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TITLE: Balancing Compliance and Innovation in Dutch Financial Institutions under the EU AI Act

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Abstract

This thesis examines how the EU Artificial Intelligence Act (EU AI Act) affects AI adoption in the Dutch financial sector. Applying Rogers' Diffusion of Innovations theory and drawing on 14 interviews with both direct implementers (such as banks and asset managers) and ecosystem actors (including regulators, consultants, advisors, and researchers), the study explores how regulatory conditions and AI system characteristics influence adoption and implementation decisions. While the Act imposes new compliance burdens, it also strengthens governance structures and strategic engagement. Key factors shaping institutional responses include perceived business value, alignment with existing controls, and organisational capacity. Ecosystem actors play a critical role in supporting implementation and mitigating regulatory uncertainty. The findings contribute to a deeper understanding of how innovation and regulation may interact in complex, highly regulated environments.

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1. Introduction

The integration of Artificial Intelligence (AI) in the financial services sector has long supported core institutional processes, from strategic decision-making and service delivery to risk governance and regulatory compliance. While this trend is not new, 2024 marked a notable shift as Dutch financial institutions began to more critically reassess AI use with greater focus on accountability, transparency, and regulatory alignment. Major Dutch banks such as Rabobank, ING, and ABN AMRO started revisiting their use of AI across core business functions, from fraud detection and customer support to internal analytics and compliance. Rabobank, for example, launched internal programmes to improve transparency and explainability in its AI systems and trained over 100 employees on responsible AI practices (Eviden, 2024). ING expanded its AI applications for customer service bots, know-your-customer (KYC) processes, and data-driven decision-making, increasingly integrating legal and ethical safeguards into deployment decisions (ING, 2024). ABN AMRO integrated generative AI to support its call centre operations and improve transaction monitoring, demonstrating a shift to governance models that integrate compliance into innovation efforts (ABN AMRO, 2024a, 2024b). These cases highlight a growing reliance on AI to meet business needs while addressing regulatory expectations in the Dutch financial sector.

Beyond these large institutions, smaller Dutch financial technology (fintech) companies and insurers are also leveraging AI to enhance compliance and service delivery. Startups such as ComplianceWise, which supports banks and financial institutions in meeting regulatory obligations, and MarvelX, which focuses on improving insurance workflows through automation and analytics, contribute to the growing intersection of compliance and innovation in the sector (ComplianceWise, 2024; MarvelX, 2024).

These developments signal a broader shift: while AI offers strategic benefits, it also brings increased complexity – particularly for institutions navigating compliance, explainability, and legal accountability. This challenge is magnified in a context where existing sector-specific frameworks – such as the European Banking Authority's *Guidelines on Outsourcing Arrangements*, the European Central Bank's *Guide on Internal Models*, and the Central Bank of the Netherlands (DNB)'s *General Principles for the Use of AI* – already demand high standards of explainability, risk management, and human oversight (EBA, 2021; ECB, 2024; DNB, 2019). The potential of AI to drive financial innovation is thus closely tied to an institution's ability to demonstrate transparency, fairness, and control. Without this, organisations risk falling short of regulatory standards and exposing themselves to reputational and financial harm.

The introduction of the European Union's Artificial Intelligence Act (EU AI Act) marks a new phase in AI regulation, establishing the first comprehensive legal framework for AI across the EU. It aims to ensure that AI systems, especially those deemed high-risk, comply with key principles of safety, transparency, and fundamental rights protection (European Commission, 2024). For the financial sector, the Act introduces additional regulatory pressure on institutions deploying AI for tasks such as creditworthiness assessments, fraud detection, and biometric identification – activities which are likely to fall under the high-risk category. These institutions must now meet stringent requirements related to documentation, risk classification,

human oversight, and data governance (European Union, 2024). The Act's risk-based approach seeks to balance innovation with fundamental rights protection. Yet, many questions remain around how financial institutions will implement these obligations in practice – especially given the technical complexity of AI systems and the interplay between regulatory requirements and supervisory expectations.

This research explores how Dutch financial institutions are adapting to these emerging regulatory pressures. It takes Rogers' (2003) "Diffusion of Innovations" (DoI) theory as the primary analytical lens. The study begins by drawing on the *Innovation-Decision Process*, which outlines the sequential stages organisations follow when adopting innovations – namely, knowledge, persuasion, decision, implementation, and confirmation. This framework is particularly useful for understanding how regulatory interventions like the EU AI Act influence not only whether, but how and when AI systems are integrated into organisational workflows. Building on this, the study applies Rogers' concept of Perceived Attributes of Innovations – including relative advantage, compatibility, complexity, trialability, and observability – to examine how the characteristics of AI systems interact with regulatory expectations and shape organisational responses.

The study is guided by the following main research question: *How does the EU AI Act shape the introduction, adoption, and implementation of AI systems by organisations in the Dutch financial sector?* To address this question, the study investigates two interrelated themes:

- How the EU AI Act influences the conditions for AI adoption and implementation decisions
- How the characteristics of AI systems influence these decisions under the EU AI Act

The Dutch financial sector is chosen as the case study due to its high level of AI maturity, its existing engagement with responsible innovation, and the proactive role of ecosystem actors such as DNB and AFM in shaping supervisory expectations around AI (DNB & AFM, 2024). This setting offers a particularly rich context for examining how institutions manage the intersection between regulatory compliance and technological advancement – especially in a jurisdiction that has shown both strong digital leadership and robust regulatory alignment with EU-wide initiatives.

The relevance of this study lies in its exploration of how financial institutions navigate the tension between regulatory obligations and innovation goals. As AI systems become central to financial services, they bring risks such as bias, opacity, and discrimination – highlighting the urgent need for regulation. However, excessively rigid regulatory frameworks risk stifling innovation in a sector where AI holds significant strategic potential. While the EU AI Act seeks to mitigate these risks, there remains limited understanding of how institutions are responding to its practical demands. Recent studies continue to focus primarily on legal and technical dimensions, offering limited insight into how adoption decisions are shaped within organisational settings. Take for instance the research by Maple et al. (2023), which explores regulatory uncertainty in the financial sector, or Mirishli (2024), which analyses compliance challenges under emerging legal frameworks. The present study however addresses that gap by applying Rogers' Diffusion of Innovations theory to a tightly regulated context, generating insights into how institutions interpret, adapt

to, and integrate new legal frameworks in practice. It also highlights the role of ecosystem actors – including regulators, consultants, and legal experts – in translating legal obligations into operational practices. In doing so, it offers a practical view of how institutions navigate the evolving intersection between regulatory compliance and technological innovation.

The thesis is structured as follows: Chapter 1 introduces the research context, objectives, problem statement, and relevance, presenting the theoretical and methodological approach. Chapter 2 elaborates the theoretical framework, grounding the research in the Diffusion of Innovations theory and related concepts. Chapter 3 describes the research methodology and analytical strategy. Chapter 4 reports on the empirical findings, showing how the original plan was implemented or adapted, and interpreting results using the theoretical framework. It ends with grounded theoretical insights. Chapter 5 concludes the thesis with a summary of results, methodological reflection, theoretical implications, suggestions for future research, and practical recommendations for policy and industry.

2. Theory

2.1. Artificial Intelligence and the Financial Sector

The increasing integration of AI into financial services globally is reshaping institutional processes, particularly in areas such as risk management, customer engagement, and internal operations. While AI offers significant potential in enhancing efficiency and innovation, its deployment within financial institutions has also raised concerns regarding regulatory compliance, transparency, and ethical use (European Banking Authority, 2023; European Central Bank, 2023; EIOPA, 2024). This section introduces AI and outlines its applications in the financial sector, moving from global and European developments to the specific Dutch context. The final subsection discusses the regulatory implications of the EU Artificial Intelligence Act (AI Act) for financial institutions. In response to these concerns, a growing body of academic research has emerged, focusing on how ethical principles and regulatory expectations can be translated into operational AI governance frameworks. (Busuioc, 2021; Morley et al., 2021).

Recent empirical studies on AI governance and financial sector innovation have deepened understanding of how regulatory obligations interact with organisational decision-making. For instance, Hacker (2023) focuses on regulated sectors such as finance, showing that internal legal capacity and interpretive flexibility significantly influence an institution's ability to implement complex regulations such as the EU AI Act. Veale and Borgesius (2021) analysed the implications of GDPR uncertainty for automated decision-making, finding that regulatory vagueness can discourage innovation and result in cautious overcompliance. Zerilli et al. (2022) argued that compliance cannot rely solely on technical fixes but must incorporate institutional values such as fairness and transparency into governance structures. Technical standards like the NIST AI Risk Management Framework (2023) offers financial institutions practical tools for risk classification, documentation, and oversight – critical elements for managing high-risk AI systems. Busuioc (2021), while focused on the public sector, highlighted broader governance challenges – such as the need for explainability, trust, and accountability – which can also apply to financial institutions managing AI systems.

2.1.1. Defining Artificial Intelligence

AI is commonly defined as the capacity of machine–based systems to infer decisions, recommendations, or predictions from input data, often performing tasks that would otherwise require human intelligence. The EU AI Act adopts a definition consistent with the OECD framework for the Classification of AI Systems, referring to AI as "a machine–based system designed to operate with varying levels of autonomy, that may exhibit adaptiveness after deployment and that infers from inputs to generate outputs that can influence environments" (European Parliament, 2023; OECD, 2023). This broad categorisation encompasses rule–based algorithms, machine learning, deep learning, and increasingly, generative AI models. These developments present considerable promise, especially in domains requiring large–scale data analysis and dynamic decision–making. However, they also introduce challenges regarding explainability, data

protection, model bias, and compliance with evolving legal obligations (Floridi & Cowls, 2019; Morley et al., 2021; Busuioc, 2021).

2.1.2. AI Use in Financial Services: Global to Dutch Context

Financial institutions worldwide are adopting AI to support a variety of operations, including fraud detection, credit scoring, anti–money laundering (AML) monitoring, algorithmic trading, and customer service automation, to name a few. Multiple European regulatory bodies have documented this trend. For instance, the European Banking Authority's Special Topic Report on Artificial Intelligence (2023) outlines AI use in credit risk modelling, customer onboarding, and compliance monitoring. The European Central Bank (2023) found that over 60% of significant Eurozone banks have deployed AI, particularly in customer-facing services and trading. Similarly, the European Insurance and Occupational Pensions Authority (EIOPA, 2024) reported increased AI adoption in claims handling and risk assessment among insurers.

In the Dutch context, regulators have taken an active role in promoting responsible AI use. The Dutch Central Bank (DNB, 2019) issued sector-specific guidance emphasising explainability, risk controls, and human oversight. The joint DNB and AFM report (2024) further underscores the growing integration of AI in Dutch financial institutions, highlighting applications such as automated onboarding, portfolio risk analytics, and fraud detection. Moreover, van der Burgt (2019) observed early efforts by Dutch banks to embed AI into model risk management and internal decision-making processes. These regulatory and institutional developments reflect the Netherlands' proactive stance in aligning innovation with ethical and supervisory standards.

At the European level, the European Central Bank (ECB, 2023) found that 60% of significant banks across the Eurozone are currently employing AI, with a concentration in areas like customer–facing applications and algorithmic trading. Similarly, the European Insurance and Occupational Pensions Authority (EIOPA, 2024) reported that AI is increasingly used by insurers in claims management and risk assessment, often within tightly controlled and explainable parameters.

In the Netherlands, the adoption of AI has been actively supported by ecosystem actors such as financial regulators (DNB and AFM), industry associations, law firms, and consulting firms and is increasingly embedded in organisational workflows. Dutch financial institutions such as Rabobank, ABN AMRO, and ING have incorporated AI into different aspects of their operations – such as automated onboarding, financial planning, and predictive analytics in bond trading (DNB & AFM, 2024; van der Burgt, 2019). Dutch insurers have also introduced AI into underwriting and customer support, although many remain cautious about using generative models in customer–facing roles due to data security concerns (EIOPA, 2024; van der Burgt, 2019).

Dutch financial regulators have actively guided the adoption of AI by promoting responsible innovation, emphasising the importance of systems that are auditable, explainable, and ethically aligned. This early regulatory engagement has been instrumental in shaping Dutch financial institutions' cautious, albeit

progressive, approach to AI. As these principles closely mirror the core requirements of the EU AI Act, Dutch institutions are, in theory, well-positioned for a smooth transition towards compliance under the newly established regulation (DNB & AFM, 2024; European Union, 2024).

2.1.3. Regulatory Context: From Regional and National Guidelines to the EU AI Act

Before the adoption of the EU Artificial Intelligence Act (EU AI Act) in 2024, several European and national-level guidelines had already begun shaping expectations around the responsible use of AI in the financial sector. Notably, the European Banking Authority's Guidelines on Outsourcing Arrangements (2021) and the European Central Bank's Guide on Internal Models (2024) established early supervisory principles around explainability, governance, and risk management. At the national level, the Dutch Central Bank (DNB) issued its *General Principles for the Use of Artificial Intelligence* (2019), which outlined expectations for transparency, human oversight, and ethical alignment. Together, these early frameworks laid the groundwork for sector-specific compliance norms and informed organisational attitudes toward AI adoption.

Building on this foundation, the EU AI Act introduces a comprehensive, cross-sectoral, risk-based regulatory framework for AI applications across the European Union, including the financial sector. Applications are classified into four tiers – unacceptable, high, limited, and minimal – based on their potential societal impact (European Commission, 2024). Within financial services, high-risk designations commonly apply to AI systems used for creditworthiness assessments and pricing in insurance. These systems must comply with rigorous obligations, including:

- Robust risk management and data governance,
- Human oversight protocols,
- Technical documentation and transparency,
- Impact assessments on fundamental rights (European Parliament, 2023; European Union, 2024).

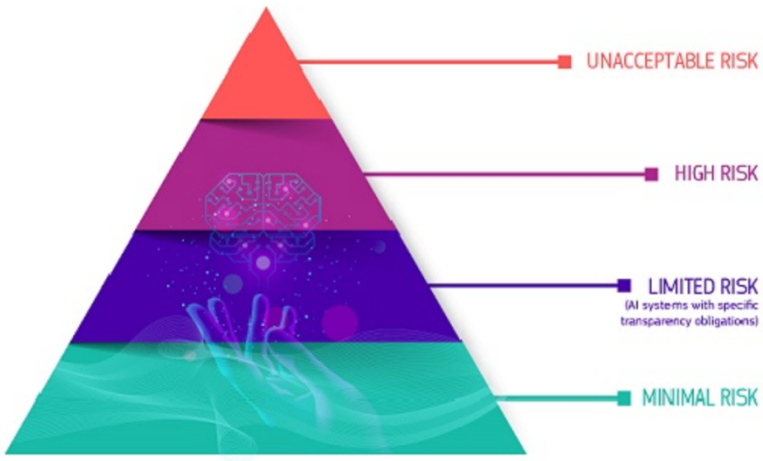

Figure 1. Risk–based classification of AI systems under the EU AI Act (European Commission, 2025)

The regulation also introduces innovation-enabling mechanisms such as regulatory sandboxes and voluntary codes of conduct for lower–risk systems. These measures aim to encourage controlled experimentation while maintaining robust protections for systemic safety and fundamental rights – an approach that reflects the EU's broader attempt to balance innovation with rights-based safeguards during the legislative process. As Palmiotto (2025) shows, this balancing act was central to the political negotiations that shaped the AI Act, with innovation incentives often weighed against the need for enforceable rights protections – an approach that also aligns with the Dutch model of responsible innovation (DNB & AFM, 2024).

The EU AI Act has the potential to directly influence AI adoption decisions within financial institutions. By imposing clear compliance obligations, the regulation compels organisations to evaluate whether existing or planned AI systems meet new legal and governance standards. This regulatory pressure not only informs risk-based decision-making but may also disincentivise adoption of complex or opaque AI tools that are harder to align with compliance expectations. For example, tools perceived as overly complex or lacking explainability may be deprioritised due to the difficulty of aligning them with the EU AI Act's transparency and oversight requirements (Busuioc, 2021; Dawson & Maricut-Akbik, 2021).

In this way, compliance is not merely a constraint but a strategic factor – influencing which AI systems are prioritised, how they are implemented, and under what conditions they are deemed viable. The EU AI Act thus does more than impose legal requirements; it actively shapes organisational behaviour and innovation strategy.

This raises a critical concern central to this study, namely in terms of how the EU AI Act is shaping the adoption and implementation of AI systems within the Dutch financial sector. To investigate this, the next section draws on Diffusion of Innovations (DoI) theory, which systematically explains how and why new technologies are either embraced, face obstacles to implementation, or are ultimately not pursued within organisations. Applying this framework enables a structured analysis of how regulatory obligations, organisational decision-making processes, and perceived innovation attributes interact to influence AI adoption and implementation decisions among Dutch financial institutions.

2.2. Diffusion of Innovations

This thesis is anchored in Everett Rogers' (2003) *Diffusion of Innovations* theory, a foundational framework that set out to explain whether, why and how new technologies are adopted, delayed, or rejected within social systems, including organisations. The theory is particularly well suited to this study for several reasons.

First, Rogers' theory has a strong track record of application in complex and highly regulated sectors such as finance, where institutional bottlenecks, legal constraints, and organisational culture significantly influence innovation uptake. For instance, Heuts and van der Kaap (2019) applied the model to examine blockchain adoption in Dutch banking, identifying regulatory ambiguity and organisational complexity as

key inhibitors. Similarly, TNO (2020) used the framework to analyse RegTech diffusion, highlighting compatibility with internal risk structures and perceived trialability as decisive for adoption. These studies confirm the framework's relevance for understanding innovation in the Dutch financial sector, where legal and compliance requirements weigh heavily on technology decisions.

Second, the theory emphasises the role of perceived attributes of innovations – relative advantage, compatibility, trialability, observability, and complexity – in shaping adoption and implementation decisions. These factors are especially relevant given the EU AI Act's detailed compliance requirements for high-risk AI systems, which mandate robust documentation, traceability, explainability, and ongoing oversight (European Union, 2024; Busuioc, 2021). For example, institutions must demonstrate transparency and human oversight in AI-based credit scoring or fraud detection tools – criteria that map directly onto Rogers' dimensions of observability and complexity. AI systems perceived as too opaque or difficult to explain are less likely to meet regulatory thresholds, thereby diminishing their perceived relative advantage and compatibility within existing compliance structures.

Third, Rogers' framework supports an integrated analysis of both technical and organisational dimensions of adoption – combining insights into system-level features (e.g., transparency, testability) with behavioural and institutional responses (e.g., risk aversion, governance readiness). This dual perspective is crucial for understanding how Dutch financial institutions are responding to the EU AI Act's evolving compliance environment and the broader regulatory ecosystem, including guidance from DNB and AFM (DNB & AFM, 2024). By bridging regulatory theory and innovation studies, the framework enables a systematic investigation of how legal expectations interact with internal decision-making logics to either accelerate or inhibit AI deployment.

In this research, DoI theory provides the structure for analysing two core themes that reflect the sub-questions: (1) how the EU AI Act changes the conditions under which financial institutions make AI adoption and implementation decisions, and (2) how characteristics of AI systems influence their adoption under the EU AI Act.

Beyond traditional applications, recent work highlights how Rogers' framework is particularly pertinent in domains shaped by digital transformation and regulatory complexity (e.g., Maple et al., 2023; Mirishli, 2024). These studies support the framework's ability to capture how legal mandates influence innovation adoption pathways in finance.

2.2.1. Changing Conditions for AI Adoption and Implementation Decisions

This part addresses the first sub-question: *How does the EU AI Act influence the conditions for AI adoption and implementation decisions?*

To analyse this, the study draws on Rogers' (2003) Innovation-Decision Process, which conceptualises the sequential stages organisations go through when considering adoption, delay, or rejection of new

technologies (refer to Figure 2 below). Each stage highlights how external factors, such as regulatory frameworks, can shape organisational decision-making. In the context of this research, the stages are interpreted in relation to the conditions introduced by the EU AI Act and their implications for AI adoption within the Dutch financial sector:

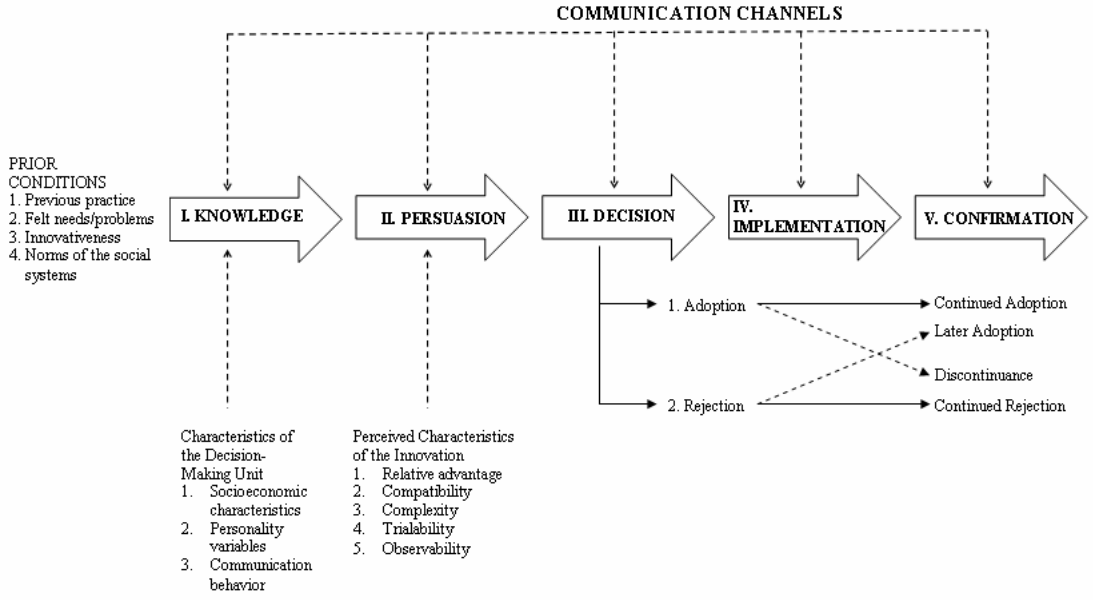

Figure 2. A model of five stages in the innovation-decision process (Rogers, 2003)

2.2.1.1. Knowledge

The organisation becomes aware of the innovation and develops an initial understanding of its purpose and functions. In the context of the EU AI Act, Dutch financial institutions must navigate complex technical, legal, and compliance information at an early stage, potentially increasing the barriers to advancing AI adoption. At the same time, awareness of the EU AI Act's innovation-enabling mechanisms – such as regulatory sandboxes and voluntary codes of conduct – can have a positive effect by signalling opportunities for controlled experimentation and regulatory guidance (European Union, 2024; OECD, 2024). These mechanisms may lower initial uncertainty and encourage early engagement with AI initiatives under supervised conditions, particularly in high-stakes environments such as finance (Palmiotto, 2025).

2.2.1.2. Persuasion

The organisation forms an attitude toward the innovation by weighing its perceived benefits against potential risks. At this stage, increasing compliance obligations – including requirements for risk management, transparency, and human oversight – may lead institutions to adopt a more cautious attitude, potentially reducing the perceived relative advantage of AI. Research has shown that regulatory pressures can have both enabling and inhibiting effects on innovation adoption, depending on how organisations interpret and internalise compliance demands. For example, Dawson and Maricut-Akbik (2021) highlight how overlapping and ambiguous legal obligations in the EU context can create uncertainty and lead to compliance-driven hesitation, while Busuioc (2021) emphasises that stronger accountability mechanisms can legitimise innovation if perceived as enhancing governance capacity rather than merely

imposing constraints. Clear regulatory guidance – by reducing interpretive ambiguity and defining the "rules of the game" – can help institutions make more confident adoption decisions (Maple et al., 2023; OECD, 2024). In the context of the EU AI Act, whether institutions perceive regulations as a constraint, or a strategic enabler may critically shape their shift from awareness to commitment.

2.2.1.3. Decision

The organisation decides whether to adopt or reject the innovation, typically following internal evaluations of legal risk, strategic alignment, and operational feasibility. Under the EU AI Act, this stage is shaped by compliance requirements such as system classification, documentation obligations, and governance structures (European Union, 2024). These requirements may present challenges in the decision-making process, particularly where legal ambiguity or perceived risk of non-compliance exists. Research has shown that when regulatory frameworks are unclear or overly complex, organisations may delay or avoid adoption altogether (Dawson & Maricut-Akbik, 2021). Importantly, the Act may also prompt institutions to reassess previously adopted AI systems – raising questions of whether continued use remains compliant, potentially leading to discontinuance (Rogers, 2003). At the same time, some AI applications previously shelved due to uncertainty may now be reconsidered under clearer guidance, enabling late adoption (Busuioc, 2021; OECD, 2024). Alignment between regulatory expectations and internal processes can lower barriers and support commitment. The extent to which institutions perceive the EU AI Act as either manageable or burdensome thus plays a key role in shaping the adoption decision.

2.2.1.4. Implementation

The innovation is operationalised within the organisation, requiring alignment with regulatory and institutional structures. In the case of high-risk AI systems, implementation under the EU AI Act demands adherence to a range of obligations – such as risk and quality management systems, human oversight protocols, and technical documentation (European Commission, 2024). These requirements may necessitate the development of new internal procedures or the modification of existing governance frameworks. Scholars note that implementation efforts are particularly challenging when legal requirements are difficult to interpret or translate into actionable workflows (Binns, 2018). The success of this stage often depends on an organisation's technical maturity, regulatory preparedness, and internal capacity to embed compliance into operational routines (Busuioc, 2021).

2.2.1.5. Confirmation

The organisation evaluates whether the innovation continues to meet expectations after implementation. In this stage, ongoing oversight and compliance monitoring become central to confirming the value and viability of the adopted system. The EU AI Act reinforces this process by requiring post-deployment accountability measures – such as periodic audits, record-keeping, and bias assessments – particularly for high-risk use cases (European Union, 2024). If AI systems consistently meet compliance thresholds and deliver expected benefits, adoption is likely to be reinforced; otherwise, organisations may adjust, scale back, or discontinue use. Research has shown that transparency, explainability, and auditability are essential factors in sustaining adoption, especially in regulated sectors. Systems that lack interpretability

may be excluded from continued use, not because of performance limitations, but due to concerns about oversight and trust (Burrell, 2016; Floridi & Cowls, 2019).

The EU AI Act, by imposing extensive obligations (European Union, 2024), reshapes the internal conditions at each stage of the adoption process, influencing both the decision to adopt and the subsequent implementation of AI system. Institutions must carefully balance the strategic benefits of AI – such as enhanced operational efficiency and improved customer service – against increased legal, operational, and reputational risks.

Historically, Dutch regulators like DNB and AFM have promoted principles of responsible innovation, encouraging transparency, explainability, and robust risk management (DNB & AFM, 2024). As a result, Dutch financial institutions may be relatively well-prepared for compliance under the EU AI Act. However, they must continue to make strategic evaluations about whether the value of adopting AI systems justifies the associated costs and regulatory complexities.

Expanding on this analysis, the next section examines how the characteristics of AI systems influence adoption and implementation decisions. As previously mentioned, Rogers' Diffusion of Innovations theory identifies five key attributes – relative advantage, compatibility, trialability, observability, and complexity – as critical factors shaping adoption. Analysing how these features interact with regulatory demands provides deeper insight into the drivers and barriers to AI adoption within Dutch financial institutions.

2.2.2. Characteristics of AI Systems and Their Influence on Adoption and Implementation Decisions

This part addresses the second sub-question: *How do the characteristics of AI systems influence adoption and implementation decisions under the EU AI Act?*

Because the adoption of AI is influenced not only by regulatory mandates but also by how organisations perceive the technologies themselves, it is essential to explore the features of AI systems that shape organisational responses. Certain characteristics can either facilitate or hinder adoption, depending on how well they align with compliance expectations and operational needs. Drawing on Rogers' perceived innovation attributes, this section examines five key characteristics that are particularly relevant to understanding adoption and implementation decisions under the EU AI Act.

2.2.2.1. Relative advantage

Relative advantage captures the extent to which an AI system is perceived as superior to existing solutions. In finance, AI can enhance efficiency, fraud detection, customer service, and risk management. However, the EU AI Act's compliance demands – including transparency, human oversight, and data governance – may temper these perceived benefits. This is because meeting these obligations often introduces additional risks and costs for organisations. For example, institutions may face potential non-compliance penalties if explainability or human oversight is insufficiently demonstrated, especially for high-risk use cases (Busuioc, 2021). Furthermore, compliance requires significant investment in human resources,

such as legal, risk, and audit personnel, to ensure data governance and accountability structures are in place (Dawson & Maricut-Akbik, 2021).

Moreover, compliance requires investments in human resources such as legal, risk, and audit personnel (EIOPA, 2024). There are also trade-offs between system effectiveness and regulatory constraints: AI models that rely on large volumes of personal data may offer improved accuracy and performance but may not be feasible under the Act's data minimisation and privacy provisions (Palmiotto, 2025; European Union, 2024). As a result, institutions may prioritise less complex but more compliant systems that align with regulatory expectations. AI systems that deliver clear improvements while meeting regulatory requirements are therefore more likely to be adopted (European Commission, 2024).

2.2.2.2. Compatibility

Compatibility reflects how well AI technologies fit within an institution's existing values, processes, and infrastructure. The EU AI Act mandates governance and oversight mechanisms, meaning AI systems must not only perform effectively but also align with legal requirements related to documentation, human oversight, and risk management (European Commission, 2024). When AI systems conflict with existing internal standards or require disproportionate procedural changes, they may be deprioritised (TNO, 2020). In contrast, institutions with mature compliance cultures and strong IT governance may find it easier to integrate AI systems under the Act, reinforcing existing structures rather than disrupting them (DiMaggio & Powell, 1983).

At the same time, the EU AI Act contributes to a broader institutional shift. It often reinforces pre-existing norms around transparency, accountability, and model governance but also acts as a catalyst for professionalising AI oversight and spreading best practices across the sector. This reflects both coercive isomorphism, where organisations responding to binding regulatory demands and normative isomorphism, as shared professional expectations evolve in response to new legal frameworks (Morley et al., 2021; DiMaggio & Powell, 1983).

2.2.2.3. Trialability

Trialability concerns the ability to test AI systems in limited settings before full-scale deployment. While the EU AI Act does not explicitly mandate trial phases, it promotes risk mitigation and transparency through robust pre-deployment assessments. Dutch regulators facilitate controlled experimentation through mechanisms like regulatory sandboxes, which allow institutions to pilot AI applications under supervisory oversight, reducing perceived risks. Sandboxes are often considered as tools for iterative learning between regulators and innovators, enabling dialogue, trust-building, and early identification of compliance concerns (Fahy, 2022).

However, Johnson (2023) cautions that sandboxes may struggle with legitimacy if regulatory boundaries and legal accountability are unclear, potentially leading to inconsistent or contested decisions. Additionally, as Raudla et al. (2023) illustrate, sandbox strategies diverge significantly across jurisdictions: while some adopt them to actively promote innovation, others remain cautious due to capacity constraints

or differing regulatory philosophies. This variation underscores that while trialability mechanisms can lower barriers to AI adoption, their success depends on institutional design, clarity of purpose, and the degree of regulator–innovator collaboration embedded in national governance frameworks.

2.2.2.4. Observability

Observability describes how visible the outcomes of an innovation are to others. In a highly regulated context, observability includes explainability, audit trails, and performance monitoring. These requirements pose challenges for AI systems, especially those based on complex models like deep learning, which are often described as "black boxes" due to their lack of transparency and interpretability (Burrell, 2016).

Floridi and Cowls (2019) emphasise that observable AI systems are crucial to earning stakeholder trust and achieving regulatory compliance. Furthermore, observable outcomes facilitate internal monitoring, public accountability, and supervisory review (Palmiotto, 2025). Institutions may therefore favour systems that produce interpretable outputs and provide traceable decision pathways – attributes that support validation, governance, and regulatory reporting.

2.2.2.5. Complexity

Complexity refers to how difficult an innovation is to understand and apply. In contrast to observability, which focuses on the visibility and transparency of outputs, complexity relates to the internal logic and functionality of a system – how understandable it is to those expected to use, govern, or oversee it. Highly complex systems require cross-functional coordination between compliance, technical, and legal teams. As noted by Maple et al. (2023), the cognitive and procedural burdens associated with managing advanced AI systems can deter adoption unless internal capability is well developed.

In financial contexts, compliance burdens can exacerbate perceived complexity. Overlapping regulatory requirements – such as the General Data Protection Regulation (GDPR), the EU Artificial Intelligence Act (EU AI Act), and the Capital Requirement Directive (CDR) – add interpretive challenges and increase the need for interdisciplinary expertise (Busuioc, 2021; Johnson, 2023). Institutions with limited capacity to interpret legal text or map obligations onto workflows often rely on consultants and legal advisors (OECD, 2024). As a result, complexity – unless mitigated by expertise or support – increases institutional resistance to adoption.

Taken together, these five characteristics shape how institutions evaluate the feasibility and desirability of AI systems under the EU AI Act. Understanding their influence is critical to assessing the broader diffusion of compliant AI technologies in regulated financial environments.

3. Methodology

3.1. Research Design

This research employs a qualitative, theory-informed case study design to examine the challenges and strategic responses of Dutch financial institutions to the EU AI Act. It follows a theory–driven approach (Levy, 2008), grounded in Rogers' Diffusion of Innovations theory (2003), and adopts a primarily deductive strategy.

The research is structured around two key components of Rogers' framework: the stages of the innovation-decision process (namely knowledge, persuasion, decision, implementation, and confirmation), and the perceived attributes of innovations (including relative advantage, compatibility, trialability, observability, and complexity). These theoretical elements guide the development of data collection instruments and the analytical approach, allowing for a structured investigation of both regulatory influences and system characteristics on adoption and implementation decisions.

While the study is grounded in established theoretical constructs, it remains open to inductive insights, allowing unanticipated themes and patterns to emerge from the field. This hybrid methodology supports both theoretical rigour and empirical responsiveness, enabling a nuanced understanding of organisational decision-making under evolving regulatory environment.

3.2. Case Selection

The Dutch financial sector is selected as a "most likely" case – a setting where regulatory effects are expected to be especially visible due to favourable preconditions (Levy, 2008). While the financial sector is already highly regulated, this does not necessarily reduce the relevance of the EU AI Act. On the contrary, the Act introduces new, cross-sectoral obligations that build on existing rules, making it possible to observe how well-governed institutions adapt. In such settings, regulatory effects may be more visible, as organisations are likely to engage early and respond in structured ways.

Several factors support this case selection. First, the Netherlands demonstrates high levels of digital maturity and institutional readiness, with over 60% of firms adopting cloud services and nearly half classified as digitally intensive (DNB, 2024a). Second, Dutch financial regulators – notably DNB and AFM – have actively promoted responsible AI innovation, creating a structured and responsive governance environment (DNB & AFM, 2024). Third, the sector already possesses well-established risk management frameworks, including sector-specific guidance on ethical AI use, internal controls, and regulatory alignment initiatives related to the EU AI Act (van der Burgt, 2019).

Given these conditions, the Dutch financial sector represents a strong institutional environment where responses to the EU AI Act are likely to be proactive, observable, and informative for broader policy learning. While some may argue it represents a "least likely" case – since AI was already heavily regulated – this research positions it as a most likely case. Its regulatory maturity enables early and structured

engagement with the Act. Whether responses reinforce existing practices or reveal new constraints, they offer valuable insight into how the regulation is interpreted and implemented in high-capacity environments.

3.3. Data Collection

To investigate how the EU AI Act shapes the adoption of AI systems in Dutch financial institutions, this study draws on two complementary sources of data: policy and regulatory analysis, and semi-structured expert interviews. This combination provides a dual perspective on both the formal expectations set by regulators and the ways in which these are interpreted, operationalised, and responded to within organisational settings.

Policy and Regulatory Analysis: A detailed examination of the EU AI Act and national supervisory publications by the Central Bank of the Netherlands (DNB) and the Netherlands Authority for the Financial Markets (AFM) is conducted to understand how formal regulatory frameworks are designed to influence AI adoption. These documents provide essential context on compliance obligations, risk expectations, and supervisory priorities, forming the basis for analysing how external institutional pressures shape internal decision-making processes.

The key documents analysed in this study include:

- *EU Artificial Intelligence Act* – The final legislative text establishing harmonised obligations for AI system development and deployment across the EU, used to identify core compliance requirements such as risk classification, documentation, and oversight (European Union, 2024).
- *DNB General Principles for the Use of AI* – Sector-specific guidance by the Dutch central bank outlining expectations around transparency, risk controls, and human oversight; used to contextualise national supervisory norms (DNB, 2019).
- *DNB & AFM Joint Report: The Impact of AI on the Financial Sector and Supervision* – This joint publication informed the study's understanding of how regulators interpret AI risks and promote responsible adoption in practice (DNB & AFM, 2024).
- *ECB Guide on Internal Models* – A supervisory framework used to assess how model governance principles intersect with AI compliance demands, particularly in high-risk financial applications (ECB, 2024).

These documents were used primarily as background material to prepare for interviews. They informed the design of the interview guide, helped identify thematic codes (e.g., transparency, model risk), and served as a reference point for interpreting how institutions respond to evolving compliance expectations.

Semi-structured Expert Interviews were conducted to capture how regulatory pressures are interpreted and enacted within organisational settings. Interviewees were purposefully selected for their institutional knowledge and strategic roles related to the implementation of AI and adherence to emerging regulatory

frameworks, including the EU AI Act. Participants represent a diverse cross-section of the Dutch financial ecosystem, including:

- **Direct implementers**, who are responsible for internal AI deployment and compliance:
    - Banking and national financial institutions:
        - Bank 1 (Interviewees 4, 10)
        - Bank 2 (Interviewee 8)
    - Pension and insurance institutions / Asset managers:
        - Asset Management (Interviewees 3a, 3b, 9)
- **Ecosystem actors**, who influence regulatory design, interpretation, and institutional readiness:
    - Public regulatory bodies, e.g. senior supervision officers and policy advisors:
        - Regulator 1 (Interviewee 5)
        - Regulator 2 (Interviewee 7)
        - Regulator 3 (Interviewee 13)
        - Regulator 4 (Interviewee 14)
    - Law firms and legal advisors specialising in financial regulation:
        - Law Firm (Interviewees 1a, 1b)
    - Consultancies offering AI and governance expertise:
        - Consulting Firm (Interviewee 11)
    - Industry associations, e.g. banking policy advisors:
        - Financial Association 1 (Interviewee 6)
        - Financial Association 2 (Interviewee 12)
    - Non-profits / Independent research on AI safety standards and algorithmic accountability:
        - Independent Research (Interviewee 2)

While the study's primary focus is on financial institutions (who are subject to direct legal obligations under the Act), it was essential to include ecosystem actors given their influential role in shaping the regulatory and operational environment. These actors support organisations in interpreting complex legal texts, developing internal governance structures, and aligning with supervisory expectations.

The rationale for including both direct implementers and ecosystem actors was to capture the complementary perspectives needed to understand how the EU AI Act is applied in practice. Direct implementers offered insights from "behind the curtains", revealing how institutions navigate internal decision-making, risk governance, and technical implementation. Ecosystem actors provided a broader perspective on regulatory design, sector-wide compliance trends, and interpretive challenges. As financial institutions often depend on these external actors for legal and strategic guidance, their inclusion is essential for analysing how adoption decisions are formed in practice. This dual perspective strengthens the study's ability to investigate the interaction between regulatory demands, institutional behaviour, and

innovation outcomes. The interview questions used to guide these conversations are provided in the Appendix.

Respondents were identified through LinkedIn outreach, personal networks, and publicly available contact details. The final sample included 15 participants; however, one withdrew prior to the interview, and one provided written responses via email. Of the 14 completed interviews, 5 were with direct implementers, while the remaining 9 were ecosystem actors. Although this creates a tilt toward external perspectives, it reflects the practical reality that financial institutions were more difficult to access and may have been cautious about discussing regulatory preparedness.

All interviews were conducted online via Microsoft Teams and lasted approximately 30 minutes, each. This format enabled flexible scheduling, broader geographic reach, and participation from professionals working in hybrid or remote settings. While online interviews reduced opportunities for informal rapport and non-verbal observation, they supported accessibility and efficiency. Participants gave explicit informed consent, and all interviews were recorded, transcribed, and anonymised in accordance with ethical research standards. For confidentiality and anonymity purposes, participants are identified only by organisational type and sector.

3.3.1. Interview Guide

To structure the semi-structured interviews, an interview guide was developed to align with the study's theoretical framework and research questions. The guide is organised around three thematic pillars:

(1) How the EU AI Act influences the conditions for AI adoption and implementation decisions

(2) How the characteristics of AI systems influence adoption and implementation decisions under the EU AI Act

(3) How organisations anticipate their AI adoption strategies evolving in response to ongoing regulatory developments related to the EU AI Act

Each interview began with a short introduction to the research. Interviewees were informed of the study's purpose, which is to explore how the EU AI Act shapes AI adoption and implementation within Dutch financial institutions. They were assured that all responses would be anonymised and treated confidentially, and that participation was voluntary and could be withdrawn at any time. Prior to recording, participants were asked to provide their explicit verbal consent. At the end of each interview, participants were thanked for their time and input. They were also asked whether they were open to follow-up contact via email if needed. This ensured potential opportunities to clarify or expand on specific points after the interview.

3.3.2. Research Limitations

The aim of this research is to provide a grounded, practice-oriented understanding of how the EU AI Act influences AI adoption decisions in the Dutch financial sector. By combining internal and ecosystem

perspectives, the study seeks to uncover both technical and institutional factors shaping compliance and innovation. While care was taken to ensure a diverse and representative sample, the findings are based on a limited number of interviews and reflect the views of selected actors within a fast-evolving policy environment. As such, the research aims to contribute to an emerging body of knowledge rather than offer definitive generalisations.

In particular, it proved challenging to secure participation from company-side actors such as banks, asset managers, and insurance firms. Many organisations did not reply to outreach efforts, while others declined due to internal policy or limited availability. As a result, the final sample contains a larger proportion of ecosystem actors – such as regulators, consultants, and legal advisors – relative to direct implementers. While these perspectives remain valuable, the underrepresentation of direct implementers may limit the generalisability of findings related to in-house adoption and compliance practices.

Furthermore, as this research was conducted within the scope of a master's thesis, time and resource constraints limited the ability to conduct additional follow-ups or expand the sample. As such, the study aims to offer exploratory insights that contribute to an emerging body of knowledge, rather than provide conclusive generalisations.

3.4. Data Analysis

3.4.1. Operationalisation of Key Concepts

The analytical approach is structured around Rogers' (2003) Diffusion of Innovations theory, operationalising two core theoretical components that frame the thematic analysis: the Innovation-Decision Process and the Perceived Attributes of Innovations. These concepts provide the foundation for examining how Dutch financial institutions navigate AI adoption under the EU AI Act.

Innovation-Decision Process

Rogers (2003) describes a five-stage process through which organisations adopt, delay, or reject innovations. In this study, each stage is interpreted in relation to the EU AI Act's regulatory context:

- **Knowledge**: Awareness and understanding of the innovation. The stage at which an organisation first becomes aware of the innovation and starts developing an understanding of its purpose and implications. In the context of the EU AI Act, this includes familiarisation with legal texts, regulatory guidance, and sector-specific interpretations.
- **Persuasion**: Formation of attitudes towards the innovation. Organisations form a favourable or unfavourable attitude toward the innovation. This stage involves weighing the perceived benefits (e.g. improved governance, innovation legitimacy) against potential risks or burdens (e.g. compliance costs, operational disruptions).
- **Decision**: The choice to adopt or reject the innovation. The organisation decides whether to adopt, reject, or postpone engagement with the innovation. This may involve internal deliberation

between business, legal, and compliance teams based on perceived strategic value and feasibility.

- **Implementation**: Putting the innovation into use. The adopted innovation is integrated into organisational processes. For AI systems, this includes deploying technical systems in line with regulatory requirements and operational standards.
- **Confirmation**: Evaluating the results and making adjustments or recommitments. The organisation evaluates the outcomes of implementation, assesses whether the innovation meets expectations, and determines whether to continue, adapt, or discontinue its use. This stage often includes monitoring, auditing, and ongoing regulatory alignment.

Perceived Attributes of Innovations

To further understand why some AI systems are adopted while others are avoided, the analysis applies Rogers' (2003) five key attributes of innovations. These attributes frame how AI technologies are evaluated under regulatory constraints:

- **Relative Advantage:** The extent to which AI systems are perceived to deliver strategic or operational benefits relative to the cost of compliance and governance obligations introduced by the EU AI Act.
- **Compatibility**: The degree to which AI systems align with existing organisational structures, particularly risk management, compliance frameworks, and regulatory expectations.
- **Trialability**: The ability to test or pilot AI systems before full deployment, allowing organisations to manage regulatory and operational risks during early stages of adoption.
- **Observability**: The visibility, explainability, and auditability of AI system behaviours and outcomes, crucial for satisfying both internal governance needs and external supervisory requirements.
- **Complexity**: The perceived difficulty of understanding, managing, and ensuring compliance for AI systems, with high complexity potentially discouraging adoption where regulatory clarity and system transparency are critical.

These operationalised concepts frame the thematic exploration of how regulatory obligations and system characteristics influence organisational adoption decisions.

3.4.2. Thematic Analysis Framework

The following table summarises the thematic framework, including themes, codes, descriptions, and example quotes:

Table 1. Thematic analysis table

Theme	Code	Description	Example
Regulatory influence on the AI adoption and implementation process	Knowledge	How organisations become informed about the EU AI Act and its requirements.	"We have a dedicated team that follow the Act"
	Persuasion	How regulatory obligations affect organisational attitudes toward AI adoption.	"The new rules make it difficult to invest in AI projects"
	Decision	How adoption and implementation decisions are made internally under regulatory pressure of the EU AI Act.	"Compliance team needs to approve before we can consider any AI-related systems"
	Implementation	How organisations deploy AI systems in alignment with EU AI Act compliance requirements.	"We have a team to monitor every AI system deployment"
	Confirmation	How organisations review and monitor AI systems after deployment to ensure ongoing compliance with the EU AI Act.	"After deployment, we check the AI systems if it fulfils compliance requirements quarterly"
Characteristics of AI systems and their influence on adoption and implementation decisions	Relative advantage	How organisations perceive the benefits of adopting AI systems relative to the compliance demands of the EU AI Act.	"It improves our workflow"
	Compatibility	How well AI systems integrate with existing structures, including those shaped by the EU AI Act.	"Our older systems need to be upgraded to accommodate the new AI system"
	Trialability	Whether AI systems can be piloted or sandboxed under EU AI Act mechanisms like regulatory sandboxes.	"It's easy to test before full–scale rollout"
	Observability	How easily system behaviour can be explained and audited under the EU AI Act's transparency and oversight rules.	"We can see the result directly after implementing the system"
	Complexity	The challenges of managing AI systems under EU AI Act obligations, including interpretability and risk classification.	"Some of our team members experience difficulty in understanding how the algorithm came to the decisions"
Outlook	Future expectations	How organisations expect their AI adoption strategies to evolve under continued EU AI Act enforcement.	"We expect more investment in AI, but only for systems that can meet compliance requirements"

3.4.3. Analytical Strategy

The data analysis followed a structured qualitative approach grounded in Rogers' Diffusion of Innovations theory. The primary strategy was deductive, guided by predefined theoretical constructs such as the perceived attributes of innovations and stages of the innovation-decision process. This allowed for systematic identification and organisation of key themes, as summarised in Table 1 (Thematic Analysis Framework).

The coding process was iterative and reflexive, following best practices outlined by Williamson and Johanson (2018), and Linneberg and Korsgaard (2019). While deductive in orientation, the analysis remained open to inductive insights. As new or unanticipated patterns emerged from the interview data, the coding structure was adapted to incorporate these elements, ensuring empirical sensitivity to participants' perspectives.

Analytical memos were used to document interpretive reflections and track how regulatory conditions and innovation characteristics influenced adoption and implementation decisions. Codes and themes were grouped manually to maintain close engagement with the material and ensure analytical transparency.

This strategy ensured a theoretically coherent and empirically grounded interpretation of how Dutch financial institutions navigate AI adoption under the evolving regulatory environment introduced by the EU AI Act.

3.5. Research Ethics

According to the Netherlands Code of Conduct for Research Integrity, academic research is grounded in "a number of guiding principles: honesty, scrupulousness, transparency, independence and responsibility" (Universities of the Netherlands, 2018, p. 6). These five principles form the ethical foundation for good research practices in the Dutch academic system and are embedded in 61 standards of conduct adopted by all universities and research institutions.

This research has been guided by these national principles, alongside the ethical guidelines proposed by Johannesson and Perjons (2021). The following four principles were applied in practice throughout this study:

- Principle 1: Protect the interests of participants. This concerns the obligation to prevent harm and safeguard participants' rights. In accordance with the principle of anonymity, no personal or identifiable information about individuals or organisations is disclosed in this study.
- Principle 2: Ensure voluntary participation based on informed consent. Participation in the interviews was entirely voluntary. Participants were provided with information about the research objectives, focus areas, and the purpose of recording. Verbal consent was explicitly requested and obtained prior to each interview. Recordings were used strictly for transcription and analysis.

- Principle 3: Operate openly and honestly. Transparency and trust were prioritised throughout the research process. Participants were informed of the academic nature of the project, how their data would be used, and how they could contact the researcher for further clarification. All data are used solely for the purpose of this thesis.
- Principle 4: Comply with applicable laws and institutional guidelines. This study adheres to Dutch national legislation, GDPR requirements, and the institutional duty of care. It also follows the Netherlands Code of Conduct for Research Integrity, ensuring responsible data handling and a supportive research environment.

In addition, the research received ethical approval through the VU Amsterdam ethical self-check procedure (reference number: 2025-3-31-730).

4. Findings

4.1. Results

This chapter presents the empirical findings of the study, based on thematic analysis of 14 interviews with stakeholders involved in or impacted by the implementation of the EU AI Act in the Dutch financial sector. The analysis is structured around two core themes: Regulatory influence on AI adoption and AI system characteristics. A third theme – Future outlook – had been added to reflect participants' expectations and strategic foresight towards the development of EU AI Act over time. Particular focus is given to the five interviews with direct implementers (Banks 1 and 2, and an Asset Management firm), while insights from regulators, financial associations, law and consulting firms, and an independent researcher serve to contextualise implementation challenges and ecosystem readiness.

4.1.1. Regulatory Influence on AI Adoption

4.1.1.1. Knowledge: Awareness of the EU AI Act

Banks and asset managers, as direct implementers, reported a generally high level of awareness of the EU AI Act. Some institutions demonstrated a proactive stance by conducting line-by-line reviews or engaging in internal training sessions to familiarise teams with the expected requirements. Interviewee 10 from bank 1 explained that "*we already early last year got a consultancy and went through the AI Act line by line*", and Interview 8 from bank 2 noted that *"our bank is very aware of the AI act in its implications"*. All interviewees (3a, 3b, 9) from the asset management firm also confirmed a high degree of awareness.

However, ecosystem actors noted that this formal awareness does not necessarily translate into practical readiness or regulatory clarity. Many institutions – even those highly engaged – face ongoing challenges in interpreting how the Act applies to their specific systems, departments, and innovation strategies. Interviewee 6 from Financial Association 1 observed that *"organisations are taking it very seriously [...] but the bigger question is like ok, how do we put something like this to practice?"*, and Interviewee 12 from Financial Association 2 added that *"the European Commission published some guidelines on the definition of AI and it actually became more unclear for the banks, what does and doesn't fall under AI"*. Interviewee 7 from Regulator 2 emphasised this uncertainty further, stating that "*they're not very sure about what they can apply and to what applications the AI Act applies*".

These reflections suggest that while the AI Act has successfully raised awareness and triggered action, a critical disconnect remains between conceptual understanding and operational implementation. This gap may limit institutions' ability to engage with the regulation in a timely and confident manner – especially in the absence of finalised secondary legislation, clear supervisory expectations, and harmonised guidance across EU and national levels.

4.1.1.2. Persuasion: Attitude toward regulation

Direct implementers generally viewed the regulation as necessary but burdensome. Banks acknowledged its value in formalising internal governance structures and elevating AI oversight but also noted that it introduces administrative complexity and may slow down innovation. Interviewee 10 from Bank 1 remarked that "*now people need to adhere to what we say because it's regulatory and we get the budget and attention*", highlighting how the EU AI Act has bolstered the authority of compliance and risk functions internally. By framing AI governance as a regulatory imperative rather than a discretionary initiative, compliance teams are now better positioned to secure executive buy-in and resource allocation. Interviewee 4 from Bank 1added that "*people want to move fast [...] and governance and how you turn it around will always create some sort of delay because of documentation or additional requirements"*. Asset managers echoed this dual perception, observing that while regulatory pressure ensures accountability, it may also sideline business and product teams in favour of compliance-led decision-making. As Interviewee 9 from Assess Management firm put it, "*so it's ridiculous and inefficient, but that's currently what is there*", referring to their organisation's internal process of applying 60 security and compliance checks to every AI solution before deployment.

Secondary stakeholders further highlighted an imbalance in regulatory readiness. Financial technology companies – fintechs, in particular, feel disproportionately burdened by the regulation's broad scope, while regulators themselves acknowledge the Act's inherent complexity and the challenge of aligning overlapping frameworks. Interviewee 6 from Financial Association 1 noted that "*the regulatory burden for the smaller and mid-sized companies, especially Fintechs, is disproportionate"*, and Interviewee 5 from Regulator 1 described the Act as "*spaghetti [...] everything is interconnected with each other*".

4.1.1.3. Decision: Structuring AI use and adoption decision

Decisions about AI implementation often follow a staged review process – initial assessment of business value, followed by evaluation of regulatory and risk implications. Institutions start by identifying whether an AI use case aligns with strategic goals and then assess what constraints or obligations it may entail under the EU AI Act. Interviewee 8 from Bank 2 explained that "*does it have potential? And then if you are from the business side, yes, it does have potential, OK. So, what do we need to factor in in terms of limitations from risk and compliance?*". Interviewee 4 from Bank 1 added that "*so there's a kind of risk assessment being done on the proposal of the idea of the solution basically that will guide whether what kind of risk might happen if you deploy that and how to contain? Is that still in our risk appetite basically?"*.

Larger financial organisations tend to structure these processes with formal committees, roadmaps, and governance layers. They create internal classifications and frameworks that align AI use cases with applicable risk categories. As Interviewee 1a from Law firm explained, "*there's a committee or people made responsible for AI governance"*, and Interviewee 8 from Bank 2 shared that "*There's a controlled testing program that covers not only the AI, but GDPR and all of the financial regulations [...] and there's a whole process that is pretty uniform for the whole company and a way of testing*".

In contrast, smaller institutions or those earlier in their AI adoption journeys may adopt more iterative approaches, relying on trial-and-error or external guidance. However, across the board, stakeholders flagged concerns that ambiguity in the Act's scope may unintentionally lead to either over-compliance or deliberate avoidance. Interviewee 9 from the Asset Management firm remarked that "*because many do not understand AI, especially leaders. When you don't understand something and you need to be in control, then you're like, OK. Then let's not do anything*" indicating a conscious decision to limit innovation to applications that fall outside of high-risk obligations. Similarly, Interviewee 11 from a Consulting firm noted that "*we're going to make this chatbot, for instance. But something else [...] scanning invoices [...] this we're not gonna do anymore because the return on investment is too low*", highlighting how organisations are narrowing their AI use cases to avoid high-cost or compliance-heavy deployments. These responses illustrate how regulatory uncertainty may distort organisational strategies – not necessarily deterring AI due to technical infeasibility, but to pre-empt perceived legal or compliance risks. Additional interview evidence suggests that some avoidance stems not only from cost, but from uncertainty. Interviewee 10 from Bank 1 noted: "*If it tips into high-risk [...] is the business case still valid?"* – implying unclear thresholds may delay or deter adoption. This highlights how ambiguity, not just burden, can shape organisational restraint. Under this light, ambiguity is not just a regulatory burden but also a factor that actively shapes organisational strategy.

4.1.1.4. Implementation: Deployment and compliance processes

Banks and asset managers have begun to establish structured deployment protocols to manage AI systems in compliance with the EU AI Act. These processes typically involve registering systems, assigning risk classifications, and applying pre-deployment standards tailored to the perceived level of risk. Interviewee 4 from Bank 1 noted that "*we have a kind of registry that where every AI system needs to be registered",* while Interviewee 8 from Bank 2 added that "*There is a classification [...] under the AI Act to see whether it is potentially, you know, prohibited, high risk [...] based on that, you see what is needed to make it compliant with the Act*".

Despite these efforts, institutions report that translating the Act's high-level principles into operational rules often requires external expertise. Consulting firms and legal advisors play a critical role in helping organisations interpret ambiguous requirements and develop frameworks fit for internal use. As Interviewee 11 from Consulting firm explained, "*we essentially help organisations to make that translation better*" and "*it contains a lot of self-assessment requirements [...] that requires more work and more knowledge*".

Monitoring compliance over time remains an evolving challenge. While many firms build on existing governance structures, AI-specific demands – such as explainability, bias mitigation, and transparency – present unique and complex challenges. Interviewee 10 from Bank 1 stated that *"monitoring compliance is – no one has this solved yet. It's going to be one of the biggest pain areas*", and Interview 2 from an Independent Research organisation noted that "*you can only deploy it when you think it's going to be OK*

[…] But you also have to do some monitoring […] to see […] is this system actually doing things that are, yeah, worse than we expected […] or has some errors or some bias inside which we did not expect".

4.1.1.5. Confirmation: Ongoing supervision and enforcement

Direct implementers are actively establishing internal control to prepare for upcoming supervisory expectations. However, the regulatory framework for enforcement remains ambiguous and is still being developed. Regulators indicated that key guidance documents and supervisory protocols are not yet finalised, even as compliance deadlines approach. Interviewee 5 from Regulatory 1 stated that "*the deadline is next year […] but the guidance won't or not all be ready at that moment",* and Interviewee 13 from Regulator 3 added that "*the problem is that these rules are not yet, in many cases, very clear […] there will be technical standards […] but this is all very slow and it's [a] question whether [they] will be in time"*.

Stakeholders from associations and research also warned of overlapping requirements across legal regimes – such as the GDPR, CRD, and internal governance rules – which may result in duplicated compliance efforts or inefficient workflows. Interviewee 12 from Financial Association 2 noted that "*the new AI Act obligations, particularly on data, data governance and technical documentation, risk duplicating efforts already mandated by these frameworks*", and Interviewee 6 from Financial Association 1 added that *"for relatively small fintechs […] they have very high costs to comply there, and that's out of proportion"*.

4.1.2. AI System Characteristics

4.1.2.1. Relative advantage: Perceived strategic value

AI is broadly perceived as valuable for improving efficiency, innovation, and business value. However, the degree of strategic advantage depends on whether systems can align with compliance expectations. while Interviewee 3b from the Asset Management firm that "*I believe we will still use it only for low risk because the risk that we don't want to make mistakes […] we want to see how we could develop it step by step*", highlighting a cautious approach where perceived strategic benefits are filtered through compliance concerns. While governance structures may gain influence in this context, as noted by Interviewee 10 from Bank 1, this does not automatically translate into perceived advantage for the AI systems themselves.

The EU AI Act appears to reinforce internal AI governance structures by adding regulatory legitimacy to oversight roles, increasing senior leadership involvement, and justifying new investments in compliance infrastructure. Interviewee 10 from Bank 1 added that "*we get the budget and attention to implement systems for good practises because it's regulatory*", and Interviewee 4 from Bank 1 further noted that "*the AI Act […] forces us to make sure we make the deadlines basically and get more management [on board]*".

4.1.2.2. Compatibility: Organisational fit and integration

Larger institutions generally reported smoother alignment between AI governance practices and existing internal control mechanisms – such as model risk management, IT governance, and audit frameworks. This compatibility allows for smoother adaptation of the EU AI Act requirements. As Interviewee 8 from Bank 2 explained, "*so it's done a categorisation […] and then based on that, you see what is needed to make it*

compliant with the Act", while Interviewee 4 from Bank 1 noted, "*we actually use existing processes that we have risk management as an example, to see how that risk rating from an AI point of view is regards to that system*", illustrating how compliance requirements help elevate AI initiatives as organisational priorities. This increased institutional support contributes to the perceived relative advantage of AI by enabling implementation through clearer mandates, greater resourcing, and stronger leadership buy-in.

In contrast, smaller financial firms and fintechs face more significant implementation challenges. Without robust compliance infrastructure or specialised teams, these organisations may struggle to operationalise the requirements effectively or at scale. Interviewee 6 from Financial Association 1 observed that *"fintechs that are half the size still face 80% of the burden"*, and Interviewee 12 from Financial Association 2 added, *"the new AI Act obligations, particularly on data, data governance and technical documentation, risk duplicating efforts already mandated by these frameworks"*.

4.1.2.3. Trialability: Testing and experimentation

Proof-of-concept (POC) and pilot phases are standard practice in larger institutions, providing controlled environments for experimentation while minimising regulatory exposure. These phased approaches enable iterative testing, stakeholder engagement, and refinement of AI models before full deployment. Interviewee 4 from Bank 1 stated, *"the system always goes through a kind of rigorous test cycle before it goes into production"*, and Interviewee 9 from Asset Management firm confirmed, "*so you have your normal process to implement new systems. And then we decided, OK. But this is AI. This is new, so they set up a separate process [...] we have the AI checks and then it goes through the regular process, so risk and compliance still have to check*".

Smaller institutions or those with less AI maturity may lack formal processes, but many still conduct limited experimentation through test environments and change management systems. As Interviewee 3b confirmed, "*we do first a book proof of concepts and we have a test environment*". However, some consultants observed that testing is not always feasible, particularly for complex or low priority use cases. Interviewee 11 from a consulting firm indicated that organisations are increasingly making strategic trade-offs about which systems to pursue, based on feasibility and expected return. As they explained, "*everybody can come up with a use case [...] but now they want to standardise the process*" and added that "*so it's not like you have unlimited innovation budget anymore – there has to be made strategic decisions [...] we're really heading towards a more strategic innovation*".

These findings suggest that trialability is a double-edged sword: while it enables risk-managed innovation in structured settings, its absence – particularly for more complex or resource-intensive systems – can become a barrier to adoption. In such instances, organisations tend to favour applications that are modular, sandbox-friendly, or come with pre-existing risk assessments, thereby mitigating the limitations of non-trialable innovations.

4.1.2.4. Observability: Transparency and explainability

For high-risk use cases such as credit scoring or customer profiling, institutions reported pressure to ensure explainability of AI outputs. Systems lacking interpretability are often excluded from deployment in favour of models that provide traceable, auditable logic. Interviewee 3a from Asset Management firm explained that "*there are two aspects to the AI, the transparency part. The first aspect is the privacy aspect and then you have the AI Act aspect and both of them are very important [...] Therefore we try to abide by both of those norms*", while Interviewee 8 added, "*especially if it's a very impactful decision [...] like a credit score [...] there it becomes extremely critical [...] you can get at least enough information so that the person affected knows why the decision went their way*".

Black-box models were frequently rejected or decommissioned, even when they offered performance advantages, due to the difficulty of justifying their outputs to internal stakeholders or regulators. Interviewee 2 from an independent research organisation stated, "*it cannot meet this bar of explainability [...] I would actually advise against using these*", and Interviewee 10 from Bank 1 added "*you can only use non-explainable things for certain use cases, right? Where we legally, regulatorily need transparency, then you can't use the black-box models [...] You're back on very traditional ML*".

Regulators and researchers further reinforced the need for quantitative and standardised transparency metrics. Interviewee 5 from Regulator 1 said "*You would expect some kind of percentage or other concrete measurements"*, and Interviewee 2 from an independent research organisation remarked, "*if you want something that can do the same as a language model but not make any mistakes and also explain why it is doing [what it does] and actually have a truthful explanation – that's a research problem*".

4.1.2.5. Complexity: Challenges of management and compliance

Institutions consistently described the complexity of AI systems themselves – rather than just the regulatory framework – as a major challenge to adoption and implementation. Interviewee 4 from Bank 1 described it as *"the entry barrier to deployment is very low [...] but then an adoption of people actually using AI system [...] I see that quite high",* noting that while AI integration into workflows is technically easy, understanding and trust remain significant hurdles. This reflects a broader concern: AI systems – especially generative and black-box models – introduce layers of technical and behavioural complexity that go beyond compliance. Interviewee 9 from an Asset Management firm echoed this, stating, *"because many do not understand AI, especially leaders. When you don't understand something and you need to be in control, then you're like, OK. Then let's not do anything"*. This perceived lack of clarity and control can delay or even prevent adoption, regardless of technical readiness.

Secondary stakeholders echoed these concerns, noting that internal capability gaps are a major bottleneck – especially when it comes to understanding and operationalising complex AI systems. Institutions often lack the legal-technical interface skills required to translate abstract legal text into operational policies. Interviewee 11 from Consulting firm stated, *"They can have people who have understanding of risks and compliance or privacy data protection. [...] But to have that in combination with*

also AI knowledge, that's rather rare. That's really a new type of sport", and Interviewee 1a from Law firm added, *"like with many other EU legal instruments [...] it becomes a boundary for entrance. So very small party or a small group of persons cannot no longer easily set up a company in EU because all these rules have become really complex to understand and to apply"*.

Together, these findings highlight that it is not just the complexity of the technology or the regulation alone that creates barriers, but their combination. The combined challenge of technical opacity and legal ambiguity makes it particularly difficult for institutions to build the internal capabilities needed for compliant AI adoption.

4.1.3. Future Outlook

Financial institutions are approaching the EU AI Act with careful consideration and measured action. While the regulation has catalysed internal reviews and governance improvements, most organisations are hesitant to commit to major transformations until the regulatory landscape is fully clarified. Interviewee 4 from Bank 1 reflected that "*we don't do it transformative yet [...] there's still an appetite to explore, prove the value*", while Interviewee 10 from Bank 1 noted that *"I think it's the high-risk use cases we'll think twice about [...] there's a lot of stuff you need to do to make sure you're adherent and a lot of liability. So, I think the business case is really going to have to be robust before we do something high risk"*.

These observations reflect how institutions are viewing the Act more as a signal for long-term transformation rather than a roadmap for immediate change. Rather than rushing into broad implementation, firms are prioritising operational readiness and evaluating which systems may be affected. Interviewee 8 from Bank 2 stated, "*I don't think the AI Act is really the driver [...] it's just something there that needs to be complied with*". Interviewee 9 from Asset Management firm added, "*our current process is not facilitating the adoption of AI. It's actually slowing it down*".

This selectiveness underscores a measured, risk-aware approach to innovation. While new use cases are still being explored, they are evaluated with heightened scrutiny and aligned closely with core compliance strategies. As Interviewee 6 from Financial Association 1 noted, "*the financial institutions are taking it very seriously, dominantly driven by an inherent, risk averse mentality*".

Despite these hesitations, a forward-looking mindset is beginning to take shape across the financial sector. Some stakeholders view this transition period as an opportunity to professionalise AI governance and build organisational resilience. Interviewee 11 from Consulting firm observed, "*we're really heading towards a more strategic innovation*".

Importantly, a regulatory perspective reinforces this outlook, underscoring the need for patience and adaptability as the guidance continues to evolve. Interviewee 14 from Regulator 4 concluded, "*the AI Act is a product safety regulation, not competition law. Product Safety Regulations are a feature, not a bug in a developed economy. Without them, markets that depend on tech-driven innovations would never take off*

and bring benefits to citizens. […] European consumers – and businesses including those in the financial sector – can now welcome the AI Act to the EU's hugely successful family of Product Safety Regulations".

In summary, while the sector remains cautious, there is a growing recognition that those who invest early in strategic alignment and governance with the EU AI Act will be better positioned for future compliance and innovation.

4.2. Discussion

This chapter integrates the empirical findings with Rogers' Diffusion of Innovations theory to analyse how the EU AI Act influence AI adoption in the Dutch financial sector. Rogers' model provides a well-established framework for understanding how innovations diffuse within social systems, focusing on two key dimensions: the sequential innovation-decision process (knowledge, persuasion, decision, implementation, confirmation) and the perceived attributes of the innovation (relative advantage, compatibility, complexity, trialability, observability). The discussion draws on insights from both direct implementers – namely Bank 1, Bank 2, and an asset management firm – and ecosystem actors, including regulators, a law firm, a consulting firm, financial associations, and an independent researcher.

By mapping institutional behaviours and challenges onto this framework and grounding the analysis in regulatory texts and supervisory insights (e.g., DNB's AI supervision guidelines, AFM's innovation oversight reports, and the EU AI Act's provisions), this chapter presents a comprehensive view of the evolving relationship between regulatory intervention and innovation diffusion within a high-stakes financial context.

4.2.1. Regulatory Influence on AI Adoption

4.2.1.1. Knowledge: Awareness of the EU AI Act

The findings show that large institutions demonstrated early awareness of the EU AI Act, often initiated through internal compliance assessments and legal consultation. Banks and asset managers initiated internal briefings and system audits to prepare for regulatory requirements. This early knowledge acquisition aligns with Rogers' (2003) theory, which identifies awareness as a prerequisite for adoption. Ecosystem actors such as law firms and consultants played a critical role in this phase by supporting interpretation of regulatory texts and facilitating knowledge transfer. Their efforts helped translate the EU AI Act's broad legislative framework into practical, actionable insights for financial institutions.

4.2.1.2. Persuasion: Attitude Toward Regulation

The regulation's influence on institutional attitudes is mixed. Direct implementers recognised that regulatory legitimacy enhances internal governance and supports budget approvals for AI initiatives. However, the complexity of the Act's scope and risk classification introduced caution, leading to hesitation institutions. Many institutions, particularly fintechs and smaller firms, face challenges in aligning AI projects with compliance expectations. Ecosystem actors highlighted that interpretive ambiguity often leads institutions to adopt overly cautious designs or avoid AI deployment altogether. These dynamics

correspond to Rogers' persuasion stage, where institutions weigh perceived benefits against perceived regulatory burden.

4.2.1.3. Decision: Structuring AI Use and Adoption Decision

Decision-making around AI adoption is increasingly structured, especially in larger banks, where internal taxonomies and classification frameworks guide which use cases proceed. These processes are typically developed with legal input and supported by third-party advisors to ensure alignment with regulatory boundaries. In this phase, ecosystem actors serve as enablers of decision-making by translating legal provisions into risk-based classifications and actionable operational guidance.

4.2.1.4. Implementation: Deployment and Compliance Processes

Adopting institutions are formalising AI governance protocols, including registries, risk classifications, and pre-deployment checklists. While these developments reflect progress in Rogers' implementation stage, significant challenges remain in operationalising legal requirements. Both direct implementers and ecosystem actors emphasise that translating broad legal principles into concrete organisational processes – particularly concerning documentation, explainability, and human oversight – requires external support. To overcome challenges in technical and legal interpretation, institutions routinely engage consultants and legal advisors.

4.2.1.5. Confirmation: Ongoing Supervision and Enforcement

Post-deployment evaluation and compliance assurance remain an emerging area. Institutions are beginning to build compliance monitoring capabilities, but supervisory expectations continue to evolve. Regulators acknowledge that enforcement protocols and sector-specific guidance are still in development. Meanwhile, financial associations and independent researchers caution that overlapping legal frameworks – such as the GDPR and CRD adds further complexity, often leading to duplicated controls and fragmented oversight structures.

4.2.2. AI System Characteristics

4.2.2.1. Relative advantage: Perceived strategic value

AI systems with demonstrable business value – such as those used for automation, fraud detection, and client servicing – are more likely to be adopted. However, their perceived relative advantage is increasingly filtered through a compliance lens. Under the EU AI Act, systems that align well with regulatory expectations are seen as more strategically viable, while technically superior but opaque solutions are deprioritised. Several institutions reported consciously limiting their use of AI to low-risk applications to avoid the burden of complex compliance obligations. This reflects the trade-off between performance and governance: institutions may favour less complex but more interpretable models to ensure regulatory alignment. As Rogers suggests, relative advantage is context-dependent; in this case, the ability to manage legal requirements increases the perceived value of AI systems. The Act also indirectly reinforces this dimension by positioning AI governance as a strategic priority, leading to increased engagement from senior management and broader cross-functional teams. Ecosystem actors – particularly consultants and

legal experts – support this shift by helping institutions frame AI governance not merely as a compliance task, but as a source of legitimacy and strategic differentiation.

4.2.2.2. Compatibility: Organisational fit and integration

The compatibility of AI systems with existing organisational processes significantly influences adoption decisions. Larger financial institutions reported strong alignment between their internal governance structures – such as model risk management and IT control systems – and the procedural expectations of the EU AI Act. This structural compatibility facilitates smoother operationalisation of compliance. In contrast, smaller institutions face substantial integration challenges due to limited in-house compliance capacity. These firms often depend on law firms and consultants to map regulatory obligations onto their workflows. Ecosystem actors thus act as intermediaries, enabling the translation of legal obligations into practical governance models. This difference shows that institutional readiness affects how the Act is viewed – organisations with strong compliance frameworks see it as a natural fit, while others see it as a disruptive challenge.

4.2.2.3. Trialability: Testing and experimentation

In a risk-averse sector like finance, the ability to test AI systems before full deployment is essential for safe adoption. Larger financial institutions tend to implement AI through staged processes, including proof-of-concept testing and sandbox pilots to minimise compliance risks. Such environments, developed with regulatory or advisory input, provide early feedback on matters such as risk classification and documentation. However, as Johnson (2023) cautions, the effectiveness of sandboxes can vary significantly due to unclear roles, limited scope, or weak integration into institutional governance structures. To deliver meaningful value, trial-based approaches need clear design and integration into existing institutional frameworks.

4.2.2.4. Observability: Transparency and explainability

High-risk AI systems must meet stringent standards for explainability, auditability, and performance monitoring – core elements of Rogers' concept of observability. In practice, financial institutions often avoid deploying opaque or complex models if they cannot meet governance or regulatory expectations, even if those models offer higher performance. As a result, observability acts as a key gatekeeper for adoption: systems that cannot be clearly explained or reliably monitored are typically excluded from sensitive use cases. While consultants and researchers continue to call for better performance indicators and transparency metrics, practical tools to support these needs remain scarce. This limitation makes it more difficult for institutions to reach the confirmation stage, where they must demonstrate that AI systems function as intended and comply with evolving standards.

4.2.2.5. Complexity: Challenges of management and compliance

The inherent complexity of AI systems – especially opaque or high-risk models – was widely seen as a barrier to adoption. Institutions struggle to understand, monitor, and integrate such systems, particularly when explainability and oversight are limited. This technical challenge is compounded by regulatory

demands under the EU AI Act, making it harder to demonstrate compliance. For many organisations, the issue is not just interpreting the rules but understanding how AI systems behave and how to evidence that behaviour. As a result, many rely on external consultants to bridge gaps in internal capability. Perceived system complexity lowers adoption likelihood unless institutions can simplify, outsource, or embed effective management practices.

4.2.3. Future Outlook

The future trajectory of AI adoption in the Dutch financial sector under the EU AI Act is expected to unfold incrementally, shaped by regulatory clarity, institutional readiness, and the maturity of compliance ecosystems. Empirical findings suggests that well-resourced institutions are more likely to progress through the innovation-decision process at a faster pace. These actors are leveraging established governance infrastructures and engaging proactively with regulatory developments. In contrast, smaller financial institutions continue to operate with greater caution, constrained by limited capacity, uncertainty around legal interpretations, and dependency on external support. This divergence reinforces the significance of institutional context in determining the pace and scope of adoption.

Looking ahead, the full implementation of the EU AI Act is anticipated to accelerate the diffusion of AI governance practices. However, adoption is likely to remain selective, with institutions favouring low-risk, high-value AI applications that exhibits manageable risks and clear alignment with compliance requirements. High-risk or complex AI systems will likely be postponed until regulatory guidance becomes more standardised and operationally feasible. Across the sector, the observed strategic approach reflects a broader shift toward compliance-led innovation, in which legal and ethical considerations play an increasingly central role in shaping technological deployment.

Ecosystem actors will remain critical to this transformation. By co-producing guidance frameworks, offering interpretive expertise, and facilitating regulatory experimentation, they reduce perceived complexity and enable actionable compliance strategies. Their continued involvement is essential, particularly for institutions lacking the internal capability to interpret and implement evolving obligations. In this regard, the role of intermediaries extends beyond support to that of systemic enablers in the regulatory diffusion process.

From a theoretical standpoint, the findings reinforce Rogers' (2003) view that innovation adoption is a socially embedded process, influenced not only by the characteristics of the innovation itself but also by the network of actors and institutions surrounding it. The adoption of AI under the EU AI Act will ultimately depend on how effectively this ecosystem can harmonise interpretive ambiguities, facilitate knowledge sharing, and integrate legal requirements into routine organisational practice.

Strategically, ensuring the responsible diffusion of AI requires sustained investment in governance capacity, collaborative regulatory interpretation, and cross-sector alignment of standards. For both regulators and financial institutions, success will depend on effectively integrating innovation and

compliance to foster long-term resilience, accountability, and trust in AI systems deployed within high-stakes financial environments.

5. Conclusion

This thesis investigated how the EU Artificial Intelligence Act (EU AI Act) influences the adoption and implementation of AI systems within the Dutch financial sector. Applying Rogers' Diffusion of Innovations (DoI) theory as the analytical framework, the study was guided by the following main research question: *How does the EU AI Act shape the introduction, adoption, and implementation of AI systems by organisations in the Dutch financial sector?*

To address this question, the study investigated two interrelated themes:

- How the EU AI Act influences the conditions for AI adoption and implementation decisions.
- How the characteristics of AI systems influence these decisions under the EU AI Act.

Drawing on qualitative data from 14 semi-structured interviews with stakeholders – including representatives from two major banks, one asset management firm, regulators, legal experts, a consultant, an independent researcher, and financial associations – this study provided a comprehensive view of how regulatory frameworks interact with innovation processes in a highly regulated domain. The findings reveal that the EU AI Act operates as both a regulatory constraint and an institutional enabler. While it introduces significant compliance demands, legal uncertainty, and overlapping obligations, it also legitimises internal governance efforts, strengthens oversight capabilities, and prompts investment in responsible AI practices.

Regarding the first research question, the Act reshapes the conditions of adoption by creating structured governance expectations, which institutions must interpret and integrate into internal decision-making processes. Larger organisations, benefiting from established compliance frameworks, show higher preparedness for proactive engagement with the Act, in contrast to smaller organisations hindered by resource limitations. The innovation-decision stages outlined by Rogers – knowledge, persuasion, decision, implementation, and confirmation – serve as a clear analytical lens, highlighting how the Act's regulatory pressures manifest in organisational attitudes, decision structures, deployment protocols, and compliance monitoring practices.

Addressing the second research question, the characteristics of AI systems – namely relative advantage, compatibility, trialability, observability, and complexity – significantly influence adoption decisions under the Act. AI systems that are seen as strategically valuable, aligned with existing controls, testable in pilot phases, observable through explainable outputs, and manageable in complexity are more likely to be adopted. Conversely, opaque, complex, or high-risk models face resistance due to difficulties in meeting regulatory expectations – especially regarding transparency, oversight, and traceability.

Taken altogether, the answer to the main research question is that the EU AI Act functions both as a compliance driver and a strategic inflection point in the adoption of AI systems. While it raises barriers for opaque or high-risk systems, it simultaneously incentivises responsible innovation by embedding AI governance into broader institutional processes. The Act compels organisations to make more deliberate,

risk-aware decisions, aligning AI development and deployment with legal expectations and internal capabilities. This dual function – constraining unaccountable experimentation while legitimising responsible innovation – ultimately shapes which AI systems are adopted and how they are deployed across the Dutch financial sector.

Ecosystem actors (including regulators, consultants, and legal advisors) play a critical intermediary role in this process. They support institutional preparedness by clarifying regulatory expectations, facilitating experimentation (e.g., through regulatory sandboxes), and connecting abstract legal standards to organisational routines. Their contributions enable both strategic alignment and operational feasibility in the face of evolving compliance obligations.

This study is subject to several limitations that influence the scope and generalisability of its findings. First, limited access to financial institutions – such as banks, asset managers, insurers, and fintech firms – restricted insights into internal decision-making processes. Although ecosystem actors provided valuable perspectives, the underrepresentation of direct implementers limits the depth of organisational analysis. Second, the research was conducted during an early phase of the EU AI Act's development, when many technical standards and supervisory guidelines were still pending. As a result, interview responses often reflected forward-looking interpretations rather than concrete implementation experiences. Third, the study's exclusive focus on the Dutch financial sector limits generalisability to other jurisdictions. The Netherlands' regulatory maturity and proactive supervision provide a distinct context that may not reflect conditions elsewhere in the EU. Lastly, the qualitative approach prioritised exploratory depth over statistical representativeness. Findings are based on a purposive sample and reflect perspectives within a specific regulatory and institutional setting.

Additionally, a limitation of this research lies in the theoretical framework, which engages relatively narrowly with diverse scientific literature beyond Rogers and a few key governance scholars. This study could benefit from deeper dialogue with empirical literature on regulatory adaptation, legal compliance in innovation management, and sectoral governance capacity (e.g. Thomas, 2006; Heuts & van der Kaap, 2019; TNO, 2020).

The findings offer several implications for policy and practice. Financial institutions should invest in strengthening AI governance – particularly in areas such as risk classification, documentation, and explainability. For smaller firms, scalable compliance processes will be essential to meet legal obligations without disproportionate costs. Regulatory authorities should continue translating legal requirements into practical tools – such as checklists, templates, and regulatory sandboxes – to reduce ambiguity and support implementation, particularly for high-risk systems. Ecosystem actors – including law firms, consultants, and associations – can play a key role by facilitating sector-wide learning, supporting implementation, and bridging the gap between regulation and operational practice.

Further research could explore how AI adoption evolves as the EU AI Act transitions from legislation to enforcement. Longitudinal studies would provide insight into institutional adaptation over time.

Comparative research across EU member states could highlight how national contexts shape regulatory interpretation and implementation strategies. In-depth studies of specific institution types – such as fintechs versus large banks – would clarify how organisational size, structure, and capabilities influence compliance approaches. Finally, future research could assess the effectiveness of regulatory instruments – such as sandboxes, post-deployment monitoring, and explainability metrics – in fostering responsible and scalable AI adoption.

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Appendix

Guiding Interview Questions

Table 2. Guiding interview questions for final institutions

Theme	**Code**	**Guiding question**
Regulatory influence on the AI adoption process	Knowledge	How aware is your organisation of the EU AI Act and its requirements related to AI systems?
	Persuasion	How does the EU AI Act influence internal attitudes toward AI adoption?
	Decision	How does your organisation decide whether to adopt or reject an AI system?
	Implementation	How does your organisation ensure AI deployment complies with the EU AI Act?
	Confirmation	How does your organisation monitor AI systems to maintain compliance with the EU AI Act?
Characteristics of AI systems and their influence on adoption and implementation decisions	Relative advantage	What benefits do you expect from adopting AI systems under the EU AI Act?
	Compatibility	How well do AI systems fit your organisation's compliance and risk structures?
	Trialability	Can AI systems be tested or piloted before full deployment?
	Observability	How important is transparency when your organisation decides to adopt an AI system?
	Complexity	How challenging is it for your organisation to understand and work with AI systems?
Outlook	Future expectations	How do you see your organisation's AI adoption strategy evolving under the EU AI Act in the coming years?

Table 3. Guiding interview questions for ecosystem actors (regulators, financial associations, law firm, consulting firm, independent researcher)

Theme	**Code**	**Guiding question**
Regulatory influence on the AI adoption process	Knowledge	How prepared are (EU/Dutch) financial institutions for the EU AI Act, in your view?
	Persuasion	Do institutions see the Act as a burden or an opportunity for AI innovation?
	Decision	What compliance steps have (EU/Dutch) financial institutions taken so far in response to the EU AI Act?
	Implementation	What challenges do you see in how financial institutions implement the EU AI Act? How do you support or supervise their implementation efforts?
	Confirmation	What compliance steps have (EU/Dutch) financial institutions taken so far in response to the EU AI Act?
Characteristics of AI systems and their influence on adoption and implementation decisions	Relative advantage	Do institutions see the Act as a burden or an opportunity for AI innovation?
	Compatibility	What challenges do you see in how financial institutions implement the EU AI Act?
	Trialability	What compliance steps have (EU/Dutch) financial institutions taken so far in response to the EU AI Act?
	Observability	How do you support or supervise their implementation efforts?
	Complexity	What challenges do you see in how financial institutions implement the EU AI Act?
Outlook	Future expectations	How prepared are (EU/Dutch) financial institutions for the EU AI Act, in your view? Do institutions see the Act as a burden or an opportunity for AI innovation?