML checks, automate reporting, and reduce regulatory risk through real-time monitoring and compliance workflows.
Fintech CyberSec	Delivers security solutions for threat detection, data protection, and secure user access across digital platforms.	Used by banks and fintechs to secure transactions, protect customer data, detect fraud, and meet cybersecurity regulations.
WealthTech	Offers digital tools for investment management, portfolio analytics, robo-advisory, and client engagement.	Enables asset managers and advisors to provide personalised investment services, automate portfolio rebalancing, and enhance client reporting.
InsurTech	Uses automation and data-driven insights to digitise insurance underwriting, claims processing, and policy management.	Financial institutions offering or partnering with insurers use InsurTech to streamline operations, offer embedded insurance, and enhance customer experience.
RiskTech	Provides analytics and monitoring tools to assess, predict, and manage financial, operational, and compliance risks.	Used to manage credit risk, market volatility, stress testing, and operational risk reporting, especially for regulatory compliance and strategic planning.
AaaS	Offers real-time financial analytics, forecasting, and insights via APIs or dashboards powered by cloud infrastructure.	Supports decision-making in treasury, lending, and investment by providing access to live financial data, scenario modeling, and predictive insights.
IAM	Ensures secure and compliant user authentication and access control, often using biometrics or adaptive risk models.	Enables secure onboarding, transaction authorization, and identity verification for customers and employees across digital channels.
Client-Facing Solutions	AI-driven customer support tools that deliver automated assistance through chat, voice, or integrated digital platforms.	Used to handle client inquiries, streamline onboarding, provide 24/7 support, and offer a unified interface for customer interaction.

Another big financial cloud computing application is payment services, which tend to be offered to merchants and other businesses outside of the financial industry itself. The biggest European fintech by market size is Adyen, with a 43.8 billion USD market capitalisation, operating in this sector (Thompsett, 2023).

Cloud computing capabilities are highly valuable to companies across all sectors. For financial institutions, cloud-based platforms have enhanced revenue generation by enabling the use of customer insights to develop more scalable, market-relevant solutions with faster time-to-market, while also optimising the monetisation of data assets (Deloitte, 2024; Nutalapati, 2024; Sabbani, 2023). Given their central role in society, financial institutions face unique challenges, challenges for which these SaaS solutions may even prove indispensable. Whether this indispensability holds true, and whether it extends to AI within cloud computing, is explored further in Chapter 4.1.3. For now, it is evident that financial institutions are increasingly turning to cloud computing and SaaS solutions to meet rising customer expectations in a market that, by now, encompasses virtually everyone. Banks, lenders, and (pension) funds form the financial backbone of both developed and emerging economies. Beyond achieving scale, they must continuously expand their product and service offerings to remain competitive, adopting smarter solutions in a regulatory landscape that has evolved alongside the very technologies designed to navigate it.

SaaS providers are responding to this complexity by delivering advanced technological solutions, offering strategic advisory services on cloud adoption, and equipping clients, especially those unsure of where to begin, with the necessary tools to succeed. The fundamental mechanics of this business model are illustrated in Figure 3. The figure presents the fintech SaaS business model targeting financial institutions, structured according to the Business Model Canvas (BMC) introduced by Osterwalder and Pigneur (2010). This baseline B2B model outlines the typical partners SaaS providers engage with, the key activities they perform for clients, the resources they depend on to create value, their core value propositions, the types of customer relationships they maintain, the customer segments they serve, the channels through which they communicate and deliver value, and the common cost and revenue structures they operate within.

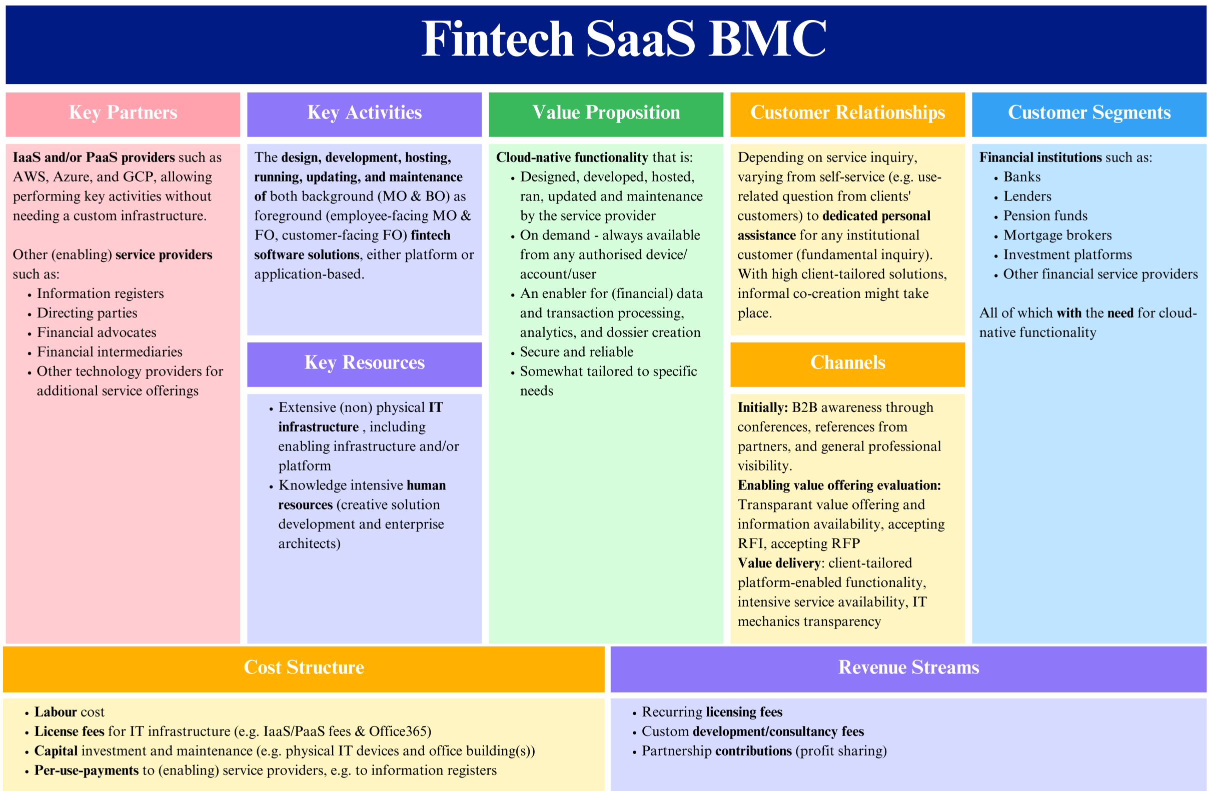

Figure 3: A general fintech SaaS Business Model Canvas, including the most common range of service models within the boundaries abstractly described

2.2.3 The Provider-Client Relationship

The provider-client relationship in B2B environments varies. Often, the extent to which one can speak of an actual relationship depends on the operating model of the SaaS provider and the needs of institutions. In general, when an industry requires customised environments and functionality, the relationship between the stakeholders is tight. Those involved know each other and speak to each other regularly, and maintain this relationship through regular check-ins. Near the end of the technology procurement process, client leads work together with target department representatives to work out the technical and organisational aspects of an intended contract agreement, initiating the professional relationship that these individuals maintain. On the other hand, companies offering standard solutions, or application-based SaaS, have a less tight relationship with their clients. B2B customer service inquiries are usually digital or through fundamental CRM systems. This type of relationship is less common in the world of fintech SaaS for institutional clients. The necessity for more personal, and often tailored, solution development processes is discussed in Chapters 4 and 5.

2.2.4 One Size Fits All?

Although the benefits of cloud computing with SaaS as a delivery method are clear, this does not mean it is the best solution for all organisations. The utility of fintech SaaS solutions depends on organisations' operating models and demand for (third-party) technology. While fintech SaaS could offer a variety of solutions to businesses, the customer segment is defined by its demand for no-headache platform services. Customer segments, listed in Figure 3, include banks, lenders, pension funds, mortgage brokers, investment platforms, and other financial service providers that offer more focused solutions that might run on top of another provider's platform. Within these segments, the utility a SaaS fintech might provide varies. As emphasised by Waters (2005), SaaS is especially beneficial for global enterprises that have low IT resources for the target departments, do not require integration with other applications, have mostly external users, have a low capital budget, medium security needs, and require high velocity of updates. Note that the combination of characteristics of this "ideal target client" is uncommonly combined in the world of financial institutions. For example, financial institutions generally require the highest security measures possible, and global enterprises often have high turnovers and, therefore, high capital budgets. Moreover, institutions with goals that might have geopolitical preferences might have other remarks on SaaS functionality due to the persisting reliance on geographically consolidated cloud computing enablers located in the US. New alternatives are emerging, such as supermarket chain Lidl's owner, Schwartz Digits, offering European cloud solutions, and the EU's efforts to provide a framework for other EU cloud initiatives, called Gaia-X (Horovits, 2024).

2.3 Technology Adoption in Financial Institutions

To effectively examine the factors influencing financial institutions' decision-making regarding the adoption of AI within fintech SaaS solutions, a range of established technology adoption models can be drawn upon. The underlying variables forming the basis of these models might be relevant to formulate a research framework that best facilitates effective and inclusive exploration of decision-making at financial institutions. This section provides an overview of adoption models relevant to AI technologies embedded in enabling infrastructures such as SaaS.

Some technology adoption models are more relevant than others. In this study, the most suitable adoption models have been identified through a search strategy targeting technology adoption or acceptance models on the intersection of AI and fintech. In Appendix B, the search query can be found that aimed to identify recent papers on this combination of topics. This search resulted in twelve relevant papers in which technology adoption models were used to investigate the adoption of AI in finance (among other sectors), or related disruptive and/or enabling technologies such as big data and Internet of Things (IoT) (Akhtar et al., 2024; Alfzari et al., 2025; Andarwati et al., 2025; Elnaggar et al., 2025; Immanuel & Vinitha, 2025; Kelly et al., 2022; Kim et al., 2017; Papathomas et al., 2025; Park & Yoon, 2024; Soon et al., 2016; Vorm & Combs, 2022; Wang et al., 2023).

Out of these twelve studies, eleven used an (extended) version of the Technology Acceptance Model (TAM) as introduced by F. D. Davis (1989). Five used a version of Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), providing product managers with the insights to design technology that is adopted by those with higher risk perceptions. As these models seem to be appropriate for a similar research context, these models will be investigated further to see how they can be used in this study. Other models were Value-based Adoption Model (VAM), Elaboration Likelihood Model (ELM), and a Digital Governance Framework (DGF). Although these models were not highly represented in numbers among the papers, they did demonstrate that a wide variety of models can be used, depending on the characteristics of the unit of analysis. An overview of all of these models is given in Table 4, including the context of the works in which they were featured.

Table 4: Quantification of models used for similar contexts as AI adoption in finance

Papers	TAM	UTAUT(-2)	VAM	ELM	DGF	Study Context
Akhtar et al. (2024)	✓					FinTech adoption by students, focusing on AI familiarity, gov. support, and innovativeness.
Alfzari et al. (2025)	✓				✓	AI adoption in portfolio management, with digital governance as a moderator.
Andarwati et al. (2025)	✓	✓				Adoption of AI-based Islamic fintech (E-Mudharabah) by MSMEs.
Elnaggar et al. (2025)	✓					AI use in Egyptian banks, focus on user attitudes and benefits.
Immanuel and Vinitha (2025)	✓					Ethical concerns and trust in AI-based investment decision-making.
Kelly et al. (2022)	✓	✓				Adoption of AI in health and consumer tech using extended UTAUT2 (trust, optimism, etc.).
Kim et al. (2017)		✓	✓	✓		Smart home IoT adoption, combining usability, value, and persuasion models.
Papathomas et al. (2025)	✓	✓				AI adoption in investment management in Greece; focus on stakeholder perceptions.
Park and Yoon (2024)	✓		✓			Retail investor trust in AI-generated robo-advice; focus on transparency and value.
Soon et al. (2016)	✓	✓				FinTech adoption in Southeast Asia; combines trust, UTAUT constructs, and usability.
Vorm and Combs (2022)	✓					North American wealth managers adopting AI; focus on TAM and trust.
Wang et al. (2023)	✓					Generative AI adoption in investment; perceived transparency and usefulness.

It should be emphasised that these models are typically employed in quantitative (causal) research, where independent variables are strictly defined as measurable constructs, and their effect on a dependent variable is empirically tested. In the context of this study, however, the variables from these models serve a different function: they act as a starting point for exploring a broader range of factors that currently challenge decision-making processes and outcomes in financial institutions. The goal is not to test the validity or applicability of these models in the specific context of AI in fintech SaaS, but rather to use them as conceptual tools for structuring inquiry.

A closer examination of the models reveals considerable overlap, with many studies adapting them to their specific contexts. Combined or extended versions of these frameworks are more common than strictly applying a single model. The TAM proposes that two factors, namely the perceived usefulness and perceived ease of use, determine one's intention to use a technology (F. D. Davis, 1989). The developers of the model already foreshadow that these factors are influenced by other factors depending on the situation in which they are applied. However, the model's main objective remains to explain innovative behaviour in terms of the intention to, and actual use of an innovative technology, such as AI (Elnaggar et al., 2025). Moreover, F. D. Davis (1989) emphasises that the attitude of those who will interact with a potential disruption is a critical determinant of the extent to which they will 'engage' with it. Therefore, the TAM will allow for to creation of understanding on how the characteristics of stakeholders in financial institutions' technology procurement decision-making affect its outcomes. In line with Davis' expectations of the application of his model, Immanuel and Vinitha (2025) extend the TAM, including ethical concerns and social norms in the model, for their study on AI adoption within investment management and recommendations on how to build sound AI systems on all fronts. Akhtar et al. (2024) do something similar, by looking at individuals' innovativeness and technical knowledge as well as government support and their effect on the use of AI-powered fintech offerings by student populations. Note that in this current study, the act of "using" a technology is included in the definition of "adoption". The formal definition of "AI adoption" can be found in Appendix A. Alfzari et al. (2025) use both TAM as a digital governance framework, emphasising the rudimentary role of digital governance to effectively reap the benefits of AI in finance. The need for context-specific additions to TAM is nicely encompassed by Andarwati et al. (2025), which found that facilitating conditions and social influence are other topics with major effects on use and acceptance of AI-driven solutions in finance. For their research on AI-driven Islamic finance platforms for micro, small, and medium enterprises (MSMEs), they found that these two factors, borrowed from the UTAUT model, were crucial in explaining variance.

UTAUT is a combination of TAM and other theoretical models that addresses acceptance on the institutional level (Venkatesh et al., 2003). It focuses on information systems and behaviour leading to their use by both individuals and organisations within them. Along with TAM's PU and PEOU, social norms and facilitating conditions are factored in by this model to look at what impacts decision-makers' adoption behaviour (Andarwati et al., 2025; Immanuel & Vinitha, 2025; Soon et al., 2016; Venkatesh et al., 2003). Social influence could entail the perceptions of adoption actions by significant others, on both a personal and professional level. Facilitating conditions are often measured through addressing current and future availability of organisational and personal support during the adoption and respective use of a technology (Kelly et al., 2022; Venkatesh et al., 2003). In the context of AI-powered tools from fintech SaaS firms, these variables might translate into exploring external pressure when looking at institutional interest for AI, and the adoption decisions that are the result. Moreover, the addition of the notions of UTAUT allows for initiating a reflection of financial institutions on the support that might enable mutual value exchange in their (potential) relationship with SaaS providers and more effective adoption of AI tools.

Therefore, elements from TAM and UTAUT will be drawn upon. Moreover, the EU's regulatory landscape poses specific challenges for all involved with AI and (social) banking. Therefore, the role of (digital) governance should be a topic of inquiry. It is also worth noting that these models are applied across both institutional and consumer adoption contexts. This study focuses on the organisational level, particularly on individuals within financial institutions who are involved in technology procurement decisions. While not the primary focus, the influence of stakeholder characteristics—especially those of decision-makers—on organisational outcomes is a topic of interest. One might ask to what extent the traits or perspectives of individuals involved in procurement shape the adoption decision, in combination with model-based variables. Since both models have been applied to both organisational and individual perceptions of AI adoption, they provide a flexible foundation for addressing the various angles this study may encompass.

Looking ahead, these traditional adoption models from the literature should be–as seen in most, if not all, similar cases discussed–extended with even more study-specific areas of interest. Perhaps this is even more important in exploratory research, as there is no measurable construct that shows to what extent the variance in financial institutions' adoption decisions is caused by unknown variables. In Chapter 2.5, additional important considerations are explained.

2.4 Conceptual Gaps in Existing Research

While a growing body of literature addresses the increasing relevance of AI and SaaS in financial services, critical conceptual and empirical gaps persist, particularly concerning the synergistic interplay between these technologies and real-world adoption by financial institutions. Existing studies often take a technology-centric stance, emphasising the capabilities of AI or the operational efficiencies of SaaS independently (Chen et al., 2018; García-Fernández et al., 2024; Ionescu & Diaconita, 2023). However, few studies adequately examine the intersection of both technologies, i.e. fintech SaaS platforms augmented by AI functionality, through the lens of institutional decision-makers.

Despite the widespread belief that cloud computing is the foundation of the financial industry's future and that AI will play a transformative role, how decision-makers within financial institutions perceive and prioritise these technologies remains underexplored. Although AI tooling built into SaaS infrastructures appears promising, the "low-hanging fruit" versus more advanced AI functionalities remain undefined in practice. In many cases, SaaS adoption is studied as a general trend, and AI as a technological innovation, without adequately addressing the challenges or opportunities that emerge when these are bundled in real-world B2B environments.

Three major shortcomings can be identified in the existing literature. Firstly, there is limited empirical insight into real-world decision-making. Research very rarely investigates the actual perspectives of institutional stakeholders who make technology procurement decisions. As noted by Mahalle et al. (2021), an understanding of stakeholder-specific dynamics, including those of project managers, IT strategists, and regulatory teams, is crucial for understanding context-specific barriers. Secondly, there seems to be an overemphasis on technological potential over practical implementation. While studies showcase the theoretical benefits of AI and cloud infrastructure very well, they often neglect to explore adoption constraints in operational, regulatory, and legacy systems contexts. For example, while AI-enabled automation and data analytics are widely praised, implementation is slow with trust issues, security concerns, and governance complexities persisting, according to Rahman et al. (2021). Finally, there is insufficient attention to synergistic dynamics. Very little research explores how SaaS design choices and AI capabilities interact with institutional structures and constraints. Misra and Doneria (2018) argue that understanding these technologies through a synergistic and symbiotic lens is essential to grasp the business value they can bring. However, such an integrative perspective is largely missing in fintech-specific studies.

This study acknowledges that it investigates two interrelated but distinct technologies: AI and SaaS. While the modern version that we know now of each of these technologies has been the subject of individual research streams since the early 2000s (Oliveira & Figueiredo, 2023; Qian et al., 2009), combining the two introduces new complexities. Most notably, the value of AI functionalities often depends on cloud infrastructure, which enables scalable computing and the processing of vast datasets. These capabilities are essential requirements for AI applications such as fraud detection, credit scoring, and personalised financial insights. However, this coupling introduces challenges beyond technical components. Financial institutions must navigate through a system in which reputational, regulatory, and operational implications of outsourcing AI-powered solutions to external cloud-based providers are necessary to meet customer demand. In Europe, where regulatory oversight is particularly strong, concerns about data sovereignty, explainability, and third-party risk are especially notable.

The literature rarely reflects on the perspectives of those who are most influential in technology adoption decisions: mid-to-senior-level stakeholders in IT, strategy, compliance, and innovation functions within financial institutions. These individuals assess not only the technological readiness of a solution but also its organisational compatibility, regulatory feasibility, and strategic fit. Furthermore, as highlighted by Rahman et al. (2021), the evolving nature of AI technologies and the accompanying shifts in their definitions mean that institutional perceptions are dynamic and context-specific.

This study contributes by re-evaluating these perceptions in light of current technological maturity and other factors influencing the European fintech landscape. It also seeks to uncover how providers can prioritise the design of their offerings and engage in collaborative mechanisms to improve adoption rates and support sustainable client growth.

2.5 Research Framework

In this section, the research framework will be described that is used to guide the exploration of what drives financial institutions to consider AI-powered tools from SaaS providers, what challenges they face in their decision-making, and what SaaS providers can do to enable (more effective) adoption of their service offerings. In Chapter 2.1, AI's rise in financial services has been described, showcasing its potential for financial institutions. Chapter 2.2 complemented this by showcasing a similar growing trajectory of importance for cloud computing. The research framework is aimed at guiding the exploration of where these technologies meet in the context that is the fintech SaaS provider and institutional customer relationship. It will address the three subquestions by combining traditional technology adoption models with context-specific considerations surrounding the fintech SaaS business model.

As outlined in Chapters 2.1 and 2.2, the initial interest of financial institutions in AI-powered tools seems to stem from a combination of technological opportunity and strategic necessity. AI offers solutions to long-standing operational inefficiencies while enabling new forms of value creation. When accessed through flexible SaaS infrastructures, these tools should become more accessible, scalable, and aligned with evolving industry demands, making them an attractive proposition for institutions seeking to innovate while managing risk and complexity. Concerning this first subquestion, the aim is to verify and expand these high-level thoughts, and really explore what is considered to be the most obvious applications of AI-powered tools in fintech SaaS to adopt for financial institutions, and discuss other factors other than technological potential and value that drive adoption intentions.

An interesting framework capturing strategic innovation initiatives is the idea by Howell-Barber et al. (2013) in which they express that financial firms must consider business, procedural, and technical factors when formulating a cloud computing SaaS strategy. As this current study focuses on AI integrated within cloud-based fintech infrastructures, AI can be understood as a technical component within a broader SaaS strategy. Consequently, strategic considerations and their relationship to initial interests in AI, along with the challenges they face in deploying it strategically and how this prescribes priorities for SaaS providers and other mitigation strategies, form the research framework that guides this exploratory study.

Reflecting on the traditional models discussed in Chapter 2.3, TAM, UTAUT, and the DGF will be essential for studying the adoption of and challenges with fintech SaaS AI offerings. With TAM, perspectives on the technical usability of AI-powered tools and their effect on perceptions shaping decisions can be explored. Moreover, the highly recognised framework by F. D. Davis (1989) allows for explaining how innovative behaviour leads to adoption. With the additional pillars from UTAUT, the institutional perspective, including external professional and individual pressure, and a wide variety of facilitating conditions and service elements, will enrich these findings and should link the individual's characteristics to their effects on decision-making on the organisational level. Finally, the regulatory framework, a topic outlined in multiple sections already, is known to be an important disabler of accelerated adoption of AI in the EU, and should therefore be a topic of further exploration within the specific context of this study.

Howell-Barber et al.'s framework specifies a wide variety of factors that the operating model of financial firms commonly includes (Howell-Barber et al., 2013). Regarding the technological aspects, the general question of whether or not to develop cloud computing (CC) AI capability in-house or enable it through third-party SaaS providers is at hand (Ionescu & Diaconita, 2023; Rahman et al., 2021). Moreover, other operational considerations for SaaS applications are included here, e.g. the deployment of AI tools in FO, MO, and/or BO processes (Choithani et al., 2022; Durães et al., 2023; Holdsworth & Scapicchio, 2025; Joshi, 2025; Keller et al., 2023; Magrani & Da Silva, 2023; Noreen et al., 2023; Oliveira &

Figueiredo, 2023; Sarker, 2021; Trancoso et al., 2023). The question of whether or not the tools will interact with and by whom is included (Mucci, 2024). For this study, factors from TAM and UTAUT are also considered under the technological dimension. Perceptions and user intentions surrounding the technology might lead to fundamental insights (F. D. Davis, 1989; Lazo & Ebardo, 2023; Sengupta & Srivastava, 2020), as well as technosocial and facilitating conditions in the organisation (Andarwati et al., 2025; Venkatesh et al., 2003). The business pillar encompasses competitive (Almansour, 2022; Ma, 2007; Waters, 2005), financial (Dan & Guo, 2018; Fong et al., 2021; Misra & Doneria, 2018; Park & Yoon, 2024; Sabbani, 2023), and executive aspects of adoption intentions, challenges, and mitigation strategies. Moreover, the external and trendiness of the technology should be included here, such as the AI hype and customer demand (Bayram et al., 2022; Fox & Collins, 2025; Irimia-Diéguez et al., 2023; Lee & Chen, 2022; Rahman et al., 2021). Thirdly, the procedural pillar includes procurement, knowledge (Glabiszewski & Zastempowski, 2017), and supplier relationship management (Lazo & Ebardo, 2023) and their implications for the decision-making process. Finally, all of these strategic dimensions must be compliant with the boundaries of the technological ecosystems they aim to conquer (Alfzari et al., 2025; Joseph, 2025; Lazo & Ebardo, 2023; Mahalle et al., 2021; Mangold, 2022), and will therefore be seen as a fundamental area of investigation and data collection. In Figure 4, the research framework is visualised.

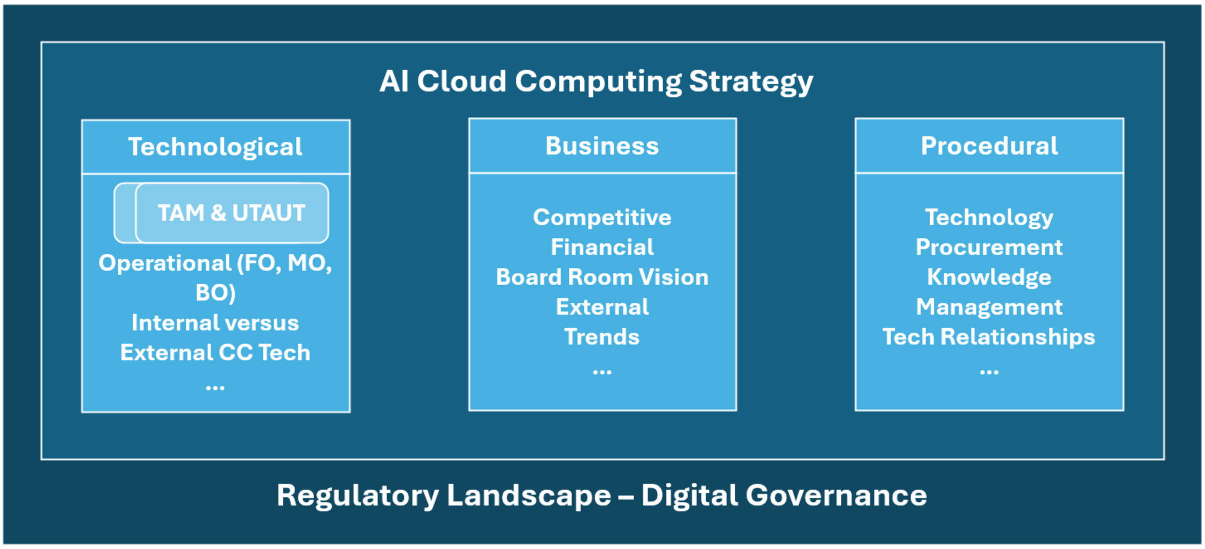

Figure 4: Research framework to guide exploratory data collection, including the strategic pillars for financial firms' cloud computing strategy by Howell-Barber et al. (2013), TAM by F. D. Davis (1989), and UTAUT by Venkatesh et al. (2003), to explore AI adoption decisions through fintech SaaS solutions by financial institutions

In Chapter 3.2, it is shown how all these elements have been integrated into the design of the data collection methods of this study.

3 Research Methodology

3.1 Research Design

The objective of this study was to deepen the understanding of AI adoption in fintech SaaS by identifying and addressing the factors that influence financial institutions' decisions to adopt or reject AI-powered tooling from SaaS providers. Current research does not cover the specific societal context of financial institutions and how it affects the adoption of disruptive AI functionality in cloud computing in their operations.

This study adopted a qualitative research design to explore financial institutions' AI-driven fintech SaaS technology procurement decisions. These services are offered by SaaS providers offering financial cloud computing solutions to institutional customers. Given the limited prior research and the need to develop an in-depth understanding of nuanced interactions between SaaS providers and their clients, a flexible, exploratory approach was employed. This research strategy aligned with the study's objective, which sought to generate a comprehensive understanding of strategic technological, business, and procedural factors within the European regulatory landscape shaping AI adoption in the fintech sector. The qualitative nature of this study allowed for rich data collection and the identification of emergent themes that quantitative approaches may have overlooked.

While qualitative research formed the primary foundation of this study, different research strategies were combined, and a mixed-method approach was used to enable a comprehensive and rigorous examination of the research questions and to enhance data triangulation. The research strategies that were expected to encapsulate AI adoption within the fintech sector most effectively were ethnography and grounded theory. With these research strategies, interference in the routine functioning of the system was unnecessary. The research was conducted in a natural and non-contrived setting with minimal interference with the normal flow of events. The unit of analysis of this study was organisations, as AI adoption decisions on the organisational level were sought to be examined. Note that the study was of a cross-sectional nature. All data have been gathered over a few weeks, and no change over time was measured or part of the research objective.

3.2 Data Collection

Firstly, observational methods and ethnographic elements were integrated. As the research was conducted at a SaaS provider, insights could be gained through real-life interactions with both internal developers of AI tools and clients. The collection of this data occurred informally, creating context regarding the operating model of a typical SaaS provider offering a core banking platform. Especially gathering insights in the organisational structure, technology-driven culture, and collaborative ecosystem in which providers and clients operate, proved to be a foundational step. It formed the basis of defining an average business model of fintech SaaS and guided the design of the literature review and interview scripts. Moreover, the ideas of those involved at the SaaS provider on the underlying causes of restrained adoption guided the initial deployment and design of these two data collection methods. Note that constant reflection on the generalisability of these observational insights was needed to mitigate potential bias that exists within the specific context of the SaaS provider where the research was conducted. The findings were cross-referenced with other information sources, and the information acquired was pragmatically evaluated. Differences in technology perceptions among SaaS providers were apparent, but the boundaries within which they operate were found to be similar.

To put findings into a broader literary perspective, the context-specific findings of aspects influencing financial institutions' decision-making concerning AI-powered tools in fintech SaaS were compared with literature on AI in the world of finance, cloud computing, and AI adoption. The search strategy for this literature review can be found in Appendix B. Moreover, synthesis of the literature allowed for potential context-specific insights to be cross-referenced in interviews. Therefore, the results presented in Chapter 4 contain a lot of insights from literature that also came up in the interviews. Combining these two sources of input formed the basis for rich, contextual insights in fintech SaaS AI tools among financial institutions.

Primary data were collected through semi-structured interviews with both representatives at service providers and financial institutions. The interviews were designed to explore what aspects drive financial institutions to look at AI-powered solutions and where they see the most potential for value creation and organisation-wide improvements. Moreover, key challenges that play a decisive role in the decision-making processes were explored. Finally, strategies to address the most pressing and impactful challenges were sought after. The interview script was designed according to the research framework schematically shown in Chapter 2.5 Figure 4. The interviews were divided into three sections, each of which was aimed at answering one of the sub-questions and allowed for an open conversation about topics surrounding that line of inquiry. The three main topics discussed were funnelled to collect as much information as possible, starting with broader open questions, and asking for specific value propositions, challenges, and risk mitigation strategies according to the concepts from TAM, UTAUT, and the overarching strategic dimensions formulated in the research framework. This order of questioning ensured that no suggestions were given initially to avoid a leading train-of-thought bias. As interview participants from two sides of the fintech SaaS provider-client relationship were sought, two versions of a similar interview script were used. These scripts differed in the formulation of the questions, but essentially targeted to collect the same information from two different perspectives. The interview script for financial institutions is found in Appendix C, where the questions, potential follow-up questions and other probing questions are shown. Moreover, each question showcases which aspect of the research framework it is targeted to cover. However, note that this was the initial script, which served to find topics of interest according to the direction of the answers provided the the open questions. The script is quite short for the third part on strategies to deal with the challenges to improve adoption. However, the section discussing them contains a lot of insights regardless, through a conversation initiated based on the questions and some probing.

Throughout conducting interviews, topics emerged that were not specifically anticipated, nor received attention from scholars. These topics, ranging from the futureproofness of AI solutions and the SaaS business model as we know it to the question of whether AI is indispensable and worth the hype in finance, inspired the design of the findings section, and especially the implications section. The beauty of exploratory research is that emerging topics, even when they can be considered as fundamental in hindsight, only emerge when asking open-ended questions in a conversation-style interview. The notion that participating in this study meant that one was in for an interesting conversation was something that was emphasised when contacting interview prospects. Moreover, it is pivotal to explore these topics further when they seemingly play a role in real-world considerations.

3.3 Participant Selection

AI adoption in financial institutions is an emerging topic. Both sides of the SaaS provider-client relationship have their own perspectives on AI as a technology, competency, and as a strategic asset that is either bought from a vendor or built in-house. To understand the process from initial interest to the initiative to build a competency for whichever reason, and the challenges that eventually lead to adoption or rejection, interview participants from both SaaS providers and institutional customers were sought. Moreover, with many other involved parties that influence the messaging and strategic approach to AI technology in finance, professionals from related company types were also included in the search. This study aimed to achieve a sample size range of 9-17 formal participants, as this is commonly sufficient for narrowly defined research topics and relatively homogenous populations (Hennink & Kaiser, 2021), both of which were true for this research. 15 people have been interviewed at the end. The responses were found to converge at around 11 interviews. However, due to the diverse backgrounds of all participants, from three different levels of involvement, this number would be lower if the participants had been part of a homogenous group, e.g. only those working at banks.

Participants were mostly sought through LinkedIn. The logical search functionality of LinkedIn allowed for targeted searches for banking professionals and others with relevant and related job descriptions. The initial search focused on looking for procurement-related job descriptions at financial institutions. However, those working in procurement often do not carry that in their title. In hindsight, it became clear that procurement is often just one part of their responsibilities. Others, around 20, were approached through email, but returned no responses if not introduced through someone else. 4 participants were found through the facilitating company. In total, 134 individuals were approached, resulting in 15 interviewees. The response rate was therefore approximately 11.9%.

For all participants, recent experience in finance was a must. Although involvement with AI in previous or current roles was not deemed a must to participate in the interview, all participants had had some form of experience with adopting AI within their current or former employer, 11 of which were actively involved with AI, or had AI in their job title. An overview of interview participants is found in Table 5.

Table 5: Overview of interviewees

Participant ID	Company Type	Role
P1	Technology Firm	Risk & Compliance Officer
P2	SaaS Provider	Sales Engineer
P3	Banking Association	Executive
P4	Consultancy Firm	Researcher
P5	Bank	IT Engineer
P6	Consultancy Firm	AI Consultant
P7	Bank	Executive
P8	SaaS Provider	Sales
P9	SaaS Provider	IT Architect
P10	SaaS Provider	AI Architect
P11	Bank	IT Engineer
P12	Consultancy Firm	AI Consultant
P13	Financial Institution	Project Manager
P14	Bank	IT Engineer
P15	Bank	Data Scientist

It was found limiting to be an intern at a SaaS provider when looking for participants working for (in)direct competitors. Although the facilitating company does not have AI as a core offering, people working at similar firms are reluctant to share anything development-related. Of course, it was explicitly mentioned that the insights will and would only be used for academic purposes, but concerns remained, leading to 5 explicit no's.

3.4 Data Analysis

This study employed thematic analysis methodology to synthesise the qualitative data collection through the interviews. The Gioia method was used as a reference for this analysis, which is aimed at enabling inductive theory building. In other words, letting concepts and theoretical insights emerge from the data, rather than testing existing theories (Gioia et al., 2012). To organise the interview transcripts and allow for systematic and interactive coding, in which all the steps could be reproduced and revised continuously, ATLAS.TI software was used. Moreover, this software was used to create initial visualisations and allow for idea generation on insightful figures to represent the qualitative data quantitatively. Before the coding process, all the recordings were compared to the transcripts to make sure the correct words were captured by the automated transcript generator of MS Teams. Moreover, this allowed for familiarisation with the data and taking notes of initial thoughts.

The initial coding stage involved closely capturing the summative essence of participant responses with first-order concepts, and placing them under the relevant subquestion as formulated in Chapter 1.3. According to the Gioia method, these codes were kept close to the words and meanings of the participants, maintaining a participant-centric view. This led to a very comprehensive list of concepts. However, repeated mentions of similar notions were not counted multiple times when they reflected an emphasis on an earlier point. Only when a similar notion was mentioned in the answer to a different question, aiming to retrieve similar information, was it counted again, given that the notion was introduced within a relatively different context. This way, overrepresentation of notions due to participants' conversational style was minimised. Finding the sweet spot for this initial coding phase took some effort and iterations, and a balance between capturing the participant-centric essence and avoiding repetitiveness was essayed.

Sometimes, the boundary between concepts throughout the study's three central subquestions was blurry. For example, when discussing AI's initial appeal as a technology for financial institutions, or a lack thereof, could also be represented by formulating it as an adoption challenge. Moreover, adoption challenges often imply connected mitigation strategies, without participants having to mention them explicitly. For example, when a participant mentions prerequisites that tend not to be met during a technology procurement orientation, on one hand, a code could be generated capturing the challenge of prerequisites not being met, or poorly communicated, and on the other hand, a code could be generated reciting prerequisites that simply have to be met, or have to be made a priority by SaaS providers. Often, the notion was only marked as either one of those, depending on the type of information actually addressing the question at hand.

During the second-order coding phase, the concepts were analysed and patterns between codes were identified to create sub-themes, or categories, among the comprehensive list of quotations and their codes. During this phase, the participants' wording was let go to some extent. During this phase, theoretical insights started to emerge. During this phase, connections between the answers and phases in institutional decision-making became apparent. It was realised that a distinction had to be made between initial interest in AI as a technology and AI solutions with a cloud-native SaaS delivery system to operationalise the study's findings. Therefore, the chapter on the initial interests of AI ends with a distinction between AI's appeal and the question of whether or not functionality should be built in-house or should be licensed-in, putting this study's primary focus into broader institutional decision-making-related perspective within the world of this study's primary focus: AI-powered tools within the SaaS business model.

Finally, higher-level aggregate dimensions, or themes, were sought, forming the theoretical building blocks that collectively create the narrative necessary to answer the main exploratory research question. Ultimately, 13 themes consisting of 43 categories were found, grounded with 961 segments of text to which an initial code was assigned. In Chapter 4, these 961 distinct segments, assigned to a code category, are expressed throughout the Figures 6, 8, and 9, both in terms of category counts as a percentage, showcasing the distribution of the category within the theme. These numbers were obtained through an exported MS Excel sheet from ATLAS.TI, that automatically tracks and displays how often codes and the categories in which the researcher places them are mentioned to facilitate quantitative representation of qualitative findings. Almost half of all the useful aspects mentioned throughout the interviews were adoption challenges, emphasising the troubled nature of AI SaaS adoption within the world of finance.

As discussed in Chapter 3.2, the data from interviews has constantly been compared with insights from overarching concepts from the literature. Apart from cross-referencing context-specific insights that correspond with and confirm theories from either AI technology and/or cloud computing, it also sheds light on some topics that were claimed to be relevant in literature, but were not mentioned in the interviews. A few of these mismatches between theory and reality are highlighted in Chapter 4. Note that missing concepts from the interviews do not imply that the findings from the literature are not valid. It could also be a sign of incomplete interview design or biased questions and/or interview design. Perhaps participants would have confirmed the involvement of specific factors if explicitly asked. That said, exploring these unsupported topics provides a different angle of thinking, and also showcases actual factors influencing decision-making over factors that are often signalled by institutions.

On the other hand, topics that were not explicitly sought after came up during data collection. These

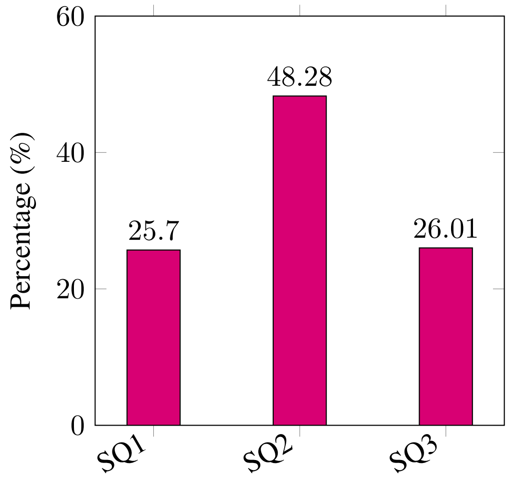

Figure 5: Distribution of qualitative data across the study's subquestions

sections were not coded following the same procedures discussed above. However, they were added to a non-subquestion-related folder, so that the discussions could be conveniently found later. The emerging topics were then linked to relevant themes and discussed in corresponding sections to provide an enriching contextual discussion, or were discussed separately in Chapter 5.

In general, the findings are represented according to the best practices described by Gioia et al. (2012). Following a clear write-up of the methodology of the coding process and a quantification of the qualitative data, the authors prescribe to condense data without omitting it. To do so, the range, depth and diversity of the data will be represented by illustrative quotes. These codes will not exclusively showcase the most common response, but will also capture variation and authenticity of notions brought up by participants (Gioia et al., 2012).

Moreover, to enrich the interpretation of the empirical findings, this study draws on the functions of the innovation systems framework by Hekkert et al. (2006). This framework identifies seven key functions that must be fulfilled for an innovation system to evolve and succeed: (1) Entrepreneurial Activities, (2) Knowledge Development, (3) Knowledge Diffusion through Networks, (4) Guidance of the Search, (5) Market Formation, (6) Resource Mobilization, and (7) Creation of Legitimacy. These functions capture the dynamic processes that underpin the emergence and scaling of innovations such as AI-powered tools in fintech SaaS. By relating themes that emerged from interviews to these system functions, the study contextualises individual observations within broader systemic innovation dynamics. This functional perspective supports a more robust explanation of how the fintech SaaS ecosystem influences and is influenced by AI adoption within financial institutions. References to these functions will be integrated throughout Chapter 4 to connect relevant empirical insights to their corresponding systemic function.

4 Findings

In this Chapter, the study's findings are presented in three sections, corresponding with the three central research questions that aim to collectively address the factors influencing institutional decision-making, resulting in either acceptance or rejection of a provider's offering, concerning AI-powered tools in fintech SaaS.

4.1 Initial Attraction

Answering the first research question, financial institutions initially become interested in AI-powered tools from SaaS providers due to their applications, the potential operational benefits they entail, and external and strategic pressure, accounting for 42.51%, 27.13%, and 23.48% of aspects brought up when asking about AI's appeal in financial institutions, respectively. An emerging topic was the incentives to outsource AI functionality to SaaS providers, specifically, bridging the gap between the interest in the technology and the initiative to take the next step towards considering AI technology from a SaaS company. This topic accounted for 6.88% of the factors mentioned. Figure 6 provides an overview of the categories (or topics) that make up these four themes and gives an idea of how often they were mentioned in the interviews, each of which will be discussed in the following sections.

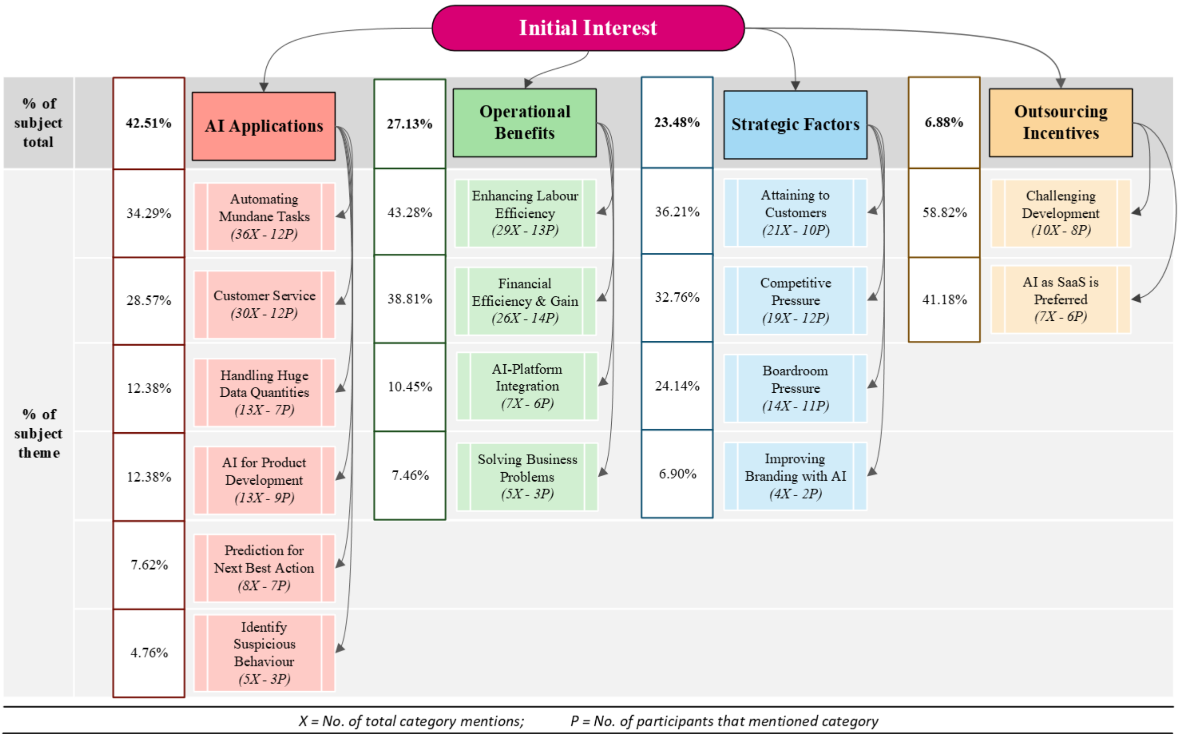

Figure 6: Categorisation and quantification of factors sparking initial interest in fintech SaaS AI at financial institutions

4.1.1 Interest in AI Applications

As outlined in Chapter 2.1, financial institutions are initially drawn to AI-powered tools due to their transformative potential across various operational and strategic domains. AI offers powerful capabilities, including automation, predictive analysis, natural language processing, and real-time decision-making. 14/15 of this study's participants recognised and emphasised AI's potential for financial institutions, through mentioning applications of AI. These applications varied from automating current operations to applying AI in new product and service offerings to institutions' clients. "I think the most value comes in more innovative applications" (P1). "And now you see that we're building a lot more really AI-centric products where [...], we're taking them as the core of a problem solution" (P5).

However, the majority of participants noted that **automating mundane tasks**, such as administrative tasks ranging from document-driven loan application evaluation to customer due diligence. Moreover, non-industry-specific applications, such as human resource management and website optimisation, were also mentioned. ”financial services [...] attract a lot of paperwork and documentation internally and externally, and that is quite a cumbersome process, which is not only time consuming but also error prone [...] that is something that everybody wants to get rid of” (P7).

AI’s appeal extends to the realm of **customer service**, where it can offer highly available and more personalised customer service through chatbots and proactive financial suggestions. ”We have a chatbot on our website [...] that is also GenAI powered and that one just gives much better results and a much higher degree of resolution for the customer than the other chatbot that was still built in the old-fashioned way” (P11). This notion is echoed by Joshi (2025), Keller et al. (2023), and Oliveira and Figueiredo (2023), signalling an increased customer support and interaction through chatbots and virtual assistants powered by LLMs and GenAI. An interesting concept mentioned by three participants from both SaaS providers, as a financial institution, was the one-stop shop. This AI-powered client-facing service, targeted at unburdening those with more complex needs, financial situations, or with active debt, acts as a single point of contact instead of having to deal with all involved parties separately. I.e., it is aimed at ”bundling companies that deal with a specific service provision. One request, for all counters” (P13).

Generally, AI can facilitate the **processing and analysis of huge quantities of data** and cross-referencing information from one data flow with another. ”If we ever connect it all, it’s going to be with AI in between, because you need something that can do that orchestration dynamically, because a customer request never comes in as a one-dimensional thing” (P5). The relevance of this capability is pointed out by Choithani et al. (2022), Holdsworth and Scapicchio (2025), and Oliveira and Figueiredo (2023), who emphasise that financial institutions rely on data-intensive operations such as credit risk evaluation, fraud detection, customer segmentation, and investment forecasting for which AI tools, particularly those utilising ML and DL, enable faster, more accurate insights than traditional methods. Another strength of AI is that it can be leveraged to transform huge streams of raw data into system-compatible formats to use for further analysis. ”The ability to convert unstructured data into structured data at scale and in a cost-effective way [...] is absolutely the biggest [...] opportunity, because with an extreme amount of processes at a bank, it just comes down to unstructured data” (P14).

AI can also be used for **improving new products and services during their development**. ”So it also teaches us to look carefully at how we call things and how we have labelled things and so on. So, apart from the fact that we might generate code, we learn a lot by exploring applications and assessing our work. And it will take our deliverables to a higher level” (P3). These insights reflect Function 2 (Knowledge Development), as institutions engage in learning-by-doing and experimentation with AI functionalities to enhance service outcomes (Hekkert et al., 2006). Other new products and services are based on improved KYCinsights and often extract their value from hyperpersonalisation throughout financial products for customers.

As mentioned before, **prediction models**, often based on ML and DL, **allow for formulating the next best action** in a variety of operations at financial institutions. ”I think their gain lies primarily in predictability: can you predict what the price is going to do? Can you predict what your mortgage is going to do? Can you predict what your payment status is going to be? What is the risk that you will ever default? Are you on a path that is profitable for them?” (P2). Moreover, prediction models can be used to anticipate transactional capacity during holidays. ”So what they did is see if they could create an AI model that could predict the peak at Easter, so that they could scale their infrastructure hardware to meet that amount of transactions” (P4).

Finally, the possibility of **using AI for AML and cybersecurity** was a topic of discussion. More specifically, AI could be used to find suspicious patterns in transactional data. Another use case is ”an AI that can read, understand, and interpret security findings” (P2). According to the most recent research, AI is essential for fraud detection and prevention of risk in banking (Rahman et al., 2021). Although this category does not consist of an overwhelming amount of total mentions, it does outline a pattern between this section discussing AI's value-adding potential, and the AI adoption challenges in Chapter 4.2: some concerns regarding AI technology could, in theory, be resolved with AI. Admittedly, this could result in a downward spiral of reluctance to tackle any challenge surrounding AI. One clear thing is that AI's applications have a huge potential to shape the future of automation at financial institutions, and that they are in fact on their radars.

4.1.2 Operational Benefits through AI Adoption

According to Chen et al. (2018), Deloitte (2024), Fong et al. (2021), Ionescu and Diaconita (2023), and Lazo and Ebardo (2023), adopting AI functionalities aligns with the core objectives of financial institutions: improving efficiency, reducing costs, enhancing customer experiences, and maintaining a competitive edge in a rapidly digitising market. The first two of these core objectives can be considered operational benefits and correspond with the most significant operational factors mentioned by participants that drive AI's appeal.

Labour efficiency has two sides: lowering total full-time employees (FTEs) by replacing the workforce with AI-powered systems and augmenting employees so that they can handle more work than before. "Yes, repetitive tasks. Those will be replaced. It is also true that AI agents will never take over 100% of your work, but it will ensure that you can do your work 4 times, 400% more efficiently" (P9). Many participants recognised the hybrid approach to AI and its effect on labour efficiency, where some activities could be fully replaced by AI entities, such as administrative tasks, while other tasks still needed humans as the primary case officer, leveraging AI to go through steps more effectively. "I can imagine that it can help people enormously to remove those boring tasks from their work, as they are already overflowing" (P15). In any case, time savings are certain once AI is implemented and put to work. The impact of AI on future workforce distribution at financial institutions is discussed in Chapter 5.3.2. Another angle to improving the efficiency of the workforce is when introducing a chatbot that can answer low complexity questions, an employee can spend more time on complex service requests, enhancing service quality for some, while effectively answering questions of others needing less attention.

Of course, labour efficiency and cost efficiency go hand in hand. Therefore, the second most mentioned operational benefit is **financial efficiency and gain** from adopting AI-powered SaaS solutions. On one hand, generating more earnings from, for example from new products and services and from improved revenue streams from investments, was mentioned by participants. "Extensions of that are, of course, commercial opportunities, so can we drive revenue? Can we drive fees?" (P5). "A lot of people are reaching out from the tech companies to talk about AI, and how we can actually install some of their models or pipelines into the financial services space to build revenue for them" (P7). Moreover, AI-enabled marketing research allows for more effective campaigns to increase return on ad spend (ROAS) through AI-powered AB testing, mentioned by P4 and P12. Note that this AI functionality is not unique for financial institutions, but has been increasingly deployed for personalising marketing efforts in financial services (Mozier, 2025). On the other hand, current costs can be saved by employing some of the low-hanging fruits in the world of AI that increase the efficiency of employees, such as Microsoft Copilot. "We just think that we can save a lot of money by applying this technology. [...] We can reorganise a lot of processes with this, optimise them or just completely transform them" (P11). Moreover, AI within a cloud native infrastructure can help financial institutions prepare for an increased number of financial transactions, keeping up with the growing demand for digital financial services (Fox & Collins, 2025; Irimia-Diéguez et al., 2023). "I think most of the use cases [...] make sure that tomorrow when we grow, we should not have to grow in our support or operations department accordingly. So we can still keep up with our current cost base" (P7).

Six participants explicitly mentioned that **AI technology being embedded into SaaS platforms** is what adds additional value. "The fact that it all fits together and [...] is focused on exactly what a certain group of customers wants, that is added value in my opinion" (P10). This notion includes streamlining

MO processes and backlog optimisation. Most importantly, this notion steers clear of the idea that an AI solution is mainly attractive due to the AI aspects. These aspects improve SaaS solutions' operational efficiency by leveraging AI as a technology that is simply best suited for the task at hand. "So instead of thinking about services, we tried to create microservices that are essentially embedded in the APIs" (P3). This operational benefit is paired with the possibility to outsource the infrastructure needed for this technological synergy, lowering the operational burden even further. The appeal of SaaS providers, and how it translates into procurement-related decision-making, is discussed in Chapter 4.1.4.

This **problem-centred approach** was, surprisingly, only explicitly mentioned by three participants. "Well, I've rarely encountered an organisation that's not open to a solution to a problem that's been identified to really hurt. We were just sitting at the table with the CEO now. Well, it was costing them money, right?" (P6). Perhaps, AI is too new or upcoming to be treated as a tool in a system engineer's toolbox. As emphasised by participant 7: "I have the feeling that we are past the hype phase, right, because there was also a hype period where it was more like OK, we just need to do something with AI because everybody is doing it, and I think there is more rationalisation coming in that space now, where I feel that people are looking for genuine solutions with AI at the moment. And that's also what I see in my role, that the business counterparts mostly reach out with the problems they think might be solved by AI [...] so that's how it is progressing, I would say". This shift from a hype-driven tech push to rationalisation and problem-driven solution procurement might still be in the early stages, as demonstrated by the distribution of this study's findings.

4.1.3 External and Strategic Pressure to Adopt AI

Initial attraction is also reinforced by external pressure. As noted in Chapter 2.3, financial institutions face mounting expectations from customers, regulators, and competitors to modernise. The strategic orientation of institutions toward AI adoption mirrors Function 4 (Guidance of the Search) formulated by Hekkert et al. (2006), where customer and competitor expectations influence innovation direction. In this study, the most significant external drivers to adopt AI were found to be customer expectations and competitive pressure. The notion that regulators are forcing financial institutions to modernise in general might be true, but it is not reflected by the results of this study, which entails modernisation through AI adoption.

For starters, cloud-native AI tools help financial institutions to **meet customer demand** for modern and increasingly available financial services. "We are trying to go more digital; [...] a service that allows you to meet your banking needs without people; [...] it is now also seen as a sign of the times, of people who just want to be able to arrange something on their phone. Why can't I just apply for a mortgage on my phone, right? I don't have to go to some guy behind a desk for that, do I? I think that's really old-fashioned. And AI simply plays a pivotal role in that" (P5). This customer demand is not only driven by convenience, but it is also an expectation due to their familiarity with highly available GenAI models. "But also just what customers expect, they can also just inquire ChatGPT on their phone" (P14). Affirmatively, Alnaser et al. (2023) state that utilising AI is no longer discretionary for financial institutions and that it is an essential tool to meet customer expectations and maintain customer satisfaction.

Another non-application and operational factor influencing decision-making is the **competitive pressure to adopt AI**. "The competition is the one that is most vocalised as the reason, because if we don't do this, our competitor is already three months ahead of us" (P1). Almansour (2022) emphasises that fintechs leverage technology in a way that can disrupt the financial services industry. For incumbent banks and financial institutions, this implies competitive risk if technology captured within the concept of Industry 4.0 is not leveraged. To stay competitive, AI plays a key role for banks looking to claim segments of new up-and-coming markets. This reflects Function 5 (Market Formation) of a fruitful innovation system, where emerging expectations create early markets for AI-powered SaaS in financial services (Hekkert et al., 2006). Meeting customer expectations and consequently demand is essential for institutions to retain customers and stay competitive. "I think there will come a point where customers expect it; actually, what we just said with that one example of that digital assistant, where you can't really participate anymore if you don't have that" (P10). On the other hand, the technological experience with AI that competitors gain by moving first is a consideration for financial institutions to adopt AI solutions, to ensure that they are not technologically behind when AI's potential is undisputed. "Time has another aspect, and that has more to do with: are you the first, second, or are you the ninth? So the moment you make the decision faster, you can develop faster" (P2). This also leads to institutions copying the working principles of successful competitors' AI-powered services. "Of course, if a bank comes up with something that makes everyone fall backwards off their chair, then others will copy it" (P3). In general, fear of missing out (FOMO) in terms of attracting and retaining customers and technological capability development are apparent, especially for commercial banks and other commercial parties. "It's 100% FOMO, the fear of missing out, especially if you're a public company and you have [...] investors and so on" (P12).

Another hierarchical entity with a decisive influence on the decision-making surrounding AI adoption at financial institutions is the board of directors, who tend to apply **boardroom pressure to consider AI technology organisation-wide**. Of course, the board of directors represents the interests of shareholders, as that applies to an organisation. The drive from the executive level is catalysed by the potential operational benefits and the competitive landscape. One could argue that all strategic and financial aspects shape the perceptions of management, leading to organisational interest in AI technology. Of course, the decisive power of the board and executives makes it so that AI is incorporated into strategic procurement and/or development strategies. This drive to innovate with AI grows with the maturity of the technology. After shooting down AI technology as a whole initially, participant 3's board changes direction completely: "Then we had another board meeting in May the year after that, and they asked why we weren't doing anything about it, so that's how fast it goes". Moreover, personal drives from managers to excel in leveraging AI to hit their targets were also mentioned by two participants. "I think the internal stakeholders, right? That is a huge drive, especially from senior management who just want or need to have all this. They have a target that they have to do something with this; so there is definitely pressure on that" (P11).

Another reason for boardroom pressure is the possibility of **improving an institution's branding with AI**. "There is quite a lot of criticism on the financial market at the moment. So the moment you can rebrand yourself to your hip and happening and AI-driven and blah blah blah, that is good for investors" (P2). Not only does this signal modernisation to potential investors or current shareholders. It might also be a sales point for tech-savvy customers, looking for a more customisable experience. Again, positive AI publicity might signal to customers that they are the right fit for their expectations. This is underscored by Lee and Chen (2022), Noreen et al. (2023), and Rahman et al. (2021) stating that AI tools represent a visible and strategic investment in innovation, which can serve as a signal of technological leadership and forward-thinking service delivery. In a highly competitive and regulated sector, being seen as innovative can enhance a firm's reputation and market positioning. A clear connection with other categories in this theme is apparent. However, in Chapter 4.2.1, the downside of this strategic box-ticking behaviour and how it contributes to a lack of actual value creation is discussed. Moreover, a discussion on AI messaging by both institutions and SaaS providers versus actual AI capabilities will underscore the challenging market and sales environment playing a role in provider selection and filtering.

A potential of AI that has not been mentioned by any of the participants is **leveraging AI to more effectively pursue environmental, social, and governance (ESG) principles** across financial institutions. Using AI to become more sustainable and possibly adhere to environmental targets from regulators and European sustainability goals could, at some point, be an external or societal pressure that will lead to increased interest from financial institutions in AI. As pointed out by participant 5: "As a bank, you are in the middle of society. We also say: we have a social function, and then you have no choice but to implement what happens in society in the bank". In Chapter 5.4, a short section is dedicated to exploring this topic that does not seem to play a role yet for financial institutions as a main aspect influencing initial interest.

Is the AI hype justified, and is the technology indispensable? Strategic interest in AI solutions from SaaS providers is not only driven by their perceived benefits but also by the widespread hype surrounding AI. As discussed in Chapter 2.1.3, AI is considered a key enabler in navigating the evolving financial services landscape, with increasing demands for capacity and service quality. According to Almansour (2022), AI enables scalable solutions, making it potentially critical depending on a bank's expansion strategy and medium- to long-term goals.

Yet, despite AI's transformative potential, a central question emerges: are traditional technological solutions equally capable of addressing the complexity of the financial sector? In other words, does the hype inflate the perceived indispensability of AI? Participant 15 offered an insightful reflection on how decision-makers often fail to consider the risks associated with maintaining the status quo when evaluating AI-driven alternatives: "Then you have to remember that not using an AI and having that backlog, also carries risks. But [...] you usually look [...] less at the risks of the status quo and more at the risks of if they do do it" (P15). This perspective can be extended to the underappreciation of (improving) non-AI technologies, which may be equally capable of anticipating change, yet are often overshadowed by the hype influencing strategic decision-making. This is particularly relevant in the financial sector, where regulatory constraints tend to be significantly more stringent than in other industries.

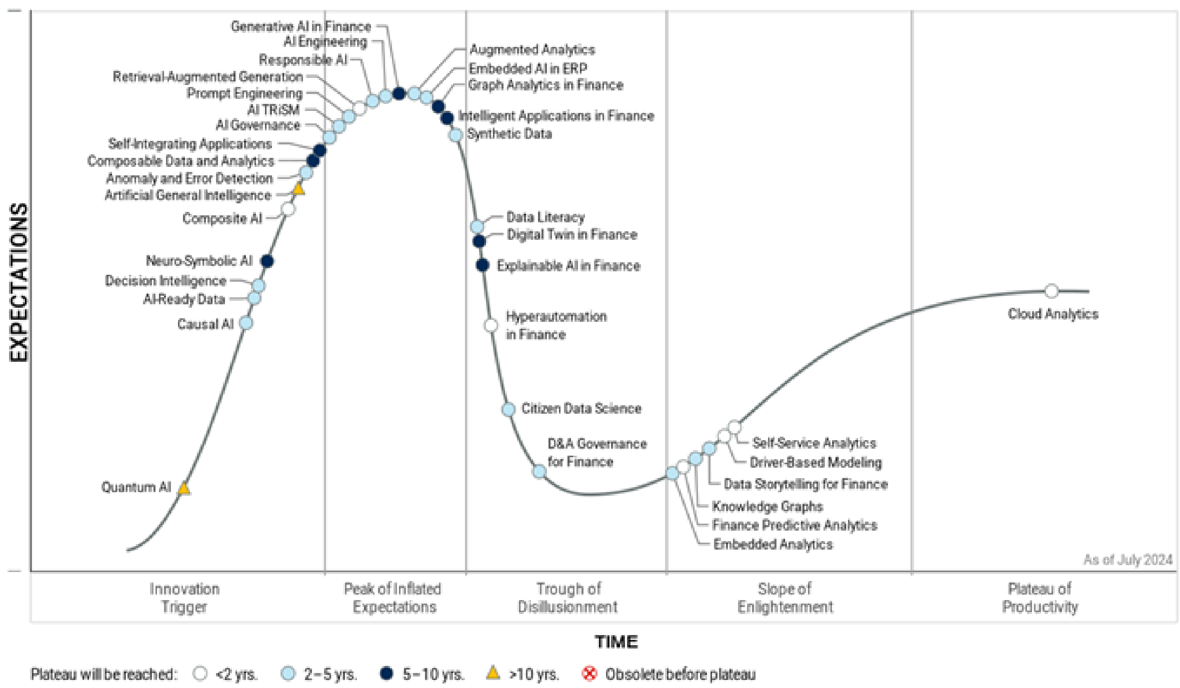

Figure 7: Gartner's hype cycle for generative AI as of August 2024. From "Gartner Hype Cycle Shows Generative AI in Finance is at the Peak of Inflated Expectation," by Gartner (2024). https://www.gartner.com/en/newsroom/press-releases/2024-08-20-gartner-hype-cycle-shows-generative-ai-in-finance-is-at-the-peak-of-inflated-expectations. Copyright (2024) by Gartner. Reprinted with public permission.

Regarding the current position of AI in the financial sector on Gartner's hype cycle (Figure 7), participant opinions varied. Three participants indicated that the hype may already be fading, marked by growing disenchantment as early promises fail to materialise. As one participant noted: "I wonder whether AI in the financial world might not be a little bit past its peak by now. Those expectations of eight years ago – they have only moderately come true, and much more was expected of it than you actually see now" (P4).

Others distinguished between more established forms of AI, such as ML and DL, and newer, more disruptive forms like generative AI. This reflects the differing stages in the hype cycle, where technologies like predictive analytics and hyperautomation are further along than generative AI: "I mean, for the businesses that I've known, ML algorithms are pretty embedded. So from that perspective, I expect them to be further refined in the coming period, of course. [...] Most of the hype that I'm referring to is GenAI, because again, there you see the models are still undergoing refinement to actually create output which can be used directly by businesses" (P7).

Still, many acknowledged that the hype surrounding AI in finance is real. On whether this hype and the FOMO it often generates are justified, participant views were divided. Five participants expressed the belief that AI is essential for maintaining a competitive edge: "And I think that [..] if you are now busy without those kinds of things, then you will fall behind or make yourself redundant, because you cannot compensate for that with people" (P5). In contrast, four participants believed that financial institutions can remain competitive without being explicitly AI-centric. Notably, some companies considered to be ahead of the curve do not yet view AI as a core competence, though they acknowledge it may become one in the future: "I don't think we're there yet. Both banks and [...] I would characterise as being, at least in the pack, perhaps towards the front of the pack in terms of the AI adoption. Would I say that they've got it in there as a core competency? Absolutely not" (P1). "I don't think there are any really huge things that are completely taken over by AI right now. [...] Will that be the case in ten years? [...] Yeah, or at least I have the feeling that [...] that is going to happen, or is happening" (P10).

One consequence of the hype, as noted by several participants, is the often inefficient push to deploy AI, sometimes for problems that may be better addressed through other means. This is frequently attributed to the accessibility and marketing of public AI platforms: "Secondly, of course, you also have that Chat-GPT has done a good job of marketing. In terms of AI, you have a lot of people who just say: we need to use AI. It's a bit like: you have a hammer and you're looking for a nail. [...] Let's be honest, when something is in a bit of a hype cycle, then you also have that sometimes people just go looking" (P15).

This dynamic also fosters anxiety among employees, who associate AI initiatives with job insecurity: "The thing is that the hype around AI doesn't really help because they're trying to say, OK, we see some Sam Altman and all these guys talking about cost-labour economics, no jobs are needed, everything is AI-native and so on. This is ********, at least in the current state of affairs. But people see that. And then they see their boss suggesting to implement AI and, of course, they connect the dots and they say, OK, they wanna they wanna fire me" (P12). This resistance to AI adoption, driven by fear of redundancy, will be explored further in Chapter 4.2.5, which discusses the broader integration challenges faced by financial institutions.

4.1.4 Incentives to Outsource AI to SaaS Providers

Taking into account the various aspects discussed so far, it becomes clear that AI adoption holds significant appeal for financial institutions. However, decision-makers are tasked with operationalising this growing interest, whether originating from top-down strategy or bottom-up enthusiasm, through effective capability management. This typically results in a strategic choice: to build AI capabilities in-house or to buy them from third-party providers. In this buy-versus-build context, participants described a variety of factors influencing their initial decision-making process.

As outlined in Chapter 2.2, SaaS delivery models eliminate the need for in-house infrastructure by providing cloud-native, scalable access to advanced AI functionalities. These platforms are especially attractive to smaller or digitally progressive financial institutions, allowing them to bypass the traditional hurdles of cost and complexity (Capgemini, 2024; Howell-Barber et al., 2013). This concept, broadly reflected in participant perspectives, is also embedded in the BMCdiscussed in Chapter 2.2.2.

A recurring theme among participants favouring the "buy" approach, interpreted here as licensing AI tools through platform supplier agreements, was the difficulty of developing AI tools internally. Eight participants cited the sheer complexity of development as a key reason for turning to SaaS providers. As one participant remarked: "Especially where you need reasonably big developer or deployment teams. You have to cover the development of it, the integration of it, the testing of it, the user interface aspects and so on. And getting those all right is challenging, very challenging" (P1).

Beyond technical hurdles, organisational rigidity also incentivises outsourcing. By relying on external providers, institutions can sidestep internal barriers such as legacy systems and bureaucratic resistance. As one participant put it: "Under the right circumstances, a small startup always has an advantage because you don't carry the legacy; you're not the lumbering elephant, you don't have as many risk colleagues when I have to approve those things" (P5). This aligns with Function 1 of innovation systems as defined by Hekkert et al. (2006), highlighting the role of entrepreneurial activity in exploring AI-centric product development. Moreover, the financial burden of developing an entirely new AI system can be prohibitively high, particularly when the functionality is not unique to the institution itself. In such cases, a buying strategy is often favoured: "Look, the moment we build software that doesn't solve something that's unique to us, then we have to ask ourselves very hard whether we want to do that; and you can see that in the software that we buy" (P5).

As illustrated in Figure 6, two primary drivers shape the preference for AI delivered via SaaS providers. The first, as discussed, is the technical and organisational difficulty of developing solutions in-house. The second is the recognition that **cloud-native SaaS tools tend to function better out of the box**, require less ongoing effort, and enhance institutional resilience and future-readiness. As supported by Dan and Guo (2018), Fong et al. (2021), and Sabbani (2023), AI SaaS solutions reduce both upfront investments and operational burdens while ensuring institutions stay agile and up-to-date with fast-moving AI developments. Engaging in a provider-client relationship helps institutions share the responsibility of keeping pace with both technological innovation and shifting regulatory demands.

That said, initial enthusiasm for AI does not always translate into action, i.e., buying or building. Sometimes, a basic cost-benefit analysis, whether formal or intuitive, leads institutions to conclude that the effort or expense outweighs the potential gain. These cost-benefit dynamics, often forming the silent backdrop to strategic choices, will be the focus of the next chapter.

This chapter has shown the benefits of AI with a SaaS delivery method, which predominantly aligns with the performance expectancy construct from both TAM and UTAUT, as institutions expressed interest in AI for its potential to generate operational efficiencies and strategic advantage. In addition, perceived social influence in the form of peer pressure, customer expectations, and regulatory trends plays a role in sparking initial interest. Some responses also reflect elements of perceived usefulness from TAM as they relate AI adoption to value creation in service delivery. In the next Chapter, the challenges in the world of technology management at financial institutions regarding AI functionality are discussed, highlighting all the factors that count towards the cost to some extent. As noted in the context of AI hype, its perceived benefits can often be exaggerated. As will become clear, the same is true for its challenges, especially given the pace of change and the relative scarcity of institutional expertise in AI.

4.2 Barriers to Adopting AI in Fintech

To understand how to engage with financial institutions more effectively to achieve mutual value creation, the challenges troubling fintech SaaS solutions must be thoroughly understood, encaptured by this study's second research question. This study identified five main themes of challenges influencing the decision-making processes of financial institutions. The biggest theme was factors captured by institutions' internal processes, politics, and procurement management, accounting for 34.70% of responses. Other challenging areas were technology and performance concerns (19.83%), being exposed to third-party risks (18.10%), regulations and compliance concerns (15.52%), and the anticipation of challenging implementation and onboarding trajectories (11.85%). These five themes consist of sixteen categories (Figure 8), each of which will be shortly discussed.

4.2.1 Institutional Process, Politics, and Procurement

All participants mentioned that the technology procurement process at financial institutions is challenging and is limiting swift and seamless processes. This process seems to be affected heavily by the addition of AI to already complex and time-consuming processes. These internal dynamics and intricacies have not been discussed in the literature in the context of AI-powered fintech SaaS tools.

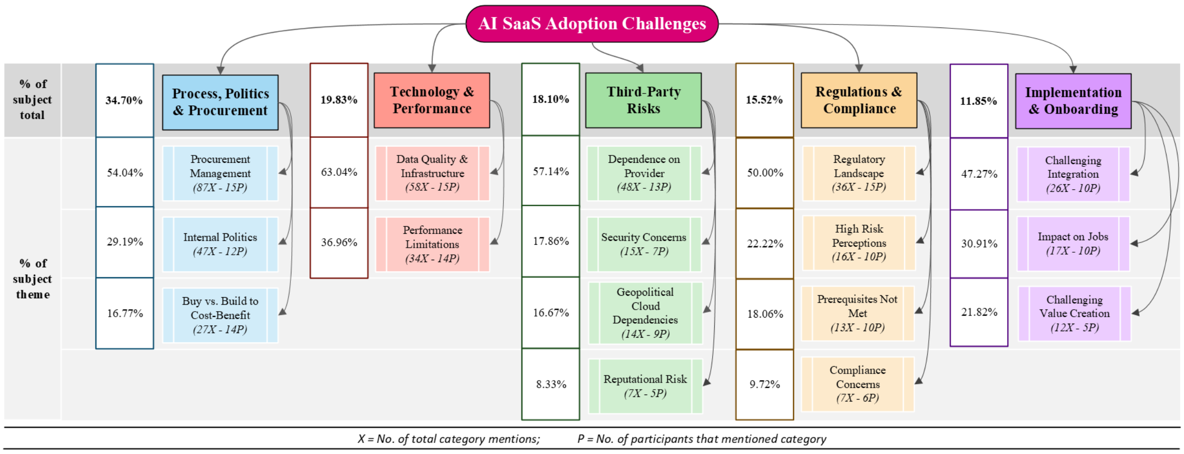

Figure 8: Categorisation and quantification of fintech SaaS AI adoption challenges

Challenges in procurement management were mentioned 87 times by participants, ten of which attribute this troubled internal process to very slow and complex assessment procedures. Once a SaaS provider has their foot in the door, through being part of an request for information (RFI) and/or request for proposal (RFP), a lot of supporting information is required. A huge number of assessments are involved, ranging from data protection impact assessments and cloud security assessments to bias assessments. So, getting a deployment live often starts with an administrative monstrosity, simply taking up a lot of time. ”If something goes through procurement, you’re screwed. I mean, you don’t want to know what they want to know. You’re treated like you’re building the new headquarters” (P3).

Moreover, the knowledge to initially set up the list of what an institution wants to know is scattered all over the organisation, but also to assess the information provided by all the SaaS providers in the ’request-for’ stages. As expressed by participant 1, the combination of this fragmented procurement process and the time it takes to set it all up leads to constant re-do’s and re-evaluations: ”When generative AI first came out, it required [...] all different kinds of assessments. [...] These were not synergised at all; they were all sorts of stand-alone assessments. So if you were trying to get a deployment live [...] we would probably have to repeat some of those because you go [...] through the AI life cycle until the final version. When I saw that, I realised that nobody is going to get this approved with this workflow. Because by the time you’ve done the 12th assessment, the developers have moved on to something quite radically different, or not radically different. Even just a little bit different, and then you have to start again” (P1). This rate of change in AI software, usually utilising an agile way of working, is incompatible with the way financial institutions assess technology, not only tech offered through SaaS, but also technology from internal development teams.

At the basis of these procurement processes are risk-driven initial assessments, focused on the underlying technology of a service offering. This is not only the AI component in the whole service offering. Working in the cloud comes with its risks, and combining the two makes for an even heavier assessment procedure upfront. Moreover, getting a foot in the door is a whole different beast to conquer. The initial scanning of potential SaaS providers is a process with standard requirements, but no standard as to how to meet them. ”You have to write to several parties. You have to have done some market research. [...] That is simply a mandatory process. [...] How do you get on an RFI list? Yes, that can be simply because you have an existing relationship with a vendor [...]; or they have emailed you; or procurement happens to know someone; or they come up as the first hit on Google when a market research is done; or they are simply known in the market” (P15). Factors increasing a provider’s chances are its status, or the degree to which they are known, and visibility, both online and through commercial conferences.

The procurement department typically only becomes involved once the decision to license-in a technology has already been made. By that stage, considerable effort has often gone into formulating the idea and overcoming the inertia of the status quo, long before any market offerings are even assessed. This assessment process usually results in either no vendors being selected or a very limited shortlist of one or a few parties based on their submitted proposals. At that point, a new question arises: can these selected vendors actually deliver what is needed? Often, there is a mismatch between the initial problem that triggered the procurement process and the actual solutions offered, or the situation may have evolved by the time decisions are being made. While the financial sector increasingly embraces agile methodologies such as Scrum, it becomes evident that agility is difficult to achieve when it depends on switching between external vendors. As a result, institutions frequently opt to stay with their existing vendor, who is already integrated and technically compatible. This dynamic often means that the best technological solution is not adopted. Moreover, in some instances, high-potential solutions adopted in one department do not find their way to other departments, due to a lack of a synergised strategy. ”New solutions are often completely spread across the entire organisation, which actually makes it a bit of a dead end, even if there is a good solution” (P4). Instead, internal procurement processes, organisational politics, and decision-making structures create limitations that lead institutions to prioritise continuity over innovation.

One could argue that the initiative to consider AI solutions often reflects a broader tension between ineffective decentralised and centralised decision-making structures. On one hand, individual employees or teams with the inspiration or drive to innovate frequently lack the authority to make decisive moves. On the other hand, centralised technology pushed from higher management can result in top-down mandates that burden product managers with the complex task of integrating AI into business lines, often without a clearly defined problem to solve. This dual inefficiency leaves AI exploration caught between ambition without power and directives without direction.

Participants emphasised these **troubling internal politics** within financial institutions, highlighting a perceived lack of genuine adoption intent, strategic clarity, and a prevailing preference to preserve the status quo. ”I would say that the biggest issue for banks is actually coming up with a holistic strategy there” (P1). This appears to stem partly from a lack of internal expertise and, equally, from the absence of a compelling need to act. ”This is still a very new skill set in the market, you would not always find all the people to do it fully on your own. And you might also need some support in defining the strategy or defining the vision” (P7). ”It is not a top priority at major banks now either” (P4). In some cases, it also seems to be a deliberate strategic choice not to act, influenced by varying levels of risk appetite across institutions. Non-commercial entities, for instance, face less top-down and competitive pressure to innovate beyond internal efficiency improvements. ”Yes, and what value do you want to add? One financial sector is much more tech-minded than the other, so I think it’s mainly about what risks you dare to take. With what bravado do you dare to enter that tech sector, and how progressive are you as an organisation?” (P13). Five participants described a clear drive to maintain the current way of working, characterised by a wait-and-see attitude. Two of them specifically attributed this inertia to higher management, noting that those in leadership are rarely held accountable for decisions they choose not to make. ”The moment you start to challenge the status quo, people will be against you” (P2).

For SaaS providers, delivering substantial benefits at relatively low costs can be a decisive factor in tipping the balance toward acceptance of AI-powered tools. This **cost-benefit balance** forms the foundation of nearly every technology adoption decision, as emphasised by eight participants. However, evaluating the value of a technological solution is rarely straightforward; such business problems are often complex and cannot be reduced to a simple mathematical analysis. This analysis becomes more manageable when a SaaS provider is already engaged through an existing service contract with the financial institution. In such cases, the provider and its cloud capabilities have already been vetted, potentially shortening the time-to-market for AI tools. Seven participants identified ROI as the most important factor when making a high-level assessment of an AI offering. ”To make it really easy, we are already using a copilot in Microsoft 365 [...], so is it more: are we really going to get the efficiency out of it that it is worth the extra license fee from Microsoft? [...] That is actually the only question regarding adoption” (P14). In the previously discussed buy-versus-build dilemma, this return on investment (ROI) logic extends to considerations such as how many developers could be hired for the same cost as a SaaS license. It is important to note, however, that SaaS providers are not accountable for every cost component included in a financial institution's internal trade-off. Perceptions of cost, shaped by institutional procedures, approval structures, and budget cycles, often influence the outcome as much as the actual price tag. These challenges correspond with Function 6 (Resource Mobilisation) of the system of innovation, describing the diffusion of disruptive technology through system stakeholders, highlighting the institutional frictions in mobilising capital and labour for AI adoption Hekkert et al. (2006).

4.2.2 Technological Challenges and Performance Concerns

The costs of a SaaS solution often include the anticipated effort to adopt AI SaaS effectively to the point it delivers actual value. This anticipated effort is partly shaped by risk perceptions of the SaaS offering. The remaining four themes of this Chapter all cover different aspects of institutions' concerns and risk perceptions surrounding fintech SaaS AI.

One of the most pressing technological performance concerns is **the quality of the data and how it is handled by AI tools**. Five participants emphasised that an AI system is only as reliable as the data it consumes. As participant 6 colourfully put it, even a highly advanced model cannot compensate for poor-quality input: "you can throw some GenAI over it; then it might turn into a unicorn turd, but it's still a turd" (P6). Beyond data quality, four participants highlighted the inherent bias present in data. This introduces concerns about the fairness and accuracy of AI outputs, depending on the datasets used for training. These concerns extend beyond external or vendor-provided datasets to include the financial institutions' own data. "You can have bias in different places in your model. That can be in your input data. That can be on your model side, so the modelled relationships, or on the output side. I have yet to come across the first unbiased dataset" (P15).

Another recurring issue is the risk of cross-contamination between systems. SaaS vendors often operate in shared cloud environments—either across different clients or across internal departments—raising concerns about data leakage or unintended access. Traditionally, financial institutions have addressed this through strict access controls and data silos. However, six participants pointed out that data silos significantly limit the usability of data or complicate the process of navigating legacy infrastructure to extract value. "Also, because those networks of banks are often very segmented. Are you going to break through that firewall, are you going to get into the internal network and retrieve data there, or does it have to be sent to you? [...] Those are the bigger technological questions" (P2). Finally, the majority of participants highlighted the inherent sensitivity of financial data and the associated privacy concerns. These concerns amplify all the aforementioned issues, placing even greater pressure on institutions to ensure careful handling of AI implementation. "AI and LLMs are quickly becoming about data. [...] in addition to risk management is our profession, is that we have to be careful with the data that we have from our customers. Yes, so that in combination with GenAI also often gives sufficient attention to [...] do you think carefully before you turn something like that on?" (P11).

Additional **performance-related concerns** include the fear of inconsistent model responses or hallucinations, especially problematic when these errors occur in client-facing tools, which were identified in the previous chapter as one of the most significant applications financial institutions are exploring. "If that is directly with a customer, yes, then the customer is constantly shown something that is not to be trusted. So I understand that people are still afraid there" (P10). The variability in AI-generated responses marks a clear departure from traditional systems, which tend to behave in a consistent, rules-based manner. This shift contributes to institutional reluctance to adopt AI more broadly. "You have to put yourself in the shoes of these people, the ones that are actually signing off on this investments; they are guys and gals with [...] decades of experience and they've always worked with predictable software that, if if it's well coded [...] it will behave as expected. OK, this is no longer the case. So it's a huge shift in mindset that I'm pretty convinced most companies are not doing, and I would bet a [...] this is particular to Europe, that most companies won't move a needle until they are forced to" (P12).

Another limitation is AI's inability to generate genuinely novel ideas. When used to develop customisable customer journeys or to design new products and services, its reliance on existing (and often outdated) data can suppress innovation. "It's going to be very hard to generate new things. The moment you put everything in AI, everything stays the same because your data source is old. So you're never going to come up with new ideas, innovations" (P2). Financial institutions also tend to have high expectations for new technologies. To address the risk of outdated or unrepresentative data, SaaS providers could offer models that adapt and improve over time using the institution's own data. However, six participants highlighted that after lengthy assessments and anticipation, the reality often falls short. Providers may underdeliver, particularly when the model comes untrained. This poses not just a performance issue, but a marketing one: how can providers promise specific outcomes if performance depends entirely on data quality at the client side? Additionally, the more time a model needs to adapt to proprietary data, the greater the risk that the underlying model becomes outdated. "If you look at it in terms of its performance risks or accuracy [...] if you get new products, circumstances change, then the output can no longer be accurate. If you've even fine-tuned your model, or you've really trained an ML model, then yes, it's going to be out of date and therefore not as accurate, not as performant" (P1).

4.2.3 Third-Party Risks

According to Kunkel (2023), third-party risk refers to the potential threats a company faces when it involves external entities, such as vendors, suppliers, partners, contractors, or service providers, in its operations, infrastructure, or supply chains. According to the author, these risks arise when such parties gain access to internal data, including systems, processes, intellectual property, customer details, or internal communications. K. Davis (2015) reported that third-party risk is escalating due to increased outsourcing aimed at cost reduction, heightened regulatory scrutiny with significant fines, and growing reputational impacts from publicised failures or breaches. The global spread of information amplifies these risks, prompting boards to view third-party risk as a significant strategic concern. However, organisations often lack a clear, centralised oversight structure, with responsibility sometimes falling narrowly to procurement rather than being approached from an enterprise-wide perspective.

In the relationship between fintech SaaS AI providers and financial institutions, the issue of **dependence on providers** was repeatedly emphasised. First and foremost, nine participants highlighted that many financial institutions lack in-house AI expertise. This means they are not only dependent on providers for software access but, in some cases, also rely on them to know what is in their best interest. This creates a dual dependency: on the technology itself and on the strategic understanding of how to apply it. This is catalysed by institutions' needs for continuity and regular updates, especially within the complex societal and regulatory landscape they operate. At times, this raises concerns about technological lock-in, especially when a solution works exceptionally well and internal workflows adapt accordingly. Institutions begin to question whether they could replace the tool if the provider's system fails. It positions them in a vulnerable place, where commercial motivations may outweigh the provider's obligation to deliver only what the institution genuinely needs. "I think that maybe the people sitting across from us are not the right ones. [..] Often there is, for example, one lost person somewhere who [...] follows the AI news, for example, and can ask some critical questions" (P10).

Naturally, some larger, tech-savvy banks do possess the internal competence to scrutinise vendors more thoroughly. However, as participant 5 pointed out, third-party solutions are not always assessed by those with the most relevant expertise. "Not always by the people who know the most about it. That leads to you sometimes making concessions. Whereas if you do develop it in-house, you can ensure that there is a much better problem and market fit" (P5). This observation underscores a structural challenge: the ideal customer segment for AI SaaS providers is precisely the one that lacks the knowledge to build such tools internally. If they had this expertise, they would be far less likely to opt for licensing in the first place. Still, assessing and adopting AI from SaaS providers remains a knowledge-intensive task. This was explicitly noted by eight participants, reinforcing the asymmetry in expertise. "What you do see [...] is that there is insufficient technological market knowledge. And that is why we use or abuse our IT suppliers for that" (P13).

As discussed in Chapter 4.2.2, concerns regarding data (breaches) shape the risk perceptions that influence AI adoption decision-making. An important extension of this, mentioned by multiple participants, is the **dependence on providers for the security of customer data**, which plays a crucial role in shaping perceptions of cloud-native AI tools. ”How do these SaaS solutions make sure that the data is safe and secured for the customers?” (P7). In fact, security was repeatedly described as a critical barrier. ”The biggest pain in the *** [...] is the chief security officer, [...] the cybersecurity guys 100%. They will block every single thing. And I mean to be fair, they’re doing their job” (P12).

Damaging the trust that customers place in the secure handling of their data is a major fear among financial institutions. ”That’s a reputation. Yeah, it comes on foot and goes on horseback. And if you mess that up, you’re gone in no time” (P5). The potential for such breaches to cause **irreversible damage to an institution’s reputation** was explicitly emphasised by five participants. ”I could already see the headlines in my mind, so I had a very intensive process with our privacy officers” (P13).

This dependency on SaaS providers often extends into an additional layer of reliance, namely, on underlying infrastructure services such as IaaS or PaaS providers. With a new US administration in office, nine participants raised concerns about the geopolitical implications of relying on American tech infrastructure. All of the “big three” IaaS platforms, AWS, Azure, and GCP, are U.S.-based. ”Although now, of course, with the administration of Donald Trump, everyone is starting to doubt whether they want to store their information in the United States. So that is a new complicating factor” (P3).

These fears are not unfounded. Klaas Knot, president of the Dutch central bank (De Nederlandsche Bank (DNB)), recently warned that European financial institutions are overly dependent on the US, particularly in digital infrastructure and international payments like the SWIFT system, amongst growing geopolitical and economic uncertainties (NOS, 2024). The DNB has highlighted rising cyber threats, doubts about ongoing US reliability, and the heavy dependence on American cloud and tech services. It urges European institutions to reduce this reliance and prepare for a future in which continued support from the US cannot be taken for granted. Of course, most financial institutions cannot influence global politics, so these concerns may not significantly affect day-to-day decision-making. However, the implications are relevant for both banks and fintech SaaS providers. ”Imagine that you, as a large European bank, are dependent on solutions from the US for all your LLMs that are central to your customer journey because they are technologically ahead of other solutions. Then you have to take into account: what if the Trump Administration starts imposing all kinds of requirements on all of that at some point? How do you deal with that as a European bank or as a global player in the financial world? How are you going to position yourself then?” (P4).

Some participants noted that legal and contractual measures, such as ensuring that data is stored on European soil, might offer some reassurance, even when using US-based platforms. However, this does not always alleviate the concern. ”At the same time I think: you can see how Trump and his entire administration don’t give a damn about that and are pursuing their own plan. They don’t give a damn about legislation. How much will he care about service agreements that have been made with those companies for large banks?” (P4). These concerns are not merely speculative. Recently, operations at the International Criminal Court (ICC) in The Hague were disrupted when Microsoft, under pressure due to arrest warrants for Israeli and American allies, revoked Outlook email access, among other services (Quell, 2025). In Chapter 5.1, Europe’s stance on cloud-driven AI and how it compares to the American approach is explored further.

4.2.4 Regulatory Landscape & Compliance

Rahman et al. (2021) found that AI adoption in banking would be more effective if the regulatory framework included clear and specific guidelines. The study also notes that some banks refrain from proactively pursuing AI implementation precisely due to this regulatory ambiguity. This sentiment was echoed across all interviews. Participants unanimously identified the regulatory landscape as a significant challenge that shapes decisions around third-party fintech SaaS solutions. ”The regulations are a factor. And the choice and the shaping of the use cases are definitely a factor where regulations come in” (P1).

Institutions often fear **non-compliance with the rules** and expectations of central banks and other regulatory authorities. This fear stems not only from the threat of severe financial penalties but also from the scrutiny such investigations entail. ”They want to make the technology and its applications transparent, and also transparent training of the models, so that they can be sure that the Authority Financial Markets (AFM) will not come up with objections regarding poor transparency, et cetera” (P4).

In addition to the financial risks, reputational damage remains a concern. The dependence on external developers of licensed AI solutions further amplifies this risk, as internal knowledge about the model’s workings is often limited, making it difficult to fully assess compliance and trustworthiness. Furthermore, the constantly evolving regulatory landscape covering AI, cloud computing, and open banking creates persistent uncertainty that procurement departments must navigate.

All these factors contribute to **elevated risk perceptions surrounding AI** within financial institutions. Given their societal role and the sensitive nature of the data they handle, banks and related institutions tend to be highly risk-averse and operate under intense regulatory oversight. Interestingly, some participants saw AI not just as a source of risk but also as a potential solution to some of the inefficiencies introduced by that same oversight. ”In financial services, it is such a heavily regulated environment that it does attract a lot of paperwork and documentation internally and externally, and that is quite a cumbersome process, which is not only time-consuming but also error-prone. And I think those are the areas which are, maybe, the first use cases that I see for AI, because that is something that everybody wants to get rid of” (P7).

Despite these opportunities, the overarching sense of risk is shaped by a lack of understanding about how AI systems work, particularly in relation to data processing behind the user interface. ”It is not transparent anyway; you do have algorithms that are a bit more transparent, but they have much lower accuracy. If you look at the ML algorithms, they have become better and better, and it is increasingly difficult for a human to understand what is happening there” (P10).

In some instances, participants noted that the **high standards for security, risk management, compliance, and regulatory robustness** demanded by financial institutions **are simply not met** by SaaS providers, or are only partially addressed on their product roadmaps. Generally, AI tools provided by vendors who are not yet under a service agreement have to be more mature than those offered in existing client relationships. This implies that the nature of the relationship between institution and vendor can influence both the quality of the offering and the procurement strategy, a point elaborated on in Chapter 4.3. Experimentation with sensitive financial or transactional data is rarely permitted, and market-ready tools that meet all compliance criteria remain scarce. ”Speaking about financial services, there were some use cases in some projects which didn’t get off the ground because they’re prohibited” (P1). As a result, even highly promising projects that receive approval from technical and financial departments are often ultimately blocked by risk or compliance teams.

Lastly, **compliance concerns**, while related to regulation and legal obligations, go a step further by incorporating organisation-specific standards and practices. Because of the critical nature of their services, financial institutions often maintain strict internal compliance frameworks that go beyond external regulatory requirements. ”The reason being that again in the financial services world, where you need to be within the boundaries of compliance and regulations, you cannot give it away fully to an outsourcing party, especially when it deals with this kind of impact” (P7).

Even in cases where compliance is not an active blocker, it remains one of the most important boxes that must be checked during procurement. It actively shapes AI vendor selection, especially when assessing competing tools. Often, the provider who can clearly communicate their compliance posture early in the process has a significant advantage in making the shortlist, provided that the delivery lives up to the regulatory and technological expectations.

4.2.5 Integration and Onboarding Challenges

Boustani (2022) argues that most financial institutions feel compelled to embrace AI and its derivatives but remain uncertain about how to effectively deploy them. This finding is strongly reflected in this study, where 10 participants identified effective AI deployment as a persistent challenge. Even after evaluating a vendor, assessing its offering, and ensuring regulatory and compliance requirements are met, previous experiences with **poorly synergised migration and integration** processes can elevate perceived costs and risks. Such experiences often contribute to the technological lock-in discussed earlier. ”We are now experiencing [...] that there are lock-ins with parties that we want to get into, but IT said, man, we had so many problems getting that previous tool implemented; even though it has limitations, never mind. This is the most difficult thing in sales. [...] What is going to motivate you to convince IT to do a very difficult migration?” (P8).

Migration challenges are especially pronounced when transitioning from legacy systems to cloud infrastructure or between cloud platforms. While these issues are not specific to AI, they often act as a precursor to AI-related complications. Even after the foundational migration is complete, the integration of AI tools remains complex. Obstacles such as a lack of internal experience with AI, incompatible IT environments, and unstructured data formats frequently hinder seamless integration. Rahman et al. (2021) note that “the arrival of new technologies has significantly changed the requirement for skills beyond the technology sector,” underscoring the need for non-technical staff to both work with and configure these systems.

This also seems to depend on the ability of vendors to transfer the necessary information to streamline the technical integration for the institution’s IT department, mentioned by six participants. ”It can be quite difficult to work with vendors to get security-related information, understand what they’re doing with the data, and get indemnities out of them” (P1). Even when vendors provide sufficient support, institutions vary widely in their ability to disseminate new technologies internally. ”There is quite a difference in the maturity of the IT organisation and the capacity for adoption between those two alone. [...] is quite modern, or hip. They are reasonably capable of spreading new technology in their organisation, independently. [...] you have to take completely by the hand” (P2).

Another factor influencing decision-making was the **impact potential AI tools might have on the workforce**, and the resistance that automation might result in. The fear of job loss was mentioned by ten participants explicitly. ”Yeah, there is a sense of fear [...] for these use cases. [...] People are very excited to use copilot, but they’re very reluctant to share numbers on a time that they save using it, because that’s indeed the fear that [...] if we save 4 hours a week or something, it will add up to some amount of FTEs on that part” (P7). Boustani (2022) echoes this compromised feeling of job security with the proliferation of AI as a technology, emphasising that AI has the potential to render, e.g. back office and data entry jobs obsolete. However, the author also argues that this is, again, short-term fears that do not hold in the long term: ”Data suggests that the proliferation of AI could be accompanied by a rise in banking jobs”.

A short-term fear of making unpopular cuts in the workforce, or having to reassemble a workforce under the new circumstances, is apparent. Op top of that, shifting around FTEs heightens the risk of a technological lock-in, and dependence on continuous and reliable performance of the adopted tools. Good messaging aimed at worried employees seems to be a start. ”There’s real resistance to change. A lot of people fear the technology, so they will gladly not collaborate in adopting it [...] because people feel that they are being substituted. So there’s certainly an effort, educational effort, internally to really help people understand that this is a tool” (P12). On the question of whether or not jobs will actually be lost, Rahman et al. (2021) emphasises that some tasks will be automated and jobs will be destroyed, but others will be created. Regardless, the use of disruptive technology, under the conceptual umbrella of industry 4.0, could create technostress among employees (Almansour, 2022).

Lastly, the challenge of actually **generating value from AI tools** was identified as a key barrier. Beyond employee resistance, a lack of trust in the technology was cited as a major hurdle. ”That didn’t get off the ground then, people just don’t trust it. You see that too [...] in the AI domain, that things sometimes seem too good to be true [...] while they really are that good” (P6). Moreover, three participants stressed that deriving value from AI tools often requires active effort on the part of the financial institution itself. The scaling and realisation of potential benefits are not automatic and demand institutional commitment. ”But it’s really in that first phase; can we get out of it what’s in it? And I often find that delivering on the promises that you start with [...] at some point is very much up to us, so at some point it’s our own problem to make sure it reaches its potential” (P5).

The barriers identified in these last five sections map closely to effort expectancy and facilitating conditions. Concerns around integration complexity, procurement, and regulatory compliance indicate low perceived ease of use and highlight the importance of institutional enablers. Uncertainty about AI’s performance and organisational inertia also link to perceived risk, an extension of TAM that helps explain reluctance even when usefulness is acknowledged. Additionally, lack of trust in third parties relates to social influence, especially when internal decision-makers defer to legal or compliance teams.

4.3 Addressing the Challenges

Combining both implicitly and explicitly mentioned strategies for reducing risk perceptions, and thereby the perceived total cost of AI tools, yields several important insights for SaaS providers, and potentially for financial institutions themselves. This study identified four themes of strategies used to address the challenges that hinder streamlined decision-making at financial institutions, answering this study’s third and final research question. These pillars loosely correspond to different phases within the adoption trajectory: from the initial expression of interest, through the issuance of an RFI and/or RFP, to the evaluation of vendor offerings and the ultimate selection of a preferred solution. The key strategic pillars identified were: proactive and collaborative implementation of solutions (29.60%), effective communication around de-risked AI offerings (27.20%), and best practices to technically derisk AI products and services during development (25.20%). In addition, a smaller but notable share of strategies (18%) focused on aspects of service delivery that are peripheral to the technological core of the SaaS offering but remain essential in shaping client perceptions. Each of these categories, as visualised in Figure 9, is discussed in this chapter. They are presented in reverse chronological order of the provider’s service acquisition process, starting with those most often mentioned by participants, thus indirectly reflecting the perceived prioritisation for SaaS vendors aiming to win new contracts in the financial sector.

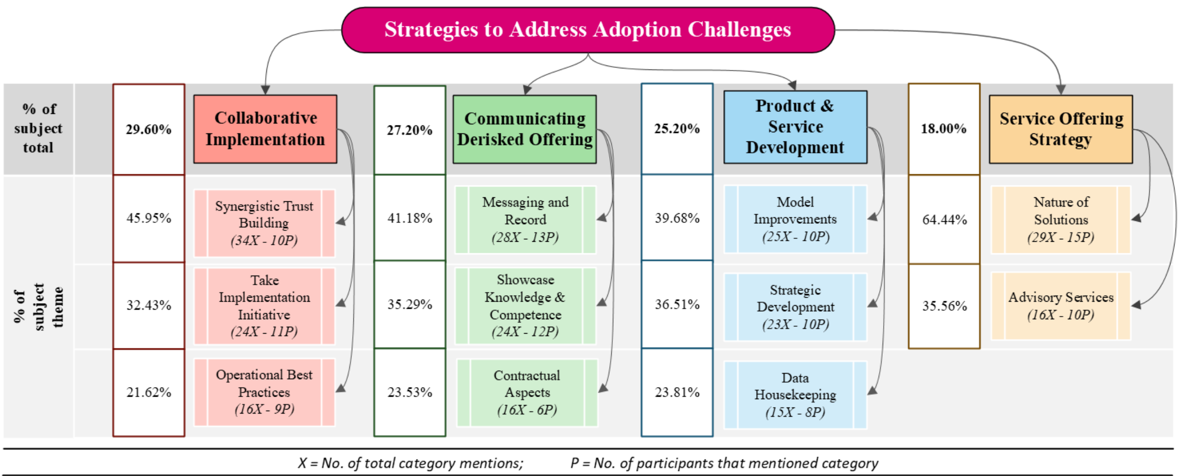

Figure 9: Categorisation and quantification of strategies to address and mitigate adoption challenges

4.3.1 Collaborative Implementation and Onboarding

It should be acknowledged that implementing a disruptive technology stepwise is often difficult. When the perceptions of risk are high and people fear the implications that a technology, especially AI, has on the current state of things, effective implementation is challenging. A driver of high risk perceptions and overall fear is the lack of experience and technical knowledge to both understand and effectively start leveraging a tool in daily operations. Therefore, involving people in the process is essential to facilitate smoother adoption. Ten participants emphasised a clear role for the SaaS providers in this process. ”Especially asking where the fear or [...] inexperience lies. So that you understand where the other person stands. And then I would [...] still offer a helping hand somewhere to work together” (P13).

A **synergistic approach to build trust** is needed where the provider and client are co-owners of the problem that is challenging integration and onboarding. This process entails involving the people who a tool might affect, whether that be in terms of interacting with a tool, reading a tool's output to make decisions, or even when a tool will substitute a portion of the work one does. Moreover, this involvement in technological processes can mitigate the perceptions or risks that are in the way of adopting AI technology. ”All those people all have an opinion and are all afraid of what that kind of technology can do and where it can go wrong. And unknown makes unloved. Because we now have those conversations [...] the risk perceptions are immediately much less great” (P5).

At the basis of this is both the realisation that some jobs will disappear while others will change is necessary to effectively approach this challenge. When resistance due to fear of job loss is encountered, clear internal communication is needed, possibly facilitated by SaaS vendors. Especially because these short-term worries, shown by (Almansour, 2022) not to be completely true, often do seem to hinder adoption through basing adoption decisions. Long-term effects on adoption must be emphasised in order to ensure objective bottom-up signalling and evaluation that might affect decision-making higher up. ”I think it is important that an organisation talks to people, and you can do that bottom up or top down [..], but that everyone understands it, and that they also know what they are working with and what is happening” (P6). Additionally, training and reskilling people simultaneously is important for tools, both internally developed as well as tools that are licensed from SaaS providers, echoed by Almansour (2022).

On top of that, five interviewees mentioned that effectively implementing an AI tool is not a straightforward process that will impact the organisation in a single way. Instead of viewing tools as an inescapable evil, SaaS providers should focus on making AI and its implementation part of a learning process at financial institutions, where they present themselves as an agile learning partner for those with ideas on how to improve both the tools themselves and their implementation. ”My approach is always [...], just implement that standard SaaS solution from an agile way of working and [...] gain experience with it. Along the way, we can refine that thing to our custom solution” (P13). This is an example of Function 3 of the innovation system described by Hekkert et al. (2006), where co-development facilitates mutual learning and transfer of AI-related knowledge across organisational boundaries.

As SaaS providers are often the experts on the technology and on what is needed for effective implementation, eleven participants highlighted the need for a **proactive attitude from SaaS providers to effectively implement their AI solutions**. ”Yes, the initiative can come from the market. Well, then I see our IT supplier as the market” (P13). With some institutions' dependency on SaaS providers for the tech and the tendency to stick to the status quo, ”invest well in an adoption process, so don't just throw an IT solution over the fence. [...] Organise fun inspiration sessions around it, set up workshops; make sure you have the ears and eyes in the department” (P15). This also includes taking the initiative to provide the IT department with the materials necessary to understand what it does, how it works, and how they can design surrounding processes for integration. A big part of this is understanding the (technological) concerns and addressing them, showing competence and initiative simultaneously. ”I've just been in sessions with [...] where they say, well, you can't record, [...] but now we're going to explain how it works under the hood. [...] And then we're specifically going to focus [...] on the data stream, because we want to know [...] where that's going, right?” (P11).

Finally, some **operational best practices** can help financial institutions to gradually build trust with an application during the implementation phase. Running pilots is one of them, where a step-wise expansion of use-cases allows institutions to further assess the operational effects on their organisation. Another method to do so is to run shadow processes parallel to their own systems, to evaluate the performance of a system before making it the primary operation. Both these processes allow for a derisked model evaluation pivotal for further decision-making concerning organisation-wide implementation. Four participants emphasised that a lot of institutions prefer incremental improvements and small iterations, especially when an AI tool is client-facing, as emphasised by participant 5: "So that means that the requirements are much more stringent there. You want to see much more proof of concepts, you are going to test much slower, you are going to do much smaller pilots with test control groups around it".

4.3.2 Risk-Accurate Communication of Service Offering

Thirteen participants highlighted that **maintaining a proven track record**, combined with consistent, **effective communication around AI tools**, is essential for gaining visibility and being shortlisted during the procurement process. One straightforward way to establish credibility is by obtaining certifications. For SaaS providers operating in the Netherlands, ISO27001 serves as a minimum benchmark for information security management systems (Forum Standaardisatie, 2013). Equivalent certifications exist across Europe. This finding perfectly illustrates the core of Function 7 (Creation of Legitimacy) as described by Hekkert et al. (2006). With the already discussed necessity of internal advocates and vendors collaborating to counter institutional resistance to normalise AI adoption, legitimacy is built both through tangible (certifications) and intangible (collaborative synergies) delivery methods. When targeting multinational financial institutions, such as globally operating banks, it is crucial to understand the regulatory landscape of each target market. This enables broader diffusion of services without disproportionately increasing effort across markets. Although strategically pursuing such certifications is not groundbreaking, holding more of them than competitors effectively reduces perceived risk and anticipated implementation costs.

Furthermore, strategic messaging that conveys continuity and a forward-looking vision aligned with the pace of AI development is critical. "Just having the best is absolutely no reason for people to buy it. If your story around it is not right, your website is not right, your messaging is not right, your targeting is not right, you are just not going to sell it" (P2). "Yes, and are they also products that fit into a continuity perspective? Or is it just an intermediate step? That vision has to be there; if you don't know where you're going, then it's not something that can generate longevity" (P5). These insights also underscore the importance of effective sales practices. While articulating and quantifying potential results remains a challenge, linking AI offerings to clear operational improvements within a well-defined vision that anticipates future developments is vital. "How is change management of the product? In GenAI specifically, at some point you're going to get more and more models or other models are added. Yes, you also have to [...] know what the consequences of that will be" (P11).

Demonstrating domain knowledge and competence is equally important. One of the main advantages of fintech SaaS providers is their familiarity with the specific risks associated with their technologies. Leveraging this expertise means actively engaging with operational risk and compliance processes, for example, by conducting self-assessments of AI tools. This positions providers as lower-risk options during evaluation phases, helping reduce perceived costs from the outset. Additionally, nine participants pointed to the importance of making AI tools explainable, particularly for procurement officers and decision-makers who may not have technical backgrounds. "So as long as we're not able to explain everything simply, I also see the future of AI adoption as sober. [...] I think explaining it simply, whether it's to your grandmother or to the CEO, is the key to success for financial institutions" (P3).

In addition to showcasing technological and regulatory fluency, several **contractual mechanisms** were identified that help ease concerns among risk and compliance departments. Five participants stressed the importance of clearly defining ownership of risks and establishing accountability frameworks. ”Those RAKI matrices [...] so where you actually look at each sub-topic [...] who is responsible in which scenario?” (P14). Further, elements such as detailed access controls, contingency planning, and clear terms and conditions were identified as critical differentiators when institutions are selecting between providers.

4.3.3 Best Practices for Product and Service Development

As seen in Chapter 4.2.2, there is a range of technological concerns and potential performative issues that financial institutions are wary of. In the previous sections, non-technological strategies and best practices have been discussed that can mediate between perceptions of high cost and effective adoption. According to Freeman et al. (2021), AI assurance to a tool’s user base is also important, and quite some technological strategies such as quantifying bias in data, tool performance, overall trustworthiness of outputs and its security exist that can make tools more reliable, dependable, explainable, and fair. In general, lowering the perception of risk is only valid when a model is genuinely less risky than it is perceived to be by potential clients. The objective should not be to sell risky tools more effectively, but rather to foster an ecosystem in which the inherent risks of AI are accurately contextualised relative to the actual threats they pose. As mentioned previously, AI models will make mistakes, and while there are strategies to reduce both the number of risks and their impact on an organisation, these models remain tools with inherent advantages and disadvantages. In this regard, SaaS providers should only communicate the risk profile of their tools, for example through certifications, if the technology meets those corresponding standards.

That said, participants frequently described **improvements to AI models** that ease the complexity of implementing third-party tools through intelligent design. Nine participants mentioned the importance of constant model verification, which can be achieved by creating test suites that break down an AI tool’s mechanisms into individual steps, thereby enhancing explainability. ”And there’s a model on the model to check whether [...] it gives the right answer. You know, and that had to be checked by hand; and now they have a second model that actually validates what the first model spits out to the customer [...]. Very layered” (P11). Verification is not limited to the model’s internal consistency. In addition, comparisons with new models and adaptations to new data formats must be ongoing. ”I think where we are now is we have a little bit more rationalisation, those are just development cycles that we go through” (P5).

Furthermore, setting up guardrails is essential to ensure that a model only accesses pre-specified data sources and remains confined to its defined operational boundaries. To mitigate variation in performance or inconsistency in answers, particularly in tools powered by GenAI, outputs should be structured using predefined prompts and parameters. This is especially relevant in evaluative contexts, such as loan assessments. ”So that is really important to set guardrails around these models to ensure they don’t say anything they shouldn’t” (P12). Another useful practice involves evaluating a model’s accuracy for each specific use case before deployment. ”Setting boundaries on when you can use the model, of sorts” (P9).

Ten interviewees identified **strategic infrastructural factors** that facilitate smoother integration with the existing systems of financial institutions. Designing tools that can be flexibly applied across various contexts allows institutions to explore low-risk use cases more freely. Modular tool design enables less disruptive, iterative improvement and better alignment with institutional needs for building trust and evaluating performance. ”So it is then a matter of testing and deploying it where it can be checked and only rolling it out later” (P3). This approach returns some of the initiative to users and developers at financial institutions, encouraging experimentation and adaptation to operational changes. ”That you can indeed adapt modules on a platform. I also think that it partly has to do with the culture of your company, right? Are you also agile as a company to be able to adapt?” (P11). Moreover, this flexibility allows financial institutions to absorb platform or tool updates without requiring major structural changes during the duration of a service contract.

Another important enabler of this flexibility lies in designing SaaS platforms with AI integration in mind, particularly regarding **data housekeeping**. Strategic management of up-to-date, anonymised, and unambiguous data, used exclusively within internal environments, can significantly reduce perceived risks relating to privacy, performance, and third-party dependencies. At the foundation of this lies the evaluation of data quality and formatting to ensure that ML, DL, and GenAI algorithms interpret data more effectively, resulting in higher accuracy and more stable performance. According to James et al. (2023), the success of statistical models requires careful attention to data quality, dimensionality, and missing values, along with well-considered strategies for data splitting and test error estimation. For other data types, AI itself can be leveraged to improve the interpretability of documents and reduce ambiguity. ”But that has everything to do with the quality of our own data. Is everything described sharply and punctually? So it also teaches us a lot to look carefully at how we call things and how we have labelled things and so on” (P3). Three participants noted that tools are generally considered less risky when they do not rely on personal data, but instead work with selected anonymised datapoints. For example, comparing anonymised data with a lender’s acceptance policy can help mitigate compliance concerns and legal ambiguity. Another benefit of minimising reliance on data is that it reduces the need for intensive training, enabling more out-of-the-box functionality. This addresses a previously identified issue, where the time required to train a model is outpaced by the speed at which the underlying technology evolves. When institutional parameters such as acceptance policies change, updating the model becomes a matter of modifying input materials, thereby ensuring continued operational performance without interruptions.

4.3.4 Service Offering Strategies

Strategic choices in product and service development can reduce both the actual and perceived cost and effort of integration. Additionally, several participants mentioned that the nature of the services a provider offers, whether in terms of the core technological offering or the role assumed within the provider-client relationship, plays a similarly important role.

Regarding the **nature of the solution offering**, designing platforms as standardised foundations on which custom AI tools can be built (agile, flexible, and out-of-the-box) is a key enabler of introducing AI as a complementary service. For clients already under a service contract, embedding AI in core functionalities provides an unobtrusive entry point. Avoiding overly prominent AI branding may be prudent, as it can raise risk perceptions. This approach leverages existing trust in proven systems to introduce AI as a natural extension of a provider’s efficiency objectives. As a result, clients are gradually exposed to and build confidence in a provider’s AI capabilities without needing to engage in immediate integration. Improvements in transaction speeds and lead times for complex customer operations in the mid and back offices should become noticeable. AI becomes part of a routine system update in existing business lines, serving as a stepping stone for gaining trust and offering additional value-adding tools. ”So to bring the cost of integration of custom solutions from 70 cents to 30 cents, standard solutions are needed. [...] Promoting standard solutions does not mean that functionality has to be standard, but it does mean that you go to a plug-and-play environment [...] where there is a kind of robustness after which you can choose any product you need” (P3).

Striking the right balance between standardised offerings and tailor-made, client-specific adaptations is complex and may vary based on the current relationship between provider and client. This is also where the contrast between the participants was prominent. When asked which one met the professional needs of financial institutions, about half of the participants noted customisable solutions, whereas about a quarter of the participants opted for standard solutions. The remainder of the interviewees emphasised the undeniable need for a combination of both for a service offering to be considered in the first place, and to be adopted in a later phase. Bottom line was that participants, explicitly or implicitly, agreed that custom tools provide the most value when integrated into a standard foundation that is already part of the core offering. While financial institutions often stress the need for bespoke solutions, this frequently translates into offering standard systems that can dynamically adapt to the institution’s unique context. ”It’s automation of customisation. [...] Look, every company is a fingerprint. If you can scan that fingerprint and make sure that your platform can adapt to it instead of the other way around, it becomes a lot easier" (P5). Although plug-and-play tools are often regarded as standardised, AI can enable these systems to interpret the operational blueprint of their environment and adjust accordingly. This approach reduces the integration effort, cost, and perceived complexity that often leads institutions to hesitate. These institutions are often overly cautious for "the party that you still have to configure and customise for your own specific context" (P15). Finally, two interviewees mentioned offering open-source models to clients free of charge. However, the effectiveness of this approach depends on the client. For those who find it helpful in building trust, such clients may not require SaaS providers to supply the models themselves, but rather only the platform to support their deployment.

For these clients, **SaaS providers should act as advisors** on technology management, a role supported by ten participants. In this advisory capacity, a system's functional demands should be broken down into sub-problems, followed by a discussion of potential solutions using tailored software components. This approach shifts away from a technology-driven push and instead promotes a bottom-up exploration of technological possibilities grounded in real business needs, with AI as a potential means of enhancement. "Yes, they sat down at the table with the idea that we were going to apply AI in their finance, but that was not their problem at all" (P6). In addition, the often underdeveloped strategic orientation around AI within financial institutions can be addressed through this approach. "But also knowing that this is still a very new skill set in the market, you would not always find all the people to do it fully on your own. And you might also need some support in defining the strategy or defining the vision" (P7). As a result, the lack of practical problem-solving capacity in many AI offerings is mitigated from the outset. Once the business needs are clearly defined and linked to implementation ideas, the proposed AI solutions are perceived as more targeted and less risky. This is particularly true when those closest to the operational challenges are involved in the process, leading to a more rational and grounded development approach. "As a supplier, keep an eye on who you actually help and why you help them" (P2). As a result, adoption intentions are more likely to follow.

Finally, the strategies discussed in the last three sections correspond with efforts to improve facilitating conditions and positively affect behavioural intention by reducing perceived risks and onboarding complexity. Collaborative implementation, most viable product piloting, and advisory support from SaaS providers enhance effort expectancy by lowering barriers to entry. Reframing AI adoption in terms of value alignment and compliance readiness also serves to rebuild trust, indirectly supporting both social influence and performance expectancy.

5 Discussion

5.1 Discussion of Research Findings

This study aimed to explore the adoption of AI-powered tools in the context of the financial services industry with SaaS as a delivery method. In order to do so, decision-making at the receiving end of financial services, at financial institutions, has been at the basis of this exploratory industry analysis. At first, the experienced reluctance of financial institutions was considered to be a problem of service providers, meaning to offer innovative AI-driven tools with which they expect to deliver improved services that create current and future resilience to their clients. However, to fully grasp the complexity of AI adoption within the services context central to this study, it was realised early on that the perspective from both sides on the current and prospective service contracts would be valuable to consider.

With this approach, it was found that slow AI adoption cannot be seen as a one-dimensional problem for SaaS providers. With financial institutions emphasising the drivers of interest, often championed by the strategic necessity of adopting AI-powered tools into their operational models, they can be seen as a co-owner of the problem that is ineffective adoption rates of providers' AI offerings. This problem, found to be a lack of effective mutual value creation within the client-provider relationship, needs both sides to transform their ways and adopt a more dynamic and learning-centric approach to disseminating AI throughout their service delivery models on one hand, and procurement processes on the other.

The study's findings are in line with existing theoretical insights. According to TAM, adoption decisions are influenced primarily by perceived usefulness and ease of use (F. D. Davis, 1989). Financial institutions recognise the usefulness of AI for strategic and operational goals, yet seem to lack internal clarity and readiness to act, reflecting the classic intention-behaviour gap identified in TAM literature. Meanwhile, UTAUT extends this by incorporating social influence and facilitating conditions, both of which emerged from this study as key variables complicating institutional adoption (Venkatesh et al., 2003). On a broader organisational level, the operating model framework by Howell-Barber et al. (2013) for financial institutions offers relevant context: more traditional financial institutions with federated or diversified IT models seem to be especially prone to slow or fragmented adoption, compared to those with more unified digital governance structures that supported innovation more proactively.

To guide the discussion of findings, Table 6 synthesises the key themes from Chapter 4 in relation to the study's three subquestions. It also summarised these themes, reflecting the narrative progression of institutional interest, barriers, and potential solutions regarding AI adoption in fintech SaaS. In Chapters 5.3.1 and 5.3.1, the practical implications and recommendations for SaaS providers and financial institutions are discussed, respectively.

The data collected for this study shows that interest in AI-powered tools within financial institutions is not a matter of novelty-seeking or technological opportunism, but rather reflects a pragmatic awareness of shifting industry dynamics. This aligns with perceived usefulness as defined in TAM F. D. Davis (1989), and the performance expectancy factor in UTAUT (Venkatesh et al., 2003). Notably, interviewees expressed institutional interest in AI to be across both front- and back-office applications, identifying improvements in efficiency, customer experience, and internal resource allocation as potential areas of benefit, in line with research highlighter earlier by Choithani et al. (2022), Durães et al. (2023), Holdsworth and Scapicchio (2025), Joshi (2025), Keller et al. (2023), Magrani and Da Silva (2023), Noreen et al. (2023), Oliveira and Figueiredo (2023), Sarker (2021), and Trancoso et al. (2023). Yet, while this interest is strong in principle, it often remains exploratory in practice. Although a sense of urgency is present among some institutions, partly driven by competitor activity and the desire to future-proof their offerings, it does not consistently translate into concrete, actionable implementation plans.

A recurring theme in the interviews was that institutional interest in AI is often decoupled from a clear understanding of its technical or organisational implications. This situation reinforces the notion of

Table 6: Themes mapped to research questions and summarised individually

Research Question	Empirical Theme	Summary
SQ1: Why do financial institutions initially become interested in AI-powered tools?	Interest in AI Applications	Financial institutions express broad curiosity about AI's potential across different areas of service delivery.
	Operational Benefits through AI Adoption	AI is viewed as a strategic lever for increasing efficiency and improving both internal workflows and customer engagement.
	External and Strategic Pressure to Adopt AI	Competitive dynamics and future-proofing logic create pressure to explore AI solutions.
	Incentives to Outsource AI to SaaS Providers	Internal capacity constraints and resource considerations lead institutions to favour outsourcing to specialised SaaS vendors.
SQ2: What are the key challenges in financial institutions' decision-making regarding AI adoption?	Institutional Process, Politics, and Procurement	Internal processes and risk-averse procurement structures slow down decision-making and hinder experimentation.
	Technological Challenges and Performance Concerns	Legacy infrastructure and uncertainty about AI model reliability create barriers to integration.
	Third-Party Risks	Concerns about vendor lock-in, data security, and reliance on foreign cloud providers inhibit trust.
	Regulatory Landscape and Compliance	Regulatory ambiguity and compliance risks disincentivise innovation and stall adoption.
	Integration and Onboarding Challenges	Seamless integration into existing systems remains a major hurdle for AI-enabled SaaS tools.
SQ3: How can SaaS providers address the challenges that hinder the adoption of AI-powered tools?	Collaborative Implementation and Onboarding	Co-development and guided onboarding foster trust and reduce institutional friction.
	Risk-Accurate Communication of Service Offering	Clear and tailored communication about risk and value increases client receptivity.
	Best Practices for Product and Service Development	Providers adopting modularity and flexibility in design see better institutional alignment.
	Service Offering Strategies	Tailored service models that reflect institutional constraints enhance the likelihood of adoption.

incomplete facilitating conditions in UTAUT, where enthusiasm fails to manifest due to organisational inertia or unclear execution pathways. Interviewees often framed SaaS as a convenient vehicle for AI capability, particularly given internal IT limitations, consistent with Howell-Barber et al.'s point that institutions prefer SaaS when their internal infrastructure cannot support full-scale innovation (Howell-Barber et al., 2013).

These perceived benefits are counterbalanced by structural concerns. As the findings in Chapter 4 demonstrated, procurement processes are often slow-moving and misaligned with the iterative nature of AI development. These dynamics are symptomatic of institutional structures that are risk-averse and heavily siloed, elements that can suppress technology adoption, regardless of perceived benefit.

Beyond procurement, other technical and organisational challenges compound adoption friction. Performance concerns, particularly around the maturity, explainability, and reliability of AI models, were frequently raised. These concerns often reflect a fear of opaque decision-making or adverse outcomes, which in the financial services sector can have reputational or even legal consequences. Such hesitation reflects what Rahman et al. (2021) and Misra and Doneria (2018) describe as the 'black box dilemma' of AI, which undermines user trust and impedes approval from internal risk and compliance teams.

Relatedly, integration and onboarding challenges emerged as a consistent pain point. Particularly in institutions that rely on legacy systems, integrating externally developed AI tools was seen as technically burdensome, costly, and risky. This mirrors the observations made by Ionescu and Diaconita (2023) and Chen et al. (2018), who stress that without adequate IT infrastructure and cross-departmental coordination, the perceived implementation effort can outweigh expected benefits, an insight well-aligned with the facilitating conditions factor of UTAUT.

Third-party risks were also frequently mentioned, encompassing concerns over vendor lock-in, data security, and loss of control over critical systems. Especially in contexts where AI tools rely on foreign-owned cloud infrastructure, institutions cited geopolitical dependencies and data sovereignty concerns. These issues have become more pronounced in the wake of increasing global scrutiny over cross-border data flows and are particularly relevant for EU-based institutions subject to current and forthcoming AI regulation frameworks.

Regulatory considerations further deepen hesitant decision-making. Many institutions view the regulatory landscape as a source of uncertainty rather than support, especially when internal compliance functions interpret new AI-based tools through a liability lens. This echoes findings from Lazo and Ebardo (2023) and García-Fernández et al. (2024), who argue that the evolving and often ambiguous nature of regulation actively undermines experimentation and trust in AI services, particularly in Europe.

Despite these barriers, this study found that effective collaboration and mutual adaptation can yield promising outcomes. When institutions and providers are to engage in co-development or iterative onboarding, friction ought to be reduced and internal ownership increased. Providers that align their product strategies with institutional limitations, such as by offering modular, risk-aware solutions, are seen as more trustworthy and strategically aligned. These findings validate the call by Chen et al. (2018) and Mahalle et al. (2021) for context-sensitive SaaS design practices in AI implementation.

One important observation from the interviews is that the institutional interest in AI is not taking place in a vacuum. Particularly in European financial institutions, broader cultural and regulatory narratives surrounding AI play an influential role in shaping how adoption is framed internally. As discussed in Chapter 4.1.3, several participants referred to the prevailing AI 'hype', a public and media-driven optimism around AI's transformative potential, which simultaneously raises institutional expectations and increases reputational sensitivity. These insights point to a more nuanced form of AI sensibility: institutions are navigating not only strategic and operational questions, but also societal and ethical expectations. In this regard, the EU's broader positioning on trustworthy AI, digital sovereignty, and the AI Act adds an important contextual layer to the adoption conversation. A discussion of how these auxiliary pressures interact with institutional logic, risk culture, and vendor engagement strategies follows as a final auxiliary discussion of this section, which extends the findings discussed here.

Taken together, these findings illustrate that AI adoption in financial institutions is shaped by a complex interplay between organisational structures, regulatory environments, and provider adaptability. While technology itself may be ready, institutional capacity, risk frameworks, and governance maturity remain key determinants of adoption. As Howell-Barber et al. (2013) argue, adoption success ultimately depends not only on the strength of the technology but on how well it integrates with the institution's operating model and strategic posture. Therefore, SaaS providers should move beyond technical capability alone and tailor their offerings to the institutional realities of their clients, turning AI from a promise into practice.

EU's AI Standpoint and AI Sensibility The regulatory approach of the emerged in this study as both a structural enabler and a practical constraint in the adoption of AI by financial institutions. On the one hand, participants acknowledged the strategic intent behind the EU's regulatory attitude, namely, aiming to embed transparency, fairness, and ethical alignment into AI deployment. On the other hand, several participants observed that the current form and pace of regulation may restrict innovation and limit competitiveness, particularly when viewed in the context of global technological dynamics.

Multiple interviewees explicitly linked regulatory caution to the risk of falling behind global competitors. As participant two noted: “What the EU is trying to do now with this legislation where we say, yes, we are going to use AI responsibly… But the Chinese and the Americans, and the Russians are not doing that. So if you limit it now, you will be behind for the next 10 years”. This sentiment reflects broader concerns that a rigid regulatory framework could result in inferior products or delayed adoption, especially when financial institutions are forced to prioritise compliance over value creation. “So basically you’re going to deliver them an inferior product to make the governance, compliance and risk people happy. Are you really doing the banks a favour?” (P2).

In parallel, several participants raised concerns about regulatory fragmentation and the strategic dependency this might create on non-European technology providers. As participant four wondered: “How do large banks ensure that they do not become completely dependent on the tech companies in America in terms of AI technology? And how do they ensure that they can continue to implement models within the law and regulations and ethical regulations in the EU?” This tension between maintaining digital sovereignty and avoiding technological lock-in was echoed by participant five, who reflected on the practical challenge of aligning innovation with evolving regulation: “We all want to ensure a secure banking system, but at the same time of course the demands that come to you must be proportionate to the technology that you have” (P5).

The perceived slowness of European regulatory systems, particularly in contrast to other regions, was another recurring theme. Participants highlighted that companies with global operations may increasingly shift innovation activities outside the EU. “If it’s not in Europe, they do it somewhere else, and then they take advantage of it. And also competition really keeps them going” (P7). While some businesses are motivated by compliance, others may be incentivised to innovate abroad to avoid the perceived rigidity of the European market. This has implications not only for AI adoption but also for the concentration of technological capabilities beyond European jurisdiction.

Moreover, while regulation may be seen as slowing progress, it also acts as a protective mechanism. Institutions acknowledged that stricter requirements around data localisation and transparency can help ensure ethical usage of AI. “Make sure your data storage processing is completely in-house. [...] Then you can guarantee that you are safe; and be able to show that transparently” (P9). Such views highlight that within the EU’s cautious approach lies an opportunity for trusted, compliant, and future-proof AI deployment, provided that the accompanying governance does not overly constrain experimentation or disproportionately favour large incumbents over emerging innovators.

Overall, the EU’s regulatory framework plays a dual role. While offering important safeguards and a normative model for responsible AI, it also introduces frictions that may slow down adoption and the decision-making processes that lead to acceptance of solutions rather than rejection. In a global context where agility and scale are strategic assets, the challenge for EU-based institutions lies in balancing compliance with competitiveness within the regulatory landscape, particularly as geographic inconsistencies in regulation and political outcomes continue to shape the global AI landscape. These geographical differences in the regulatory landscape are not necessarily caused by risk appetite only. According to Ipsos (2024), European citizens are moderately excited about products and services using AI. Although nervousness was found to be higher among financial institutions than in other institutions in a general sense, average risk perceptions leading to nervousness surrounding the technology are lower in the EU than in the US (Figure 10). Perhaps, a misrepresentation of perceptions of AI technology exists. Although the EU’s ecosystem clearly demands companies to jump through a lot of hoops in the regulatory landscape, this might not represent the nervousness surrounding a technology. This nervousness just leads to different actions in different systems. Although the US seems to be more nervous regarding AI-powered functionality, the regulatory landscape does not necessarily act on this by creating more guidelines and policies. In the US, the government relies on more of a self-regulating ecosystem, where companies at the forefront of AI technology are expected to behave desirably, and take away the concerns of those that might be affected. The question of whether this is something that happens is another.

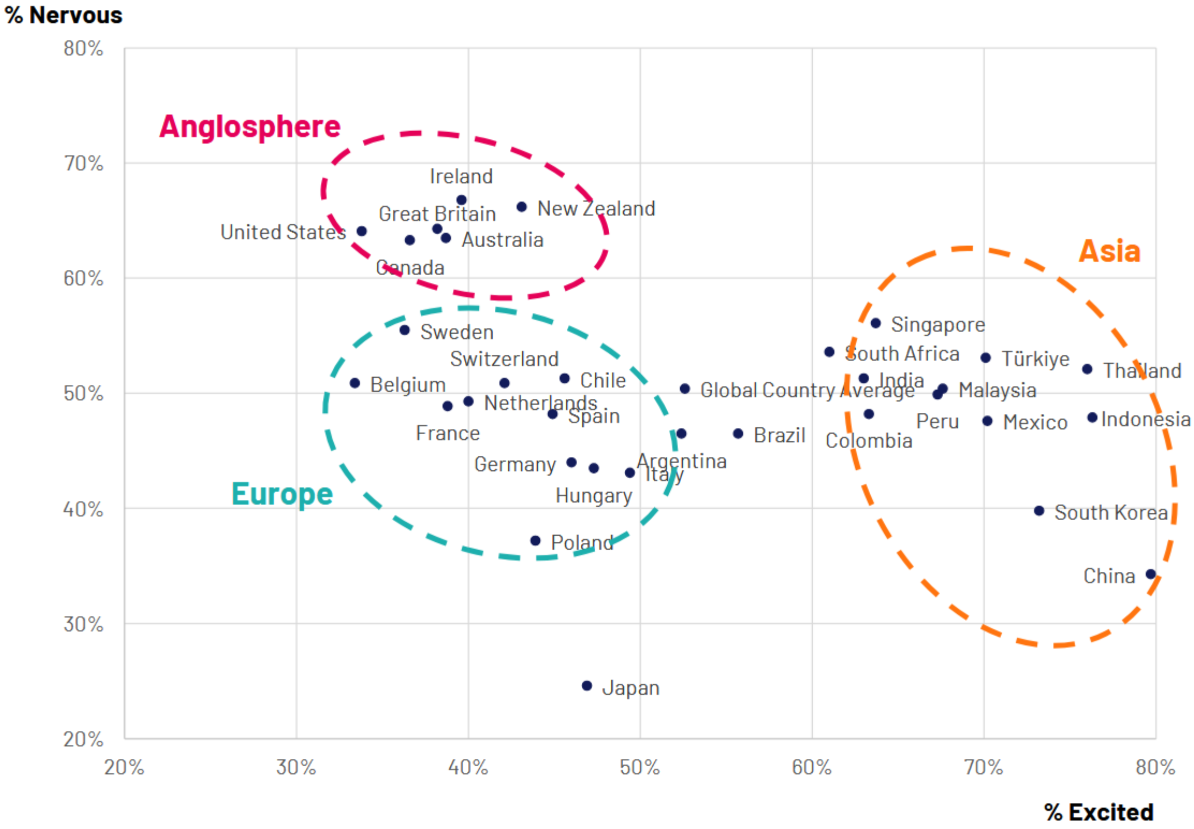

Figure 10: Geographical overview of degree of excitement versus nervousness regarding AI-powered products and services. From *"Ipsos AI Monitor 2024"* (p. 17), by Ipsos (2024) https://www.ipsos.com/sites/default/files/ct/news/documents/2024-06/Ipsos-AI-Monitor-2024-final-APAC.pdf. Copyright (2024) by Ipsos. Reprinted with permission.

While technological progress is widely recognised as essential for financial institutions to remain competitive, several participants cautioned against losing sight of the need for deliberate and responsible AI adoption. The pace of development, combined with pressure from competitors and hype-driven narratives, can get in the way of fundamental questions around purpose, risk, and long-term societal implications. As participant one remarked: “Generally speaking, I think if you’re not adopting AI, judiciously, in a good way, then you do risk falling behind”. Yet, that same participant also questioned the assumptions behind industry urgency, pointing out: “when I hear something like ‘our competitor is 3 months ahead,’ I often wonder [...] what risks and what compliance shortcuts are they also perhaps taking?” (P3).

These reflections align with earlier observations on the AI hype cycle in Chapter 4.1.3, where inflated expectations were seen to distort internal communication and inflate risk tolerance to some extent. Several participants warned that AI, while powerful, remains a tool, one that is inherently neutral but not necessarily consistent with organisational values in its use. “You can’t really make an AI tool that can be considered like a Swiss army knife, and then expect all its parts to be used for just its purpose” (P1). As such, its effectiveness depends not just on performance but on how well its use aligns with institutional culture, compliance structures, and broader societal norms. Some participants voiced concern about the social and ethical risks that emerge when institutions lose this alignment. Participant two described how seemingly harmless uses of AI, such as insurance-related risk modelling, can evolve into ethically questionable practices: “The conclusion of that machine learning algorithm was that you need people with a higher birth year. [...] The concept that someone is younger is not a concept that an AI knows unless you explain it to it” (P2). These examples underscore the importance of critical reflection on not only what AI can do, but what it should do. As participant five noted, reputational integrity plays a key role here: “Because ultimately the trust that customers have in our bank [...] that is a reputation. Yes, that comes on foot and leaves on horseback” (P5).

In addition, the importance of explainability was a recurring theme, particularly in high-stakes financial decision-making. AI systems that cannot justify or clarify their decisions were seen as unsuitable for many use cases. “You just get an outcome, but you can’t explain why. That makes that some use cases get eliminated” (P10). This not only complicates regulatory compliance but may also erode employee and customer trust.

Finally, several participants pointed to the need for clearer, more human-centric communication about AI. While technical sophistication is increasing, understanding within institutions often lags behind. Participant three summarised this concern: “So as long as we are not able to explain everything simply, I also see the future of AI adoption as bleak. If we cannot explain to your grandmother simply how it works, then we still have a problem”. This point also connects back to the ongoing conversation around the future of labour in Chapter 4.2.5, where concerns were raised not just about job displacement, but about the growing disconnect between decision-makers, technical teams, and the broader societal role of financial services.

5.2 Theoretical Implications

This study contributes to theory by exploring the adoption of AI-powered tools in the context of financial institutions through the lens of SaaS service delivery. In doing so, it responds to gaps in existing adoption frameworks by highlighting how organisational and systemic dynamics shape technology integration beyond user intention alone. The use of the TAM and UTAUT models provided a useful starting point, yet the findings indicate that their constructs are not readily transferable to the institutional context at financial organisations without further elaboration. Particularly, the performance expectancy and facilitating conditions factors from UTAUT, and the perceived usefulness-intention link in TAM, do not fully account for the institutional complexities that dominate decision-making in financial services.

What this study makes clear is that institutional interest in AI is not just shaped by attitudes and expectations at the individual or departmental level, but is deeply embedded in organisational governance, regulatory interpretation, and infrastructural lock-in. As such, there is a need to revisit and expand dominant adoption frameworks to accommodate a broader governance-centric perspective. Elements from the Digital Governance Framework offer useful conceptual additions by highlighting how digital maturity, internal alignment, and compliance logic impact adoption momentum. Future theoretical models would benefit from incorporating such governance-infused conditions more explicitly.

Additionally, the study shows how the internal structure of financial institutions influences their ability to act on adoption intentions. Building on Howell-Barber et al.’s model of operating models in financial services (Howell-Barber et al., 2013), the findings suggest that fragmented or centralised IT and procurement structures act as moderating variables between perceived benefits and implementation outcomes, the extent of which could be a topic for further research. This institutional heterogeneity remains under-theorised in classical adoption literature. Moreover, while TAM and UTAUT generally assume a one-directional relationship from technology provider to user, the findings here stress the need for a co-creative and relational view of AI adoption in SaaS ecosystems. Mutual value creation, built through collaboration and early-stage engagement, appears to be a core condition for adoption success, particularly in high-risk, regulated domains such as banking.

Several themes also emerged that call for an updated view of risk and trust in adoption models. Where traditional frameworks treat these elements as background factors or barriers to overcome, the present findings suggest they are dynamic and evolve over time. In the context of fintech SaaS, trust is not simply granted. It must be actively built through onboarding, transparency, and the demonstration of long-term commitment. Similarly, perceived risk is shaped not only by the nature of the AI tool itself but by the institutional lens through which it is assessed. This invites a more processual and relational understanding of trust and risk in B2B AI adoption.

Furthermore, the study highlights the unique theoretical status of the AI–SaaS bundle as an object of study. Rather than being treated as discrete technological categories, AI and SaaS are experienced by institutions as mutually reinforcing, and sometimes mutually complicating. Their convergence introduces new forms of dependency (e.g. on facilitating cloud vendors), as well as new forms of opportunity, particularly in terms of scalability and modularity. This synergistic configuration is not yet adequately reflected in the current literature.

Another insight, particularly relevant in the European context, concerns the discrepancy between the public narrative of AI and the internal reality of financial institutions. While AI hype and media attention create pressure to act, the internal framing of AI remains cautious and conditional. This divergence between external symbolic framing and internal pragmatic rationality adds complexity to how theoretical models conceptualise decision-making under reputational, regulatory, and ethical scrutiny.

Additionally, when seen through the lens of innovation system thinking, the findings of this study illustrate how adoption processes in financial institutions serve not only technological purposes but also knowledge development, internal alignment, and legitimacy building. This connects institutional AI adoption to broader systemic functions in the innovation ecosystem, as described by Hekkert et al. (2006). It supports a functional view of adoption as contributing to internal innovation capabilities, not merely external efficiency gains.

Finally, this study invites reflection on what adoption means in practice. Rather than a binary or static decision point, adoption emerges here as a phased process, starting with strategic interest and exploration, moving through procurement and onboarding, and maturing into continuous improvement cycles. This lifecycle view of adoption requires theoretical frameworks that are more temporally aware and better equipped to capture ongoing and long-lasting processes of alignment and iteration.

These theoretical implications extend current knowledge on institutional technology adoption by highlighting the dynamic, contextual, and often co-constructed nature of decision-making in the financial services sector. At the same time, they point to a number of conceptual and empirical limitations that warrant further investigation. Section 5.4 reflects on these limitations and outlines theoretical routes for future research to address them.

5.3 Practical Implications and Recommendations

5.3.1 Implications and Recommendations for SaaS Providers

The findings of this study offer several implications for SaaS providers seeking to deliver AI-powered tools to financial institutions. These implications do not merely concern technical functionality or market opportunity, but reflect a more fundamental challenge: the alignment of product offerings and engagement strategies with the governance structures, risk cultures, and decision-making logics of their institutional clients. This alignment needs to be sensitive to where the institution sits in its adoption journey, whether it is a prospective client considering engagement for the first time or an existing partner navigating integration and scale-up. Both scenarios present unique, yet interrelated, demands.

For prospective clients, institutional interest in AI is often driven by strategic ambition or innovation mandates. However, this interest is not always rooted in a clear understanding of what the technology can or should deliver. This creates a discrepancy between early-stage enthusiasm and later-stage adoption barriers, particularly once procurement processes and compliance reviews are triggered. SaaS providers can respond by adopting a more context-sensitive approach to early engagement. Rather than assuming that AI capabilities speak for themselves, providers should position their tools as part of broader problem-solving strategies. By explicitly linking offerings to the operational and strategic priorities of the institution, such as workflow optimisation, data-driven compliance, or resource efficiency, providers are more likely to generate sustained traction beyond the initial spark of interest. For example, simply engaging with customers without a proof-of-concept, but equipped with a list of things institutions tend to do manually and showing how to automate a piece of that with them, not only communicates the understanding of problems clients face, but also that you have the knowledge to apply AI to their context.

A clear example of this was given by participant four, who described how a (prospective) institutional client had seen surges in digital transactions around public holidays, yet lacked a systematic way to plan infrastructure accordingly. ”So what they did is see if they could create an AI model that could predict the peak at Easter, so that they could scale their infrastructure hardware to meet that amount of transactions” (P4). In this case, a well-defined operational issue was addressed through a targeted AI model, with direct and measurable value for the institution. Providers can use similar framing when approaching new clients, illustrating specific input-output scenarios to bridge the abstract potential of AI with immediate institutional needs.

Expectation management is key in this regard. The study revealed that overpromising or relying on generalised AI narratives risks undermining trust when institutions encounter the realities of integration. Instead, a more constructive strategy is to align projected outcomes with the actual use cases and constraints of the institution. This includes acknowledging the limitations of the tool, setting realistic adoption timelines, and engaging stakeholders in defining success criteria from the outset. In doing so, providers not only refine their communication strategies but also improve long-term satisfaction by avoiding misalignment between promise and delivery.

Product development can benefit similarly from this orientation. Rather than assuming institutional interest is centred on technological novelty, providers should take signals from what financial institutions actually hope to gain through adoption, namely operational efficiency, regulatory robustness, competitive positioning, and enhanced customer experience. These priorities, identified in this study, offer a roadmap for shaping product features, service architecture, and support models that correspond to real institutional demand, not assumed technical interest. For instance, a provider could build a simple tool that allows risk teams to extract specific clauses from regulation documents and match them to internal control structures. The feature might not be AI-intensive, but it could solve a pressing compliance task. Moreover, framing it as a risk-alignment solution rather than a futuristic innovation makes it easier to adopt.

Once an institution has entered into a client relationship, the dynamic shifts from access to deepening. Here, the importance of co-development and collaborative onboarding becomes paramount. Providers who offer modular, incremental implementation paths and embed institutional stakeholders in onboarding practices tend to foster a stronger sense of trust and ownership. This process is especially important in environments characterised by siloed decision-making or constrained IT infrastructures, where large-scale transformation is rarely feasible. For example, a provider could collaborate with a bank’s risk department to pilot a model using a single anonymised dataset on one internal server before scaling the system further. These kinds of staged deployments not only reduce perceived risk but also generate valuable internal champions within the client organisation.

Moreover, institutions are more likely to proceed when SaaS offerings can demonstrate post-contract flexibility and responsiveness to evolving needs. This calls for a layered engagement model that accommodates the diversity of actors within financial institutions, such as compliance officers, procurement managers, IT architects, and end-users alike. For example, providers can build in engagement checkpoints after each onboarding milestone and tailor update cycles to accommodate stakeholder input and internal audit cycles, rather than pushing standardised development and update timelines.

Beyond product and service considerations, the study points to a more strategic implication: SaaS providers must shift from being mere vendors to becoming co-navigators in the adoption journey. This involves recognising how early-stage drivers of interest, such as innovation rhetoric or strategic imperatives, often encounter resistance in later stages due to procurement friction, integration difficulty, or risk perceptions. Providers that anticipate and prevent this friction, by offering clear documentation, transparent governance models, and region-specific regulatory support, position themselves not only as solution developers but as implementation partners. Offering explainability reports, risk-mitigation plans, and tailored integration roadmaps can lower uncertainty and strengthen institutional confidence in the long-term viability of the offering.

Importantly, this credibility does not only stem from outward communication. The study also highlights that SaaS providers can gradually implement AI within their own operational workflows and in their core offerings, not as a promotional tactic, but as a genuine strategy to optimise delivery, reduce friction, and demonstrate internal alignment with AI capability. By showcasing internal use of AI for service optimisation, documentation generation, or customer success monitoring, providers set an example of how AI can be embedded meaningfully and responsibly. For example, providers might consider using AI internally to summarise regulatory updates across jurisdictions and trigger alerts for relevant internal teams. Such an application could reduce preparation time for compliance responses while improving awareness and speed of internal alignment. Similarly, simple MO or BO optimisations in a controllable environment as part of a provider's core offering, such as automating data extraction from documents in loan application processing, can showcase competence in applying AI to critical operations. If implemented transparently and safely, these use cases not only support operational efficiency but also signal to clients that AI is being integrated responsibly and meaningfully within the provider's own systems.

Finally, the European regulatory context presents both a challenge and an opportunity. Providers that proactively anticipate data sovereignty concerns, align their services with incoming legislation such as the EU AI Act, and show sensitivity to local governance cultures are more likely to be perceived as trustworthy partners. Offering region-specific compliance kits or guidance documents during procurement can ease the burden on internal legal teams and build goodwill from the outset. The most straightforward way to do so is by creating, running, and communicating self-assessments for all sorts of risks identified in this study, and getting certified or updating certifications as soon as possible.

Taken together, these implications suggest that what matters most is not only the technical strength or novelty of the AI solution, but the degree to which it is developed and delivered with institutional realities in mind. Providers that combine solution excellence with a deep sensitivity to governance structures, stakeholder dynamics, and adoption frictions are more likely to gain institutional trust and navigate the complexity of AI deployment in financial services. It is this combination of technological capability and institution-centric engagement that distinguishes providers best positioned to succeed in the evolving AI-fintech ecosystem.

The effect of AI on the future SaaS business model Admittedly, the results of this study do not provide a guaranteed or universally applicable action plan for every provider. As discussed in Chapter 2.2.2, the fintech SaaS BMC comprises a variety of business models, each serving different areas of digital finance. However, these models share common principles, such as delivering AI capabilities through the cloud and targeting a similar ideal client segment. During the interviews, a recurring theme was the potential impact of AI on the fintech SaaS business model itself. Beyond prioritising development areas, communicating de-risked offerings, and complementing cloud-based platforms, providers must consider how AI can benefit their own operations and how the value of their AI offerings may evolve amid rapid technological advancement.

On one hand, the complex domain knowledge required to develop and deploy AI models within a cloud-native infrastructure appears increasingly scarce and monetised, following the broader societal shift toward a knowledge economy, which limits the distribution of expertise and associated productivity gains (Powell & Snellman, 2004). Since SaaS providers already possess such knowledge in-house, this trend may favour them, offering opportunities to capitalise on AI development with less competition from clients' in-house teams, who often have limited flexibility to experiment with disruptive technologies.

This is especially true for financial institutions, which take a risky assumption first position in developing functionality and have to operate under strict supervision from governing institutions.

On the other hand, AI may enable institutions to access the rich body of public knowledge, lowering the effort and cost of developing AI-powered tools. This could reduce reliance on external expertise and reconfigure the traditional balance between buying and building technology. The resulting workforce augmentation may shift buy-versus-build considerations toward in-house development. This transformation is supported by Poquet and De Laat (2021), who argue that AI will significantly affect the concept of lifelong learning. Naturally, such changes on the client side will have implications for the operations of SaaS providers. Indeed, these developments in organisational knowledge management are relevant across sectors. Jarrahi et al. (2022) elaborates that AI enhances "the creation, storage and retrieval, sharing, and application of knowledge" (p. 1) across industries. As a result, SaaS providers must respond to the possibility that financial institutions will develop technological capabilities similar to their own and critically reflect on their business models, as "eventually, knowledge is not worth much anymore" (P9).

The extent to which SaaS providers can adapt their business models to the pace and scope of AI-driven change at financial institutions will determine how their value propositions and customer segments are affected. According to participant 10, the effect on knowledge dissemination to their clients will not change the core of their value propositions. In the age of AI, industry connections and the engagement with other stakeholders, such as other service providers and financial intermediaries, will continue to be of value, even with more in-house capabilities on the client side. They identify the non-technical factors to make an AI tool valuable now and in the future. "It's not that absolutely nobody [...] could build that [...]. So how come we still sell it? For the simple reason that we are part of a larger network, that we are right in that market, that we have the right connections. [...]. The fact that it all fits together and [...] is focused on exactly what a certain group of customers wants, that is added value in my opinion [...] and that it is part of a larger ecosystem, and that ecosystem is not going to be replaced just like that" (P10).

This notion corresponds with one of the pro-buy notions discussed in the previous chapter, in which the embeddedness of AI solutions was identified to be part of fintech SaaS AI's overall appeal, which does not seem to change under the influence of improved knowledge management. However, it is also clear that the added value might entail a shift in the balance of a standard platform and the custom tools built on top. If the continuous value proposition is the tailor-made nature of a provider's offering, this disrupted balance might affect the appeal that is the embeddedness of solutions, and the new equilibrium might render either the value proposition of embeddedness or the customisability of solutions obsolete. Moreover, the uniqueness of your tailored solutions, if the embeddedness becomes obsolete, is something to treasure. "Of course, as a SaaS organisation, you want to standardise as much as possible, because yes, then you can go faster, then you can scale, etc. I think that customisation will become easier, so how relevant is that basis then? Maybe the technology that facilitates that customisation will actually be your basis later. And then the question is, yes, how unique is that tooling then?" (P6).

In addition, the possibility of AI-driven product development at SaaS providers was considered. Again, this notion is two sides of the same coin, and the same might hold true for financial institutions. However, some considerations in the buy versus build dilemma still hold, where even with lower required effort to build, a buy strategy is utilised as a solution if not unique to the organisation, a consideration mentioned by two participants. Perhaps AI for financial product development will affect different businesses in the current customer segments differently, depending on their own expertise and tech-savviness and disseminative capacity. "If I'm going to use an AI module, I can increase my expertise to a six or a seven out of ten, and that can just be enough for a smart guy to think, you know, I'm going to build it myself, if necessary in some kind of low code environment. With ChatGPT, you can go a long way [...]. So I certainly think there are considerable risks there" (P13). For more traditional financial institutions that depend on a SaaS provider for more core functionality, the boundary to build will still remain high, as the process of learning through AI has not taken place to the same extent as their more modern counterparts. As found in this study, the lack of knowledge seems to affect the perceptions of complexity (and risks) tremendously, and a lack of experience with AI might not provide improved knowledge management for the same reasons that AI adoption is challenging, and decision-making often leads to rejection rather than acceptance of AI-powered tools from SaaS vendors. While for more modern and IT-heavy financial institutions, the abundance of IT knowledge, catalysed by lowering the boundary of exploring and exploiting knowledge, might lead to loosening time constraints and perceptions of effort even further, making them opt for build more often. "Well, I wonder how that's going to go in the future. [...] When you look at how easy it is to create solutions... Won't you just hire [...] some vibe coder or something?" (P6).

On the other hand, it was highlighted that the choice between a buy or a build strategy might not change that much. "Since we can build it more efficiently ourselves, that should also mean that the SaaS platforms will become more efficient in that and therefore probably cheaper compared to before. So the cost picture should be brought down on both sides, so that it remains the same discussion in terms of cost-benefit" (P14). Overall, participants displayed that it is difficult to say to what extent the factors influencing current decision-making will be affected in the future, but underscored that the principles on which decisions are based, cost-benefit analyses, will remain at the basis.

In the buy versus build discussion and the cost-benefit analysis that is fundamental, the timeline of efforts must be included. In the moment, it might look cheaper to build something in-house, but the added value of a SaaS provider is that clients can expect updates and no headache about maintenance and continuous support for the tools themselves, echoed by Dempsey and Kelliher (2017). "One of the biggest [...] reasons for me to adopt SaaS in the past has been the comfort or the assurance it gives for maintenance and for support and for enhancement [...] Even with AI in place, [...] my engineers can do it in an easier way, but you will still have to maintain it, and you will still have to make sure that you update it on a regular basis because of new business requests or because of outdated libraries, whatever, right? So on that part, it still remains a question, do you want to do that on your own, or do you want to ask somebody else to do it?" (P7).

Another factor that might change the AI SaaS landscape is the competitive landscape. AI allows for more disruptive market entries, not only with impactful AI-first business models, but also with more (cost) efficient similar business models and AI-enabled 'traditional' service offerings in the cloud, in addition to competitive pressure that is the internal teams at SaaS providers' current clientele. "The biggest change we're going to see in AI is that all those companies are going to see new competitors emerge which are much thinner, less people inside, so they can compete in costs and that forces you to drop costs to stay competitive. [...] It squeezes your margins and then is when you start to think about really implementing the technology internally as well" (P12). On the other hand, competition from others is not as pressing when a provider plays their cards right, as some experience is irreplaceable in the short term. "On the other hand, I do think that you can/should also use your current advantageous competitive edge. An idea provider will always, if you do it right, maintain an advantage [...]. A company must be constantly on the move. The continuity of the company is not having a vision and a product for 100 years" (P13). Extending on this, AI becoming almost a public good might even be advantageous to SaaS providers with both the maturity and knowledge base and the technical agility to develop AI solutions. "I think that in the beginning that might even be to the advantage of SaaS vendors, because they might be able to respond to that more easily [...] than we can do that ourselves in our adoption timeline of AI" (P14).

5.3.2 Implications and Recommendations for Financial Institutions

The findings presented in this study carry several implications for financial institutions navigating the adoption of AI-powered tools delivered through fintech SaaS platforms. As the external landscape becomes increasingly shaped by digital-first actors and regulatory complexity, institutions are faced with the dual challenge of modernising their technology stack while preserving stability, trust, and compliance. In this context, the study suggests that internal innovation ambitions are often present, but struggle to translate into sustained adoption behaviour due to organisational frictions, procurement constraints, and interpretive uncertainty surrounding AI's actual value and risk.

A key insight concerns the role financial institutions play not only as buyers of technology, but as informal co-creators of its application and implementation. Institutions that approach SaaS partnerships as collaborative rather than transactional are more likely to arrive at offerings that align with internal needs, strategic priorities, and regulatory boundaries. This implies a need for institutions to reconsider how they participate in vendor relationships, especially with respect to early-stage engagement. By contributing domain knowledge, use case specifics, and structured feedback, financial institutions can exert meaningful influence on solution design, thereby lowering the chances of late-stage misalignment and increasing the likelihood of adoption outcomes that are both impactful and viable.

At the same time, the study highlights that many institutions remain hindered by legacy governance models that are ill-equipped for iterative or cross-functional decision-making. Traditional procurement processes often create bottlenecks when evaluating AI-driven services, as their assessment mechanisms are designed for more static, linear technologies. As a result, initial interest in AI tools, often sparked by client demand or strategic curiosity, is frequently disconnected from actual procurement decisions. This disconnect underscores the importance of internal governance awareness or even reform, particularly around technology sourcing, evaluation, and integration. Institutions may benefit from introducing more agile, cross-departmental structures for evaluating emerging technologies, with clearer ownership over experimentation, risk assessment, and compliance alignment, reflected by Persaud (2005).

The findings also suggest that risk perception plays a disproportionately strong role in shaping AI adoption outcomes. Rather than stemming from technical concerns alone, these perceptions are often reinforced by a lack of internal familiarity with AI's operating principles, insufficient interpretability or transparency, and overall regulatory ambiguity. This results in overcautiousness that may stall innovation initiatives despite institutional interest. Financial institutions could mitigate this by investing in internal AI literacy, both at the decision-making and operational levels. Doing so would not only enable more accurate assessments of proposed solutions but would also empower institutions to articulate requirements and boundary conditions more effectively when engaging with SaaS providers.

In operational terms, financial institutions looking to adopt AI through SaaS delivery models should also reflect on their own cloud-readiness and data maturity. As pointed out by Howell-Barber et al. (2013), AI strategy cannot be seen separately from a cloud computing SaaS strategy, and in this modern day and age, the two cannot be seen separately from one another. Institutions with fragmented data infrastructures or low cloud adoption rates are likely to face disproportionate onboarding costs, undermining the potential benefits of AI tooling. A phased approach, starting with tangential or non-core applications such as onboarding automation or internal analytics, may serve as a lower-risk pathway to build internal confidence and operational readiness before expanding to more complex use cases for AI tools, a notion echoed by Misra and Doneria (2018) in the context of the adoption of cloud technology. Moreover, preparing data structures for AI implementation should be a priority for financial institutions to facilitate mutual value creation and adopt solutions from third-party providers more effectively and reliably (Schmelzer, 2019), especially when derisked (and untrained) plug-and-play solutions are opted that depend on institutions' own data quality and compatibility to create value.

Ultimately, the findings indicate that successful AI adoption is not primarily determined by the capabilities of the tools themselves, but by the institutional environment into which they are introduced. Adoption outcomes are shaped by internal structures, trust in external providers, and the institution's ability to translate technological potential into operational reality through collaborative effort. As such, AI integration should be treated as an organisational innovation process, in which alignment across departments, governance frameworks, and user expectations from customers is critical. Institutions that embrace this complexity and invest in more reflexive, co-creative approaches are likely to derive greater value from their AI engagements and maintain strategic relevance in a rapidly evolving financial ecosystem.

An emerging topic throughout the study was the potential impact of AI on the financial workforce. This surfaced as a limiting consideration that, in some cases, contributed to reluctance in adopting AI or even communicating possible use cases and their benefits upward to management. As AI automates manual and repetitive tasks, particularly those involving administrative processes or customer due diligence activities, the nature of labour within financial institutions is bound to evolve. Employees who previously performed such tasks may be reassigned to new roles or responsibilities. The extent to which this restructuring proves successful largely depends on an institution's ability to prepare both technically and culturally, through knowledge-building and managing employee expectations.

For example, an employee who currently assesses documents based on policy or loan criteria might transition into a quality assurance role, focusing on validating AI-generated output, or take on more applications by leveraging AI-enabled recommendations to guide attention to key indicators. As one participant noted: "But if you can replace a team of 10, for example, loan underwriters with 2 underwriters, then you still need them to do random checks to see if the tool is still working properly. I think that will continue" (P3). Another added: "A junior administrative employee is suddenly a finance director, so to speak. But you have to have the knowledge and experience to assess the output" (P6).

While the total number of jobs may remain relatively stable in the medium to long term, the competencies required will shift considerably. As participant 7 points out, "the skill set would definitely shift". This evolution implies that some existing roles may become obsolete, while new roles emerge, requiring institutions to rethink workforce planning. "So the kind of skills that we need today versus the skills that we would need together with AI would be different. But I do not see a change in the number of total jobs as a whole. You know, [...] in this case, for example, a loan approver, [...] we don't need that much anymore because AI can do that research or your background checks already. But for example, we would need somebody who can do more cross-selling on top of that [...] And today we do not have that capacity" (P7).

Nevertheless, AI will remain a tool, for now, and maintaining awareness of the hype surrounding it can support financial institutions in approaching the technology more realistically, especially when it comes to its impact on people and roles. This sentiment is reflected by participant twelve: "Klarna was [...] one of the companies that bet strongly on GenAI early on, in particular for customer support, and they recently pulled back many of the claims they made. In fact, they had initially put a hiring freeze on customer support agents, humans, and they recently rolled back that decision, and they're back to hiring humans. [...] There's a lot of hype and hype always exaggerates things" (P12). The need for thoughtful and realistic adoption of AI is further discussed in Chapter 5.1.

5.4 Limitations and Future Research

This research offers a nuanced perspective on the adoption of AI-powered tools in fintech SaaS by European financial institutions and their providers. While the study contributes valuable insight into institutional priorities, barriers, and strategic decision-making processes, it is important to consider its limitations in order to both contextualise the findings and inform future research agendas.

First, the study's geographic scope is firmly situated within the EU. Financial institutions and fintech providers in this region operate under distinct regulatory structures, including the GDPR and the forthcoming AI Act, which are globally unique in their emphasis on precaution and human-centric governance (Joseph, 2025; Pagallo, 2025). This has significant implications for AI-related procurement, trust-building, and institutional readiness. However, these same features limit the generalisability of the findings to other jurisdictions, where regulatory approaches may be more permissive or market-driven. For instance, the competitive AI deployment strategies common in North American firms (Chakraborty, 2021), or the state-coordinated innovation in Asia-Pacific regions such as Singapore or South Korea (Ukonu, 2025), are shaped by institutional norms and incentive structures that differ considerably from the European model. While the governance-heavy European context provides a valuable lens to study risk-sensitive adoption, it also introduces a level of friction that may not be present elsewhere. Future research would benefit from comparative analyses that compare EU cases with those from other economic zones to disentangle which adoption barriers and drivers are context-dependent and which are more broadly applicable across geographies.

Second, the participant pool, though purposefully selected to represent both fintech providers and institutional buyers, remains relatively modest in size and skewed towards mid- to senior-level professionals. The multi-functional roles of many participants enabled a layered understanding of adoption-related decision-making. However, this also means that the perspectives presented often represent an aggregated or weighted average of viewpoints, potentially leaving the severity of certain factors underemphasised. While voices from frontline employees, regulators, cybersecurity experts, and IT compliance officers were not entirely absent, they were not represented in sufficient numbers to fully capture their viewpoints. Although the sample included variation in both institution and provider size, the client-side representation leaned towards more legacy-bound institutions, those likely to face the greatest challenges when integrating third-party AI solutions. Furthermore, the organisations willing to participate in academic research may inherently constitute a self-selecting subset of the industry: more innovation-oriented, more transparent, and perhaps more optimistic about the role of AI in financial services. Institutions that declined to participate may hold more sceptical or risk-averse views. As such, future studies should aim to both broaden the inclusion of underrepresented perspectives and, conversely, narrow the focus when seeking deeper, more granular insight. Embedded casework, regulator partnerships, or anonymous large-sample surveys could support both objectives by facilitating a deeper contextualisation of findings and extending their relevance across the wider ecosystem.

Third, the study's exploratory and cross-sectional nature necessarily imposes temporal limitations. It captures a snapshot of institutional sentiments during a moment of rapid technological and regulatory development. However, AI capabilities are evolving quickly, and so are institutional policies, internal capacity, and governance mechanisms. Longitudinal studies that track adoption decisions from initial interest through to implementation and eventual adaptation or disengagement would significantly deepen our understanding of institutional learning, iterative onboarding, and the durability of adoption incentives over time.

Fourth, the methodological approach, anchored in qualitative thematic analysis, offered rich interpretive depth, yet, as with all qualitative research, is subject to potential researcher bias. While themes were grounded in established frameworks and developed using reflexive coding practices, interpretive decisions necessarily reflect subjective judgment. Follow-up studies using mixed-method designs or inter-coder validation could further solidify the reliability and replicability of key themes, especially around contested constructs such as trust, explainability, or institutional alignment.

Taken together, these limitations highlight several concrete directions for future research. One critical step forward lies in developing comparative case studies that examine the full lifecycle of AI adoption across different regulatory environments and institutional contexts. Such studies could provide deeper insight into how technology procurement unfolds in practice and how contextual features such as regulatory clarity, vendor positioning, and internal capacity shape real-world adoption trajectories. Comparative research should not only span regions but also types of financial institutions, exploring how smaller firms, pension funds, or insurance providers differ in their adoption logic compared to large multinational banks.

In parallel, more applied research could examine how abstract adoption constructs, such as model transparency, compliance readiness, and third-party risk, can be operationalised into procurement metrics. For instance, standardised frameworks for communicating explainability, benchmarking onboarding friction, or assessing institutional AI maturity could directly support better alignment between SaaS providers and clients. Such research might also explore quality validation protocols, including audits of algorithmic performance over time, or joint testing environments where client data is used to iteratively co-develop and improve AI solutions.

These operational concerns also raise questions about the relevance and adaptability of theoretical models. While this study drew primarily on TAM and UTAUT, its findings suggest that neither model in isolation fully captures the institutional complexity of AI adoption in regulated B2B contexts. Constructs such as ”facilitating conditions” or ”perceived usefulness” may apply differently in a context where decisions are shaped by overlapping legal, strategic, and reputational considerations, rather than by user utility alone. Future research could contribute by extending these models with institutional and governance-oriented variables or by developing new hybrid frameworks that explicitly accommodate vendor-client dynamics, compliance pressure, and trust asymmetries in high-stakes technology decisions. Empirical validation of such models through larger-sample or cross-sector studies would offer a valuable contribution to the broader technology adoption literature.

Another important research direction relates to the study's implications for adjacent sectors. While some adoption dynamics, such as concerns over risk, onboarding, or explainability, are likely to be shared across industries, others are specific to the institutional role of finance. Financial institutions serve as systemic stabilisers and are subject to far-reaching supervisory oversight. In contrast, industries like logistics or retail may adopt AI with fewer compliance concerns, but face different customer expectations or value chain complexities. The findings presented here, especially those concerning regulatory friction, procurement politics, and co-development practices, may thus serve as a useful reference point, but require careful adaptation when applied beyond the financial domain. Future studies could test the generalisability of these insights through comparative sectoral research, ideally with attention to how operating models, stakeholder structures, and institutional obligations mediate adoption logic.

A particularly underexplored direction relates to the intersection of AI and sustainable finance. As discussed in more detail at the end of this chapter, none of the participants identified AI as a tool contributing to sustainability objectives, despite the literature pointing to its potential for enabling ESG-informed decision-making and responsible finance (Almansour, 2022; Bayram et al., 2022). Likewise, the energy intensity of AI systems, often cited as a growing concern in environmental discourse, was entirely absent from the challenges raised during interviews. This suggests a possible blind spot in institutional framing or prioritisation. Future research could examine whether and how AI adoption decisions account for sustainability implications, particularly in light of upcoming environmental disclosure requirements and sector-wide net-zero commitments. Investigating the material impact of AI on sustainability practices, or the lack thereof, represents a promising avenue to bridge conceptual gaps between digital innovation and sustainable finance agendas.

Finally, while Chapter 5.1 explored the EU's regulatory role, a more global institutional lens deserves further attention. Supranational actors such as the Organisation for Economic Co-operation and Development (OECD) are increasingly involved in shaping cross-border AI governance standards (OECD, 2025). These standards may converge with or diverge from regional regimes, thereby creating either harmonised incentives or conflicting compliance obligations for institutions operating internationally. The globalisation of AI governance raises important questions about regulatory interoperability, enforcement asymmetries, and cross-border procurement challenges. Future research should explore how multinational financial institutions navigate these tensions and how fintech providers adapt their strategies to meet both local compliance and global scalability requirements.

In conclusion, this study advances the conversation on AI adoption in fintech SaaS by exposing the complex web of strategic, regulatory, and institutional forces that shape decision-making. Yet, by highlighting the contingent nature of its findings, it also points toward the necessity of further research, which is geographically expansive, methodologically diverse, and theoretically adaptive to the realities of regulated digital innovation.

AI and Sustainable Finance Sustainable finance is the consideration of ESG factors in financial decision-making to contribute to a more sustainable world by investing in projects and activities with a long-term vision (European Commission, 2025). A mismatch between the literature covering strategic implementations of AI in finance and the findings of this study is the adoption of AI to effectively practice sustainable finance. Financial institutions, especially banks, are hybrid organisations that, on one hand, generate income from their consumers, but primarily drive revenue through investing in a combination of financial products. This study's findings highlighted many applications and perceived benefits of the former, but were also characterised by a lack of applications targeted at the latter. Using AI for trading has been touched upon conservatively by participants, but it is safe to say that it was not a main pillar of perceived benefits.

According to a review by Oyewole et al. (2024) of a great number of recent papers on sustainable finance, AI is increasingly recognised as a strategic enabler for sustainable finance, offering banks a range of tools to align operations with ESG criteria and support the broader sustainable development goals. Rather than serving as a standalone solution, AI enhances institutional capacity to embed sustainability more deeply into decision-making, risk management, and service delivery.

One of the key contributions of AI lies in its ability to process and analyse large volumes of heterogeneous data, ranging from satellite imagery and social media signals to financial disclosures and environmental records (Wipfler, 2024). This allows financial institutions to more accurately assess ESG risks, monitor sustainability performance, and anticipate the impact of environmental factors such as climate change on asset valuation and loan repayment capacity (Bayram et al., 2022). AI models can simulate a variety of climate scenarios and their effects on financial portfolios, improving both foresight and resilience. In parallel, tools that quantify physical climate risks and support dynamic loan pricing or insurance models offer new pathways for risk-adjusted lending in vulnerable markets.

In the investment domain, AI facilitates the identification of opportunities that generate both financial and societal returns. Machine learning models can surface impact-driven projects, such as those in clean energy, sustainable infrastructure, or inclusive finance, by detecting relevant patterns across structured and unstructured datasets (Wipfler, 2024). Intelligent algorithms can support high-accuracy green finance analysis, improving the targeting and efficiency of capital allocation. Additionally, AI-generated synthetic datasets create new testing grounds for ESG-aligned financial products, improving model robustness while reducing regulatory or privacy concerns in early development phases (Oyewole et al., 2024). Operationally, AI continues to improve core banking functions such as fraud detection, credit scoring, and customer service, while also contributing to broader sustainability efforts. This includes combating greenwashing through automated sentiment and content analysis, enhancing transparency across green bonds and socially responsible investment products, and supporting responsible consumption by embedding financial literacy and behavioural nudges into client-facing tools (Bayram et al., 2022; Oyewole et al., 2024; Wipfler, 2024). AI also enables sustainable supply chain management and helps institutions reduce their carbon footprint through more efficient resource use and emissions tracking (Park & Yoon, 2024). Moreover, AI-powered platforms can enhance financial inclusion by broadening access to services for underbanked populations and SMEs, particularly in emerging markets (Bayram et al., 2022). By offering tailored microfinance solutions, agricultural loans, and low-cost digital payment systems, these platforms help reduce inequality and foster inclusive economic growth, goals central to sustainable finance.

AI holds significant potential to accelerate the transition toward sustainable banking by making ESG integration more actionable, investments more impact-oriented, and operations more efficient and inclusive. However, the realisation of this potential depends on financial institutions' ability to approach AI not only as a technological opportunity but as a catalyst for systemic change within their organisational models and societal contributions. However, it seems that other factors dominate the perceptions about AI's potential within financial institutions.

On the other hand, while the interviews in this study uncovered a range of practical, organisational, and regulatory considerations regarding AI adoption in financial institutions, one notable omission was the discussion of AI's environmental footprint, particularly its energy intensity and implications for sustainability objectives. As recent analysis by the ECB highlights, the increasing computational demand of AI, especially LLMs and GenAI systems, raises significant concerns related to energy consumption and its knock-on effects on both resource markets and national electricity systems (Burian & Stalla-Bourdillon, 2025).

Although AI holds potential for enabling sustainable finance through enhanced ESG integration and green investment targeting, its own operational sustainability remains underexplored in the financial sector. As emphasised by the ECB, projected growth in energy demand from AI-driven data centres is expected to contribute materially to national electricity usage, with potential localised price pressures and infrastructure strain. In scenarios where this demand is met through natural gas, modest but non-negligible upward pressure on gas prices is anticipated. Alternatively, meeting demand with renewables may increase the need for critical minerals, though global supply chains may buffer against significant price spikes. As financial institutions position themselves as leaders of sustainable transformation, further attention should be paid to the indirect environmental impact of the digital infrastructure underpinning AI deployment. This includes assessing the carbon footprint of AI-powered tools, as well as actively considering energy efficiency and sourcing practices when engaging with SaaS providers.

6 Conclusion

This thesis set out to explore the adoption of AI-powered tools in fintech SaaS from the perspective of European financial institutions and AI SaaS providers. Initially framed as a provider-centric challenge, why financial institutions resist adoption despite the apparent value of AI, the research gradually revealed a more nuanced dynamic: adoption is not hampered by a single stakeholder or technical deficiency, but by a systemic misalignment between both sides of the provider–client relationship. This mutual misalignment gives rise to what can be characterised as a lack of mutual value creation. In this context, adoption barriers are not simply obstacles to be overcome by individual stakeholders, but symptoms of a deeper disconnection in how value, responsibility, and risk are conceptualised, negotiated, and operationalised between institutions and providers.

This realisation shaped the interpretation of the findings and formed the central axis of the discussion. While providers are often driven by technological opportunity and innovation mandates, institutions approach AI adoption with caution, shaped by complex governance structures, reputational considerations, and compliance obligations. What emerges is a dual ownership of the problem: SaaS providers and financial institutions are both problem holders and problem solvers, and sustainable adoption can only be achieved through co-construction and shared alignment.

To answer the first subquestion, why financial institutions initially become interested in AI-powered tools, it was found that institutional interest stems from three main sources. First, AI is seen as a lever for operational efficiency, with the potential to optimise internal workflows and reduce costs. Second, external pressures, particularly competitive positioning and public expectations, create a sense of urgency to explore AI-driven capabilities. And third, a growing awareness of the limitations of in-house development leads institutions to consider external providers, especially those offering modular, cloud-native solutions. However, this interest is often exploratory and remains loosely coupled to strategic clarity. Financial institutions are intrigued by AI's potential, but rarely have clearly defined use cases or cross-functional alignment on how AI should be implemented.

The second subquestion concerned the key challenges shaping institutional decision-making. Five clusters of barriers emerged: procedural rigidity, technological uncertainty, third-party risk, regulatory ambiguity, and onboarding complexity. Institutions often lack the organisational agility to trial or scale AI tools, especially when existing systems are legacy-bound. Risk-averse procurement practices and strict internal controls create bottlenecks that inhibit experimentation. Technological concerns, such as explainability and integration, persist, particularly for models that operate as 'black boxes' or rely on foreign infrastructure. Moreover, regulatory uncertainty, especially under the evolving AI Act, further stalls adoption, as institutions interpret new rules conservatively. Even when initial interest exists, the friction introduced by these challenges often overrides enthusiasm.

Addressing the third subquestion, how providers can overcome these challenges, requires moving beyond technical refinement alone. This study underscores the need for more adaptive, context-sensitive service models. AI SaaS providers should take on advisory roles, engaging institutions early in the value definition process and co-developing solutions that reflect institutional constraints. Trust must be earned through transparency, realistic timelines, and measurable deliverables. Tailoring communication around AI's organisational impact rather than abstract capabilities also emerged as critical. Providers who structure their offerings around operational relevance, regulatory fit, and institutional capability are more likely to foster long-term adoption momentum. Strategies such as modular onboarding, collaborative proof-of-concepts, and role-sensitive onboarding support stand out as particularly effective.

Beyond the primary research questions, the study surfaced several auxiliary insights. The AI–SaaS bundle, as experienced by institutions, represents a distinctive object of study that introduces novel forms of dependency and opportunity. Public narratives around AI were found to diverge from internal institutional realities, revealing symbolic pressures that complicate adoption discourse. Moreover, adoption is best viewed not as a static binary event, but as a phased, iterative process of alignment, experimentation, and institutional learning.

In addition to these findings, the study offers several practical implications for both SaaS providers and financial institutions. For providers, adoption readiness is not solely a function of technical performance but of institutional fit. Effective adoption requires providers to act not just as vendors but as strategic partners that are capable of articulating value in institutional language, facilitating onboarding within constrained environments, and iteratively adjusting based on client feedback. In this regard, two distinct but interrelated strategies emerge. First, providers seeking to win new service contracts for AI-powered tools must invest in clear, use-case-driven communication and adopt modular service delivery models that reduce onboarding friction. Second, providers can build long-term trust and institutional credibility by applying AI internally in their own core functionalities, such as risk modelling, compliance monitoring, or client servicing. Demonstrating successful, responsible internal use of AI signals operational maturity and regulatory sensitivity, and can help providers gain legitimacy in the eyes of their institutional clients. For institutions, the findings emphasise the importance of internal alignment. Without a shared vision and cross-departmental engagement, even promising technologies will struggle to take root. Both parties are therefore encouraged to invest in building mutual understanding, early-stage co-development processes, and risk-sharing frameworks that foster long-term trust.

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Finally, this thesis highlighted several thematic and methodological directions for future research. First, the study's exploratory, EU-focused design invites further work that tests the generalisability of its findings across geographies, institutional types, and regulatory environments. Comparative studies could help distinguish which adoption dynamics are context-specific and which reflect broader structural patterns in regulated AI procurement. Likewise, future research could extend and refine existing adoption models such as TAM and UTAUT to better account for institutional governance, vendor–client dynamics, and compliance-driven risk perception. Additional work might also examine how trust, explainability, and risk are operationalised in procurement settings, or explore quality validation protocols for AI tools once implemented. Within this wider landscape of future inquiry, one particular gap stood out: the potential role of AI in advancing sustainable finance. As discussed in Section 5.4, none of the participants identified environmental or ESG-related concerns as relevant to AI adoption decisions, despite growing academic and policy attention to these topics. Similarly, energy consumption, frequently cited in the literature as a concern related to large-scale AI deployment, was not raised. This absence suggests either a misalignment between academic discourse and institutional practice or a temporary blind spot in adoption framing. Future research could therefore usefully explore how AI is positioned within sustainability agendas, particularly in contexts where ESG regulation is more mature or public pressure is more pronounced.

Looking ahead, one area that warrants closer attention is how the rise of generative and widely accessible

AI tools may gradually reshape the SaaS business model itself. While this study primarily focused on adoption from the client's perspective, it became apparent during the analysis that many institutional expectations toward AI functionality are evolving rapidly. As discussed in Section 5.3.1, the current value proposition of SaaS providers often rests on their knowledge-intensive services and technical specialisation, attributes that justify outsourcing decisions in the buy-versus-build equation. However, as general-purpose AI becomes more accessible, configurable, and commoditised, this asymmetry in knowledge and capability may diminish. This could, over time, challenge existing provider-client dynamics, shift expectations toward co-development or customisation, and reduce switching barriers. Although these developments are not yet dominant, they hint at a future in which the SaaS model may evolve from tool provision toward more fluid, partnership-based configurations. Further research could explore how such shifts affect provider strategies, pricing models, and institutional expectations over time.

In sum, this thesis advances the understanding of institutional AI adoption by shifting the focus from user-centred acceptance models to co-constructed, context-bound processes of decision-making. In doing so, it positions AI adoption not merely as a technological implementation challenge but as a shared institutional undertaking, one that requires strategic alignment, mutual trust, and an honest confrontation of the friction between innovation ambition and regulatory reality.

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Appendix

A Definitions of key concepts

Artificial Intelligence (AI): Defined by IBM's Stryker and Kavlakoglu, 2024 as ”technology that enables computers and machines to simulate human learning, comprehension, problem solving, decision making, creativity and autonomy” (p.1). This includes the technology's conceptual derivatives, displayed in Figure 2, such as ML, DL, and LLMs powered through GenAI technology.

AI adoption: The action or fact of choosing to engage in the pursuit of an AI-powered tool developed by an entity other than itself. This includes in-licensing (software services with) AI-powered functionality and/or starting to use AI-powered functionality included in established software licenses. Use of internally developed AI-powered tools falls outside the scope of this research and, therefore, the definition used.

Mutual value exchange: In the context of AI development, mutual value exchange is similar to data-driven co-development partnerships. Consisting of collaborative efforts, including data contribution collaborations, AI co-creation, and exploratory collaboration. In this context, all these agreements are assumed to be implicit to better suit the nature of what SaaS providers do. They are not primarily custom AI tools developers but are simply trying to improve their service offering with AI-embedded (sub)solutions.

Machine Learning: Machine learning is a foundational subfield of AI, dating back to early conceptualisations such as Alan Turing's vision of systems that could learn from experience (Oliveira & Figueiredo, 2023). At its core, ML involves building statistical models that improve their performance by learning from data. These systems are trained on historical datasets, referred to as training sets, and use this knowledge to make predictions or identify patterns in new, unseen data known as the test set. During development, a validation set may also be used to fine-tune the model's parameters before final evaluation. Machine learning systems are broadly categorised based on the nature of their output. If the model predicts numerical values (e.g., sales or stock prices), it is performing regression. If it predicts categorical outcomes (e.g., spam or not-spam, fraudulent or legitimate transactions), it is performing classification (James et al., 2023; Oliveira & Figueiredo, 2023). For qualitative outcomes, one-hot encoding is often used to convert categorical variables into a numerical format suitable for analysis (James et al., 2023). Beyond prediction, ML is also used for inference, i.e. understanding relationships between variables and identifying which factors contribute most to a given outcome.

Deep Learning: Deep Learning is a subset of Machine Learning. It is considered a core technology of the Fourth Industrial Revolution (Industry 4.0) (Sarker, 2021). DL methods use multilayered neural networks to simulate the complex decision-making power of the human brain (Durães et al., 2023; Holdsworth & Scapicchio, 2025; Magrani & Da Silva, 2023; Neves & De Almeida, 2023; Oliveira & Figueiredo, 2023). The term ”deep” in Deep Learning refers to the use of multiple layers in these neural networks. Whereas standard networks have only a few layers, deep networks can consist of hundreds to thousands of layers (Durães et al., 2023; Holdsworth & Scapicchio, 2025). DL systems can learn by recognising patterns in many layers of raw data. It does this by learning to transform its input into a somewhat more abstract and composite representation at each layer, allowing for complex hierarchical representations of huge amounts of data (Mucci, 2024; Oliveira & Figueiredo, 2023; Sarker, 2021). Applications span industries and company types. Moreover, Sarker (2021) emphasises that it is also the backbone of many widespread LLMs and GenAI models through enabling natural language processing (NLP).

Generative AI and Large Language Models: According to Pagallo (2025) and García-Fernández et al. (2024), generative AI is a type of AI that uses deep learning to find patterns in existing data to create novel outputs by generating derived synthetic content from the data sources it is given. The authors establish LLMs as a subcategory of GenAI, which uses probability-based NLP technology to produce language-based outputs. Bell (2024) further elaborates this by stating that all LLMs are a form of Generative AI, but the same does not apply vice versa. However, with the development of so-called multimodal language models, which can process other data sources than text, such as photos and videos, and can have similar formats as an output, the distinction between generative AI and large language models may collapse or become less apparent.

Agentic AI: Agentic AI represents a somewhat novel system within the AI world that can independently pursue complex, multi-step goals with minimal human oversight. Agentic AI enables businesses to have automated systems that react dynamically to changing circumstances and contexts, surpassing rule-based systems that operate on structured instructions. Current literature on agentic AI highlights its huge potential, but also addresses ethical challenges and focuses on maintaining a sense of oversight on agents' activities to ensure safe and accountable practices. Shavit et al. (2023) and Wu et al. (2023) highlight the blurred boundaries between current AI systems, such as the widely adopted GenAI models from OpenAI, and AI agents, by using a definition of agents that emphasises agents' unspecified behaviour upfront, and their ability to contribute towards achieving a specific goal consistently for some time. Shavit et al. (2023) also introduces a system to define the degree of agenticness, in which higher goal complexity, environment complexity, adaptability, and degree of independence correspond with a higher degree of agenticness of an AI system. With these fields' dynamically changing technological capabilities, current literature focuses on exploring applications and attempting inclusive definitions to guide regulators and developers (Acharya et al., 2025; Shavit et al., 2023). In this study, agentic AI is not included in the general definition of AI. However, the blurred lines between the most modern AI systems and formal agents are acknowledged and will be a topic that will be explored shortly in collecting new data in this study.

B Search strategy

Purpose-driven search strategies for the main body of the Literature Review are illustrated in this section. Two main search strategies were adopted, where a combination of highly cited papers in the field of AI adoption in finance and the most recent works on the topic form the basis of the literature review. If the filter for recent papers led to only a small number of papers to appear, or a set of papers that were not deemed relevant, the filter was adjusted or removed completely, and the focus was shifted to citations rather than recency. Moreover, it was noted that often, the scope of recent papers was narrower than older works with a lot of citations, which can be expected wit the way research works.

To gather a comprehensive collection of literature that can act as the basis for all the things the Literature Review is aimed to tackle, multiple queries are used to ensure the inclusion of the most impactful and recent works on the topic. Formulating queries was an iterative process where the aim was to get the most relevant papers necessary to answer all the questions that needed to be answered. Note that the results had some overlap in papers. Note that OpenAI's ChatGPT launched in late November of 2022, pioneering the large-scale adoption of LLMs or GenAI. Due to this first large-scale public exposure of this powerful functionality of AI, research interest in LLMs has surged since early 2023, rationalising the search strategy for more recent works. When going through the results of each query, the titles and abstracts of the resulting top 50 articles were manually scanned to see if they are relevant. For each query, the list of relevant articles was exported in LaTeX format, facilitated by Scopus' export options. After iteratively applying filters and adjusting queries, a total of 57 papers (in)directly relevant to this research were found. Note that some are used in the literature review, while some were saved in case general claims would be supported in the context of this study during and after the data analysis process. Note that it is or was possible to combine these queries into one, but to prevent a misrepresentation of the actual process, they are shown separately. Also, note that the queries shown are to enhance rigour and repeatability, but will result in a different set of articles over time. In this report, they are aimed to illustrate the general direction of the search strategy. Lastly, note that many articles used throughout this paper were also found through a more informal search, and ad hoc approach based on conversations and ethnographic involvement.

- Query 1: TITLE-ABS-KEY (ai AND (adoption OR acceptance OR implementation OR deployment) AND (finance OR banking OR fintech))
- Query 2: TITLE-ABS-KEY (ai AND (finance OR banking OR fintech))
- Query 3: TITLE-ABS-KEY (ai AND (adoption OR acceptance OR implementation OR deployment) AND (finance OR banking OR fintech) AND (saas OR "software-as-a-service" OR "software as a service" OR "digital financial services" OR "cloud" OR aws OR azure))
- Query 4: TITLE-ABS-KEY ("technology adoption model" OR "adoption model" OR "acceptance model" AND ai OR "Artificial Intelligence" AND finance OR banking OR fintech) - This query was aimed specifically at finding adoption models for AI used in the context of finance that can be used to guide and structure the interview. This resulted in the cases outlined in CHpater 2.3.

C Interview Script

Warmup

Can you briefly explain your role and responsibilities within your organisation and share something about your affinity with AI?

- *How does your organisation view the use of AI? Would you consider it a core competence?*

Initial Interest (Sub-question 1)

Technological & Business Dimension

What attracts your organisation to AI-driven tools within your SaaS infrastructure? What improvements are typically expected, and where can the most value be realised?

- *What do you consider the "low-hanging fruit" in the world of AI applications on SaaS platforms? And what is just above that?* (**Technological – TAM: PU & PEOU)**

- *What improvements would you expect in terms of your operational performance? E.g. automation, decision-making, customer service?* **(Technological – Operational (FO, MO, BO) + TAM: PU)**

- *Are cost savings a primary objective?* **(Business – Financial)**

Technological, Business & Procedural Dimension

To what extent do internal or external stakeholders/shareholders influence your organisation's interest in adopting such tools?

- *E.g. competitive landscape (rivalry), board room expectations, executive vision?* **(Business – Competitive, Board Room Vision + UTAUT: Social Influence & Facilitating Conditions)**
- *E.g. outsourcing knowledge, overall procurement vision?* **(Procedural – Procurement & Knowledge Management)**

- *Do you think the current hype around AI is justified in the world of finance? Is AI indispensable right now, and how do you see that changing over the next 10 years?* **(Business – External & Trends)**

Main Adoption Challenges (Sub-question 2)

Technological, Business & Procedural

How easy or difficult do you consider the implementation and use of AI-driven SaaS tools from vendors?

- *Which parts of the process do you consider the most challenging? E.g. evaluation, ease-of-use, integration, costs, internal/external resistance, etc?* **(Technological, Business & Procedural)**

Technological & Procedural

What does a relationship between a SaaS provider and a financial institution like a bank typically look like?

- *How does such a collaboration come about?* **(Procedural – Procurement, Knowledge and Technology Management)**

- *What are the main AI-related requirements for a vendor before and during a collaboration/contract?* **(Technological – UTAUT: Facilitating Conditions + Procedural – Procurement, Knowledge and Technology Management)**

Business & Procedural

What organisational challenges or internal dynamics complicate the decision-making process around adopting new AI technology from SaaS providers?

- *What does that process usually look like? Who do you typically collaborate with, and where do bottlenecks arise within the organisation?*
- *How do different departments or leadership influence this process?* **(Business – Board Room Vision + Procedural)**

Technological

Are there highly technological concerns?

- *E.g. data quality, security, system integration (compatibility with legacy systems), and/or explainability of third-party AI solutions in CC?*

Regulatory Landscape – Governance and Compliance
How do current and upcoming regulations (like the AI Act, GDPR) affect your conversations with vendors?

- *Are there compliance concerns that frequently delay or block projects?*
- *How can a vendor effectively communicate that their AI tools comply with regulations?*
- *Is it possible to design AI tools with future compliance in mind, not just current rules?*

Addressing Challenges (Sub-question 3)

Technological, Business & Procedural
What do you see as the most effective ways to facilitate the adoption of AI tools from SaaS providers? What should SaaS providers prioritise?

- *How do you view the balance between customisation and standardisation in the banking sector?* **(Technological – UTAUT: Facilitating Conditions + Procedural)**

Technological & Procedural

What is your opinion on co-creation, pilot projects, or data-sharing collaborations? Do you think these approaches can accelerate adoption or better align AI with the needs of organisations like yours?

- *Do you have examples from previous collaborations?*
- *What were the main lessons learned from those collaborations?*

Closing

Are there any other important challenges that influence decision-making within institutions like yours that we haven't yet discussed?

What advice would you give to SaaS providers who want to improve the adoption of their AI tools in your sector?

D Reflection on the use of AI

For some parts of the report, the free version of ChatGPT-4 was used to improve grammar, sentence-level structure, and choice of words with an emphasis on maintaining the style of writing. This was done by feeding the application a fully completed and written text, including citations, and asking ChatGPT to improve said aspects. Then, the response was checked and adjusted to make sure it was still authentic and uniquely put as I did it myself. Moreover, the free version of Grammarly was used, which is partly powered by AI, to help during the writing process with the choice of words and punctuation. Finally, ChatGPT-4 was used to help with LaTeX formatting and solving figure sizing issues and specific LaTeX library-related questions.

ATLAS.TI offers AI-powered coding functionality, which was tested with a test document (generated by ChatGPT). It did not prove useful at all, and ATLAS.TI sends documents it codes with AI to OpenAI, which seems sensitive. I therefore did not test or use it with actual (anonymised) transcripts.