Artificial Intelligence as a Strategic Resource for Competitive Repositioning

A multiple case study of European financial institutions

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After five months of hard work, I can proudly say that my master’s thesis is finished. Finishing my thesis marks the end of my life as a student and means I enter a new phase in life. I look back at a wonderful time of studying for 4 years at Erasmus University and closing the chapter by studying for a year at Tilburg University. Despite the fact that I feel a bit sorrowful about closing this amazing chapter, I am looking forward to starting a new period of my life.

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Abstract

Financial institutions are under pressure to reposition themselves amid rapid market shifts, regulatory changes, and technological disruptions. This thesis addresses the need for banks to adapt their competitive positioning and explores the emerging role of artificial intelligence (AI) as a strategic resource in this process. Correspondingly, this research investigates how European banks can leverage AI investments to enhance competitive repositioning. The study adopts a qualitative, multiple case study design, analysing four major European banks: ING, ABN AMRO, Deutsche Bank, and Commerzbank. To carry out the study, secondary data (e.g., annual reports and industry reports) was collected and analysed to uncover patterns in AI-driven strategic repositioning across the cases.

Key findings reveal that strategic AI investments facilitate meaningful repositioning when crucial organisational enablers are present. These include strong leadership commitment, advanced digital infrastructure, effective data governance, and an innovation-orientated culture. The ING case, characterised by the strongest enablers and minimal inhibitors, leveraged their AI investments to enhance their operational efficiency, customer personalisation, and data-driven decision-making to achieve a notable competitive repositioning. In contrast, banks with weaker internal enablers or significant inhibitors struggled to translate their AI investments into strategic repositioning. The study's findings contribute to existing theoretical frameworks such as the Resource-Based View, Dynamic Capabilities, and Strategic Balance Theory. The findings confirm the RBV and DC frameworks by demonstrating that AI's value is realised through firm-specific capability development and agile adoption, rather than mere possession of the technology. Furthermore, it underscores the importance of how banks must innovate while maintaining regulatory compliance and legitimacy, adhering to the Strategic Balance theory. The thesis concludes with recommendations for future research, calling for longitudinal studies and broader industry comparisons.

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Chapter 1: Introduction

1.1 Problem indication

In any industry, firms must develop strong competitive positioning in order to distinguish themselves from rivals (Dess & Davis, 1984). 'Firms positioning' is a term that applies when firms position themselves within an industry in comparison to rivals. It may be achieved through strategies such as differentiation, cost leadership, or niche (Deephouse, 1999). However, competitive positioning is not static. Firms need to reposition on a regular basis in response to competitive pressures or new market opportunities (Wang & Shaver, 2013). Firms may have to reposition when a more dominant competitor enters their market, making their previous strategy irrelevant, or repositioning happens when firms try to take advantage of emerging market opportunities. The competitive position of a firm directly affects both financial and operational performance (Chen & Miller, 1994). Firms that succeed in differentiation or cost leadership tend to perform better than others on efficiency, profitability, and customer satisfaction (Powell, 2001).

While competitive positioning is crucial, firms need to continuously reposition in response to changes in the market. Past research demonstrates that successful repositioning leads to increased market share, profitability, and firm survival (Wang & Shaver, 2013). However poorly executed repositioning can lead to higher costs or failure of the firm. To address these challenges, firms must seek strategic resources to enable effective and responsive repositioning. A possible resource for firms is artificial intelligence, which offers the company the ability to reposition while mitigating the cost and the risk involved in the process. In response to challenges such as high competition, strict regulations and fluctuating customer needs, companies are increasingly trying to utilize AI as a way to augment the products and services, boost efficiency, and optimise decision-making. Moreover, AI allows businesses to reposition if there's industry change or disruption, moving from cost leadership to differentiation (or vice versa) through automation, predictive analytics, and AI-facilitated customer personalisation.

Repositioning, in the view of Wang & Shaver (2013), is a response to competitive pressures. Artificial intelligence facilitates the firms in responding and shifting more effectively. AI-driven decision-making assists firms in reallocating resources, adjusting pricing models, and making market decisions promptly. While AI is becoming more vital in financial services, the link between AI-based competitive positioning and firm performance is relatively underexplored in the existing literature. Strategic investments in AI can change the competitive playing field for financial service companies (Brynjolfsson & McAfee, 2017). Existing literature highlights that AI improves the capability of a firm in three aspects. First, by automating processes to improve efficiency, reduce cost, and increase processing speed. Second, AI enhances decision-making through predictive analytics, fraud detection, and risk analysis. Third, through customer experience personalisation, resulting in improved engagement and retention.

Strategic balance theory contends that firms must trade off legitimacy against differentiation. Firms that are too similar to competitors face price competition, and firms that are too different face legitimacy and adaptation challenges (Deephouse,1999). The Resource-Based View (Barney, 1991) also argues that firms with valuable, rare, inimitable, and non-substitutable resources achieve sustainable competitive advantages. Based on the Dynamic Capabilities perspective (Teece et al. 1997), firms investing in AI must develop the ability to integrate, adapt, and reconfigure their strategies in response to industry changes. Financial institutions that are successful in leveraging AI can strengthen their position in the market and achieve long-term competitive benefits. While AI is reshaping a number of industries, the financial industry has a few unique challenges.

Banks and other financial institutions operate in a highly competitive, strict regulated, and technology-driven environment. Unlike other industries, financial organisations cannot easily exit their markets, thus repositioning within their industry is essential. AI implementation is often driven by the need for fraud detection and regulatory compliance. AI applications are growing with use cases in customer experience, operational efficiency, and risk management. AI-driven chatbots and robot-advisors enhance customer experience. Additionally, automated processing and compliance monitoring increase operational effectiveness. In risk management, AI is used in fraud detection and credit scoring.

Despite these innovations, the majority of financial institutions are struggling to leverage AI to reposition for competitiveness. The ability to align AI investments with strategic objectives will be one of the key success determinants in the changing financial environment. This study aims to explore how AI-based competitive positioning strategies enable financial firms to differentiate, respond to marketplace dynamics, and sustain long-term industry leadership.

1.2 Problem statement and research questions

Firms across industries, and especially financial institutions, face continuous pressure to maintain a strong competitive position. In response to changing market dynamics, regulatory changes and technological advancements, financial institutions must frequently reposition themselves in order to remain competitive. Even with the increasing adoption of AI in financial services, many firms still struggle to understand how AI contributes to strategic repositioning. This study seeks to explore and address the gap in literature by investigating the role of AI in enabling financial institutions to reposition effectively. Specifically, it aims to answer the following problem statement:

''How can European financial institutions leverage strategic AI investments to enhance their competitive positioning?''

This study seeks to attempt the following sub-questions to answer the problem statement:

1. What is competitive positioning and when do firms have to reposition themselves in the market space?
2. How will AI change the financial industry?
3. How could financial institutions leverage strategic AI investments for effective competitive repositioning?
4. Which organisational factors can explain the varying degrees of success by European financial institutions in AI-driven competitive repositioning?
5. What are the best-practice recommendations for European financial institutions to implement AI-driven competitive repositioning?

Research questions 1 and 2 are answered by means of a literature review, and the remaining questions are based on a qualitative study. The study will use a qualitative approach to examine how companies leverage strategic AI investments for competitive repositioning. The unit of analysis of this study will be European commercial banks. The Eisenhardt Method (Eisenhardt, 1989) guides the case selection, data collection, and analysis to ensure a solid theory-building process based on empirical insights. Financial institutions serve as an ideal setting for this study due to their highly competitive, regulated and technology-driven environment, making repositioning more complex and constrained. The increasing adoption of AI in financial services is driven by necessity.

Selected cases are based on theoretical sampling (Eisenhardt & Graebner, 2007) focusing on:

1. Firms that demonstrate strategic AI investments.
2. Firms that operate in financial markets, such as commercial banks.
3. Have adopted AI for repositioning within the last 5 years.

The study will examine four financial institutions; two larger commercial banks and two modest commercial banks, allowing for cross-case comparisons (Eisenhardt, 1989) to identify patterns and variations in AI-driven repositioning strategies. This sample size will ensure in-depth analysis of AI-driven repositioning strategies, while still maintaining theoretical saturation.

1.3 Thesis structure

A literature review will be conducted in the following chapter to examine and synthesise theoretical concepts supporting this study. This includes foundational theories of competitive positioning such as the Resource-Based View (RBV), Dynamic Capabilities Framework, and the Strategic Balance Theory. Following the literature review, the research methodology will cover the research design, sampling strategy, the process of data collection and analysis, guided by Eisenhardt's theory-building approach. The results will then be presented, offering insights into how financial institutions are using AI to reposition themselves and what factors affect these efforts. The discussion will outline the relevance of the findings in the context of existing academic work. Finally, the study will reach a conclusion followed by theoretical and practical contributions, study limitations, and recommendations for future research.

Chapter 2: Literature Review

The purpose of this chapter is to overview and synthesise existing theoretical and empirical literature related to the strategic use of AI in competitive positioning and repositioning. The overview creates a foundation for the research and is used to address the first two sub-questions:

1. What is competitive positioning and when do firms need to reposition themselves in the market space?
2. How will AI change the financial industry?

The chapter is structured by four thematic pillars. Section 2.1 presents theoretical explanations of competitive advantage including the Resource-Based View (RBV), the Dynamic Capabilities (DC) theory, and the Strategic Balance Theory. Section 2.2 addresses the concept of competitive positioning and repositioning and, in this case, highlights flexibility and agility in responding to changing environments, particularly in the finance industry. Then, section 2.3 addresses the role of AI to transform strategic decision making, firm capabilities and customer engagement and evaluates AI as a resource and mechanism for change within organisations. Finally, section 2.4 encapsulates organisational conditions that enable or inhibit AI-driven repositioning. This includes internal enablers such as leadership, digital infrastructure, and strategic alignment. Barriers such as regulation and ethics are also addressed. The chapter ends by identifying the gaps in literature, particularly around the empirical knowledge of the role and contribution of AI to the financial industry.

2.1 RBV, Dynamic Capabilities, and Strategic Balance

2.1.1 Resource-Based View (RBV)

The Resource-Based View (Barney, 1991) claims that through developing and leveraging unique resources that are valuable, rare, inimitable, and non-substitutable (VRIN), a firm achieves sustainable competitive advantage. In the new age of AI, resources such as data infrastructure, owned algorithms, and predictive analytics meet these criteria (Li, Zhang & Wang, 2024). However, critics argue that the firm's ability to adapt to resources over time is underemphasised in the RBV framework. Powell (2001) mentions that resource value is not static. Due to fast-moving markets, yesterday's unique assets can quickly become obsolete. This limitation has led to the evolution of more dynamic strategy frameworks.

2.1.2 Dynamic Capabilities Framework

Teece, Pisano, and Shuen (1997) introduced the concept of dynamic capabilities (DCs) as a response to criticism against the relevance of RBV in more dynamic settings. Dynamic capabilities have been described as the ability of a firm to reorganise internal and external resources to conform to changing environments and conditions. The three basic processes; sensing, seizing, and transforming, are increasingly more relevant in AI strategy, where firms must continually seek out new opportunities, adopt new technologies and adapt their business models. Further building the framework, Wilden, Devinney, and Dowling (2013) determined that DCs positively affect firm performance, particularly in conjunction with structure and strategy. Further, Guo, Yang, and Yang (2021) point out that strategic alignment between DCs and IT flexibility facilitates responsiveness and innovation. Their finding suggests that the interaction between organisational routines and IT infrastructure is necessary to influence competitive outcomes. This is supported by De Paula Pereira et al. (2024) with case research in the banking sector, where highly DC-mature banks are shown to be more successful at digital transformation, especially in adopting AI. Soto Setzke, Wenzel, and Wolf (2023) are among the latest contributors examining how AI-specific dynamics such as rapid prototyping, iterative model updating, and adaptive algorithmic deployment enable firms to respond to fast-evolving market contexts. In banking, where one-to-one interaction and timely information are valuable, AI-congruent capabilities allow banks to position themselves proactively rather than reactively. Their study underscores that sensing changes through data on customer behaviour, for instance, is much more effective if complemented by in-house AI development capability.

2.1.3 Strategic Balance Theory

Deephouse (1999) provides a different view: the Strategic Balance theory, which states that firms must conform to industry norms to maintain legitimacy and differentiate to achieve competitive advantage. Overconformity can lead to price wars, and excessive uniqueness can lead to loss of legitimacy by a company, especially in highly regulated industries such as banking. This balance between conformity and uniqueness that a firm must adhere to, is even more complex in AI-based strategy. Banks must innovate through AI tools while maintaining explainability, transparency, and compliance, elements that directly affect their perceived institutional legitimacy (Martins, Ribeiro & Figueiredo, 2024).

2.2 Competitive Positioning and Strategic Repositioning

2.2.1 Competitive Positioning

According to Dess and Davis (1984), competitive positioning is the way a firm positions itself in relation to their rivals in terms of target market, cost structure and value offered. This positioning is often attempted to be achieved through strategic decisions like cost leadership, differentiation, or niche specialisation. When executed well, it leads to performance advantages, improved customer loyalty and enhanced market share (Porter, 1980; Dess & Davis, 1984). Chen and Miller (1994) assert that competitive advantages emerge through a cycle of attack and counterattack, where proactive and reactive moves define a firm's position. These dynamics underscore not only the importance of achieving but also sustaining a competitive position. Powell (2001) further emphasises that while much of the strategy literature is rooted in logic, the practical reality often diverges. Firms must operate under a bounded reality, incomplete information, and path dependencies, all significant factors that complicate the traditional positioning models. Pollack (1989) observes that in financial services, positioning strategies are strongly influenced by service quality, innovation, and the capacity to create customer-centric experiences. As a result of these elements being increasingly shaped by digital tools and AI technologies, positioning for firms has now become intertwined with technological capability.

2.2.2 Strategic Repositioning

Strategic repositioning involves deliberate changes in a firm's positioning stance, driven by market shifts, technological disruption, or customer migration. Wang and Shaver (2013) describe repositioning as a reaction to competition, particularly when dominant firms are challenged by competitive pressure or encroachment by rivals. Shi and Wu (2021) further expand on this by examining how firms employ the "follow the customer" strategy across various dimensions such as service scope, pricing models and delivery channels. As customer preferences shift and adapt to new technologies, firms must recalibrate their position to remain relevant. Deephouse and Carter (2005) argue for a multidimensional comprehension of repositioning, including changes in service offerings, market segments, service quality and brand perception. Beyond those changes, a compelling case study by Matthews (2011), while focusing on the education sector, highlights how institutions do not just reposition tactically but also ideologically by redefining mission, vision, and service identity. This insight applies directly to the financial sector, as banks must adapt their identities to remain functional within the increasingly digital, automated, and customer-empowered ecosystem.

Through empirical research, Maina and Kinyua (2020) confirm that financial institutions engage in repositioning in response to regulatory changes, competitive intensity, and technological advancements. In particular, AI and automation are cited in their study as crucial tools for repositioning efforts, enabling banks to differentiate through efficiency, speed and personalisation.

2.3 Artificial Intelligence and the Financial Industry

2.3.1 AI as Strategic Investments

Over the last ten years, artificial intelligence (AI) has evolved from being a supporting function to a strategic asset with the capacity to revolutionise business models. Brynjolfsson and McAfee (2017) state that AI, platforms, and crowdsourcing together symbolise a new digital capabilities era that is revolutionising entire industries. From a RBV perspective, AI systems can be seen as valuable, inimitable assets that provide a competitive edge when properly embedded in a firm's strategy.

Pajo (2024) also touches on investment strategy based on AI, stating that firms applying AI in financial decision-making are outperforming those applying traditional methods. These firms exhibit stronger risk management, portfolio diversification, and opportunity identification, all skills in alignment with Teece's (1997) dynamic capabilities perspective. Importantly, contrary to common belief, AI is not nearly as much an asset to be possessed but rather a capability to be developed and developed in accordance with changing environments.

Todmal, Pandey, and Bharti (2023) highlight the importance of AI in drawing early adopters and positioning themselves strategically to resonate with innovation-orientated segments of the market. Their research shows that AI can be utilised by companies to penetrate new niches, announce technological superiority, and establish first-mover benefits. Such benefits are frequently linked to effective repositioning.

AI also enables watching and transforming capabilities by foresight driven by data and learning organisations. This brings AI outside the scope of the simple optimisation of operations to strategic decision-making.

2.3.2 AI-Driven Transformation in Financial Institutions

Financial services are particularly in need of AI-driven transformation. As highly regulated, data-rich, and customer-sensitive environments are both restrained and incentivised to innovate. Martins, Ribeiro, and Figuereido (2024) argue that AI adoption, above enhancing efficiency, also improves resilience and customer-centricity. AI-driven systems are frequently being deployed across risk modelling, customer segmentation, fraud detection and compliance monitoring. Zohuri and Mossavar-Rahmani (2023) provide evidence showcasing that AI is reshaping banking value chains by replacing legacy processes and enabling personalised, real-time interactions. Their study indicates that firms adopting AI as part of a broader repositioning strategy outperform those that implement AI in isolated functions.

However, Maple, Prince, and Wood (2023) offer a more nuanced perspective by pointing out the ethical and regulatory challenges posed by AI. These challenges include algorithmic transparency, explainability, and data privacy, issues that are particularly pressing in finance, where trust and compliance are crucial for institutional legitimacy.

Focussing on the African banking sector, Maina and Kinyua (2020) show that AI adoption is often triggered as a necessity for repositioning due to competition, customer dissatisfaction, or regulatory changes. Their findings support the broader idea that technological shifts, especially in AI, are not just operational improvements but also key catalysts for strategic repositioning. Martins et al. (2024) further highlight that the strategic use of AI involves reassessing organisational models, ranging from hierarchical command chains to flatter tech-driven structures. This transformation often includes acquiring digital talent, reshaping governance systems and implementing AI in strategic planning. Pollack (1989) observed that service quality and innovation are the fundamentals that competitive positioning in finance historically is built on. With AI, these elements are now amplified through data-driven personalisation, instant service delivery, and predictive engagement strategies.

2.4 Organisational Enablers and Inhibitors in AI Transformation

2.4.1 Enablers

Despite the potential of AI, organisational adoption is typically patchy and full of internal barriers. Kumar and Aithal (2022) identify some of the key enablers for adoption of AI in financial services: strategic vision, leadership support, regulatory clarity, and a culture for innovation. Their framework highlights that without internal convergence, any activity in AI will struggle to scale or have strategic impact. Guo, Yang and Yang (2021) identify IT flexibility as the prime motivator in dynamic capabilities and AI programmes' integration. Their study reveals that companies are better able to absorb, modify, and utilize AI technology where reactive IT systems are present. IT flexibility contributes to quicker decision-making, reduced implementation cost, and higher returns on AI investment. De Paula Pereire et al. (2024) provide evidence from South American and European banks that further supports the fact that banks with characteristics essential for AI-based repositioning, such as dynamic capabilities, enabled leadership, and cross-functional teams, are successful in digital transformation. Martins et al. (2024) add that governance and ethics must be included in AI strategy.

Additionally, AI adoption also depends on the availability of human capabilities, according to Lazo and Ebardo (2023). They argue that proficiency among employees in data analysis, machine learning, and process automation is the key to banks internalising AI knowledge. With an unqualified workforce, AI initiatives are likely to be over-reliant on third-party vendors, lowering organisational learning. Therefore, it is important to make an investment in training and upskilling the workforce. Also, as a soft enabler, fostering a culture of learning, where experimentation and technology adoption are encouraged, enhances long-term AI capability.

2.4.2 Inhibitors

Despite the considerable opportunities that artificial intelligence presents for competitive repositioning, the adoption is often hindered by institutional and regulatory challenges. In high-stake sectors such as financial services, the lack of algorithmic transparency is one of the most pressing issues. Complex AI models, often referred to as ‘black boxes’, are raising fairness, bias and accountability concerns due to their opaque internal workings in automated decision-making (Yusuf et al., 2024).

Yusuf et al (2024) emphasise that in sectors where trust and compliance are essential, opaque AI systems could lead to unintended discrimination or errors that are difficult to correct. When institutions cannot explain why an algorithm gives a certain decision, it becomes an acute issue, as it erodes not only customer confidence but also limits regulatory oversight. Another issue that arises is that limited explainability not only creates legal exposure but also undermines the social acceptability of AI-driven systems (Mirishli, 2022). He argues that without sound audit mechanisms and an ethical framework, firms risk reputational and financial damage. Further building onto that, Zarsky (2016) discusses how lack of transparency in AI decision-making conflicts with the financial industry's demand for traceability and accountability. In his view, 'algorithmic governance' is not an option but rather a necessity to sustain institutional legitimacy and regulatory compliance. Firms that lack robust algorithmic accountability or transparency mechanisms risk undermining trust. The strategic balance theory (Deephouse, 1999) is relevant here, as firms must balance innovation with legitimacy, especially under strict regulations.

Moreover, Binns et al. (2018) stress that many financial institutions lack the organisational readiness for AI implementation. Not only technical gaps but also cultural resistance to automated decision-making lay at the roots of this issue, stemming from a perceived loss of control by senior leadership and management teams.

2.5 Gaps in Existing Literature

This literature review has examined how competitive positioning and strategic repositioning theories intersect with artificial intelligence as a transformative capability. Foundational theories such as the Resource-Based View (Barney, 1991), Dynamic Capabilities (Teece et al,. 1997), and Strategic Balance (Deephouse, 1999) provide strong conceptual frameworks to understand how firms might reposition in response to environmental change. By implementing artificial intelligence, firms are able to sense market shifts, reallocate resources, and offer differentiated, customer-centric services. This is particularly evident in financial institutions, where AI has become crucial to operational strategy and service delivery. However, some significant gaps still remain in the existing literature. There are limited empirical studies that explore how firms align AI with repositioning efforts over time. Moreover, the interaction between organisational enablers, such as culture, leadership, and flexibility, and successful AI adoption is underdeveloped. Finally, there is a very limited focus on European financial institutions, particularly in how regional regulatory and cultural contexts affect AI-driven strategy.

Chapter 3: Methodology

3.1 Research design

This study employed a qualitative, multiple-case study approach to explore how European financial institutions use artificial intelligence as a resource to reposition themselves competitively. The purpose of this thesis was to develop theory grounded in empirical evidence. A case study allowed for in-depth insights into organisational processes, challenges, and contextual factors that influence the role of AI in strategic repositioning (Yin, 2014). Qualitative research is well suited to complex phenomena such as artificial intelligence integration in banking (Yin, 2014). Due to the novelty of AI in strategic positioning, especially in sectors like banking, exploratory research provides the insight needed to reveal organisational processes, institutional responses, and cultural routines (Eisenhardt & Graebner, 2007). The primary aim of the study was theory building consistent with Eisenhardt's (1989) inductive methodology for building theory from case data. This approach was particularly useful for underexplored and complex phenomena such as AI-driven repositioning. Furthermore, this method is suitable for answering 'how' and 'why' questions related to strategy, organisational change, and innovation (Eisenhardt & Graebner, 2007).

3.2 Case Selection and Sampling Strategy

The unit of analysis was the individual financial institution. Specifically, the units were commercial banks operating within Europe. The study focused on four institutions: two from The Netherlands and two from Germany. From each country, one bank was selected that has successfully implemented AI as part of their repositioning strategy, and one bank that has made AI investments but has not effectively repositioned. This contrastive design led to a comparative structure for understanding not only best practices but also barriers and missed opportunities (Seawright & Gerring, 2008).

The criteria for cases being included in the study were not only firms that demonstrate strategic AI investments, operate in financial markets, and have adopted AI for repositioning within the last 5 years, but also accessibility to annual and industry reports was taken into account. The study examines four commercial banks: ING and ABN AMRO were chosen from The Netherlands, while Deutsche Bank and Commerzbank were picked from Germany. ING and Deutsche Bank both represent firms that seem like they have successfully strategically integrated AI to drive digital transformation and repositioning efforts. For instance, ING has used AI in several applications, including credit risk modelling, customer personalisation, and operational efficiency. Similarly, Deutsche Bank has implemented AI in compliance automation and trade analytics, contributing to cost leadership and innovation signalling. Contrarily, ABN AMRO and Commerzbank have invested in AI technologies, but they have faced challenges in translating these investments into strategic repositioning. Both firms encountered barriers such as fragmented implementation, organisational resistance, and limited alignment between AI initiatives and strategic objectives. This contrastive sample offers insights into the enablers and inhibitors of AI-driven competitive repositioning across institutions of comparable size and market scope.

3.3 Data Collection

For the study, data was collected from multiple sources to enhance the credibility and reliability of the findings. This approach aligns with the method of data triangulation, which is a key part of the robust case study methodology (Yin, 2014). Several primary sources were included and used in the study. First, publicly available annual reports and strategic plans. Secondly, press releases, media coverage, and conference statements. Thirdly, industry reports on AI implementation and innovation in European banking were included. Besides primary sources, some secondary sources were also used that are listed in the appendix. The sources included peer-reviewed articles about the selected banks, EU regulatory frameworks and digital innovation documents relevant to AI adoption, and fintech market intelligence platforms. Annual reports were valuable for identifying strategic goals, technological investments, and reported outcomes related to AI. Moreover, press releases and media coverage provided external validation or contradiction of internal claims, while industry white papers offered contextual insights into sector-wide trends. Data were collected for the period 2019–2024 to ensure recency, especially given the rapid evolution of AI technologies in financial services. The documents were collected systematically using keyword searches (e.g., “AI strategy”, “financial sector”, “repositioning”) in online databases and institutional websites.

3.4 Data Analysis

The data analysis followed a structured, iterative process in line with grounded theory principles and the methodology proposed by Eisenhardt (1989). The following three stages of analysis were applied: within-case analysis, cross-case comparison, and triangulation. To support this process, thematic coding was applied manually, using an inductive approach.

3.4.1 Within-Case Analysis

The first step was to conduct a within-case analysis for each of the four banks. Each bank was analysed independently to create context and a detailed story for the bank’s AI strategy, decision-making reasoning, and observed repositioning outcomes. This step involved the identification of key events and strategic initiatives related to AI implementation, mostly based on public disclosures, industry reports and annual reports.

3.4.2 Cross-Case Comparison

Following the within-case-analysis, the subsequent step was to conduct a cross-case comparison of the cases, as per Eisenhardt's (1989) logic of theoretical replication, where every case confirms or falsifies emerging theoretical results. Pattern matching was subsequently applied across the four cases to look for commonalities and differences in how commercial banks utilised AI-driven repositioning programmes.

To enhance the cross-case comparison, the within-case analysis themes were all identified and converted into ordinal scores. The scoring method used complies with Eisenhardt's (1989) recommendation to enable pattern finding across diverse cases by systematically comparing emergent constructs. A three-point scale was utilised for every theme. Themes scored as enablers or strategic implications were rated on a scale between 1 (low) and 3 (high), which measured the degree, maturity, or intensity of implementation. Reverse-scoring was applied to themes that were classified as inhibitors, i.e., organisational resistance or legacy IT infrastructure. On this scale, a score of 1 indicated extreme constraint (high), while a score of 3 indicated minimal limitation (low). This reversal of the score ensured that across all topics, higher scores always reflected more favourable settings for AI-powered strategic repositioning. The first column of "Table 1: Label-to-score conversion table", contains the labels, ranging from high to low, followed by columns that link the score to the labels and a small description of the reason given for that score. From the fourth column and further to the right are the scoring columns that address the scoring of the inhibitors and is closed by a column that provides a small description of the score.

Table 1: Label-to-score conversion table

Label	Score (enabler/outcome)	Meaning (enabler/outcome)	Score (inhibitor)	Meaning (inhibitor)
High	3	Strong capability, full integration or maturity	1	Severe constraint or barrier
Medium	2	Some progress, partial implementation	2	Medium-level constraint
Low	1	Weak or absent capability	3	Minor or no constraint

3.4.3 Triangulation

To increase and guarantee the validity and credibility of the findings, methodological triangulation was employed in the analysis. This involved cross-checking data from different sources, such as media, annual reports, and third-party industry analysis. Triangulation was beneficial in two aspects: first, it helped in confirming the reliability of patterns that emerged during coding. For instance, if a bank's repositioning was attributed to increased personalisation through AI, this rationale was corroborated both by internal reports and external evaluations. Secondly, triangulation helped identify contradictions or gaps in the data, which were resolved as possibilities to clarify or qualify the emerging theoretical model. When evidence that contradicted the current codes was discovered, analysis went back to the original source material and coding framework to clear up inconsistencies, addressing them either through further analysis or marking them as probable limitations or boundary conditions in the study's findings.

Chapter 4: Results

4.1 Within-Case Analysis

4.1.1 Bank ING

ING Bank, based in Amsterdam, is a global and prominent financial institution in The Netherlands that operates in over 40 nations with over 39.5 million customers (ING, 2025), meaning that it maintains a dominant position within the banking industry in Europe. During the mid-2010s, ING began its official adoption of artificial intelligence as part of a larger strategic shift in the bank towards digital banking and customer-driven innovation, evidenced by their 'Accelerating Think Forward' strategy implemented in 2016. ING spent over 800 million euros on digital transformation initiatives, which were specifically aimed at enhancing customer experience and automating processes (De Winter et al., 2022). In 2023, the bank launched an AI-based generative customer care bot in collaboration with McKinsey's QuantumBlack. It was the first among multiple steps from a larger vision to use artificial intelligence for customer interaction enhancement, operational efficiency, and employee productivity (McKinsey & Company, 2023). The chatbot was successful as it answered 20% more customer queries without any involvement of humans, indicating its touch in service delivery.

The most important organisational enablers which helped ING achieve success in implementing AI are as follows: ING possesses a robust data infrastructure that can facilitate real-time analytics and machine learning solutions. Furthermore, the bank's leadership demonstrated ongoing and proactive support for digital transformation and innovation. The bank created a dedicated AI internal committee, including IT and business leaders, that was responsible for overseeing large-scale deployments of AI and ensuring that any investment in AI is strategically positioned (McKinsey & Company, 2023). From a human resources standpoint, ING has invested in internal AI capabilities, balancing external partnerships with talent development programmes to develop employee skills in data science and analytics. ING's organisational culture, as with other factors that have been previously named as being key AI enablers such as agile working practices, multidisciplinary working, and experimentation openness, further facilitates innovation (Kumar & Aithal, 2022; Guo, Yang, & Yang, 2021). Additionally, IT flexibility is beneficial to ING. The bank’s flexible and modular IT architecture facilitates the flexible deployment of AI at scale across different business units and geographies. This responsiveness accelerates implementation cycles and reduces integration costs, ultimately developing a more responsive and dynamic AI-driven innovation strategy.

AI has been playing a significant role in ING's repositioning strategy. The launch of sophisticated digital services, such as the AI customer service assistant, enhanced customer service experience through reduced solution time and improved service accuracy (McKinsey & Company, 2023). At the organisational level, the use of AI has automated routine work, thus freeing up the human resource for more value-based and sophisticated functions. At a general level, these investments have transformed ING into a more technology-driven and customer-centric organization in the market. Public relations and industry media coverage constantly position ING at the forefront of AI technology in European banking, reinforcing the reputation of ING as a digital technology and innovation leader (Zohuri & Mossavar-Rahmani, 2023). Such positioning reflects a mix of differentiation and operational excellence aligned with previous theoretical propositions regarding AI-facilitated change (Brynjolfsson & McAfee, 2017).

Despite ING's success, the integration of artificial intelligence has not been without challenges for the bank. One of the main issues that the bank struggles with is regulation. The recent approval of the European Union's Artificial Intelligence Act in 2024, is requiring financial institutions now to meet higher levels of transparency, explainability, and data protection requirements, especially when employing high-risk AI tools (Nannini, 2024). As a result of this act, organisations must implement extensive monitoring procedures and technological safety measures to ensure AI models are equitable, auditable, and explainable. For ING, this means the activity introduces an added level of complexity in managing AI deployments, particularly used in customer interaction or decision-making functions.

ING's dependence on third-party technology providers, in particular large U.S.-based companies offering cloud computing and AI platforms, is yet another constraint. In spite of the fact that such partnerships expose the bank to cutting-edge capacities and elastic infrastructure, at the same time it also exposes possible risks in terms of vendor lock-in, data privacy, and jurisdictional oversight (Reuters, 2024). Financial constraints also arise as the cost of generative AI models and complementary infrastructure continues to increase and corporations struggle more and more to balance these investments against near-term profitability objectives. Recent industry reports indicate that investing and opportunity costs of AI experimentation, such as model training, infrastructure maintenance, and upskilling the workforce may be costly and are not always materialised at one time through tangible returns (Stadig, 2024). For ING, this requires a subtle balance between investing in innovation and meeting shareholder expectations.

In conclusion, while ING made notable strides in the strategic use of AI and became a European banking industry innovator, ongoing regulatory, technological, financial, and organisational barriers continue to frame the direction and the outcomes of its AI-facilitated transformation.

4.1.2 Bank ABN AMRO

ABN AMRO, with its headquarters in Amsterdam, is catering to more than 5 million retail customers and 365,000 commercial customers (ABN AMRO, 2023), establishing it as The Netherlands' third-largest bank. The bank offers services, mostly in the Dutch market, in retail, private, and corporate banking. ABN AMRO has experienced a series of restructurings since the global crisis and its subsequent nationalisation in 2008, designed to improve efficiency, reduce exposure to risk, and address the increasingly digital banking industry. In the late 2010s, the 'Banking for Better' strategy was announced, indicating a digital transformation with artificial intelligence in an effort to enhance customer service and resilience operations. (ABN AMRO 2022). ABN AMRO AI's journey was initially focused on chatbots and process automation. In recent years, the bank shifted towards more advanced AI applications, including generative AI and natural language processing (NLP) systems. In order to scale the bank's generative AI capabilities across both customer service and internal functions, ABN AMRO adopted, in collaboration with Microsoft and Capgemini, Microsoft Copilot Studio (Capgemini, 2024). This forward-looking approach led to the creation of a unique 'Gen AI factory', a setup utilised to industrialise AI usage within the company. Through this setup, ABN AMRO was able to create two AI agents: 'Anna' for retail customers and 'Abby' for internal employees. Together, these chatbots process over 3.5 million conversations each year, leveraging Microsoft's Azure AI Language to improve intent recognition and query answering (Microsoft, 2024).

ABN AMRO's AI implementation has been supported by modest organisational ability. The firm has laid a data foundation by utilizing Microsoft's Azure offerings to enable scalable AI development and monitoring (Microsoft, 2024). Moreover, ABN AMRO also established a management team that leads AI development and regulatory compliance, consisting of business leaders, data scientists, and compliance officers (Capgemini, 2024). The presence of such an architecture is in ideal alignment with studies into enablers for the adoption of AI, where cross-functional teamwork and governance controls have been discovered to be essential success factors (Guo, Yang, & Yang, 2021; Kumar & Aithal, 2022).

The effects of ABN AMRO's investment in AI are evident but still limited. At an operational level, AI has achieved faster internal service and customer service response times through the utilisation of chatbots 'Anna' and 'Abby'. At a broader strategic repositioning, e.g., growing into new markets, transforming service models, or a shift of strategic focus, there is weak evidence. Despite the documentation of ABN AMRO innovation dedication, industry public information and industry analyses suggest AI has had limited change in the bank's market position and business model until now. Technology is applied mostly as an accelerator of existing services rather than a driver for value differentiation and new top lines (Capgemini, 2024; ABN AMRO, 2023).

While ABN AMRO used generative AI pilots both for intranet and customer-facing applications, the bank has not indicated substantial efforts on predictive analytics, AI-based credit-assessment, or algorithmic advisory solutions. This limited range of use could suggest that the bank remains riskaverse in issuing extensive financial-scale rollouts of high-impact AI functionalities, possibly due to the wide-ranging regulatory obligations exerted by AI in banking. (ABN AMRO, 2023; Capgemini, 2024). Moreover, publicly available information suggests no internal upskilling plan like other big European banks. While ABN AMRO is implementing responsible AI architectures, the absence of disclosures on digital literacy, cultural readiness, or future talent strategies suggests that AI capability might be unevenly spread across departments. These results are in line with broader banking issues, whereby the adoption of AI is often thwarted by long-standing organisational customs and infrastructures (Zohuri & Mossavar-Rahmani, 2023).

Overall, ABN AMRO has shifted to leverage AI, with a focus on internal efficiency and service enhancement rather than broader market transformation. Even as its GenAI Factory launch and application of generative AI capabilities reflect operational innovation, the bank has not yet been able to translate these efforts into effective strategic repositioning. Conservative deployment, limited range of usage, and organisational constraints, such as conservative governance and uneven digital readiness, continue to moderate the pace and efficacy of its AI-driven transformation.

4.1.3 Bank Deutsche Bank

Frankfurt-founded Deutsche Bank is a multinationally active and large-sized financial institution, with operations in over 57 countries, over 85,000 employees, and over 21 million customers (Deutsche Bank, 2025). The bank provides services across the investment, corporate, private, and retail banking segments. As a component of its long-term strategic vision, its "Global Hausbank" strategy, Deutsche Bank wishes to become a customer's trusted partner in the increasingly digitised economy (Deutsche Bank, 2023a).

Deutsche Bank's strategic adoption of AI began to accelerate in the early 2020s, with a focus on customer service, compliance, and operational excellence. The bank also partnered with Google Cloud to enable migration of nearly 260 applications to the cloud, which would enable Deutsche Bank to leverage advanced AI and machine learning capabilities. (Leukert 2025). Deutsche Bank embarked on an AI initiative in 2023 to concentrate on seven strategic use cases across the bank, such as risk modelling, client onboarding, automation of software development, and generative AI employee support tools (Deutsche Bank, 2023b). The bank partnered with technology firms to take these initiatives forward. One of those collaborations was with NVIDIA to implement high-performance AI computing into bank operations, including real-time fraud detection and advanced forecasting (Writer, 2023). Deutsche Bank invested in building organisational capabilities to support these AI initiatives. The bank established an AI governance framework to attain ethical and regulatory compliance in employing AI (Deutsche Bank, 2024). Further, through a partnership with Google Cloud, Deutsche Bank also carried out a training programme for which 6000 staff received cloud and AI training over the first 18 months (Leukert, 2025). This skills enhancement activity has been central to creating an innovation and technical competence culture.

Deutsche Bank's AI strategy provides tangible results that align with the bank's overall vision of being a digitally innovative, customer-focused, and operationally efficient financial institution. Through process optimisation, such as AI-driven automation, the workload in processes such as compliance, customer onboarding, and internal support services has been reduced to a great extent. According to Deutsche Bank (2023), these applications are expected to lower the cost-to-income ratio, a major performance objective of the bank's 'Global Hausbank' strategy. The most important areas of transformation have been fraud detection and risk modelling. With the utilisation of NVIDIA's provided AI infrastructure, Deutsche Bank reinforced real-time analysis abilities, enabling quicker response times against imminent security threats and enhanced risk forecasting (NVIDIA, 2023). At the same time, generative AI technologies have been integrated into software development methodologies and staff support systems designed to assist personnel with coding, document summarising, and retrieval of internal knowledge to free up human capital for more valuable tasks (Deutsche Bank, 2023). The bank is increasingly being positioned within industry media as one of the more assertive European banks in the AI arena (Quartz, 2024), supplementing its attempt to build market credibility. Thus, AI becomes an impetus to internal change and external signalling, both of which are key components within their strategic repositioning initiative.

Deutsche Bank also has several hurdles that continue to constrain their AI initiatives. One of the key organisational challenges stems from the bank's historically fragmented IT architecture. Over its long history, Deutsche Bank has acquired and consolidated numerous other banks, most recently Postbank. The acquisitions and mergers led to siloed IT development practices that created hurdles to the implementation of AI throughout the organisation in a seamless way. A clear example of that challenge came with integrating Post Bank's retail business into Deutsche Bank's core system. The final phase of the IT consolidation was completed in mid-2023, but technical issues soon affected the system, leading to customer lockouts, inconvenience, and disruption to banking services, as well as an increase in complaints of service failures (Reuters 2023a). This led BaFin, Germany's financial regulator, to appoint a monitor and have nearly 10,000 complaints from customers reported by September 2023 (Reuters, 2023b). In addition to infrastructure constraints, Deutsche Bank must deal with changing regulations. The implementation of regulations, such as the EU Artificial Intelligence Act, requires the bank to invest even further in auditability, transparency, documentation, and ethical governance. In conclusion, while Deutsche Bank's AI strategy supports incremental repositioning by improving operational efficiency and fostering internal innovation, the overall pace and direction of its transformation remain shaped by enduring challenges, such as legacy systems, regulatory demands, vendor dependence, and talent shortages.

4.1.4 Bank Commerzbank

Commerzbank AG, based in Frankfurt, is Germany's fourth-largest bank by total assets and a major provider of financial services to private, small business and corporate clients. Commerzbank has around 11 million private and small business clients, as well as 30,000 corporate clients, mostly based in Germany and Central Europe (Commerzbank, 2024). Over the past decades, Commerzbank has carried out considerable restructuring due to profitability challenges, digital transformation, and fintech growth pressure. The bank vowed to accelerate digitisation and operational excellence, like the use of artificial intelligence as a long-term driver for change in the context of 'Strategy 2024' (Commerzbank, 2023).

The institution's formal experimentation with AI was set in the late 2010s, starting with efforts on Robotic Process Automation (RPA) to take care of routine tasks in loan processing and compliance validation. The initial automation formed a basis for further advanced integration of AI later. Commerzbank created its 'Data and AI campus' in 2022, aimed at facilitating data governance, model building, and AI use case exploration across business units (Commerzbank, 2023). The AI investments done by Commerzbank were mainly intended to improve internal efficiency, risk management, and fraud detection. An evident example of this internal efficiency involves the automatic categorisation of over 400,000 routine incoming client emails and documents every month. This system employs artificial intelligence to direct queries to teams, reducing manual efforts and improving turnaround times (Commerzbank, 2023). In the area of trade finance, AI is now used as a natural language processing tool to read and understand the complex and unstructured data in contracts, which enhances risk analysis and ensures compliance oversight.

To support such deployments, Commerzbank has also established a formal governance structure for data and AI projects to ensure consistency, ethical applicability, and regulatory compliance. The bank consolidated their AI-related initiatives as part of its strategy refashioning 'Momentum' in 2025 by implementing the new role of Chief of Data & AI Officer (Commerzbank, 2025a). The organisational restructuring formalised the integration of objectives, data foundation, and AI governance.

Despite these efforts, Commerzbank faced a number of internal and strategic issues in using AI for competitive repositioning. Up to 2025, the bank has not introduced AI-based systems like personalisation engines and predictive customer interactions, which are becoming more of a norm among the competitors in the European market. Commerzbank launched, in May 2025, their avatar 'Ava', an artificial intelligence-powered bot that would act as the digital customer assistant with their banking transaction (Commerzbank, 2025b). In spite of the fact that this is one step ahead in the direction of using AI for repositioning, most of the competitors had already implemented a similar assistant years earlier.

4.2 Cross-Case Analysis

This section of the research outlines a cross-case comparison of the four banks: ING, ABN AMRO, Deutsche Bank, and Commerzbank, based on their approaches to AI-driven strategic repositioning. Following the Eisenhardt (1989) grounded theory, the analysis is based on themes identified through within-case coding and compares emerging patterns across cases using a matrix of thematic codes. The results are organised into three analytical categories: (1) Organisational Enablers, (2) Organisational Inhibitors, and (3) Strategic Use of AI.

4.2.1 Organisational enablers

This category includes the themes of executive support, digital infrastructure, and data governance, all factors that facilitate organisational readiness for AI implementation. ING clearly distinguishes himself by scoring high scores across all enabler themes. The bank benefits from strong top-management commitment, a well-developed digital infrastructure, and thorough data governance policies. These listed conditions create an environment that allows for AI-driven innovation and experimentation. In contrast, ABN AMRO and Deutsche Bank show weaker enabling conditions. ABN AMRO displays a moderate executive engagement but suffers from developing infrastructure and only intermediate-level data governance. Deutsche Bank, while slightly ahead in governance, also faces infrastructure challenges and does not demonstrate significant strong commitment to AI as a strategic driver for repositioning. Commerzbank, though digitally less aggressive and more cautious, presents a more balanced picture. While the executive support is moderate, the bank infrastructure is more stable but not cutting-edge. The bank's data governance capabilities remain underdeveloped, preventing it from being able to scale AI initiatives securely and compliantly.

4.2.2 Organisational inhibitors

This category examines internal obstacles to AI repositioning, including organisational resistance and outdated legacy IT systems. ING leads again with the most favourable profile, scoring low both on organisational resistance and legacy IT systems. The bank's ability to modernise legacy

IT systems and cultivate a transform-supportive culture functions as a crucial enabler for successful deployment of AI. By contrast, ABN AMRO and Deutsche Bank both struggle with organisational resistance and outdated legacy systems. The inhibitors of both banks reflect deep-rooted structural and cultural inertia that restrict responsiveness to AI-related change. The persistence of legacy system constraints further amplifies these challenges, as implementing AI in outdated systems through workarounds tends to be costly and requires a lot of effort. Commerzbank, despite facing similar constraints by legacy systems, experiences slightly lower internal resistance. This may be attributed to the bank's prudent strategy, narrower scope, and limited experimentation, which reduces internal friction but also slows down innovation.

4.2.3 Strategic use of AI

The third and final category focuses on the degree to which AI has been strategically implemented by financial institutions across customer engagement, cost reduction, and risk management. Across all three domains, ING demonstrates a clear and integrated use of artificial intelligence. For ING, their AI supports personalised customer experiences, automates back-office functions, and enhances predictive risk modelling. The bank's AI strategy showcases a mature implementation phase. Deutsche Bank uses AI more selectively, particularly in risk management, where it shows decent strength. However, the bank's usage of AI in customer-centric services and cost optimisation remains limited. ABN AMRO shows low implementation across all areas, especially in risk management, which may be influenced by recently heightened regulatory scrutiny and limited internal capacity. Commerzbank scores the lowest overall, again underscoring its conservative approach and limited strategic integration of AI technologies.

4.2.4 Cross-Case Synthesis

From the cross-case analysis a clear pattern emerges: banks that combine strong enablers, weak inhibitors, and broad AI usage, such as ING, demonstrate the highest level of strategic repositioning through AI. Conversely, banks with weak or mixed enablers, strong inhibitors, and fragmented AI use (ABN AMRO, Deutsche Bank, Commerzbank) have a hard time making meaningful changes to their positions. First, the success of ING's implementation doesn't just come from using AI in a lot of different ways; it also comes from including AI in the bank's bigger plan to change. AI was used in more than just one department or for a few specific tasks; it was used to improve customer experience, control risk, and make operations more efficient. Not only did this level of integration demand advanced technology, but it also required internal organisational readiness. The executives at ING were very supportive, the IT backbone was flexible, and the company had cross-functional teams that let them try new things and grow over time. Second, a middle tier emerges, where AI is utilised with considerable success but limited in breadth or influence due to inconsistent internal alignment, particularly seen in Deutsche Bank. Its efforts in fraud detection and compliance automation signal clear application of AI for risk mitigation and cost reduction. However, organisational issues such as fragmented infrastructure and problems from legacy system mergers impeded the bank's ability to scale AI across business units. Third, both ABN AMRO and Commerzbank are examples of companies who are looking at AI exploitation but haven't been able to use it to gain a big competitive edge yet. Both banks have initiated artificial intelligence projects, including customer service chatbots and automation in back-office activities, although these initiatives remain confined to support roles or internal process improvements. In all cases, cultural resistance, caution from regulators, and a lack of internal resources slowed growth.

A noticeable key differentiator across cases is how deep AI is embedded in each institution's long-term vision. ING's case showcases how AI can be leveraged for repositioning when it is integrated into the firm's identity as a tech-forward, customer-centric bank. For Deutsche Bank, the vision is visible, but it is unevenly executed. ABN AMRO and Commerzbank employ AI more as an add-on than a force for strategic change. Moreover, the role of inhibitors, in particular, legacy IT systems and internal resistance, played a crucial part in the determination of success. All the banks, except for ING, struggled with systems or mindsets that were not designed for swift data-driven innovation, while ING reaped the benefits of success due to prior investments in modular, scalable infrastructure and an agile culture.

These results support Eisenhardt's (1989) suggestion to use both similarity and contrast when looking for cross-case patterns. As a positive deviant case, ING reveals the conditions in which AI can effectively facilitate strategic repositioning. Conversely, the three lower-performing banks exemplify how various combinations of constraints hinder transformation. Despite having comparable external resources, Deutsche Bank and ABN AMRO score well below ING, underscoring the importance of internal organisational capabilities. These insights align with recent literature on digital transformation which emphasises the importance of leadership alignment (Bharadwaj et al., 2013), digital capability maturity (Warner & Wäger, 2019), and cultural openness to change (Westerman et al., 2014). Moreover, these results support the theoretical framing that AI-driven strategic repositioning is not solely a technological problem but a deeply organisational one.

Table 2: Banks labeled according to Cross-Case analysis.

Theme	Reverse scored?	ING	ABN AMRO	Deutsche Bank	Commerzbank
Executive support	No	High	Moderate	Moderate	Moderate
Digital infrastructure	No	High	Moderate	Moderate	Moderate
Data governance	No	High	Moderate	Low	Moderate
Organisational resistance	Yes	Low	High	Moderate	High
Legacy IT systems	Yes	Low	High	Moderate	High
Regulatory barriers	Yes	Moderate	High	High	Moderate
AI for customer engagement	No	High	Moderate	Moderate	Low
AI for cost reduction	No	Moderate	Low	High	Moderate
AI for risk management	No	High	Low	High	Low

Table 3: Thematic scoring framework

Theme	ING	ABN AMRO	Deutsche Bank	Commerzbank
Executive support	3	2	2	2
Digital infrastructure	3	2	2	2
Data governance	3	2	1	2
Organisational resistance	3	1	2	1
Legacy IT systems	3	1	2	1
Regulatory barriers	2	1	1	2
AI for customer engagement	3	2	2	1
AI for cost reduction	2	1	3	2
AI for risk management	3	1	3	1
Total	25	13	18	14

Chapter 5: Discussion

5.1 Key findings

The study set out to answer the central question: '*How can European financial institutions leverage strategic AI investments to enhance their competitive positioning?'*. To answer this question, a multiple case study design was set up and conducted using four European commercial banks: ING, ABN AMRO, Deutsche Bank, and Commerzbank. The study led to several key findings. First, the research suggests that AI is not solely a technological resource but also a strategic enabler of repositioning. ING, being the positive deviant, exemplifies how strong organisational enablers (top-management commitment, advanced infrastructure, and data governance), low organisational inhibitors, and integrated AI use across customer engagement, risk, and cost domains contribute to successful repositioning. Conversely, ABN AMRO and Commerzbank reveal how partial adoption, organisational resistance, and limited integration constrain repositioning efforts. Deutsche Bank lies in between, showcasing strong AI capabilities in areas such as risk but is constrained by legacy systems and inconsistent organisational coherence.

The findings furnish direct answers to the sub-questions asked in Chapter 1. In the literature review it was established that firms must reposition when customer expectations, technologies, or regulatory environments change. This study confirms that AI facilitates such repositioning through automation, analytics, and personalised services. Furthermore, organisational factors such as leadership, infrastructure, and governance explain the difference in outcomes.

5.2 Theoretical implications

The study adds to three existing theoretical concepts: The Resource-Based View (RBV), Dynamic capabilities (DC), and the Strategic Balance Theory. The study affirms, in accordance with the RB, that AI-related resources, such as algorithms, data, and infrastructure, contribute to a competitive advantage for a firm. However, the findings nuance the RBV by showing that solely possessing AI does not guarantee a superior performance over other firms. The value created by artificial intelligence is very dependent on organisational capabilities like governance, talent, and leadership. For example, ING's successful implementation does not just stem from acquiring AI tools but also from embedding those tools in its processes, culture, and strategy. The bank turned AI effectively into an organisational capability, rather than a strategic resource. ABN AMRO and Commerzbank had similar access to external AI technologies, but a lack of strong internal processes or cultures to fully exploit them resulted in a weaker competitive impact. The study extends RBV by showing that AI's strategic value arises when firms transform AI resources into firm-specific capabilities, reinforcing that VRIN resources alone are not enough without an organisational ability to support them. For instance, while AI algorithms can be accessible to different firms, ING's ability in embedding such algorithms into its customer-focused operational practices and data-driven decisions (firm-specific abilities) played a crucial role in achieving their strategic impact. This is closely aligned with the DC view, according to which merely sensing AI opportunities must be followed by successfully taking advantage of such opportunities and re-engineering organisational processes to attain an actual competitive advantage. This interplay suggests that RBV and DC are more than additive but could be multiplicative in the context of AI; the value generated from AI resources is significantly enhanced by powerful dynamic capabilities that allow for efficient utilisation, synergistic combination, and ongoing refinement of them.

From a dynamic capabilities (DC) perspective, the findings reinforce the importance of a firm's ability to continuously sense opportunities, seize them, and transform itself in response to technological change (Teece et al., 1997). The case of ING demonstrates how existing strong dynamic capabilities; the bank's management sensed the emerging digital opportunities in AI early on, seized them by investing in AI-driven initiatives (e.g., customer personalisation, credit risk AI models), and transformed internal structures and cultures (agile teams, data-driven decision processes), are needed to support these changes. This enabled ING to reconfigure its resources and service offerings in line with market shifts, which is precisely what the DC theory advocates. The three other cases demonstrated risk of weaker dynamic capabilities. For instance, Deutsche Bank did develop and implement some AI solutions, suggesting an ability to seize opportunities. However, its slower transformation (mostly due to outdated core systems and siloed implementation) highlighted an incapability to reconfigure and transform. Similarly, ABN AMRO and Commerzbank were slower to adapt their organisational structures and cultures, which limited the impact of their AI investments. Overall, the findings support the Dynamic Capabilities theoretical framework by showing that the front-runners in AI-driven repositioning not only invest in new technologies but also continuously adapt their processes, skills, and business models.

Furthermore, the findings also add value to the theory of strategic balance (Deephouse, 1999). In the context of AI adoption, this translates to adopting cutting-edge AI innovations to differentiate services while also adhering to banking norms, regulations, and stakeholder expectations to avoid credibility or compliance crises. The study's findings indicate that ING struck an effective balance. The bank implemented different AI strategies but still operated within the bounds of the regulations and industry conventions. ABN AMRO and Commerzbank had a more prudent strategy. This over-conformity, which led to an inability to differentiate, potentially limited the pace of strategic repositioning. The study contained no cases of firms that engaged in a reckless AI strategy. Nevertheless, the need to balance innovation and legitimacy is evident in these cases.

5.3 Managerial and practical implications

This research has important implications for banking executives, technology managers, and industry regulators aiming to harness artificial intelligence for strategic repositioning. Banks that had top management with strong commitment to AI initiatives proved to be a stronger enabler of AI-driven change than lukewarm leadership commitment. It is important for a bank to possess a clear strategic vision from leadership, as it signals organisational seriousness about AI, allocates sufficient resources, and helps align AI projects with long-term business goals.

Moreover, strong technological foundations are crucial to enrol AI at scale. The cross-case analysis revealed that the bank with an advanced digital infrastructure and data governance (ING) was able to deploy AI more broadly and effectively compared to the other cases. In practice, this means that banks must modernise their IT systems and implement strong data management practices to support AI implementation and usage. As a result of no reliable data and scalable infrastructure, even the best AI algorithms will underperform. This was evident in the cases, as outdated legacy IT systems were identified as a major hindrance for ABN AMRO and Commerzbank.

At last, given the heavy regulation in banking, managers must balance innovation with compliance. To manage this, banks could engage in conversations with external regulatory bodies and internal compliance teams before developing and implementing AI systems. By doing so, banks can find ways to innovate within allowed boundaries, turning regulatory compliance into a competitive advantage. In conclusion, there is a clear roadmap for banks to follow: build the right internal conditions, integrate AI into the core strategy, and manage external constraints cautiously. Banks that will adhere to this plan are more likely to achieve meaningful competitive repositioning in the age of AI.

5.4 Limitations and future research

Several key limitations provide insightful directions for future research. First, the study relied solely on publicly available secondary data, such as but not limited to, annual reports, industry reports and white papers. While this may provide information about the banks, it does not capture internal decision-making processes or the organisational culture fully. Future research could conduct interviews or use ethnographic methods for deeper insights. Second, the scope of this study is focused on European banks, in particular The Netherlands and Germany, which may limit generalisability. Comparative studies in different regions or industries would enrich understanding of contextual factors in AI-driven repositioning. Third, the research took a snapshot picture of AI strategies between 2019 and 2024. Longitudinal studies could provide a better grasp on the dynamic evolution of AI capabilities and their strategic impact over time. Fourth, the study focused primarily on the effect of positive organisational outcomes; future research could explore (unintended) consequences, such as ethical failures, job displacement, or regulatory sanctions. Finally, the interaction between AI and human decision-making remains underexplored. Future research could study the dynamics of organisational learning in the age of AI. For example, research could look at whether AI-driven insights supplement or even substitute for human wisdom in critical strategic banking decisions, particularly in complex domains such as advanced risk assessment or strategic planning, where human oversight and contextual awareness remain paramount. It is essential to understand this shifting dynamic as banking entities become increasingly reliant on AI. This will ensure that such advanced systems facilitate a continuous learning cycle that enables and does not de-skill human decision-makers, thereby maintaining a robust, agile, and ethical strategic core.

In conclusion, while the study offers valuable insights into AI-driven strategic repositioning, it reveals that there is a need for future research evolving relationships between AI, strategy, and organisational transformation.

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Appendix

Declaration of AI

I declare that I have read, understood, and complied with the AI use policy as stated in the syllabus, and that the thesis has been written by me, using AI tools only as a support, e.g. to improve readability. For the thesis ChatGPTo4, Google Gemini, Grammarly and Quillbot have been used. The first two tools were used to acquire academic literature and structurize my chapters, while the latter two tools were used to correct spelling and improve grammar.

URLs for each of the AI bots:

ChatGPT04: https://chatgpt.com/

Google Gemini: https://gemini.google.com/

Grammarly: https://www.grammarly.com

Quillbot: https://quillbot.com