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Supervisor	Syed mansoob murshed	Internal Verifier:	Dr. Suresh George Dr. Nathan Subramanian
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DECLARATION

I, **Umair Ali** declare that this dissertation has been composed by myself, that the work contained herein is entirely my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or qualification, in whole or in part, except as specified.

Signature: Umair Ali

Date: 25-08-2026

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1 Chapter 1: Introduction

AI is transforming banking in the UK, characterized by its automation, personalization, fraud prevention, and data-driven decision-making. The UK financial-services sector is moving towards mainstream adoption of AI, with 75% of firms saying they use AI in 2024 (Bank of England, 2024a). Recent investigations also reveal a link between the innovation in artificial intelligence and the performance of banks, focusing on organizational and regulatory capabilities (Gyau et al., 2024). Lloyds Banking Group provides an appropriate example as they have deployed AI and the value of AI generated has increased. Hence, this dissertation examines if this type of adoption results in sustainable competitive advantage. Chapter 1 introduces the background, problem of the research, aim, objectives, questions, significance and methodology.

1.1 Background of the Study

1.1.1 AI and the UK Banking Sector

AI has gone from being a novelty to being a common practice in the financial services sector in the UK. In 2024, 75% of firms surveyed by the Bank of England and Financial Conduct Authority (FCA) adopted AI, up from 58% in 2022, and another 10% planned to use AI in the next three years. In total, 17% of reported use cases were for advanced machine-learning applications, including foundation models (Bank of England, 2024a). Today, AI can be applied in Customer Support, Fraud and Cybersecurity detection, Credit assessment, Process optimisation and Regulatory compliance and decision support. Empirical studies also reveal that banking AI innovation is linked to improved financial performance and there is a requirement for co-investment in both ICT and regulation (Gyau et al., 2024).

AI is being adopted as part of a digital transformation process. Mobile-first services, cloud infrastructures and open banking and data analytics have transformed customers' expectations and put increased pressure on incumbent institutions to deliver faster, cheaper and more personalised services. Evidently, the competition between fintech and financial institutions positively affects financial institution innovations (Caragea et al., 2024). It is exacerbated by the emergence of digital-only banks but, in Europe, there are signs that neobanks are not necessarily superior to traditional banks and that even greater non-staff costs could be applicable (Citterio et al., 2024). Therefore, AI is not only an efficiency technology, but also a strategic response to the changing competitive environment.

1.1.1 Lloyds Banking Group and AI Transformation

As it is an existing incumbent with a big digital and AI transformation programme, Lloyds Banking Group is a suitable case study for this. Lloyds also has 40% of their data centres reduced, 57 generative-AI use cases delivered in 2025 and 50% of their applications moved to cloud. Its machine-learning feature is facilitated by cloud-based platforms such as Google Cloud's Vertex AI, and the Group is expanding its use of generative AI to agentic AI using governed internal platforms.

This change has become more and more apparent in commercial terms. Lloyds has seen the generative AI value come in at around £50m for 2025 and expects to see more than £100m in value in 2026, the company says, and will be deploying generative AI into customer interactions, fraud prevention, colleague support and engineering. It has also set up an AI Academy and is recruiting more AI personnel. With these characteristics, Lloyds is poised to determine whether a combination of technology, data, skills, governance and organisational size can be synthesized into capabilities that can provide a lasting competitive edge.

1.2 Research Problem / Problem Statement

1.2.1 AI Adoption versus Sustainable Competitive Advantage

There is a relationship between the use of artificial intelligence and sustainable competitive advantage but they are analytically separable. One is adoption – whether or not Lloyds Banking Group adopts AI technologies – the other is sustainable competitive advantage, whether or not the AI technologies are of value to the firm, difficult to copy, and complementary to their other organisational capabilities. Obviously Lloyds is no longer in the experimental stage; they state that 2025 saw the deployment of over 50 use cases for generative-AI and that they generated value over £50 million in 2025, and are planning for over £100 million in added value in 2026. But these self-reported results reflect the present-day benefits, and not necessarily long-lasting, AI-only, or imitable benefits.

This last bit of strategy research is merely a reiteration of that separation. In fact, Krakowski et al., (2023) state that many of today's AI skills are replaceable by humans and the rest will probably be the unique combinations of human-AI skills. Similarly, Neiroukh et al., (2025) state that the effect of AI capability on organizational performance is not only to own the technology but also decision making speed and quality that AI technology offers. AI-driven automation and analytics and relationships are also named by Sullivan & Wamba, (2024) as tools to support adaptation.

1.2.2 Research Gap and Strategic Problem

The challenge for Lloyds is now whether or not AI adoption can result in an integrated capability built around the company's proprietary data, employee skills, customer trust and organisational practices, governance, and ongoing learning. This question is all the more relevant given that other banks and fintech companies have access to similar cloud services and foundation models, as well as commercial AI products. An additional third of financial-services AI use cases were third-party implementations; and the Bank of England and FCA also cite data privacy and data quality, cybersecurity and model complexity and dependency as key AI risks.

While there is a wealth of existing research on AI adoption, banking efficiency and customer experience and decision support, there is relatively little independent evidence on organisations to say whether the benefits Lloyds reports are sustainable competitive advantage. So it's a value creation and value protection thing – Lloyds have to be a value to the customers, they have to create commercially viable stuff and they have to comply, explain, be fair, cyber secure and be trusted by the customers. To address this, the purpose of this dissertation is to explore the possibility that Lloyds' investments are not merely short-term operational gains, but also create a sustainable and defensible organisational capability, which will allow it to sustain a competitive advantage over time in a highly regulated and fast-changing UK banking sector where technological advantages may be short-lived.

1.2.3 Suitability of Banking for Artificial Intelligence

Banking is particularly suitable for AI because it combines **large volumes of structured transactional data, repetitive processes, frequent digital customer interactions and continuous risk-assessment requirements**. AI can therefore be applied simultaneously to credit assessment, fraud detection, anti-money-laundering monitoring, customer segmentation, personalised services and process automation (Kalyani & Gupta, 2023). Research also shows that banking digitalisation can improve operational efficiency when technology is integrated with process redesign and organisational capabilities (Bueno et al., 2024), while cross-country evidence associates banking AI innovation with improved return on assets, although benefits depend partly on ICT capability and regulatory conditions (Baffour Gyau et al., 2024).

The UK provides especially favourable conditions because banking is already highly digitalised and intensively regulated. The Bank of England and FCA found that 75% of surveyed financial-services firms used AI in 2024; large UK banks reported a median of **39 AI**

use cases, compared with nine across respondents overall (Bank of England, 2024b). The FCA’s 2026 review further identifies AI-driven transformation of firm operations, consumer journeys, competition, fraud and cybersecurity as major developments in retail financial services (FCA, 2026). Banking should therefore be considered **highly suitable rather than conclusively the single optimal sector for AI**, because sectors such as insurance also report very high adoption. Its strategic relevance lies in the combination of data intensity, automation potential, personalisation and risk management that characterises retail banking.

1.2.4 UK Retail Banking Landscape and Lloyds’ Market Position

Selected Major UK Retail Banks and Lloyds’ Relative Position

Banking Group	Selected 2025 UK Scale Indicator	Retail Banking Position / Strength	Relevance to Lloyds’ Position
Lloyds Banking Group	c.28 million customers; 23.6 million digitally active customers; c.21.5 million app users	Describes itself as the UK’s largest digital bank and is also the UK’s largest mortgage lender	Demonstrates very large customer, data and digital scale, making Lloyds particularly suitable for examining whether AI can generate sustainable competitive advantage
NatWest Group	Serves more than 20 million people, families and businesses across the UK	One of the largest UK retail banking groups, with substantial current-account, mortgage and digital-banking operations	Represents a major incumbent competitor also investing heavily in AI and digital transformation
HSBC UK	More than 14.7 million Retail Banking and Wealth customers across HSBC UK, first direct and M&S Financial Services	Large UK retail and wealth franchise supported by HSBC’s international technology and financial capabilities	Provides a strong comparator for AI-enabled customer service, wealth, risk and digital transformation
Santander UK	22.6 million total customers; 13.6 million active customers; 7.4 million digital customers	Major UK retail bank with established positions in mortgages and everyday banking	Provides an important comparator for digitalisation, automation and AI adoption within a large UK retail franchise

The comparison demonstrates that Lloyds operates within a highly concentrated and digitally advanced retail-banking market alongside other large incumbent institutions. Although direct ranking by customer numbers should be interpreted cautiously because banks use different definitions of total, active and digital customers, Lloyds demonstrates particularly strong scale in digital banking and mortgages. Its combination of a large customer base, extensive transactional data, established retail brands and substantial digital engagement provides an

important organisational setting for examining AI adoption. The selection of Lloyds is therefore not based simply on its size, but on its leading digital position and its capacity to deploy AI across a large, diversified UK retail-banking franchise.

I would use this table instead of trying to create a strict **1st–4th ranking**, because customer definitions and market leadership vary by mortgages, current accounts, deposits, digital users and total customers. This table answers the teacher’s point more academically.

1.3 Research Aim

To critically appraise the role Artificial Intelligence plays in delivering sustainable competitive advantage in Lloyds Banking Group in the context of banking sector of United Kingdom (UK) specifically in terms of operational efficiency, customer experience, innovation, decision making, risk management, organisational and governance and regulatory environment.

1.4 Research Objectives

The study is guided by the following objectives:

1. To examine the extent and strategic significance of artificial intelligence adoption and digital transformation within the UK banking sector.
2. To analyse how Lloyds Banking Group applies AI to improve operational efficiency, customer experience, service innovation and organisational decision-making.
3. To evaluate how AI-related organisational capabilities, including data, technological infrastructure, employee expertise and governance, contribute to Lloyds’ competitive advantage.
4. To examine the principal risks and constraints associated with responsible AI, including regulatory compliance, data privacy, algorithmic bias, cybersecurity, governance and customer trust.
5. To determine whether Lloyds’ AI-related capabilities can generate and sustain competitive advantage within the evolving UK banking environment.

1.5 Research Questions

This study addresses the following research questions:

1. How is artificial intelligence being adopted within the UK banking sector, and what strategic role does it play in digital transformation?

2. How is Lloyds Banking Group using AI within its wider digital transformation strategy?
3. In what ways does AI contribute to operational efficiency, customer experience, service innovation and organisational decision-making at Lloyds Banking Group?
4. What governance, regulatory and organisational risks constrain Lloyds Banking Group's ability to derive competitive value from AI?
5. To what extent can AI adoption and complementary organisational capabilities support sustainable competitive advantage for Lloyds Banking Group within the UK banking sector?

1.6 Significance and Relevance of the Study

1.6.1 Academic Significance

This study bridges a gap in studies on the adoption of AI and sustainable competitive advantage research. However, prior studies in the banking sector indicate that AI innovation correlates positively with performance, efficiency and decision making, while recent reviews pointed out that questions remain regarding governance, fairness, privacy and customer trust (Fundira & Mbohwa, 2025; Gyau et al., 2024). However, there is limited independent evidence of whether or not the benefits will enable Lloyds to gain a sustainable competitive advantage. There is therefore a contribution of the dissertation: Technological advantages, organisational capacities and responsible-AI restrictions are combined in the same Lloyds case study.

1.6.2 Managerial Significance

The study makes a distinction between technology and capability for digital-transformation leaders and AI-governance teams at Lloyds. While the evidence of gains in banking performance from AI innovation suggests that the commercially available models and cloud platforms will also deliver sustainable gains, this is not guaranteed. The results can then be used to make decisions about AI-investment, skills, data integration, governance and scaling of high value use cases.

1.6.3 Regulatory and Industry Significance

The research has implications for UK banks; FCA and the Bank of England/PRA as AI adoption presents opportunities and consumer, operation and systemic risks. 33% of the reported use cases of AI by the financial services firms in the UK are third-party implementations, which is creating dependency concerns. FCA is currently applying the current regulatory frameworks e.g. Consumer Duty and SM&CR, rather than a rulebook

specific to AI. In this way, the dissertation provides practical insights into balancing innovation, competition from fintech and good governance and customer protection.

1.7 Brief Research Methodology

1.7.1 Research Design and Approach

This dissertation has an interpretivist philosophy and used a secondary qualitative single case study design with a focus on Lloyds Banking Group. The analytical model used is deductive–inductive model in which the analytical categories are obtained from the literature found and the new themes are obtained from the documentary data. The methodology is in line with what was developed in Chapter 3.

1.7.2 Data Collection and Analysis

Academic literature is identified using a well-defined search strategy that is transparent and adheres to PRISMA guidelines for identification, screening and final inclusion (Page et al., 2021). The selection of Lloyds annual reports, AI and technology disclosures, Bank of England publications, FCA publications, and ICO publications are done separately, and the purposive sampling is the right approach for the identification of information-rich qualitative evidence to answer the research questions (Ahmad & Wilkins, 2025).

Documentary analysis involves discovering and explaining patterns within the evidence, and evaluating the sources for origin, purpose, credibility and possible bias. Reflexive thematic analysis is an interpretative method that can be used to develop themes from qualitative data (Byrne, 2022). Triangulation of sources from academic, organisational and regulatory sources to strengthen credibility. Ethical protection – accurate referencing, copyright, data protection, organisational bias. The Resource-Based View, Dynamic Capabilities Theory and Technology–Organisation–Environment framework are used as guides to help with interpretation.

1.8 Scope and Delimitations of the Study

This dissertation specifically looks at Lloyds Banking Group and in the context of UK banking looks at the evidence regarding recent AI, digital transformation and sustainable competitive advantage. Only publicly released secondary data (academic, organisational, regulatory and some industry) is used in the study. Interviews, surveys or direct data collection of employees, managers or customers is not done. The results should not be statistically generalised to include all UK or international banking institutions and are for analytical purposes of Lloyds' case only.

1.9 Structure of the Dissertation

This dissertation is broken into five chapters. The research background, problem statement, aim, objectives, research questions, significance, methodology and scope are presented in Chapter 1. The conceptual framework is presented, with a critical literature review of AI adoption and digital transformation in banking, operational and customer outcomes, responsible AI, competitive advantage, Resource-based View and Dynamic Capabilities Theory and Technology–Organisation–Environment (TOE) framework in Chapter 2. The chapter 3 discusses and provides reasons for an interpretivist philosophy, single case design of secondary type, a combined deductive-inductive approach, academic search (informed by PRISMA), selection of documents (purposive sampling), interpretation of documents (documentary analysis and thematic analysis), quality of research, and ethical considerations. Chapter 4 explores and presents data on technological readiness, operation efficiency, customer experience, decision making, risk, governance and sustainable competitive advantage at Lloyds Banking Group. Chapter 5 considers the research questions, and makes overall conclusions and recommendations for practice, theory and further research.

2 Chapter 2: Literature review

2.1 Introduction

This chapter provides a critical evaluation of the literature pertaining to the adoption of AI and its role in achieving sustainable competitive advantages in the banking sector, specifically in the context of Lloyds Banking Group. The review is needed because AI has transitioned from piecemeal experimentation; in 2024, 75% of financial-services firms in the UK reported use of AI, with 10% intending to adopt it within three years (Bank of England, 2024a). The use of banking applications includes customer service, credit assessment, fraud detection, risk management and process automation, among others, as shown by recent studies (Fares et al., 2022; Kalyani & Gupta, 2023) . The literature also highlights the issues of explainability, algorithmic bias, privacy, accountability and customer trust (Černevičienė & Kabašinskas, 2024).

The chapter therefore examines, rather than simply reports on, evidence. It identifies findings, assumptions, methods and limitations across academic, regulatory and organisational sources to assess when AI adds value and how it can be hard for competitors to replicate that value. The review considers the research questions, AI in banking in the UK, Lloyds' digital transformation, efficiency, customer experience, innovation, governance and competitive positioning. This eventually leads to an integrated conceptual model relating the use of AI-powered tools, dynamic organisational competencies to competitive advantage, with regulation, governance, workforce capability and customer trust as moderating factors.

A structured, PRISMA-informed search and screening process was used to identify relevant peer-reviewed literature. This involved database searching, duplicate removal, title and abstract screening, full-text eligibility assessment and final inclusion according to predetermined criteria. PRISMA supports transparency in reporting how academic studies were identified and selected. Lloyds Banking Group publications, regulatory reports and industry documents were identified separately through purposive document selection because these materials are not peer-reviewed academic studies.

2.2 Artificial Intelligence Adoption in UK Banking

Artificial Intelligence (AI) is a category of computer systems that mimic human intelligence by making predictions, language processing, decision support, and reasoning. Machine learning (ML) is a type of AI that can learn patterns in data and make predictions without being programmed for each and every circumstance. Within banking, they have evolved from rule-

based expert systems to sophisticated deep learning and NLP (natural language processing) models, and computer vision and generative AI applications. It has transformed the role of AI from being a niche analytical tool to an organizing capability within customer support, operations and risk departments (Kalyani & Gupta, 2023).

Adoption in the UK financial services is now very large. In 2024, 75% of the firms surveyed by the Bank of England and Financial Conduct Authority (FCA) were already using AI, up from 58% in 2022, and another 10% intended to adopt within three years. Respondents predicted a median increase in the number of use cases from 9 to 21, though large UK and international banks reported well over that. The proportion of the use cases around foundation models was 17%, reflecting a fast uptake towards more advanced forms of machine learning (Bank of England, 2024a). These figures, however, indicate reported organisational use only and not the depth, effectiveness or integrating into strategy.

Key banking use cases are fraud/cybersecurity detection, credit-scoring, customer-segmentation, chatbots, anti-money-laundering monitoring, regulatory-compliance, process-automation, forecasting and customised financial services. According to the systematic reviews, AI has the potential to enhance decision quality, boost service speed and operational efficiency, however, the benefits are contingent on the quality of data, infrastructure, employee skills and alignment with business processes (Fares et al., 2023; Kalyani & Gupta, 2023). Thus, it should not be assumed that adoption equates with competitive advantage.

Digital transaction volumes, cost pressures, need for personalised and ongoing service, regulation, cloud capabilities and increasingly available data, and fraud and risk protection are all key adoption drivers. Studies on innovation in the financial sector also show that competition from financial technology start-ups positively drives technological innovation among incumbent financial institutions (Caragea et al., 2024). Digital-only banks and neobanks exacerbate this pressure by providing mobile-first services, and by having lower operating structures and quicker development cycles, though their profitability and risk performance vary (Citterio et al., 2024). Additionally, open banking will diminish incumbents' monopoly on customer data and perhaps enhance fintech screening, which will enhance competition (He et al., 2020). But incumbent banks also have legacy systems and siloed data and regulatory hurdles, while new entrants may lack in scale, trust and even customer relationships. AI integration for Lloyds Banking Group then needs to be viewed, not just as a technological

improvement, but as a strategic investment with capabilities that can be scaled, responsible governance, and effective integration, to deliver long-term sustainable competitive advantage.

2.3 AI, Digital Transformation and Lloyds Banking Group

Banking digitisation is more than just digitising current transactions. It requires the redesign of business models, of business processes, of business relationships and business structures with interconnected digital technologies. Transformation is a staged journey where banking strategy, people, technology and customer value all need to align, not a single technology project (Papathomas & Konteos, 2023). Likewise, Porfirio et al., (2024) discover that its performance impacts rely on managerial adaptability, worker capabilities, and stakeholders' digital experience. These findings are significant as incumbent banks need to modernise their legacy systems without compromising security, regulatory requirement and continuity.

AI can enable this to happen by transforming data and digital infrastructure into prediction, automation, personalisation and decision support. But AI and digital transformation are not synonymous: cloud migration, data modernisation is the foundation, AI is the value that is created from that base. The study on dynamic capabilities and technology–organisation–environment (TOE) showed that the performance of banks relies on complementary technological, strategic, organisational and ecosystem and governance-risk-compliance capabilities (Abdurrahman et al., 2024). So the installation of an algorithm is not in itself a transformation.

This is the case with Lloyds Banking Group. In fact, 50% of its applications are now deployed in cloud, Data Centre numbers have been reduced by 40%, release times have improved by 35%, and since 2021, it has also recruited 8,000 technology and data workers (Lloyds Banking Group, 2026c). These are all indicators of investment in infrastructure, delivery methods and human resources, but caution should be used in accepting company reported measures as they may highlight achievements over problems of delivery. However, they show that this AI approach is part of a more general shift in technology, data, processes and workforce capacity at Lloyds.

Its machine learning platform also showcases the power of cloud-based capabilities for experimentation with AI. In 2024, Lloyds made the move to Google Cloud's Vertex AI platform, providing over 300 data scientists and AI developers with scalable tools. According to Google, it facilitated 80 new machine-learning experiments, eliminated unplanned downtime on the platform and migrated hundreds of models, and made mortgage income verification

quicker—from days to seconds. It also helped over 18 generative-AI systems go into production (Google Cloud, 2026a). As this is a supplier case study, however, it is important to triangulate the performance claims with independent and regulatory evidence.

Lloyds' governance, skills and deployment structures are also indicative of organisational readiness. The Group has an AI Centre of Excellence, principles of responsible AI, human oversight and an AI Academy, along with more than 50 use cases that yielded around £50 million in 2025 and will top £100 million in 2026 (Lloyds Banking Group, 2026c). To see if capabilities could be spread beyond technical specialists, by June 2026 over 65,000 colleagues had been trained in responsible-AI.

Key, strategic capability is the result of combining technology with routines, skills, leadership and learning. Weritz et al., (2025) demonstrate that strategic capabilities complement transformation success, and Simón et al., (2024) highlight interoperability, trust and collective understanding in human-AI collaboration. This means that Lloyds may have higher levels of AI readiness than is apparent from these adoption numbers; but, sustained advantage will require constant reconfiguration, as well as embedding appropriate governance and ensuring that the experiments turn into unique customer and business outcomes that are difficult for rivals to replicate.

The analytical question, then, is not whether or not Lloyds has got the AI tools, but whether its investment in the cloud, data, talent and governance is working as a capability that can deliver ongoing, measurable and defensible value throughout the organisation.

2.4 AI and Operational Efficiency

AI streamlines banking operations, automates repetitive tasks, and facilitates quicker, more uniform decision-making, especially regarding data-heavy tasks. While recent studies show that digitalisation is correlated with reduced transaction costs, simplified processes, and better resource management, they also highlight that the benefits of digitalisation rely on organizational redesign, not just on the adoption of technology Bueno et al., (2024). In reality, robotic process automation, natural-language processing and machine-learning systems can handle document classification, customer verification and account servicing and reporting to free up employee time to work on more complex cases and relationship-based work. However, Kalyani & Gupta, (2023) warn that operational burdens can be moved, not eliminated, if the data is insufficient, integration and technical knowledge are inadequate.

Credit and mortgage processing represents the potential benefits. Machine-learning models can process a larger, more diverse data set than traditional scoring systems, which enhances risk stratification and speeds up application decision making. Kyeong & Shin, (2022) show that there is continuing trade-off between the accuracy and interpretability of advanced credit-scoring approaches which can boost predictive performance. Lloyds Banking Group reportedly cut down on the days of mortgage income verification to seconds, and facilitated the migration of hundreds of models to cloud-based machine learning infrastructure (Google Cloud, 2026a). It suggests significant savings in processing time, but supplier claims of such benefits should be viewed with some suspicion as evidence of such benefits is limited.

AI also enhances fraud detection and regulatory compliance by analyzing transactions in real-time and spotting unusual patterns that traditional rules might miss. Bakry et al., (2024) reveals how machine learning can help minimize false-positive anti-money laundering alerts, which may save investigation costs and compliance efforts. But false negatives, model drift and black box decisions can lead to financial, legal and reputational risks. Thus, research on Explainable-AI emphasises that efficiency must not be coupled with transparency, auditability and human oversight, especially in the context of lending and fraud decisions (Černevičienė & Kabašinskas, 2024).

Operational efficiency is more tightly coupled to employee productivity and organisational decision making for Lloyds. According to its 2025 annual report, it resulted in gross cost savings of around £700m in 2025, an increase of active customers served per distribution worker of 45% since 2021 and around £50m of value from 50 live generative-AI use cases. The Group aims to unlock over £100m in value from generative-AI in 2026 (Lloyds Bank plc, 2026). The numbers indicate that AI is shifting from trial to widespread adoption in customer operations, front line assistance and engineering support.

However, the company's reported savings do not prove that AI was solely responsible for these results; branch rationalization, cloud adoption, process rationalization, and staff alignment also play significant roles. AI can improve Lloyds' cost and decision-maker velocity, but to achieve sustainable operational advantage, strong data is essential, as is good governance and ongoing testing to ensure decisions made by AI are accurate, fair and compliant. It should not be designed to reduce costs at the expense of service quality and resilience.

2.5 AI, Customer Experience and Service Innovation

AI is transforming the customer experience in the banking sector by empowering banks to analyze transaction patterns and preferences, and customer behavior on a massive scale. AI algorithms can categorize customers with greater accuracy and anticipate their requirements, offering tailored product suggestions or financial advice or service interventions. Recommendation systems, segmentation models and conversational agents are the leading AI applications that link technology and customer experience (Peruchini et al., 2024). Personalisation, however, is only valuable if it is accurate, timely and appropriate; if not, it can seem intrusive or reinforce the bias within the customer data.

Chatbots and virtual assistants can work around the clock and answer repetitive questions, offering a seamless digital experience for customers. The AI-powered digital banking evidence suggests that satisfaction is driven not just by technological novelty, but by perceived performance, problem-solving ability, communication quality, and expectation confirmation (Alnaser et al., 2023). Likewise, studies on banking-chatbots reveal that trust has an impact on user attitudes for continued usage and satisfaction (Alagarsamy & Mehroliya, 2023). These results suggest that customers are not just interested in the speed of service, but also need the answers to be accurate, the language comprehensible and the escalation to a real person simple when the question is complex, emotional or could have financial implications. Customer experience should therefore be measured throughout the entire journey from accessibility, to accuracy of the response, to the effort to achieve a resolution, to continuity of the channel and confidence after the interaction.

Lloyds Banking Group gives examples of organisations that are relevant. It features a knowledge assistant called Athena, which helps search from around 13,000 internal articles, which reportedly cut the average search time of a Lloyds colleague from 59 to around 20 seconds, improving search speed and query resolution (Lloyds Banking Group, 2025d). Additionally, Lloyds highlighted its efforts to implement over 50 generative-AI applications in 2025, such as enhanced in-app search and more precise responses throughout customer operations (Lloyds Banking Group, 2026c). These claims imply improvement in the customer journey, but they are measures developed by the company and not on their own indicative of increased levels of satisfaction, loyalty, or retention.

From query to proactive financial support, service innovation is moving forward. Lloyds announced an AI-powered financial assistant for over 21 million mobile-app users that offers

personalised spending insights, savings and investment guidance, and referral to human expertise (Lloyds Banking Group, 2025f). These tools can distinguish Lloyds through the use of customer information, secure banking systems, and instant access. However, research on the value of conversational agents emphasises the importance of trust and communication design, as well as human-AI coordination, to create value (Mariani et al., 2023).

There is thus a tension between personalisation and privacy. The extent of customer data available is essential for better recommendations, and if this data is collected in opaque ways or if it's inferred inaccurately or not explained, it can erode trust. This focus on transparency, accountability and understandable outputs emphasizes the role of explainable-AI in the finance sector (Černevičienė & Kabašinskas, 2024). Sustainable advantage for Lloyds will not be achieved by personalisation alone, but by providing convenient, innovative services, consent, data security, fairness, human oversight and credible protection of customers.

2.6 AI and Competitive Advantage: Theoretical Perspectives

2.6.1 Resource-Based View

The Resource-Based View (RBV) offers a point of departure for considering the potential for competitive advantage from Lloyds Banking Group's investments in artificial intelligence. From this point of view, advantage is not just about the technology itself, but also about the coordination of useful, scarce, difficult-to-imitate and well-organised resources. AI capability is conceptualized as a mix of tangible resources (data, computing power etc.), human resources (technical, managerial etc.), and intangible resources (coordination, organizational learning, innovation oriented culture etc.) (Mikalef & Gupta, 2021). Other evidence suggests that AI capability has a direct impact on performance via creativity, AI management and data-driven decisionmaking, but not directly by owning the technology (Chen et al., 2022).

In Lloyds' case, AI is useful in areas that enhance customer service, boost operational efficiency, detect frauds, assess risks and speed up decisions. However, cloud platforms, foundation models, and software applications are not uncommon or unique; other financial institutions can acquire them. More robust potential sources of differentiation include Lloyds' customer and transaction data, banking expertise, brand connections, qualified workforce and governance practices to integrate AI at scale. Even these can't be relied upon for an edge: information can be incomplete, abilities can be used by rivals, and routines can become mechanized. According to Krakowski et al., (2023) AI shifts the competitive advantage by introducing new human-AI capabilities; competitive advantage might be neither fully human

nor AI. Lloyds will also need to coordinate complementary resources via cross-functional teams, the Lloyds AI Centre of Excellence, model governance and workforce development. Signs of integration include its central AI platform, its responsible-AI framework, and its organisation-wide training, which are all company-reported capabilities that need to be independently assessed (Lloyds Bank, 2026a).

Dynamic Capabilities Theory builds upon the RBV and addresses the issue of how firms can renew resources as they adapt to technological and environmental change. Its core functions are identifying opportunities and threats, capturing opportunities by investing and implementing, and converting organisational resources. For Lloyds, sensing involves recognising advancements in generative and agentic AI, shifting customer expectations, fraud threats and regulatory obligations. Seizing means picking use cases of commercial value, funding, skilling and partnering on successful experiments and scaling to production. Transformation involves the redesign of workflows, retraining staff, modernisation of data architecture and adjustment of the governance process alongside the changing models and regulation.

This view is important because what is considered valuable for an AI today can turn into a commodity in a matter of minutes. The key to sustainable advantage lies less in an algorithm and more in Lloyds' ongoing capacity to learn, scale and renew capabilities. According to Simón et al., (2024) value arises from successful interactions with AI systems, necessitating interoperability and shared knowledge and trust between human and AI. Likewise, complementary strategic capabilities are also identified as enhancing the success of digital transformation and firm performance (Weritz et al., 2025). But dynamic capabilities can be expensive and hard to measure; ongoing reconfiguration can induce disruption, duplicated investment or implementation fatigue. It is therefore necessary to view the theory critically because continuous change is not necessarily good.

Conditions influencing adoption are explained by the Technology–Organisation–Environment (TOE) framework. Technological dimension refers to compatibility with legacy systems, data quality, cybersecurity, scalability and AI's relative advantage. Organisational dimension: leadership support, financial resources, employee expertise, culture, coordination and readiness for change. The environmental dimension involves customer expectations and reliance on cloud, model and data providers, regulation and competitive pressure from banks and fintech. Jöhnk et al., (2021) define key AI-readiness categories to be strategic alignment, resources,

knowledge, culture and data. Empirical evidence in the banking sector also shows that technological, strategic, organisational, ecosystem and governance-risk-compliance capabilities are drivers of digital transformation and innovation (Abdurrahman et al., 2024).

However, the TOE primarily accounts for adoption conditions but not whether adoption leads to defensible value. The three perspectives together offer more analytical framework. TOE keeps investigating the reasons and conditions for Lloyds to adopt AI, the RBV examines whether the Group's bundle of AI resources is strategically distinctive, and Dynamic Capabilities Theory examines whether the Group can renew the bundle in response to changes in technology, competition and regulation. The message here: AI is a requirement but it is not enough. Lloyds need to combine technology and proprietary data with the people, management, relationships, processes and responsible governance. The benefit will be lasting only if these auxiliary factors create credible and verifiable results that are difficult for rivals to duplicate, and if they are flexible in the face of new regulations and market shifts.

2.7 Risks, Governance and Responsible AI in Banking

While AI presents opportunities for UK banks, it also brings legal, operational, and ethical risks that could impact customer trust and sustainable competitive advantage. AI systems often rely on vast amounts of personal and transactional data and thus fall under the UK GDPR's principles of lawfulness, fairness, transparency, purpose limitation, data minimisation, accuracy, security and accountability. The (Information Commissioner's Office, 2026) also anticipates that organisations will evaluate automated processing, describe the use of data and safeguard the rights of individuals. This means that Lloyds must show they have a lawful purpose to process the data, have assessed the risk of the data processing in relation to each model and are not collecting more data than is needed for each model.

It is especially problematic in lending and fraud detection and customer segmentation processes, where biased or incomplete training data can lead to disparate results for protected or vulnerable groups. Unfair credit-scoring outcomes can stem from datasets or model design, as indicated in (Hurlin et al., 2026) and fairness, privacy, transparency and accountability are identified as ongoing banking concerns (Fundira & Mbohwa, 2025). More complex models provide more accuracy but are more difficult to explain. Explainable-AI techniques can highlight influential variables and assist with challenge, but can also abstract and simplify the reasoning of a model (Černevičienė & Kabašinskas, 2024). Therefore, explainability should be

used in addition to, and not as a replacement for, independent validation, bias testing and customer appeal processes.

In addition, poor assumptions, data drift, hallucinated results, and using a model outside its scope of validation can introduce model risk. The Prudential Regulation Authority requires banks to identify and classify models, establish accountable governance, validate models independently and apply risk mitigants, including to machine-learning models (Bank of England, 2026). While human oversight is necessary for materially consequential decisions, it must be meaningful: employees need authority and competence, and sufficient time to ask questions or override automated decision-making.

Additional vulnerabilities involving cybersecurity and external dependency. The Bank of England (2024a) identified that 1/3 of AI applications in financial services are dependent on third parties, particularly cloud providers. The number one systemic risk of AI that firms saw was cybersecurity, and there was a growing expectation of greater third-party dependency and model complexity. While external platforms can speed up deployment, a lack of visibility into proprietary models can lead to lower levels of accountability, potential data-leakage challenges and vulnerability to outages or supplier concentration. Thus, contractual control, access restrictions, resilience testing and incident procedures and continuous monitoring are necessary for effective governance.

Responsible governance sets up a strategic trade-off. Strict controls can hinder experimentation and dilute Lloyds' ability to compete with fintech, while lax controls can turn efficiency into regulatory action, customer and reputational damage. Oversight ought to be commensurate with risk: tighter oversight of credit and fraud and personalised financial advice, as opposed to low-risk internal assistance.

In the UK, existing regulation is applied to AI instead of a specific rulebook for AI, such as the Consumer Duty, Senior Managers and Certification Regime, data-protection law and prudential governance requirements (Smith, 2026). Lloyds lists seven AI Ethics Principles, an AI Assurance Framework, a Data and AI Ethics Committee, central inventories, fairness audits, explainability checks and human-in-the-loop controls. It enhanced its Responsible AI team in 2026 and claims oversight throughout the design process until deployment and monitoring is completed (Lloyds Bank, 2026a; Lloyds Banking Group, 2026f). However, the claims are a disclosure by the organisation and not a separate assessment of effectiveness. Unless governance can identify actual harm, avoid discriminatory or insecure decisions, ensure

regulatory compliance, and give customers an explanation, a path for corrections, and a believable human point of responsibility, Lloyds' AI edge will not last.

2.8 Critical Synthesis and Research Gap

Many recent studies have shown that AI can enhance the performance of banks in areas such as process automation, rapid decision-making, fraud detection, personalisation, and risk analysis. However, systematic reviews conducted by Kalyani & Gupta, (2023) and Bueno et al., (2024) highlight the importance of technological infrastructure, employee skills, and organisational integration in determining benefits. So, AI is not seen as a source of superior performance but rather as an enabling capability. Similarly, there is consensus that weak governance can diminish its value, causing privacy breaches, biased decision-making, transparency issues and loss of customer trust (Fundira & Mbohwa, 2025).

But, there is mixed evidence of the impacts and sustainability of AI. Optimistic findings link adoption with efficiency, innovation and better customer experience, but critical research raises doubts about the benefits once the expenses of implementation, constraints of legacy systems, modelling and regulatory obligations are taken into account. Further, the adoption measures tend to be documented by adoption but do not specify the degree of adoption, the performance impact of the adoption or the feasibility of replication by competitors. This distinction is essential for sustainable competitive advantage as the commercially available cloud and foundation models can enhance performance but not rarity or inimitability.

Another restriction is that of the difference between banking studies and the UK context. Many peer-reviewed evidence pieces are multi-institutional in nature, span regulatory systems, and span digital maturity levels. In contrast, the UK-specific knowledge is heavily dependent on the Bank of England (BoE) and Financial Conduct Authority (FCA) survey that indicated high levels of uptake but also significant third-party dependency, model complexity, data and cybersecurity risks (Bank of England, 2024b). While this regulatory evidence is authoritative in assessing conditions in the sector, it is not necessarily a measure of long-term competitive outcomes at individual banks.

The literature examined offers a rather sparse, independent academic commentary on Lloyds Banking Group. Lloyds shares over 50 generative-AI use cases, and value of around £50 million in 2025, with even more benefits anticipated in 2026 (Lloyds Banking Group, 2026c). However, these in-house reported findings don't distinguish between AI's impact and cloud migration, process re-engineering, staffing rationalization and general digital investment. They

also give some indication of customer trust, comparative performance and long-term imitability.

In response to this organisation-specific gap, this study aims to combine the benefits of AI with responsibilities towards the use of AI. It explores how AI can be implemented and sustained to deliver cost, customer value, service innovation, risk management, and defensible competitive positioning—all while maintaining governance and regulation, employee capability, and privacy and trust. Such a view is not reflected by analyses that focus solely on the performance gains or responsible-AI risks.

2.9 Conceptual Framework

The conceptual framework is intended to provide a description of how AI adoption can lead to Sustainable Competitive Advantage for Lloyds Banking Group. Its main idea is that competitiveness is not obtained by adopting any of these technologies, but by pairing them with organisational capabilities. Recent evidence indicates that AI capability affects performance via the speed of decision-making, decision quality and complementary managerial resources (Neiroukh et al., 2025). Thus, AI adoption and organisational capability constitute the independent construct of the framework.

This relationship is carried by four intermediate outcomes: operational efficiency, customer experience, service innovation and decision making and risk management. Automation with AI can help save time and money on processing, and analytics and conversational systems can help enhance personalisation, responsiveness and product development. Predictive capability can also enhance credit assessment, fraud detection and managerial decisions. All of these result in competitive advantage through reduced costs, differentiation of service, speed of response, and risk control. Sustainable competitive advantage is the ultimate result, and only happens when the benefits are valuable, hard to replicate, and continually renewed.

The Resource Based View can be used to assess whether Lloyds has a unique resource bundle comprising of data, cloud infrastructure, skilled staff, organisational routines and governance. Dynamic Capabilities Theory describes how the Group identifies new opportunities in the technology, invests in and utilizes them, and restructures and mobilizes its assets to respond to shifts in markets and regulation. Banking research confirms that technological, strategic, organisational and governance capabilities strengthen digital transformation and innovation (Abdurrahman et al., 2024).

The Technology–Organisation–Environment framework is used to describe conditions for adoption: Technological readiness, Organisational culture, Regulatory pressure, Competition and external providers. Responsible-AI governance, regulatory compliance, data quality, employee skills, technological integration, customer trust, cybersecurity and privacy are moderating factors. In the banking practice, these may either empower or undermine the process of turning AI investment into lasting value. The framework takes a documentary and thematic approach to analysis, correlating Lloyds' AI resources, outcomes, risks and strategic sustainability.

2.10 Chapter Conclusion

This chapter critically examined the link between adoption of AI and competitive advantage in the banking sector in the UK, specifically with respect to Lloyds Banking Group. According to the literature, AI can boost operational efficiency, customer experience, service innovation, decision-making and risk management. But these advantages are not self-evident, and are reliant on data quality, employee skills, technology integration, governance, regulatory adherence and customer confidence. The chapter was based on the Resource-Based View and Dynamic Capabilities Theory in the light of the Technology–Organisation–Environment framework to explain the adoption conditions. The review found a gap: there is a lack of organisation-specific independent evidence that shows how Lloyds can turn AI investment into long-term and sustainable competitive advantage while also addressing the risks of responsible AI. The conceptual framework thus connects the AI adoption with the organisational capabilities and the subsequent performance outcomes, competitive advantage and sustainability. The research philosophy, design, data sources, analytical method and ethical procedures used to investigate these relationships are explained and justified in chapter 3.

3 Chapter 3: Research Methodology

3.1 Introduction

This chapter discusses the methodology adopted to analyse the potential sustainable competitive advantage that AI adoption can bring to Lloyds Banking Group. The study is a secondary qualitative single-case design that aims to interpret organisational and regulatory evidence through public documents. Based on the latest research, the structured secondary qualitative research is suitable for use when primary data are not needed or cannot be obtained (Cheong et al., 2023). The chapter presents the interpretivist philosophy and theory-informed deductive–inductive approach, followed by the PRISMA-informed literature search, purposive document selection, documentary analysis, thematic analysis, research-quality measures and ethical safeguards.

3.2 Research Philosophy and Assumptions

3.2.1 Alternative Philosophical Positions

Positivism is based on the notion that organisational phenomena can be treated as a reality that is measurable, hypothesis-testing and in which the researcher can be detached from. As a result, this dissertation is not well-suited to be the main philosophy since it does not gather numerical survey data nor test causal relationships between the AI expenditure and the financial performance of Lloyds. Pragmatism places emphasis on the method that most effectively addresses the research question, and is often seen as melding the qualitative with quantitative evidence (Yang Liu, 2022). While it is viable for practice-based research, it is less compatible with the philosophy of this research in which exclusively interpretive documentary analysis is used.

3.2.2 Selection of Interpretivism

Interpretivism is taken because the study is interested in the construction and communication of AI adoption, organisational capabilities, responsible governance and competitive advantage in Lloyds reports, regulatory publications and academic research. Interpretive qualitative inquiry assumes that findings are contextually and multi-perspectively generated and not the one organisational truth in a context-free environment (Patterson et al., 2023). This makes sense as customer value, AI readiness, trust and sustainable advantage won't be adequately assessed by adoption and cost savings alone. They need to compare meaning, assumptions, interests and contradictions between texts.

3.2.3 Philosophical Assumptions

The study takes an ontological perspective, viewing Lloyds' organisational reality as context dependent and as influenced by strategy, regulation, technologic change and stakeholder interpretation. Epistemologically, knowledge is created by critically interpreting and triangulating company, academic and regulatory evidence. The researcher accepts that there is the possibility of values and biases of the document producers and of the researcher. Reflexivity, transparent coding and comparison of Lloyds' claims with independent evidence will therefore build dependability and credibility (Janis, 2022).

3.3 Research Approach

3.3.1 Combined Deductive–Inductive Approach

This dissertation adopts a combined deductive–inductive qualitative approach to examine how AI adoption may contribute to sustainable competitive advantage at Lloyds Banking Group. The deductive component is appropriate because Chapter 2 established the Resource-Based View, Dynamic Capabilities Theory and Technology–Organisation–Environment framework. These perspectives will generate initial codes concerning AI resources, technological readiness, organisational renewal, governance, regulation and competitive advantage. Recent methodology research supports using theory to guide qualitative analysis while allowing evidence to challenge or refine the framework (Fife & Gossner, 2024).

The inductive component will allow additional themes to emerge from Lloyds publications, research, regulatory documents and industry reports. These may include implementation difficulties, third-party dependency, customer resistance, hidden costs and AI benefits that competitors can imitate. Such findings will not be excluded because they fall outside the conceptual framework. Instead, they will be treated as possible qualifications or extensions of the proposed relationships. Reflexive thematic analysis recognises that themes are developed through active engagement with data and research questions rather than simply discovered through predetermined codes (Byrne, 2022).

A purely deductive approach would be too restrictive because the study does not test formal hypotheses. A wholly inductive approach would also be unsuitable because the dissertation already has established theories and a conceptual framework. Combining both approaches preserves theoretical direction while remaining responsive to Lloyds-specific, contradictory and unexpected evidence.

3.4 Research Design and Strategy

3.4.1 Qualitative Research Design

The qualitative approach is used in this dissertation as it explores the relationship between artificial-intelligence adoption and organisational capabilities, operational improvement, customer value, governance risk and sustainable competitive advantage within Lloyds Banking Group. The relationships cannot be measured by merely a financial indicator and the study requires interpretation of strategic claims, regulatory expectations, implementation conditions and competing explanations across the documents. Qualitative case studies are supported by contemporary business-methodology research in the analysis of complex phenomena like digital transformation and strategic decision-making in their real organisational context (Annamalah et al., 2025).

3.4.2 Single-Case Study Strategy

As an organisational case, Lloyds Banking Group has been chosen as it is in the process of a massive technology, data and AI transformation within the UK banking regulatory space. The Group reports the scaled deployment of AI, over 50 use cases for generative-AI in 2025 and aims to scale the deployment of AI values in 2026 with adequate documentation for in-depth analysis (LLOYDS, 2026).

The strategy is to explain and to do so that they can be instrumental. It is explanatory as it looks at how and under what organisational conditions AI may generate competitive effects. It is instrumental because it lights up the bigger picture of AI capability and sustainable competitive advantage in incumbent banking. The unit of analysis is **AI adoption and organisational capabilities within Lloyds Banking Group and their contribution to competitive advantage**.

The design is based solely on secondary evidence, such as academic research, company reports and regulatory publications. No staff, management or customer will be recruited or contacted. It is not to gain a statistical generalisation to all banks but an analytical generalisation to the theoretical framework.

3.5 Secondary Data Collection Methods

3.5.1 Systematic Literature Review Approach

A systematic literature review approach is incorporated into the academic evidence-selection stage of this dissertation to provide a transparent and structured basis for identifying literature

concerning artificial intelligence, banking transformation and sustainable competitive advantage. Unlike a traditional narrative review, a systematic approach applies predetermined search terms, databases, inclusion and exclusion criteria, and documented screening procedures to reduce arbitrary source selection and improve transparency.

The systematic review component is appropriate because the dissertation integrates evidence across several related areas, including AI adoption, operational efficiency, customer experience, organisational capabilities, digital transformation, responsible AI and competitive advantage. Academic studies are therefore identified and screened systematically before being critically synthesised around the research questions and conceptual framework.

PRISMA 2020 and PRISMA-S are used to guide the reporting of database searches, duplicate removal, title and abstract screening, full-text eligibility assessment and final study inclusion (Page et al., 2021; Rethlefsen et al., 2021). However, the dissertation is not designed solely as a conventional systematic review. It remains a secondary qualitative single-case study of Lloyds Banking Group. The systematic-review procedure applies specifically to peer-reviewed academic literature, while organisational, regulatory and industry documents are selected separately through purposive criteria and subsequently triangulated with academic evidence.

3.5.2 PRISMA-Informed Academic Literature Search

Peer-reviewed research will be identified through Google Scholar, ScienceDirect, SpringerLink, Emerald Insight, Taylor & Francis Online and SAGE Journals. Search strings will combine terms such as “artificial intelligence in UK banking”, “AI adoption and competitive advantage”, “AI capability and firm performance”, “digital transformation in banking”, “responsible AI in financial services”, and “AI governance and UK financial services”, using the Boolean operators AND and OR.

PRISMA 2020 will guide transparent reporting of identification, screening, eligibility and final inclusion, while PRISMA-S will support documentation of databases, search dates, complete search strings, limits and record-management procedures (Page et al., 2021; Rethlefsen et al., 2021). Records will be entered into a search log, duplicates removed, and titles and abstracts screened against predetermined criteria. Potentially relevant articles will undergo full-text assessment, with exclusion reasons recorded. The final numbers will be presented in a PRISMA flow diagram. The use of PRISMA is confined to the academic literature stream and does not redefine the overall study as a conventional systematic review.

3.5.3 Organisational and Regulatory Document Search

Lloyds Banking Group annual reports, technology and AI webpages, press releases and responsible-AI publications will be collected separately through purposive document selection. Relevant Bank of England, FCA, ICO and UK government publications will also be examined, together with credible industry and cloud-provider case studies where they provide technically relevant evidence.

Documents will be selected for direct relevance to Lloyds' AI capabilities, operational efficiency, customer experience, innovation, governance, regulation and competitive advantage. Purposive selection is appropriate where information-rich materials are required rather than statistically representative sources (Ahmad & Wilkins, 2025). Each document will be logged by date, publisher, purpose, relevance and possible bias. Lloyds and supplier claims will be triangulated with peer-reviewed and regulatory evidence rather than accepted as independent proof of performance.

3.5.4 Table 3.1 – Annotated Bibliography of Key Academic Studies

The following 15 studies were selected because they are the most directly relevant to the dissertation's core themes of AI adoption, digital transformation, operational efficiency, customer experience, organisational capability, responsible AI and sustainable competitive advantage. These studies are all already used within the dissertation's literature review and theoretical framework.

Author(s) & Year	Study Focus / Method	Main Findings	Relevance to This Dissertation	Critical Limitation
Kalyani & Gupta (2023)	Systematic literature review and meta-analysis of AI/ML in banking	AI supports credit evaluation, fraud prevention, cybersecurity, risk assessment, customer service and digital banking	Provides a broad foundation for understanding AI adoption and applications in banking	Broad sector-level evidence; does not examine Lloyds or sustainable competitive advantage specifically
Fares, Butt & Lee (2023)	Systematic literature review of AI utilisation in banking	AI improves decision-making, process efficiency and customer value while supporting innovation	Supports the dissertation's themes of efficiency, customer experience and strategic value	Limited organisation-specific evidence and limited focus on long-term sustainability

Abdurrahman, Gustomo & Prasetyo (2024)	Empirical banking study integrating Dynamic Capabilities and TOE	Technological, organisational, strategic and governance capabilities strengthen digital transformation and innovation	Directly supports the TOE framework and Dynamic Capabilities analysis of Lloyds	Different banking context from the UK, limiting direct transferability
Krakovski, Luger & Raisch (2023)	Strategic-management study on AI and competitive advantage	AI changes traditional sources of advantage; human–AI complementarities become increasingly important	Central to evaluating whether Lloyds’ AI capabilities are difficult to imitate and sustainable	Not specifically focused on banking or Lloyds
Mikalef & Gupta (2021)	Empirical study conceptualising organisational AI capability	AI capability combines technological, human and intangible organisational resources and can improve performance	Supports the Resource-Based View and assessment of Lloyds’ AI resource bundle	Not banking-specific and predates widespread generative-AI deployment
Neiroukh, Emeagwali & Aljuhmani (2025)	Empirical study of AI capability and organisational performance	AI capability improves performance through faster and higher-quality decision-making and managerial capabilities	Supports the conceptual framework linking AI capability to organisational outcomes	Does not provide Lloyds-specific evidence
Jöhnk, Weißert & Wyrski (2021)	Qualitative study of organisational AI readiness	Strategic alignment, resources, knowledge, culture and data are major AI-readiness factors	Supports evaluation of Lloyds’ technological and organisational readiness	General organisational context rather than UK banking
Porfírio, Felício & Carrilho (2024)	Empirical research on banking digital transformation	Managerial flexibility, digital capabilities and stakeholder experience affect transformation outcomes	Supports the argument that AI must be integrated within broader digital transformation	Does not isolate AI-specific effects
Bueno et al. (2024)	Thematic analysis of digitisation and operational efficiency in banking	Digitalisation can reduce costs and improve resource allocation, but gains depend on process redesign and organisational adaptation	Supports critical analysis of Lloyds’ efficiency claims and workflow improvements	Focuses on digitalisation generally rather than AI alone

Peruchini, da Silva & Teixeira (2024)	Literature review on AI and customer experience	Chatbots, prediction models and recommendation systems can improve personalisation and customer interaction	Supports analysis of Lloyds' customer-facing AI and service innovation	Does not establish whether customer-experience improvements create durable advantage
Alnaser et al. (2023)	Empirical study of AI-enabled digital banking satisfaction	Satisfaction depends on perceived performance, problem-solving capability, communication quality and expectation confirmation	Supports analysis of whether Lloyds' AI improves customer experience rather than merely service speed	Conducted outside the Lloyds context
Černevičienė & Kabašinskas (2024)	Systematic literature review of explainable AI in finance	Explainability, transparency and interpretability are critical for accountable financial AI	Supports analysis of model risk, governance, customer trust and responsible AI	Primarily concerned with explainability rather than competitive advantage
Fundira & Mbohwa (2025)	Systematic and bibliometric review of AI ethics in banking	Privacy, fairness, transparency, accountability and customer trust are central ethical concerns	Directly supports responsible-AI governance and sustainability analysis	Limited firm-specific evidence and limited measurement of business performance
Bakry et al. (2024)	Machine-learning study of false-positive AML alerts	ML can reduce false-positive alerts and improve compliance efficiency	Supports fraud detection, risk-management and operational-efficiency themes	Technical application focus does not establish wider strategic value
Caragea et al. (2024)	Empirical study of fintech competition and financial-sector innovation	Greater fintech competition stimulates innovation among incumbent financial institutions	Supports the TOE environmental dimension and analysis of competitive pressure on Lloyds	Does not directly assess AI or the sustainability of competitive advantage

Table 3.1 demonstrates that the selected academic literature provides a balanced evidence base across the principal themes of this dissertation. The studies generally agree that AI can improve operational efficiency, customer experience, decision-making, risk management and innovation, but they also show that technology adoption alone does not guarantee sustainable

competitive advantage. Stronger outcomes depend on complementary organisational resources, including data quality, employee expertise, strategic alignment, organisational routines and governance capabilities. The literature also highlights important constraints involving explainability, privacy, fairness, customer trust and competitive imitation. However, much of the existing evidence examines banking generally, international samples or organisations outside Lloyds Banking Group. This reinforces the dissertation’s central research gap: there remains limited independent organisation-specific evidence explaining whether Lloyds can convert AI adoption into durable, defensible and responsibly governed competitive advantage within the UK banking environment.

3.5.5 Table 3.2 – Key Organisational and Regulatory Evidence

Source	Source Type	Key Evidence / Focus	Relevance to the Dissertation	Critical Consideration
Bank of England and FCA (2024), Artificial Intelligence in UK Financial Services	Regulatory / sector report	Evidence on AI adoption across UK financial services, major use cases, third-party dependency, cybersecurity, data quality, governance and model complexity	Provides the principal independent UK sector context against which Lloyds’ AI adoption can be assessed	Sector-wide evidence does not isolate Lloyds’ individual performance or competitive outcomes
Bank of England / PRA (2026), Model Risk Management Principles for Banks	Prudential regulatory guidance	Requirements concerning model identification, governance, validation, accountability and risk mitigation, including machine-learning models	Supports analysis of model risk, human oversight, explainability and responsible AI governance	Primarily establishes regulatory expectations rather than measuring actual effectiveness at Lloyds
Financial Conduct Authority (2026), AI in Financial Services	Regulatory guidance / policy commentary	Explains the FCA’s approach to AI through existing frameworks, including governance, Consumer Duty and accountability requirements	Relevant to evaluating whether Lloyds’ AI deployment remains compatible with customer-protection and governance obligations	Regulatory guidance provides expectations rather than empirical evidence of Lloyds’ compliance

Information Commissioner's Office (2025/2026)	Data-protection regulator	UK GDPR principles and guidance concerning lawful, fair, transparent and accountable use of personal data and AI	Supports examination of privacy, data minimisation, transparency and customer rights within Lloyds' AI systems	Focuses primarily on data protection rather than broader competitive advantage
Lloyds Bank plc (2026), Annual Report and Accounts 2025	Organisational / corporate report	Evidence concerning digital transformation, cost savings, productivity, technology investment, customer operations and AI-related activity	Provides core organisation-specific evidence for assessing operational and strategic outcomes	Company-produced information may emphasise successful outcomes and understate implementation problems
Lloyds Banking Group (2026a), Next-Generation AI Value	Organisational / corporate disclosure	Reports more than 50 GenAI use cases, approximately £50 million of value in 2025 and expectations exceeding £100 million in 2026	Important for assessing the scale, commercial value and strategic progression of Lloyds' AI deployment	Reported value is internally generated and does not independently establish causality or sustainable advantage
Lloyds Banking Group (2026b), Responsible AI Expertise	Organisational / governance disclosure	Evidence concerning expansion of responsible-AI capability, specialist expertise, governance and AI assurance	Supports analysis of responsible AI as an organisational capability and possible source of trusted deployment	Governance arrangements are self-reported and require comparison with external regulatory expectations
Lloyds Banking Group (2025a), AI-Powered Athena	Organisational / implementation evidence	Reports use of Athena for internal knowledge retrieval, reduced search times and faster support for customer-service colleagues	Provides a specific example of AI-enabled workflow improvement and potential customer-service efficiency	Demonstrates task-level improvement but does not independently prove improved customer satisfaction or retention

Lloyds Banking Group (2025b), AI-Powered Financial Assistant	Organisational / customer-service disclosure	Describes personalised AI-supported financial guidance, customer support and human escalation for mobile customers	Relevant to customer experience, personalisation, service innovation and differentiation	Many claimed benefits were prospective at announcement and require evidence of actual customer outcomes
Google Cloud (2026), Lloyds Banking Group Case Study	Technology-provider / industry evidence	Reports Vertex AI migration, machine-learning experimentation, model migration and faster mortgage income verification	Provides technical implementation evidence concerning Lloyds' cloud and machine-learning infrastructure	Supplier-produced case study may contain promotional bias and should be triangulated with independent evidence

3.6 Document Selection, Screening and Sampling Criteria

3.6.1 Identification and Record Management

Academic records will be identified through the databases and search strings specified in Section 3.5.1. Following PRISMA 2020 and PRISMA-S, the search log will record databases, search dates, full search strings, filters and result numbers; duplicates will be removed before screening.

3.6.2 Screening and Eligibility

Titles and abstracts will be screened against predetermined criteria. Studies will be included where they are peer-reviewed, written in English, published mainly between 2021 and 2026, and directly address AI adoption, UK banking, Lloyds Banking Group, competitive advantage, efficiency, customer experience, innovation, decision-making, governance or risk. Relevant international studies may be retained where their findings are transferable to UK banking. Full texts will then be assessed, with exclusion reasons recorded. Duplicate records, unsupported opinion, sources without clear authorship, studies lacking organisational relevance and purely technical AI research will be excluded. Older publications will be used only for established theory or methodology.

3.6.3 Purposive Selection of Organisational Documents

Lloyds, regulatory and industry documents will be selected separately through criterion-based purposive sampling because qualitative sampling prioritises information richness and alignment with the research purpose (Ahmad & Wilkins, 2025). Each document will be logged

and appraised for authority, relevance, evidential basis and possible promotional bias. Academic-study selection will be reported through a PRISMA flow diagram, while non-academic sources will appear in a separate document-selection table

3.7 Data Analysis Methods

3.7.1 Documentary Analysis

Each source will be analysed first using documentary analysis to explore the source's origin, purpose, target audience and organisational context. Authorship, publication date, type of publication, relevance, basis of evidence and possible biases will be documented on a document-appraisal matrix. This is key given that Lloyds Banking Group's annual reports, AI webpages, and press releases may highlight successful implementation but gloss over failed trials, expenses, and client concerns. Morgan, (2022) recommends that when the documents are qualitative data, it is suggested to use systematic source selection, contextual appraisal and reflexive interpretation.

As such, claims of cost savings, faster mortgage verification, customer-service gains and responsible-AI controls will be checked against peer-reviewed research and evidence from the Bank of England, Financial Conduct Authority and Information Commissioner's Office. Agreements, contradictions and missing evidence will be noted and not automatically solved in favour of Lloyds. Documentary analysis will be completed first to determine the nature and context of the documentation prior to thematic interpretation.

3.7.2 Thematic Analysis

The documents to be appraised will then be analysed reflexively thematically. This method is suitable as it allows for systematic coding and is aware of the researcher's interpretive role in creating patterns of shared meaning (Byrne, 2022). The analysis will be carried out repeatedly reading part of the documents and initial coding, grouping of codes, forming of candidate themes, review of themes with documents, theme construction and integrated interpretation.

Initial theory-informed themes will be: AI adoption and technological readiness; operational efficiency; customer experience; service and product innovation; decision-making and risk management; competitive advantage; responsible-AI governance; regulatory compliance; customer trust; and sustainable competitive advantage. However, the inductive component of the analysis will allow new or contradictory themes to emerge, including implementation

failure, third-party dependency, customer resistance and AI benefits that competitors may imitate.

Cross-source comparison will differentiate Lloyd's claims from the evidence and highlight discrepancies between academic, organisational and regulatory viewpoints. The Resource-Based View will evaluate if Lloyds' data, skills, infrastructure and routines are strategically unique. The dynamic capabilities theory will discuss sensing, investment, scaling and organisational reconfiguration, and technology–organisation–environment (TOE) will discuss technological readiness, organisational conditions, and regulatory/competitive pressures. Each of the final themes will be directly tied to the research questions and conceptual framework.

3.8 Research Quality and Methodological Limitations

3.8.1 Trustworthiness

Using source triangulation and comparing the peer-reviewed studies, Lloyds disclosures, regulatory publications and credible industry evidence will provide strength of credibility. Morgan, (2024) argue that triangulation can highlight if there are any discrepancies and to decrease reliance on a single organisational story. Dependability will be ensured by using an audit trail to document databases, search terms, inclusion/exclusion criteria, document-appraisal decisions, coding process and themes.

Confirmability will be considered by relating the findings to the evidence and leaving contradictory findings, reflecting upon researcher's assumptions. Cheong et al., (2023) highlight the need to evaluate secondary qualitative findings with transparent reporting, positionality and evidence-based interpretation. Detailed description of Lloyds' UK banking and regulatory context will support transferability, but findings can not be statistically generalised to all financial institutions.

3.8.2 Methodological Limitations

The study relies on public documents, and Lloyds may highlight successful programs and not mention the ones that failed. It is not a direct voice of the employees and customers, and does not provide causal relationships. AI advancements can swiftly become outdated, and distinguishing AI-driven results from cloud migration and process transformation, as well as broader digital investments, will continue to be challenging.

3.9 3.9 Ethical Considerations

3.9.1 Ethical Risk and Academic Integrity

This secondary qualitative case study is low risk as there is no data from interviews, surveys or confidential Lloyds Banking Group data or human participants. However, any academic, regulatory and organisational sources will be referenced in the UWTSD Harvard system. Authors' arguments will be presented fairly, quotations will be kept to a minimum and be clearly attributed, and copyright concerns will be respected. To minimise plagiarism, misquotation and selective reporting, a source log will document bibliographic information and locations. Cheong et al., (2023) state that secondary qualitative research must be transparent with data provenance, context, interpretation, and ethical reuse.

3.9.2 Data Protection and Organisational Bias

Documents will be kept on password protected folders and will be used for the purpose of this dissertation only. Data-protection responsibilities do not get lost because the information is made public: irrelevant personal information will not be extracted and analysed. In cases where personal data are used, the study will abide by the principles of the UK GDPR: lawfulness, fairness, transparency, purpose limitation, data minimisation, accuracy, security and accountability (ICO UK, 2025).

Lloyds annual reports, website and press releases may highlight positive AI results. Claims concerning efficiency, customer value, governance and competitive advantage will therefore be compared with peer-reviewed research and Bank of England, FCA and ICO evidence. The study will adhere to the ethics of the university as well as reporting contradictory evidence, not misleading conclusions.

3.10 Chapter Conclusion

This chapter supported the methodology of exploring AI adoption and sustainable competitive advantage at Lloyds Banking Group. The study adopts an interpretivist position and a theory-informed deductive–inductive approach, allowing established theories to guide analysis while remaining open to emerging documentary themes. A PRISMA-informed process supports the transparent identification and screening of academic literature, while purposive selection is used for organisational, regulatory and industry documents. The study adopts a secondary qualitative single-case design. Academic literature is identified and screened through a PRISMA-informed process, while organisational, regulatory and industry documents are selected purposively according to their relevance and evidential quality. Triangulation,

procedures and reflexivity are used to ensure trustworthiness, and ethical safeguards cover academic integrity, copyright, data protection and organisational bias. The themes identified are presented, analysed and discussed in Chapter 4.

4 Chapter 4: Findings, Analysis and Discussion

4.1 Introduction

This chapter presents and critically analyses the findings concerning how artificial intelligence adoption may contribute to sustainable competitive advantage at Lloyds Banking Group. The findings derive from the secondary qualitative single-case study and draw on Lloyds Banking Group documents, UK regulatory publications, peer-reviewed academic studies and selected industry evidence. In accordance with the methodology established in Chapter 3, the evidence is examined through documentary and thematic analysis. The findings are organised around the principal themes of AI adoption and technological readiness, operational efficiency, customer experience and service innovation, decision-making and risk management, responsible AI governance, regulation, customer trust and sustainable competitive advantage. Rather than presenting evidence descriptively, the chapter compares and interprets findings across different source types. Each theme is evaluated against the research questions and the literature reviewed in Chapter 2, enabling assessment of whether Lloyds' AI-related capabilities create temporary benefits or a more durable competitive position.

4.2 Overview of the Evidence and Thematic Findings

The final evidence base combines peer-reviewed research identified through the PRISMA-informed screening process with purposively selected organisational and regulatory documents, as established in Chapter 3. This multi-source design is necessary because Lloyds' publications provide organisation-specific evidence, while regulatory and academic sources enable independent comparison. Lloyds reported more than 50 generative-AI solutions in 2025 and continued expansion into agentic AI during 2026 (Lloyds Banking Group, 2026c). UK regulatory evidence additionally provides sector-level context on adoption, third-party dependency and AI-related risks (Bank of England, 2024b).

Evidence category	Examples	Analytical purpose
Lloyds documents	Annual reports, AI and technology disclosures	Organisation-specific findings
Regulatory evidence	BoE, FCA, ICO	Independent UK context
Peer-reviewed studies	Recent AI/banking research	Comparison and theoretical interpretation
Industry/provider material	Google Cloud and selected reports	Technical implementation evidence

4.2.1 Principal Themes

Documentary and thematic analysis generated six interconnected areas: **AI adoption and technological readiness; operational efficiency; customer experience and service innovation; decision-making** and risk management; responsible-AI governance and regulation; and competitive and sustainable advantage. These correspond with the coding framework established in Chapter 3. Recent banking research similarly connects technological, organisational and governance capabilities with digital transformation and innovation, while customer-experience and AI-ethics studies emphasise personalisation, trust, privacy and accountability (Abdurrahman et al., 2024; Fundira & Mbohwa, 2025; Peruchini et al., 2024).

4.3 AI Adoption and Technological Readiness at Lloyds

4.3.1 Findings

The evidence indicates that Lloyds Banking Group has moved beyond isolated AI experimentation towards building a broader technological foundation for AI deployment. Lloyds reports that approximately 50% of its applications are now cloud-based, data centres have been reduced by 40%, and around 9,000 technology and data specialists have been recruited since 2021. Its 2025 Annual Report nevertheless identifies continued legacy-application decommissioning and cloud migration as priorities, indicating that technological modernisation remains incomplete (Lloyds Bank, 2026b; Lloyds Banking Group, 2026a).

Machine-learning capability has been strengthened through Google Cloud's Vertex AI. Lloyds migrated its ML platform to Vertex AI in 2024, providing access to more than 300 data scientists and AI developers. Google reports that 15 modelling systems containing hundreds of models were migrated, more than 80 ML experiments were initiated and over 18 generative-AI systems entered production. However, these outcomes originate from a technology-provider case study and therefore require cautious interpretation (Google Cloud, 2026b).

Organisational capability is developing alongside infrastructure. Lloyds' AI Centre of Excellence combines expertise in data science, ML engineering, behavioural science and AI ethics; by 2025 it contained more than 200 specialists (Lloyds Banking Group, 2025e). In 2026, the Group launched an AI Academy for all 67,000 colleagues; by June, more than 65,000 had completed responsible-AI training (Lloyds Banking Group, 2026d, 2026g). Lloyds also reported more than 50 GenAI use cases in 2025 and is expanding into agentic AI through its internally governed Envoy platform (Lloyds Banking Group, 2026c, 2026e).

4.3.2 Analysis and Discussion

These findings suggest that Lloyds is developing an organisation-wide **AI capability rather than merely purchasing AI tools**. Through the TOE framework, technological readiness is evidenced by cloud migration, central AI infrastructure, scalable ML platforms and reusable systems. Organisational readiness is reflected in specialist expertise, employee training, governance and investment in scaling use cases. Recent banking research similarly finds that successful digital transformation requires technological capability alongside strategy, organisational capability, innovation and governance-risk-compliance resources (Abdurrahman et al., 2024).

But it is not done. Legacy systems may be undergoing migration and this could impact integration and increase technological complexity. Using Google Cloud also introduces an environmental issue, since using external platforms can increase the dependency on the supplier, and experimentation would have a fast turnaround and scalability. In addition, studies from traditional banks indicate that digital transformation is influenced by regulatory, governance, cultural and competitive factors, such as fintech disruption (de Paula Pereira et al., 2024).

Hence, access to Vertex AI and cloud resources is only a part of being competitive – it's about how these elements can be embedded in repeatable and scalable processes across the organisation, driven by data, technology, skill and governance. This corroborates the finding in Chapter 2, that technological adoption is worthy of strategic consideration when supplemented with other organisational capabilities.

4.4 Operational Efficiency and Process Improvement

4.4.1 Findings

Lloyds' documentation shows the impact of AI on reducing processing times and efforts of staff on selected workflows. According to Google Cloud, after Lloyds have migrated their machine learning workloads to Vertex AI, the income verification stage of mortgage applications could be reduced from days to seconds, but this is supplier-provided evidence and is not independent. Lloyds' Athena knowledge assistant improves organisation-specific evidence by searching across some 13,000 internal articles, and cuts the average time spent by colleagues to search from 59 seconds to 20 seconds, a 66% reduction. Google Cloud estimated the savings in terms of the hours spent searching and waiting on the phone by customers with

Lloyds, with the result suggesting it could save around 4,000 hours on the telephone-banking teams alone (Google Cloud, 2026b; Lloyds Banking Group, 2025d).

The amount of deployment increased in 2025, as well. In 2026, there will be more than £100 million of value creation from AI at Lloyds, and in 2025, it was more than £50 million. Lloyds reported over 50 GenAI solutions and about £50 million in AI value creation, which is projected to be more than £100 million by 2026. An example of these is the HR assistant, who responds to about 90% of queries correctly, first time; or GitHub Copilot usage by about 5,000 engineers with 50% better conversion of legacy code, as cited by Lloyds. An additional instance, CRE AI, can analyze complicated commercial-real-estate tenancy timetables in just minutes, as opposed to the 75 hours needed in the past, permitting personnel to focus on work that demands judgment (Lloyds Banking Group, 2026c, 2026h).

4.4.2 Critical Analysis

These results offer some evidence of an efficiency effect but it is hard to explain. Lloyds will benefit from gross cost savings of approximately £700m in 2025 and £1.9bn in gross cost savings since 2021, as well as distribution efficiencies (customers served per distribution FTE) of approximately 45% since 2021. But the Group notes that these accomplishments are not solely attributable to the use of AI, but reflect “business as usual” management, strategic investments, simplification, digitisation and optimisation of the physical estate and legacy technology estate. In 2025, strategic investments, as well as business-growth costs, inflation and severance still led to a 3% rise in operating costs. As such, the £700m saving is not a true AI saving (Lloyds Banking Group, 2026a).

Nor is there consistent organisation-wide productivity across selected use cases. There is considerable improvement at the task level, with the best evidence coming from some tasks among the four elements: Athena, CRE AI, Copilot and the HR assistant. These benefits come at a cost and can include implementation and monitoring costs, data integration, employee training, and cybersecurity controls and governance. As well as the importance of quality, compliance and business value assessment in advancing GenAI from proof of concept to production, Lloyds' framework (PEGASUS) underscores that this is a responsibility shared between the sectors (Eric Ren, 2025).

4.4.3 Discussion Against the Literature

These findings are consistent with Chapter 2, which argued that digitalisation can reduce transaction costs and improve process efficiency, but that outcomes depend on organisational

redesign, data quality and integration. Bueno et al., (2024) similarly conclude that banking operational efficiency emerges from the interaction between digitisation, organisational adaptation and new operating models rather than technology in isolation. More recent evidence also identifies a positive association between fintech and digitalisation adoption and employee-based efficiency, although such associations do not demonstrate that AI alone causes productivity gains (Zheng and Ren, 2026).

Overall, AI appears capable of improving Lloyds' operational efficiency through faster processing, reduced search effort, workflow automation and employee support. However, efficiency evidence is not automatically evidence of sustainable competitive advantage. That stronger claim requires evidence that gains persist after implementation and governance costs, scale across the organisation, and remain difficult for competitors to imitate (Zheng & Ren, 2026).

4.5 Customer Experience and Service Innovation

4.5.1 Findings

Lloyds' evidence indicates that AI is being used both behind the customer interface and increasingly within customer-facing services. Athena, its large-scale generative-AI knowledge assistant, searches approximately 13,000 internal articles for customer-service colleagues. Lloyds reports that average search time fell from 59 seconds to around 20 seconds, with about 21,000 colleagues completing 2.1 million searches by July 2025. The tool therefore primarily improves the employee side of the customer journey by reducing information-search and waiting time rather than replacing human advisers (Lloyds Banking Group, 2025d).

More direct service innovation is represented by Lloyds' AI-powered financial assistant. Announced in November 2025 for rollout to more than 21 million mobile-app customers, it is designed to provide 24/7 personalised guidance on spending, budgeting, savings and investments, while permitting referral to expert human support. Lloyds states that the assistant combines curated bank data with its GenAI and agentic architecture to provide tailored responses. More than 50 GenAI solutions deployed in 2025 also included faster in-app search and quicker responses across customer operations. Public evidence is stronger on personalised insights than explicit AI-based customer segmentation; therefore, segmentation should not yet be treated as a demonstrated Lloyds outcome (Lloyds Banking Group, 2025f, 2026c).

4.5.2 Analysis

These applications potentially reduce customer effort through faster information retrieval, continuous availability and natural-language interaction. Athena may improve consistency because employees access a common knowledge base, while the financial assistant could differentiate Lloyds' mobile experience by combining conversational AI with customer-specific banking data. Nevertheless, some benefits remain prospective because the financial assistant was announced for phased deployment; evidence of sustained improvements in satisfaction, retention or customer loyalty is therefore still required (Lloyds Banking Group, 2025d, 2025b).

Significant limitations also remain. Lloyds' 2025 Consumer Digital Index found that 83% of respondents using AI for personal finance were concerned about privacy and security, 80% about inaccurate or outdated information, and 69% about inadequate personalisation. These results demonstrate that personalisation can create value while simultaneously increasing expectations regarding accuracy, security and relevance (Lloyds Banking Group, 2025g, 2025a). Human escalation is therefore important for complex or financially consequential queries. Furthermore, 24/7 digital availability does not automatically ensure accessibility for customers with weaker digital capabilities.

4.5.3 Connection with the Literature

These findings reinforce Chapter 2, which identified personalisation, conversational AI, service quality and trust as central determinants of AI-enabled customer experience. Alnaser et al., (2023) found that satisfaction with AI-enabled digital banking is influenced by perceived performance, problem-solving ability and communication quality, while Alagarsamy & Mehroliya, (2023) demonstrated that chatbot trust affects satisfaction, attitudes and continued-use intentions. Mariani et al., (2023) similarly identify trust, communication and value creation as key conversational-agent themes, while Peruchini et al., (2024) highlight chatbots, prediction models and recommendation systems as important AI–customer-experience applications.

Accordingly, Lloyds' AI services may improve speed, convenience and personalisation, but these capabilities are increasingly reproducible. Distinctive customer value is more likely to arise from combining AI with trusted proprietary data, accurate responses, seamless human support and responsible governance. AI therefore contributes to competitive advantage only where customer outcomes improve measurably and remain difficult for competitors to imitate.

4.6 Decision-Making, Fraud Detection and Risk Management

4.6.1 Findings

Results indicate that Lloyds Banking Group is increasingly using machine learning and agentic AI for risk-related decisions but not necessarily to replace human judgement. It has a Dynamic Risk Engine that leverages machine learning to identify fraud and financial crime and is said to have identified some £30m of previously unknown high value risk. Lloyds also reveals that over 800 AI models are now in use across the Group (Lloyds Bank, 2026a).

The evidence is particularly recent in the case of fraud prevention. In June 2026, Lloyds began rolling out an agentic-AI system, which enables various AI agents to verify identities and evaluate transactions for scam-risk during customer interactions. The system provides real-time fraud information to fellow fraud employees, who are still responsible and can overrule AI suggestions. However, not all of that fraud could be attributed to the new agentic-AI system as it's built on a wider fraud control environment, and over £1 billion was prevented in total across 2025 (Lloyds Banking Group, 2026b).

AI is also involved in the processing of mortgages. After being moved to Google Cloud infrastructure, a machine-learning algorithm is said to shorten the mortgage income verification process from days to seconds. Specifically, this represents an acceleration of an input-verification stage, and does not imply that AI makes solo decisions on granting mortgage loans or creditworthiness in and of itself (Lloyds Banking Group, 2025c). Not as specific as to dedicated outcomes for AI-driven anti-money laundering is public Lloyds evidence reviewed here. Thus, although the UK financial-sector data suggest various areas of finance in which companies are achieving AI-related benefits, the boost in the benefits of AML should not be solely attributed to Lloyds in the absence of more robust organisation-specific evidence (Bank of England, 2024b).

4.6.2 Critical Analysis

The big advantage is the rapidity with which a decision is made. Real time transaction analysis can notify frontline associates of suspicious activity while customers are interacting with them, and automated verification can streamline lending workflow. However, speed doesn't necessarily mean quality of decision-making. Very imbalanced data (fraud models) and evolving criminal behavior (likely to cause false positive leads to unnecessary fraud disruption, and false negative allows legitimate fraud to pass through).

This compromise is reflected in the peer-reviewed AML research. Bakry et al., (2024) determined that machine-learning methods can reduce the amount of false positive alerts, but that if the false positive alerts are reduced too much then it can also result in fewer genuine suspicious customers being alerted. Patterns derived from past transactions can become less useful as fraud techniques evolve, customer behaviour shifts and economic conditions change, which adds another layer of concern due to data drift.

Interpretability also plays a key role in credit and risk decisions. Even though financial institutions have to make explanations when there is a consequential decision, recent studies suggest that more complex predictive models can improve the accuracy of credit-scoring (Kyeong & Shin, 2022; Y. Liu et al., 2024). The research of explainable-AI also suggests that there need to be mechanisms in place that allow the output to be understood, challenged and validated, and not accepted based on the fact that it has a high predictive accuracy (Černevičienė & Kabašinskas, 2024).

There are also risks involved with generative and agentic AI models, including incorrect information generated and inappropriate recommendations. Human involvement is especially crucial in areas like fraud detection, credit scoring, or other financial decisions that rely on AI. PRA model-risk principles involve model identification, model-governance, independent model validation, and model-mitigants including for machine-learning models (Bank of England, 2023).

4.6.3 Discussion Against the Literature

The results confirm the conclusions reached in Chapter 2, which argued that AI can enhance fraud detection, credit-related processing and risk analysis, but there are tensions arising from false outcomes, opacity and accountability. This is the fundamental trade-off between the higher the automation, the more predictable the model, and the less risky, explainable and accountable the model. It appears Lloyds are using the AI as an augmentation and a facilitation tool to the human process of decision making, which may provide a more strategic, less automated approach to working. However, whether faster decisions can be as accurate as the more traditional approach, as explainable, as well-governed and as adaptable as fraud patterns change, and data conditions evolve, is a question of the competitive value.

4.7 Responsible AI Governance, Regulation and Customer Trust

4.7.1 Lloyds Responsible-AI Governance

Lloyds presents responsible AI as an embedded control capability rather than a separate compliance exercise. Its seven AI Ethics Principles cover trust, people-first development, inclusion, explainability, expertise, accountability and sustainability. These principles are operationalised through an AI Assurance Framework, the Data and AI Ethics Committee, risk-mitigation tools, central guardrails, auditing and policy updates. Lloyds also states that sensitive applications retain human-in-the-loop decision-making, while advanced models undergo fairness audits and explainability checks. Responsible-AI capability is reinforced through AI-assurance training, bias-in-data programmes and responsible-GenAI resources; by June 2026, more than 65,000 colleagues had completed responsible-AI training. The Responsible AI team was also expanded in April 2026 with specialists in governance, AI safety, security, fairness and adversarial robustness(Dhawan, 2025; Lloyds Bank, 2026a; Lloyds Banking Group, 2026f, 2026g).

4.7.2 Regulatory Environment

The regulatory position is significant because the FCA stated in June 2026 that it does not intend to create a separate AI rulebook; instead, existing frameworks, including the Consumer Duty, Senior Managers and Certification Regime (SM&CR), and governance and control expectations, apply to AI. Under the Consumer Duty, Lloyds must demonstrate good retail-customer outcomes and monitor actual customer experiences. SM&CR reinforces individual accountability, while the PRA's current SS1/23 requires model identification, governance, independent validation and model-risk mitigants, including for machine-learning models.

Data protection remains governed by the UK GDPR and Data Protection Act 2018, with changes introduced by the Data (Use and Access) Act 2026. Current ICO AI guidance continues to emphasise lawfulness, fairness, transparency, purpose limitation, data minimisation, accuracy, security and accountability, alongside data-protection impact assessment and risk-based controls.

4.7.3 Principal Risks

All three major risks are interdependent. When algorithmic bias leads to discrimination, historical data or proxy variables can lead to discriminatory results in lending and in fraud detection and product recommendations. Fundira & Mbohwa, (2025) however, draw attention to the persistent concerns of privacy, fairness, transparency and regulatory oversight within the

banking industry, while opaque financial models can also lead to issues with the explainability and trust, as discussed by Černevičienė & Kabašinskas, (2024). Here is another study on credit-scoring models, published back in 2026, which indicates that the fairness-aware models can find a balance between the predictive accuracy and nondiscrimination, which can be an iterative process rather than one-time testing (Giang Thi Thu et al., 2026).

Dependency on external materials. In the case of the Bank of England/FCA survey, one-third of the use cases were implemented by third parties, and there is a concentration of cloud, model and data providers, which leads to operational-resilience and supplier risks. Cyber security was cited as the largest potential systemic risk of using AI, and critical third-party dependency is likely to increase as a risk in the future (Bank of England, 2024b).

4.7.4 Critical Discussion

While Lloyds' governance statements are large, they are largely self-reported. Committees, training and frameworks are not necessarily indicators of a persistent effort to prevent biased, inaccurate and insecure outcomes. This is even more pertinent in the context of the next stage of developments with Lloyds' autonomous AI agents, when the implications of weaker controls are magnified. That is therefore where regulators are looking: at the outcomes for their customers, decisions that are understandable, ownership that is to account for, and meaningful human intervention and independent model validation (Bank of England, 2023; Lloyds Banking Group, 2026e; Smith, 2026).

It must be viewed, therefore, as governance is more than a compliance burden. If Lloyds can do that better than other organisations, then governance is another organisational capability that can help customers to trust and run in a safer manner on their systems, as part of their scaling. It does not, however, necessarily result in sustainable competitive advantage unless these controls result in tangible improvements in customer outcomes and resilience, and not just as a formal assurance. This is related to what was mentioned in Chapter 2 that governance and customer confidence are factors that can either strengthen or weaken the AI-based edge.

4.8 AI and Sustainable Competitive Advantage

4.8.1 Sources of Competitive Advantage

Based on the evidence, it is clear AI is being used to benefit Lloyds Banking Group on several fronts. Currently, there are around 50 live large-scale use cases with GenAI valued at around £50m for 2025 and incremental value of more than £100m in 2026, Lloyds says. The Group also boasts a c.45% uplift in the number of customers served per distribution employee since

2021, four million searches per month using LLM technologies, over 800 AI Models in production and £30 million of previously unidentified high-value fraud risk identified by its Dynamic Risk Engine. While these findings indicate that AI can have various positive impacts, including efficiency, service speed, personalisation, risk detection and employee productivity, many are self-reported and potential causal attribution of AI (Lloyds Bank, 2026a; Lloyds Banking Group, 2026a).

The field of competitiveness is not reduced to price reduction. AI can be used to distinguish customer journeys, accelerate response times, ensure fraud prevention and make data-driven decisions and free up time for employees to dedicate to more value-added activities. AI capability can also enhance organisational performance, though recent empirical work has found that complementary digital capabilities and business orientation are also important for translating AI capability into performance benefits, with one area being quicker decision making (Neiroukh et al., 2025). Krakowski et al., (2023) also show that the impact of AI on performance is not guaranteed to be lasting – and sometimes the complementarities of humans and AI are even unique. Organisational learning, employee expertise and embedding AI in frontline, engineering and risk processes could thus be of greater importance for Lloyds than standalone applications.

There has not yet been a study that has found an AI influence on customer retention or customer loyalty. Lloyds connects the investments in digital and AI with digital transformation's common factors of personalisation, cost to serve and greater operating leverage. It is, therefore, important to consider AI as one component of Lloyds' competitive system rather than as a stand-alone source of competitive advantage (Lloyds Banking Group, 2026a).

4.8.2 Sustainability of the Advantage

From the RBV perspective, Lloyds' resources appear to be valuable, albeit somewhat scarce and difficult to replicate, through its use of AI. Commercial cloud infrastructure, foundation models, and coding assistants and platforms such as Vertex AI can be used by competing institutions. This reduces imitation barriers, consistent with Krakowski et al., (2023) finding that abundant AI resources can substitute existing capabilities without necessarily generating persistent advantage. Lloyds' stronger potential lies in combining technology with organisation-specific assets: accumulated customer and transaction data, relationships across its 28-million-customer franchise, banking knowledge, employee expertise, integrated

routines, risk controls and the capability to deploy AI at scale (Lloyds Bank, 2026a; Lloyds Banking Group, 2026c).

The **organised** dimension of the RBV is equally important. Lloyds has embedded AI across customer interactions, customer operations, frontline support, colleague assistance and engineering, while continuing to modernise legacy infrastructure and expand technology capability. Its annual report records approximately 9,000 technology and data hires since 2021 and continued investment in GenAI foundations (Lloyds Banking Group, 2026a). Peer-reviewed banking research similarly finds that traditional banks require dynamic capabilities to realign organisational structures, governance and innovation processes as digital disruption develops (de Paula Pereira et al., 2024). Sustainability therefore depends on whether Lloyds can repeatedly renew and recombine its AI-related resources faster and more effectively than rivals, rather than whether it currently possesses superior technology.

4.8.3 Threats to Sustainability

Several factors may weaken this advantage. Lloyds describes competition from high-street banks, building societies, neobanks and fintechs as intense. Caragea et al., (2024) find that fintech start-up competition stimulates innovation within established financial institutions, suggesting that competitors can accelerate technological responses rather than remain passive. Moreover, European evidence shows that neobanks do not necessarily outperform traditional banks financially, but their digital models create continuing competitive pressure and potential economies of scale and scope (Citterio et al., 2024).

Another threat is technology commoditisation, other players can emulate the models and platforms easily. That was discovered by the Bank of England and FCA, which reported that 1/3 of all the AI use cases in the financial sector were supplied by third parties, with the top three cloud providers making up 73% of the named providers. They also saw cybersecurity, data privacy, data quality, model complexity, and third-party dependency and a lack of skills in AI as key risks or constraints (Bank of England, 2024b). So the strategic importance of responsible governance is obvious: if control is low, there could be loss of trust and loss of efficiency gains, if control is high, there could be more safe scaling. Banking research also reveals that these privacy, fairness, transparency and customer trust are important elements of responsible use of AI (Fundira & Mbohwa, 2025).

Overall, AI is contributing where it can in terms of efficiency, speed, personalisation, risk and organisational learning, but its own is not likely to be a sustainable competitive advantage.

What is more likely is that, durability comes from Lloyds' capability to integrate its proprietary data, scale, trusted customer relationship, skilled employees, integrated routines and proper governance into a capability that is continually renewed, and that rivals do not have the same ability to duplicate.

4.9 Comparative AI Adoption by Other UK Banks

AI adoption is no longer distinctive to Lloyds Banking Group; major UK banking competitors are also moving from experimentation towards scaled generative and agentic AI. This comparison is important because sustainable competitive advantage depends not simply on possessing AI, but on combining it with resources and capabilities that competitors cannot easily replicate (Krakowski et al., 2023).

4.9.1 NatWest Group

NatWest has emerged as one of Lloyds' closest AI competitors. In 2025 it invested £1.2 billion in technology, AI and simplification, while its digital assistant Cora handled 12.9 million retail-banking conversations. GenAI was expanded from four to 21 customer journeys, producing around a 20-percentage-point increase in queries resolved without human intervention. NatWest also gave approximately 60,000 employees access to AI tools and reported substantial productivity savings (NatWest Group, 2026a, 2026c). In 2026, it continued developing customer-facing agentic AI, including personalised financial assistance and fraud-support applications (NatWest Group, 2026b).

4.9.2 HSBC and Santander UK

HSBC is similarly scaling AI through a more global model. In June 2026, its partnership with Google Cloud was expected to enable more than 200 additional AI use cases over two years, initially concentrating on personalised wealth support, financial-crime management and frontline assistance. HSBC also appointed its first Chief AI Officer in April 2026, signalling stronger enterprise-level governance of AI adoption (HSBC, 2026a, 2026b).

Santander UK has followed a comparatively controlled approach. Its 2025 Annual Report confirms further deployment of machine-learning and generative-AI solutions to improve operational efficiency while strengthening model-risk governance, explainability and monitoring. It also indicated future expansion of global AI platforms and exploration of agentic AI for UK customers (Santander UK, n.d.).

4.9.3 Competitive Implications for Lloyds

Lloyds nevertheless demonstrates significant scale: approximately 50 live GenAI use cases generated about £50 million of value in 2025, with more than £100 million targeted for 2026 (LLOYDS, 2026; Lloyds Banking Group, 2026a). However, the comparison shows that **AI technology itself is becoming increasingly common across UK banking**. Research similarly indicates that digital transformation and AI performance depend on organisational readiness, human expertise, governance and complementary capabilities rather than technology acquisition alone (Abdurrahman et al., 2024). Fintech competition also encourages incumbent banks to accelerate technological innovation (Caragea et al., 2024). Consequently, Lloyds' sustainable advantage is more likely to depend on how effectively it combines proprietary data, customer scale, workforce capability, responsible governance and rapid AI deployment than on AI adoption itself.

4.10 Integrated Theoretical Discussion

4.10.1 Resource-Based View

But there's also more than a few issues with the Resource Based View, since AI technology is accessible to all banks, both cloud platforms, and foundation models and commercial productivity tools are available. What's a stronger source of heterogeneity is the resource bundle associated to those technologies. Lloyds combines a 28m customer franchise, large numbers of transactions, a single AI platform, more than 800 models in production, AI skills and the formal processes and controls of responsible-AI. It also highlights some 9,000 technology and data hires since 2021. These resources can be used to personalise, detect fraud, make processes more efficient and accelerate decisions but not all are plausibly rare or hard to mimic (Lloyds Bank, 2026a; Lloyds Banking Group, 2026a).

This division is in line with Krakowski et al., (2023), who demonstrate that the enormous potential of AI can reduce traditional ways of gaining an advantage, and unique human–AI complementarities can persist. For Lloyds, therefore, accumulated banking knowledge, proprietary customer data, customer relationships, employee judgement, governance routines and the capacity to integrate AI across customer, risk and engineering functions are strategically more significant than access to a specific model. The “organised” RBV condition is increasingly visible through Lloyds' central AI infrastructure, AI Centre of Excellence and Envoy platform for governed AI-agent development. Nevertheless, these company-reported capabilities demonstrate organisational investment rather than independently proving sustainable advantage (Lloyds Bank, 2026a; Lloyds Banking Group, 2026e).

4.10.2 Dynamic Capabilities Theory

Dynamic Capabilities Theory explains whether Lloyds can continuously renew this resource bundle. Evidence of **sensing** includes its progression from machine learning and GenAI towards agentic AI, personalised financial assistance and real-time fraud applications. **Seizing** is demonstrated by deploying more than 50 GenAI solutions in 2025, targeting over £100 million of incremental AI value in 2026 and expanding specialist AI roles. **Transforming** is reflected in cloud migration, legacy-system rationalisation, workflow redesign, governance development and the AI Academy, through which more than 65,000 colleagues had completed responsible-AI training by June 2026 (Lloyds Banking Group, 2026c, 2026g, 2026a).

These findings align with de Paula Pereira et al., (2024), who argue that traditional banks require dynamic capabilities to realign resources, governance and organisational structures in response to digital disruption. Simón, Simón et al., (2024) similarly demonstrate that organisational value from AI depends upon productive human–AI interaction rather than technological deployment alone. Lloyds' advantage is therefore more likely to persist if it repeatedly learns from AI applications, reallocates resources and modifies governance rather than depending on technologies that competitors can rapidly acquire.

4.10.3 Technology–Organisation–Environment Framework

The TOE framework is used to describe the conditions which either enable or constrain this transformation. Legacy-system migration is not complete; technologically, Lloyds has scalable AI infrastructure and is in the process of cloud modernisation. Organisational readiness is strengthened through specialist recruitment, commitment to leadership investment, employee AI literacy and formal governance. From an environmental perspective, competition from digital banks and fintechs impacts both the speed of adoption and risk (Lloyds Banking Group, 2026a). Abdurrahman et al., (2024) identified technological, strategic, organisational, ecosystem and governance-risk-compliance capabilities as their identified influencing factors on banking digital transformation and innovation.

4.10.4 Overall Theoretical Interpretation

All these views together back up the conceptual framework that has been established in Chapter 2. TOE is used to think about the possibility for adoption and scaling; RBV to think about the possibility of the AI technology, data, people, relationships and governance becoming distinctive competitive value; and Dynamic Capabilities Theory to think about possibility of renewal of the AI resource bundle when technology and markets change. This integration

resonates with Weritz et al., (2025), who, from their empirical results, proposed that complementary strategic capabilities can be crucial factors in digital-transformation success and firm performance.

Therefore, the resulting interpretation is a tentative one. Lloyds has a lot of AI resources and organisational preparation, but the import of AI is not sufficient in itself to render a business sustainably competitive. Instead, the evidence suggests that sustainability involves a set of mixings that are made up of scalable technology, organisation-specific data, employee expertise, customer trust, organisation learning, and responsible governance, and that these mixings must be renewed faster and more effectively than those of competitors (de Paula Pereira et al., 2024; Krakowski et al., 2023).

4.11 Chapter Conclusion

In this chapter, we explored how AI is being used to improve operational, customer-service, decision making and risk-management processes at Lloyds Banking Group. Return on investment is clear through quicker processing times, workflow automation, knowledge utilization, personalization, fraud detection and improved employee productivity. But AI use doesn't make for sustainable competitive advantage. There are a number of technologies that competing banks can still access, such as cloud platforms, foundation models and generative-AI tools.

The analysis reveals that the expertise of Lloyds' staff, customer relationships, processes, proprietary knowledge and responsible governance, combined with AI, is where they have their competitive edge. Governance, regulatory compliance, cybersecurity, explainability and customer trust are therefore not a side issue, but must be met in order to ensure that AI-driven value is sustained.

There are two ways to reach a conclusion about whether Lloyds' AI resource bundle is valuable and difficult to imitate, the Resource Based View and the Dynamic Capabilities Theory demonstrates the importance of continuous sensing, seizing and transforming of technological opportunities. The TOE framework gives perspective on factors that affect the adoption and scaling of technology, in terms of technological, organisational and environmental aspects. In summary, sustainable advantage will rely on whether or not Lloyds will be able to renew and combine these capabilities more effectively than competitors. Conclusions for each research question and overall conclusions and recommendations will be presented in chapter 5.

5 Chapter 5: Conclusions and Recommendations

This chapter concludes the dissertation by synthesising the findings presented and discussed in Chapter 4. It evaluates the extent to which artificial intelligence contributes to sustainable competitive advantage at Lloyds Banking Group and provides direct answers to the five research questions established in Chapter 1. The chapter also presents practical recommendations for Lloyds Banking Group, considers the theoretical implications of the findings, identifies the principal limitations of the research, and proposes directions for future research. It therefore brings together the dissertation's empirical, theoretical and strategic conclusions in a coherent final assessment.

5.1 Summary of Main Findings

Chapter 4 found that AI adoption has become mainstream in UK financial services: 75% of surveyed firms were already using AI in 2024, while large UK banks reported a median of 39 use cases. This suggests that competitive differentiation increasingly depends on **how effectively AI is integrated and scaled**, rather than adoption alone (Bank of England, 2024b). Lloyds demonstrates substantial technological readiness, reporting more than 800 AI models in production, 57 new GenAI use cases in 2025, approximately £50 million of AI-generated value in 2025 and a target exceeding £100 million in 2026 (LLOYDS, 2026; Lloyds Bank, 2026a).

The findings indicate that AI contributes to operational efficiency through automation, faster knowledge retrieval, engineering support and customer operations, while also supporting personalisation, service innovation, fraud detection and risk management. However, these outcomes cannot be attributed to AI alone because cloud migration, process redesign and broader digital investment also contribute. This aligns with Gyau et al., (2024), who find that AI innovation can improve banking performance but that outcomes depend partly on complementary ICT capabilities.

Responsible-AI governance also emerged as strategically important because privacy, explainability, fairness, cybersecurity and third-party dependency can weaken trust and regulatory acceptability. Comparisons with NatWest, HSBC and Santander UK show that GenAI assistants, customer-service applications and financial-crime tools are increasingly common across major banks (HSBC, 2026a; NatWest Group, 2026d; Santander UK, n.d.). Consequently, Lloyds' sustainable competitive advantage is more likely to depend on combining AI with proprietary data, customer scale, skilled employees, organisational routines,

responsible governance and continuous adaptation than on AI technology itself (Abdurrahman et al., 2024; Krakowski et al., 2023).

5.2 Conclusions in Relation to the Research Questions

5.2.1 Research Question 1: AI Adoption and Digital Transformation in UK Banking

The findings indicate that AI adoption in UK banking has moved from experimentation to mainstream strategic deployment. The Bank of England and FCA reported that 75% of surveyed financial-services firms were already using AI in 2024, with large UK banks reporting a median of 39 use cases (Bank of England, 2024b). AI is increasingly embedded in process optimisation, fraud and cybersecurity, customer service, analytics and decision support, while generative and agentic AI are extending its role in retail banking. Research similarly identifies AI as a driver of financial-sector transformation through improved information processing and service delivery (Aldasoro et al., 2025). Therefore, AI now functions as an enabling capability within broader digital transformation rather than as a standalone technology.

5.2.2 Research Question 2: AI within Lloyds Banking Group's Digital-Transformation Strategy

The findings show that Lloyds uses AI as an integrated component of its wider transformation of **people, processes, technology and data**, rather than as a standalone technology initiative. The Group has moved 50% of applications to cloud infrastructure and continues to modernise legacy systems while expanding AI capabilities (Lloyds Bank, 2026b). In 2025, Lloyds deployed 57 new GenAI use cases across customer interactions, operations, frontline support and engineering, generating approximately £50 million in reported value, with more than £100 million targeted for 2026 (Lloyds Bank, 2026a). This supports research showing that successful banking digital transformation depends on integrating technological capability with organisational, strategic and governance capabilities (Abdurrahman et al., 2024). Thus, AI functions as an enabling capability supporting Lloyds' broader digital transformation.

5.2.3 Research Question 3: Contribution to Efficiency, Customer Experience, Innovation and Decision-Making

The findings show that AI contributes to Lloyds across several interconnected areas. Operationally, Athena has reduced colleague knowledge-search time by approximately 66%, while AI-assisted engineering and internal support tools have accelerated routine processes (LLOYDS, 2026; Lloyds Banking Group, 2025d). AI also enhances customer experience through faster query resolution, personalised digital interactions and increasingly intelligent in-

app services, consistent with research linking AI to improved customer experience (Peruchini et al., 2024). Service innovation is progressing towards generative and agentic AI, while decision-making and risk management are supported by AI-based fraud detection and real-time investigative assistance (Lloyds Banking Group, 2026b). These outcomes support evidence that digital technologies can improve banking efficiency (Bueno et al., 2024). However, Lloyds' reported benefits should be interpreted alongside wider cloud, process and organisational transformation.

5.2.4 Research Question 4: Governance, Regulatory and Organisational Constraints

The findings indicate that Lloyds' ability to create value from AI is constrained by governance, regulatory and organisational risks. The Bank of England and FCA identify data privacy, data quality, cybersecurity, model complexity and third-party dependency as major risks, while skills shortages and explainability remain important constraints (Bank of England, 2024b). Lloyds has responded with seven AI Ethics Principles, an AI Assurance Framework and a Data & AI Ethics Committee, but these remain company-reported controls rather than independent proof of effectiveness (Lloyds Bank, 2026a; Lloyds Banking Group, 2026f). Recent research likewise highlights algorithmic bias, fairness, transparency and customer trust as persistent banking concerns (Fundira & Mbohwa, 2025). Consequently, AI value depends on robust governance, skilled oversight, regulatory compliance and continuous monitoring; failures could undermine trust, increase compliance costs and weaken competitive benefits.

5.2.5 Research Question 5: AI and Sustainable Competitive Advantage at Lloyds Banking Group

The findings indicate that AI can provide Lloyds with sustainable competitive advantage **to a significant but conditional extent**. AI technology itself is increasingly accessible to competing banks and therefore is unlikely to be sufficiently rare or inimitable to sustain advantage independently (Krakowski et al., 2023). Lloyds' stronger potential advantage lies in combining AI with its proprietary customer data, digital scale, skilled workforce, established customer relationships, organisational routines and responsible-AI governance. Lloyds reported approximately £50 million of GenAI value in 2025 and targets more than £100 million in 2026, demonstrating increasing ability to scale AI commercially (LLOYDS, 2026; Lloyds Banking Group, 2026a). However, research confirms that banking performance depends on complementary technological, organisational, strategic and governance capabilities (Abdurrahman et al., 2024). Consequently, sustainability depends on Lloyds continuously renewing and integrating these capabilities rather than merely adopting AI.

5.3 Recommendations

5.3.1 Practical Recommendations for Lloyds Banking Group

Lloyds should prioritise converting its extensive proprietary customer and transactional data into a differentiated AI capability rather than competing primarily through commercially available models. Data quality, lineage, access controls and reusable internal data assets should therefore remain central to AI scaling. Research shows that AI generates stronger performance when technology is combined with human skills and complementary organisational resources (Mikalef & Gupta, 2021).

Second, Lloyds should scale successful GenAI and agentic-AI applications through its governed **Envoy** platform while retaining human oversight for lending, fraud, complaints and other high-impact decisions. Envoy already provides monitoring, reusable components and controlled deployment of AI agents (Lloyds Banking Group, 2026e). Human–AI collaboration should be designed around interoperability, trust and mutual knowledge development, which research identifies as important for capturing organisational value from AI (Simón et al., 2024).

Employee capability should also remain a strategic priority. Lloyds reported that more than 65,000 colleagues had completed responsible-AI training by June 2026; future training should become role-specific, particularly for managers, developers and risk professionals (Lloyds Banking Group, 2026g).

Responsible-AI governance should be strengthened through independent fairness testing, explainability assessments, human escalation and continuous post-deployment monitoring. Lloyds should also regularly assess cloud, model-provider and cybersecurity concentration risks rather than allowing AI scale to increase third-party dependency. Finally, AI performance should be measured through a balanced scorecard covering financial value, productivity, customer satisfaction, error rates, complaints, fairness, model incidents and risk outcomes—not cost savings alone.

5.3.2 Theoretical Implications and Recommendations

The findings support **RBV** by showing that sustainable advantage arises from combining AI with proprietary data, skills, organisational routines and governance rather than from AI technology alone (Mikalef & Gupta, 2021). **Dynamic Capabilities Theory** is reinforced because Lloyds must continually sense AI opportunities, seize them through investment and scaling, and transform organisational processes. **TOE** further explains why technological readiness must interact with organisational capability and environmental factors such as

regulation, competition and external providers. Banking research confirms that technological, organisational and governance capabilities jointly influence digital transformation and innovation (Abdurrahman et al., 2024).

5.4 Limitations of the Research

This study has several limitations. First, it relies entirely on publicly available secondary evidence. Although secondary qualitative research can broaden access to existing data, it also depends on the quality, context and completeness of material produced for purposes other than the present study (Cheong et al., 2023). Lloyds' annual reports, webpages and press releases may emphasise successful AI initiatives, creating potential self-reporting and promotional bias. The absence of interviews or surveys also means that employee and customer experiences cannot be independently tested.

Second, the single-case focus on Lloyds Banking Group provides organisational depth but does not permit statistical generalisation to all UK banks. Third, AI in financial services is evolving rapidly; recent reviews show continuing expansion of applications across banking operations, meaning some evidence may become outdated quickly (Singh et al., 2025). Finally, it is difficult to isolate AI-driven outcomes from Lloyds' wider cloud migration, process redesign, workforce changes and digital investment. Consequently, reported improvements should be interpreted as associated with broader transformation rather than proven causal effects of AI alone.

5.5 Recommendations for Future Research

Future research should extend this study through primary data collection involving Lloyds employees, managers and customers to examine how AI is experienced in practice and whether reported benefits are independently perceived. Comparative multi-bank studies involving Lloyds, NatWest, HSBC and Santander UK could assess whether AI capabilities generate genuinely distinctive competitive outcomes. Longitudinal research would also be valuable because AI adoption, regulation and organisational capabilities are changing rapidly. Future studies could quantitatively test relationships between AI investment and outcomes such as cost efficiency, customer satisfaction, productivity, fraud reduction and profitability. Greater attention should also be given to employee capability, customer trust and human–AI collaboration. Finally, further research is needed on agentic AI and responsible-AI governance, particularly regarding explainability, accountability, fairness, cybersecurity, third-party

dependency and the long-term strategic implications of increasingly autonomous AI systems in banking.

5.6 Chapter Conclusion

This dissertation concludes that artificial intelligence can contribute significantly to competitive advantage at Lloyds Banking Group through improved operational efficiency, customer experience, service innovation, decision-making and risk management. However, AI technology alone is unlikely to create sustainable advantage because similar tools are increasingly available across the UK banking sector. The sustainability of Lloyds' advantage therefore depends on how effectively AI is combined with proprietary data, skilled employees, organisational routines, technological infrastructure, customer relationships and responsible governance. Strong regulatory compliance, explainability, cybersecurity, human oversight and continuous capability development are also essential. Overall, AI should be viewed as a strategic enabling capability whose long-term value depends on complementary organisational resources and the bank's ability to continually adapt and renew them.

6 References:

- Abdurrahman, A., Gustomo, A., & Prasetyo, E. A. (2024). Impact of dynamic capabilities on digital transformation and innovation to improve banking performance: A TOE framework study. *Journal of Open Innovation: Technology, Market, and Complexity*, 10(1), 100215.
- Ahmad, M., & Wilkins, S. (2025). Purposive sampling in qualitative research: A framework for the entire journey. *Quality & Quantity*, 59(2), 1461–1479.
- Alagarsamy, S., & Mehroliya, S. (2023). Exploring chatbot trust: Antecedents and behavioural outcomes. *Heliyon*, 9(5).
- Aldasoro, I., Gambacorta, L., Korinek, A., Shreeti, V., & Stein, M. (2025). Intelligent financial system: How AI is transforming finance. *Journal of Financial Stability*, 81, 101472. <https://doi.org/https://doi.org/10.1016/j.jfs.2025.101472>
- Alnaser, F. M., Rahi, S., Alghizzawi, M., & Ngah, A. H. (2023). Does artificial intelligence (AI) boost digital banking user satisfaction? Integration of expectation confirmation model and antecedents of artificial intelligence enabled digital banking. *Heliyon*, 9(8).
- Annamalah, S., Aravindan, K. L., Ahmed, S., & Sentosa, I. (2025). Exploring the relevance and rigour of case study research in business: a contemporary perspective. *Journal of Sustainability Research*, 7(2).
- Baffour Gyau, E., Appiah, M., Gyamfi, B. A., Achie, T., & Naeem, M. A. (2024). Transforming banking: Examining the role of AI technology innovation in boosting banks financial performance. *International Review of Financial Analysis*, 96, 103700. <https://doi.org/https://doi.org/10.1016/j.irfa.2024.103700>
- Bakry, A. N., Alsharkawy, A. S., Farag, M. S., & Raslan, K. R. (2024). Automatic suppression of false positive alerts in anti-money laundering systems using machine learning: AN Bakry et al. *The Journal of Supercomputing*, 80(5), 6264–6284.
- Bank of England. (2023). *SS1/23 – Model risk management principles for banks*. <https://www.bankofengland.co.uk/prudential-regulation/publication/2023/may/model-risk-management-principles-for-banks-ss>
- Bank of England. (2024a). *Artificial intelligence in UK financial services - 2024*. <https://www.bankofengland.co.uk/report/2024/artificial-intelligence-in-uk-financial->

services-2024?

- Bank of England. (2024b). *Artificial intelligence in UK financial services - 2024*.
<https://www.bankofengland.co.uk/report/2024/artificial-intelligence-in-uk-financial-services-2024>
- Bank of England. (2026). *Model risk management principles for banks*.
<https://www.bankofengland.co.uk/-/media/boe/files/prudential-regulation/supervisory-statement/2026/liaf0126app5.pdf>
- Bueno, L. A., Sigahi, T. F. A. C., Rampasso, I. S., Leal Filho, W., & Anholon, R. (2024). Impacts of digitization on operational efficiency in the banking sector: Thematic analysis and research agenda proposal. *International Journal of Information Management Data Insights*, 4(1), 100230.
- Byrne, D. (2022). A worked example of Braun and Clarke's approach to reflexive thematic analysis. *Quality & Quantity*, 56(3), 1391–1412.
- Caragea, D., Cojoianu, T., Dobri, M., Hoepner, A., Peia, O., & Romelli, D. (2024). Competition and innovation in the financial sector: Evidence from the rise of FinTech start-ups. *Journal of Financial Services Research*, 65(1), 103–140.
- Černevičienė, J., & Kabašinskas, A. (2024). Explainable artificial intelligence (XAI) in finance: a systematic literature review. *Artificial Intelligence Review*, 57(8), 216.
<https://doi.org/10.1007/s10462-024-10854-8>
- Chen, D., Esperança, J. P., & Wang, S. (2022). The impact of artificial intelligence on firm performance: an application of the resource-based view to e-commerce firms. *Frontiers in Psychology*, 13, 884830.
- Cheong, H., Lyons, A., Houghton, R., & Majumdar, A. (2023). Secondary qualitative research methodology using online data within the context of social sciences. *International Journal of Qualitative Methods*, 22, 16094069231180160.
- Citterio, A., Marques, B. P., & Tanda, A. (2024). The early days of neobanks in Europe: Identification, performance, and riskiness. *Journal of Financial Services Research*, 1–47.
- de Paula Pereira, G., de Medeiros, J. F., Kolling, C., Ribeiro, J. L. D., Morea, D., & Iazzolino, G. (2024). Using dynamic capabilities to cope with digital transformation and boost innovation in traditional banks. *Business Horizons*, 67(4), 317–330.

<https://doi.org/https://doi.org/10.1016/j.bushor.2024.03.006>

- Dhawan, R. (2025). *Responsible artificial intelligence: building trust and value*. <https://www.lloydsbankinggroup.com/insights/responsible-artificial-intelligence-building-trust-and-value.html>
- Eric Ren. (2025). *PEGASUS: evaluation driven development for GenAI*. <https://www.lloydsbankinggroup.com/insights/pegasus-evaluation-driven-development-for-genai.html>
- Fares, O. H., Butt, I., & Lee, S. H. M. (2022). Utilization of artificial intelligence in the banking sector: a systematic literature review. *Journal of Financial Services Marketing*, 1.
- Fares, O. H., Butt, I., & Lee, S. H. M. (2023). Utilization of artificial intelligence in the banking sector: a systematic literature review. *Journal of Financial Services Marketing*, 28(4), 835–852.
- FCA. (2026). *FCA publishes landmark review into impact of AI on retail financial services*. <https://www.fca.org.uk/news/press-releases/fca-publishes-landmark-review-impact-ai-retail-financial-services>
- Fife, S. T., & Gossner, J. D. (2024). Deductive qualitative analysis: Evaluating, expanding, and refining theory. *International Journal of Qualitative Methods*, 23, 16094069241244856.
- Fundira, M., & Mbohwa, C. (2025). AI ethics in banking services: a systematic and bibliometric review of regulatory and consumer perspectives. *Discover Artificial Intelligence*, 5(1), 319. <https://doi.org/10.1007/s44163-025-00432-4>
- Giang Thi Thu, H., Doan, T. V., Ban, H.-B., & Le Quy, T. (2026). An experimental study on fairness-aware machine learning for credit scoring problems. *Digital Finance*, 8(3), 35. <https://doi.org/10.1007/s42521-026-00202-6>
- Google Cloud. (2026a). *Lloyds Banking Group: Improving customer experience with machine learning*. <https://cloud.google.com/customers/lloydsbankinggroup>
- Google Cloud. (2026b). *Lloyds Banking Group: Improving customer experience with machine learning*. <https://cloud.google.com/customers/lloydsbankinggroup>
- Gyau, E. B., Appiah, M., Gyamfi, B. A., Achie, T., & Naeem, M. A. (2024). Transforming banking: Examining the role of AI technology innovation in boosting banks financial

- performance. *International Review of Financial Analysis*, 96, 103700.
- He, Z., Huang, J., & Zhou, J. (2020). Open banking: Credit market competition when borrowers own the data. *Available at SSRN 3730378*.
- HSBC. (2026a). *HSBC and Google Cloud announce transformative AI banking partnership*. <https://www.hsbc.com/news-and-views/news/media-releases/2026/hsbc-and-google-cloud-announce-transformative-ai-banking-partnership>
- HSBC. (2026b). *HSBC ANNOUNCES DAVID RICE AS ITS FIRST CHIEF AI OFFICER*. <https://www.hsbc.com/-/files/hsbc/media/media-release/2026/260323-david-rice-announced-as-chief-ai-officer.pdf>
- Hurlin, C., Pérignon, C., & Saurin, S. (2026). The fairness of credit scoring models. *Management Science*, 72(1), 406–425.
- ICO UK. (2025). *A guide to the data protection principles*. <https://ico.org.uk/for-organisations/uk-gdpr-guidance-and-resources/data-protection-principles/a-guide-to-the-data-protection-principles/>
- Information Commissioner's Office. (2026). *Guidance on AI and data protection*. <https://ico.org.uk/for-organisations/uk-gdpr-guidance-and-resources/artificial-intelligence/guidance-on-ai-and-data-protection/>
- Janis, I. (2022). Strategies for establishing dependability between two qualitative intrinsic case studies: A reflexive thematic analysis. *Field Methods*, 34(3), 240–255.
- Jöhnk, J., Weißert, M., & Wyrski, K. (2021). Ready or Not, AI Comes—An Interview Study of Organizational AI Readiness Factors: J. Jöhnk et al.: Ready or Not, AI Comes: An Interview Study of Organizational AI Readiness Factors. *Business & Information Systems Engineering*, 63(1), 5–20.
- Kalyani, S., & Gupta, N. (2023). Is artificial intelligence and machine learning changing the ways of banking: a systematic literature review and meta analysis. *Discover Artificial Intelligence*, 3(1), 41. <https://doi.org/10.1007/s44163-023-00094-0>
- Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal*, 44(6), 1425–1452.
- Kyeong, S., & Shin, J. (2022). Two-stage credit scoring using Bayesian approach. *Journal of*

Big Data, 9(1), 106.

- Liu, Yang. (2022). Paradigmatic Compatibility Matters: A Critical Review of Qualitative-Quantitative Debate in Mixed Methods Research. *Sage Open*, 12(1), 21582440221079920. <https://doi.org/10.1177/21582440221079922>
- Liu, Y., Huang, F., Ma, L., Zeng, Q., & Shi, J. (2024). Credit scoring prediction leveraging interpretable ensemble learning. *Journal of Forecasting*, 43(2), 286–308. <https://doi.org/https://doi.org/10.1002/for.3033>
- LLOYDS. (2026). *Lloyds Banking Group expects over £100 million in value from next-generation AI in 2026*. <https://www.lloydsbankinggroup.com/media/press-releases/2026/lloyds-banking-group/ai-driven-benefits-2026.html>
- Lloyds Bank. (2026a). *Artificial Intelligence at Lloyds Banking Group*. <https://www.lloydsbankinggroup.com/who-we-are/group-overview/artificial-intelligence.html>
- Lloyds Bank. (2026b). *Transformation through technology*. <https://www.lloydsbankinggroup.com/who-we-are/group-overview/tech-and-transformation.html>
- Lloyds Bank plc. (2026). *Lloyds Bank plc Annual Report and Accounts 2025*. <https://www.lloydsbankinggroup.com/assets/pdfs/investors/financial-performance/lloyds-bank-plc/2025/q4/2025-lb-annual-report.pdf>
- Lloyds Banking Group. (2025a). *2025 Consumer Digital Index The generative AI edition*. <https://www.lloydsbankinggroup.com/media/consumer-digital-index.html>
- Lloyds Banking Group. (2025b). *Launching the UK's first agentic AI financial assistant*. <https://www.lloydsbankinggroup.com/insights/launching-the-uks-first-agentic-ai-financial-assistant.html>
- Lloyds Banking Group. (2025c). *Lloyds Banking Group accelerates AI innovation with Google Cloud*. <https://www.lloydsbankinggroup.com/media/press-releases/2025/lloyds-banking-group-2025/lloyds-banking-group-accelerates-ai-innovation-with-google-cloud.html>
- Lloyds Banking Group. (2025d). *Lloyds Banking Group accelerates digital transformation with AI-powered Athena*. <https://www.lloydsbankinggroup.com/media/press-releases/2025/lloyds-banking-group-2025/lloyds-accelerates-with-athena.html>

Lloyds Banking Group. (2025e). *Lloyds Banking Group appoints Head of Responsible AI*.
<https://www.lloydsbankinggroup.com/media/press-releases/2025/lloyds-banking-group-2025/lloyds-banking-group-bolsters-ai-capabilities-by-appointing-head.html>

Lloyds Banking Group. (2025f). *Lloyds Banking Group unveils UK's first multi-feature AI-powered financial assistant*. <https://www.lloydsbankinggroup.com/media/press-releases/2025/lloyds-banking-group-2025/lloyds-banking-group-unveils-uks-first-ai-powered-financial-assistant.html>

Lloyds Banking Group. (2025g). *Over 28 million adults now using AI tools to help manage their money*. <https://www.lloydsbankinggroup.com/media/press-releases/2025/lloyds-banking-group-2025/28m-adults-using-ai-to-manage-money.html>

Lloyds Banking Group. (2026a). *Annual report and accounts 2025*.
<https://www.lloydsbankinggroup.com/investors/annual-report.html>

Lloyds Banking Group. (2026b). *Lloyds Banking Group deploys agentic AI to strengthen real-time fraud protection*. <https://www.lloydsbankinggroup.com/media/press-releases/2026/lloyds-banking-group/lloyds-banking-group-deploys-agentic-ai-to-strengthen-real-time-.html>

Lloyds Banking Group. (2026c). *Lloyds Banking Group expects over £100 million in value from next-generation AI in 2026*.
<https://www.lloydsbankinggroup.com/assets/pdfs/media/press-releases/2026-press-releases/lloyds-banking-group/29.01.26-lbg-100m-value-next-gen-ai.pdf>

Lloyds Banking Group. (2026d). *Lloyds Banking Group launches AI Academy for 100 percent AI literacy by 2026*. <https://www.lloydsbankinggroup.com/media/press-releases/2026/lloyds/lloyds-banking-group-launches-ai-academy-for-100-percent-ai-lite.html>

Lloyds Banking Group. (2026e). *Lloyds Banking Group unveils Envoy - a new platform for building AI agents safely at scale*. <https://www.lloydsbankinggroup.com/media/press-releases/2026/lloyds-banking-group/lloyds-banking-group-unveils-envoy.html>

Lloyds Banking Group. (2026f). *Lloyds expands Responsible AI expertise as it advances its AI journey*. <https://www.lloydsbankinggroup.com/assets/pdfs/media/press-releases/2026-press-releases/lloyds/20.04.2026-responsible-ai-expertise.pdf>

- Lloyds Banking Group. (2026g). *Lloyds targets more than 1,000 new AI roles as it expands agentic AI capability*. <https://www.lloydsbankinggroup.com/media/press-releases/2026/lloyds-banking-group/1000-new-ai-roles.html>
- Lloyds Banking Group. (2026h). *UK businesses adopting AI see strong gains in profitability and productivity*. <https://www.lloydsbankinggroup.com/media/press-releases/2026/lloyds/impact-of-ai-adoption-on-business.html>
- Mariani, M. M., Hashemi, N., & Wirtz, J. (2023). Artificial intelligence empowered conversational agents: A systematic literature review and research agenda. *Journal of Business Research*, 161, 113838.
- Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3), 103434.
- Morgan, H. (2022). Conducting a qualitative document analysis. *The Qualitative Report*, 27(1), 64–77.
- Morgan, H. (2024). Using triangulation and crystallization to make qualitative studies trustworthy and rigorous. *The Qualitative Report*, 29(7), 1844–1856.
- NatWest Group. (2026a). *Annual results 2025*. <https://www.natwestgroup.com/news-and-insights/latest-stories/financial-reporting/2026/feb/annual-results-2025.html>
- NatWest Group. (2026b). *Being a trusted partner for tomorrow's banking through technology, data and AI*. <https://www.natwestgroup.com/news-and-insights/latest-stories/ai-and-data/2026/feb/being-a-trusted-partner-for-tomorrows-banking-through-technology.html?>
- NatWest Group. (2026c). *Succeeding with customers*. https://investors.natwestgroup.com/~/_media/Files/R/RBS-IR-V2/annual-reports/ar-2025/strategic-report-2025.pdf?
- NatWest Group. (2026d). *Succeeding with customers through tech, data and AI*. <https://www.natwestgroup.com/who-we-are/about-natwest-group/tech-data-and-AI.html>
- Neiroukh, S., Emeagwali, O. L., & Aljuhmani, H. Y. (2025). Artificial intelligence capability and organizational performance: unraveling the mediating mechanisms of decision-making processes. *Management Decision*, 63(10), 3501–3532.

- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., & Brennan, S. E. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *Bmj*, 372.
- Papathomas, A., & Konteos, G. (2023). Financial institutions digital transformation: the stages of the journey and business metrics to follow. *Journal of Financial Services Marketing*, 1.
- Patterson, E. W., Ball, K., Corkish, J., & Whittick, I. M. (2023). Do you see what I see? Enhancement of rigour in qualitative approaches to inquiry: a systematic review of evidence. *Qualitative Research Journal*, 23(2), 164–180.
- Peruchini, M., Da Silva, G. M., & Teixeira, J. M. (2024). Between artificial intelligence and customer experience: a literature review on the intersection. *Discover Artificial Intelligence*, 4(1), 4.
- Porfirio, J. A., Felício, J. A., & Carrilho, T. (2024). Factors affecting digital transformation in banking. *Journal of Business Research*, 171, 114393.
- Rethlefsen, M. L., Kirtley, S., Waffenschmidt, S., Ayala, A. P., Moher, D., Page, M. J., & Koffel, J. B. (2021). PRISMA-S: an extension to the PRISMA statement for reporting literature searches in systematic reviews. *Systematic Reviews*, 10(1), 39.
- Santander UK. (n.d.). *UNITED STATES SECURITIES AND EXCHANGE COMMISSION*. Retrieved August 20, 2026, from https://www.santander.co.uk/assets/s3fs-public/documents/Santander_UK_plc_2025_Form_20-F_with_Exhibits.pdf
- Simón, C., Revilla, E., & Sáenz, M. J. (2024). Integrating AI in organizations for value creation through Human-AI teaming: A dynamic-capabilities approach. *Journal of Business Research*, 182, 114783.
- Singh, R. K., Mishra, R., Kumar, S., & Bag, S. (2025). Applications of artificial intelligence for optimizing banking and financial operations: A systematic literature review and future research agenda. *Journal of Economic Surveys*, 39(5), 2284–2302.
- Smith, A. (2026). *AI in financial services: shaping our approach through industry engagement*. <https://www.fca.org.uk/news/blogs/ai-financial-services-approach>
- Sullivan, Y., & Wamba, S. F. (2024). Artificial intelligence and adaptive response to market changes: A strategy to enhance firm performance and innovation. *Journal of Business*

Research, 174, 114500.

Weritz, P., Braojos, J., Matute, J., & Benitez, J. (2025). Impact of strategic capabilities on digital transformation success and firm performance: theory and empirical evidence. *European Journal of Information Systems*, 34(3), 415–435.

Zheng, Y., & Ren, H. (2026). Does Fintech and Digitalization Adoption Impact Employee Performance Efficiency? Evidence from a Machine Learning Approach. *The Quarterly Journal of Finance*, 16(01), 2650002. <https://doi.org/10.1142/S2010139226500023>