The Role Of AI-Driven Financial Strategies in Enhancing Business Performance

Jewel Thomas

Sheffield Business School, Sheffield Hallam University

Abstract

This study aims to test the development of performance of Artificial Intelligence in the UK FTSE 250 companies and FinTech companies. Also, pay attention to performance gains and the kind of AI devices that have been integrated, and the role played in operational efficiency and cost optimisation. The literature indicates that successful implementation of AI involves more than the implementation of technology. It is based on leadership commitment, change management, digital culture, and cross-functional collaboration. The study uses a secondary data methodology, where it uses company reports, industry reports and financial records to assess how AI apps lead to measuring business results. The findings indicate that Experian made performance and financial gains in efficiency and profitability regarding AI-powered model development and risk management ventures. However, Currys PLC made cost reduction and profitability boosts through Action AI and dynamic pricing systems. Revolut and Monzo were using AI to detect fraud and help in cost-efficiency with customer services, whereas Virgin Money used conversational AI to optimise service delivery. Keller Group showed how AI can improve decision-making as a governance practice. The research advises enhancing the leadership structures in place, incorporating a digital culture and making it scalable with ethics in mind in the long run.

Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction

1.1 Research Background

AI-led financial plans are defined as solutions related to artificial intelligence technologies. This includes machine learning, predictive analytics, natural language processing, and robotic process automation to make better strategic decisions, manage risk systems, forecast, and increase business efficiency within financial processes (Rane et al., 2024). The above measures involve the deployment of sophisticated algorithms in combination with financial information to identify trends, anomalies, optimise resource distribution, and aid strategic planning (Siddiqui, 2025). The applications of AI in modern business settings include credit risk assessment, fraud detection, optimisation of portfolios, forecasting cash flows, and using AI to create automated trading systems.

The UK situation is not an exception since FinTech companies like Revoult, Zepz, and Starling Bank are more adaptive to AI to manage competitive position (Beauhurst, 2025). Also, other firms in the FTSE 250 list, like Softcat, have become more AI-adaptive in the quest to maintain a competitive position and promote efficiency (Microsoft, 2024). The AI is also applied to streamline corporate financial planning among other FTSE 250 companies, increase shareholder value by making investment-oriented data-driven decisions and enhance the level of compliance by automating regulatory reporting (Atkinson, 2025). Predictive analytics, as an example, would help forecast the changes occurring in the market to make prompt corrections to investment strategies and operational commitments. Risk modelling through the use of AI enables these companies to tackle possible losses by modelling several economic scenarios (Huang, 2024).

The example of AI in the FinTech industry focuses on products and maintaining customer experience. Chatbots and virtual assistants powered by AI optimise the customer service process, and personal financial advice helps in engagement and customer retention (Nwabekee, Okpeke, & Onalaja, 2025). The use of machine learning algorithms allows credit scoring of individuals faster and more accurately, increasing the penetration of financial services. Artificial intelligence-supported fraud detection systems identify real-time transaction patterns and thus negate risks of

financial crimes (Binhammad et al., 2024). Also, algorithmic trading systems use AI to analyse big data in the market in a flash, allowing high-frequency trading involving greater accuracy and profitability. AI-enabled insights can help save costs by automating financial workflows and thus enabling skilled personnel to work on key projects. Moreover, AI can assist regulatory compliance through timely, correct reporting and keeping (Şen, 2023). Such capabilities are interpreted in highly competitive markets in terms of more efficient operation, ability to withstand risks, and increased profits.

1.2 Problem Statement

In financial management, the fast-growing technology of artificial intelligence (AI) has now changed the way organisations plan, implement, and track their strategies. The use of AI-based financial strategies has been shown to have the potential to increase the efficiency of business operations, streamline decision-making, and expand the profit margin (Al-Surmi, Bashiri, & Koliousis, 2022). However, there is a lack of empirical insight into their real influence on the performance of any business, especially in the UK market. In the case of FTSE 250 and FinTech firms, AI applications are gaining hold in predictive analytics, risk modelling, fraud detection, and automatic reporting (Ferreira, 2024). Nonetheless, there is little research on how far these implementations transform into quantifiable and sustainable improvements in performance (Fulton et al., 2024). This is further aggravated by shifting regulatory conditions and market shifts in the case of UK-based organisations.

Organisations may struggle to determine whether the adoption of AI can be truly valuable and endure over time unless solid evidence-based information is accessible (Khan et al., 2025). This drawback in knowledge poses a strategic risk where the companies may under-utilise or over-invest in the AI without performance knowledge. Therefore, the current study will be viewed rather as an analytically urgent requirement. This is to examine the problem of the importance of AI-based financial solutions and their contribution to the enhancement of business performance. This is to provide the contextually relevant insights to UK FTSE 250 and FinTech firms to derive the contextually relevant insights to make sound decisions and gain a competitive edge on a longer-term basis.

1.3 Research Rationale

It has been observed that around 75 per cent of companies in the UK in the financial services industry have implemented AI technology (Bank of England, 2024). This is higher than the figures in the 2022 joint Bank of England and Financial Conduct Authority machine learning in the UK financial services, of 58% and 14 % respectively (Bank of England, 2024). The popularity of this practice highlights the applicability of investigating the growth of human resource performance approaches mediated by AI. The UK is the third-largest AI market around the globe, after the US and China. Valued at 92 billion USD in 2024 (Business.Gov.UK, 2025). The magnitude of this investment and growth is a pointer to how AI is now taking deep roots in the financial moves of both FTSE 250 companies and FinTech companies. It is important to realise that the prevalence and increase in the adoption of AI by the financial organisations of the UK present a compelling need to gain perspective. This can reflect on how these strategies are physically improving the business performance of the organisations.

1.4 Aim and Objectives

Aim

The academic aim of this project is to critically evaluate how AI contributes to enhanced business performance among UK-based FTSE 250 and FinTech firms, using secondary data.

Research objectives

- To examine how Artificial Intelligence (AI) enhances business performance in UK FTSE 250 and FinTech companies.
- To identify and categorise the types of AI tools currently used within FTSE 250 and FinTech companies in the UK.
- To evaluate the contribution of AI technologies to operational efficiency and cost optimisation in these organisations.
- To develop strategic recommendations for the effective integration of AI to maximise overall business performance.

1.5 Research Questions

RQ1: How do AI enhance business performance in UK FTSE 250 and FinTech companies?

RQ2: What types of AI tools are used in the FTSE 250 and FinTech companies?

RQ3: To explore the contribution of AI to operational efficiency and cost optimisation.

RQ4: To provide recommendations for effective AI integration to maximise business performance.

1.6 Research Significance

This study is relevant both to the world of science and the world of business. Research-wise, it can be utilised in developing the existing knowledge on how artificial intelligence and financial strategy can be used together. This is achieved by showing specific insights about its application in improving the performance of UK-based firms in the FTSE 250 and FinTech industries. It takes up an imperfection in empirical assessment where attention stretches outside the technical application of AI to discuss the outcome of strategies and performance. On an industry level, the research results will help decision-makers to realise the actual value of using AI and where to invest resources and optimise strategies regarding implementation. The research also provides empirical evidence on how AI is able to enhance efficiency, risk management, and profitability as determined through the analysis of credible case studies. The study offers policymakers and regulators pertinent information about AI when it comes to its operational and compliance considerations to aid in wise regulation. Overall, the study contributes toward deepening the view of AI as a possible game changer in developing competitive and sustainable financial strategies.

1.7 Methodological Outline

The research philosophy employed in this study is Interpretivism, which will focus on determining what organisations attach to the meanings of AI-driven financial strategies and how they affect business performance. The research strategy of induction will imply the formation of theories based on the data observed. The potential research design is a case study where six cases of FTSE-250 listed companies

(Experian, Currys PLC, Keller Group) and FinTech firms (Revolut, Monzo, and Virgin Mobile) allow deep analysis of the situation and give contextual information. The study will rely on a qualitative research design with a longitudinal time frame to include the presence of long-term results and to study changing trends. Some keywords are: AI-driven financial strategy, business performance, artificial intelligence in the field of finance, financial decision-making, FTSE companies, and organisational strategies. English-language inclusion criteria include articles published since 2020 that pertain to a case study. Secondary databases used include qualitative secondary sources of reliable platforms. This includes McKinsey & Company, Statista, BBC, and Forbes. The data is interpreted based on content analysis, maintaining the integrity of the case.

1.8 Research Structure

- Introduction
- Literature Review
- Research Methodology
- Results and Findings
- Discussion
- Conclusion and Recommendations

Figure 1.1: Research Structure

(Source: Self-developed)

This paper is divided into six chapters. The introduction presents the research background, problem statement, rationale, significance, and objectives, setting the stage to discuss AI-based financial strategies for business performance enhancement. The Literature Review is a critical assessment of the current body of academic and industry knowledge. Therefore, it provides a detection of gaps and theoretical positions that may be applied to AI in finance, especially to FTSE 250 and FinTech companies.

The philosophy, approach, strategy, choice, time, inclusion and exclusion criteria, data collection, data analysis methods, consideration of ethics, and limitations are all explained in the Research Methodology. The Results and Findings will show the analysed data of the chosen case studies and outline possible trends and patterns. These findings are discussed and reflected in the light of the literature, explaining what they also imply in theory and in practice. Lastly, a Conclusion is provided which summarises the important insights, answers the research objectives, and gives more practical recommendations.

Chapter 2: Literature Review

2.1 Chapter Introduction

Artificial Intelligence (AI) has become one of the revolutionary concepts in contemporary business, transforming the very concept of operational models, strategic decision-making, and market positioning (Kaggwa *et al.* 2024). Among the FTSE 250 and FinTech companies based in the UK, AI is being adopted to increase productivity and optimise costs, as well as to develop a differentiated customer experience. Whether it is machine learning algorithms to enhance forecasting within the market or natural language processing systems allowing new levels of customer service solutions, AI technologies are becoming an integral part of organisational performance (Mitta, 2022).

This chapter critically examines the existing literature on AI adoption, the classification of AI tools, and their impact on business performance. It also examines challenges, strategic integration approaches, and theoretical perspectives. This helps identify the gap in the prevailing literature sources.

2.2 AI Adoption in Business Organisations

The use of AI has become one of the most characteristic features of organisational transformation. Businesses across various sectors have recognised the potential of AI to drive efficiency, innovation, and competitiveness in the market (Holmström 2022). The UK specifically has seen a realisation of this trend, especially in FTSE 250 companies and newer FinTech ventures. The digitalisation effort is finding its footing in the form of AI becoming a key driver of growth in the business world. The growing possibilities of AI tools, ranging from sophisticated data analytics to predictive modelling, have turned it into a strategic requirement for maintaining a competitive edge (Aakula, Saini, & Ahmad, 2024).

Strategic reasons that underpin the implementation of AI are typically driven by the need to address competitive pressure, regulatory requirements, and the rapidly evolving needs of customers (Kulkov, 2021). In large, established companies, AI

enables the processing of vast amounts of data from their operations and markets, identifying performance deficiencies, and making informed strategic decisions in real-time. On the contrary, the focus of AI implementation in agile FinTech enterprises often falls on introducing new financial services, enhancing customer interactions, and driving rapid growth in small industries. The AI is viewed as important to both sectors as a means of enabling operational agility, but the nuances and extent of its use differ based on the size and positioning of organisations in the market (Kitsios & Kamariotou, 2021).

For example, AI implementation within an FTSE 250 environment is evident in this Group plc, a diversified engineering firm that has adopted AI-driven predictive maintenance systems across its operations. These systems process real-time data on the performance of equipment to predict faults that may occur before they happen, thereby reducing downtime and maintenance costs (Rudko *et al.* 2021). This adoption indicates that through AI, the reliability of operations is enhanced, cost savings are increased, and a culture of making data-driven decisions is supported in large-scale industrial operations. On the contrary, Revolut presents an alternative adoption method in FinTech, utilising AI as part of its fraud detection and personalised financial services (Aldoseri, Al-Khalifa & Hamouda 2024). Machine learning algorithms on the platform analyse millions of transactions each day to flag unusual patterns that suggest fraud, as well as provide spending insights specific to each customer. It highlights that the development of AI can help both to strengthen security and provide a custom user experience at the same time. This also helps FinTech companies stand out in a highly competitive market (Rudko, Bashirpour Bonab & Bellini 2021).

2.3 Different Types and Categories of AI Tools that are used by business organisations

Business AI applications can be divided into three main categories, which include the machine learning system, natural language processing (NLP) applications and robotic process automation (RPA) solutions. Machine learning refers to an algorithmic strategy that facilitates the identification of trends in a huge amount of information and the making of estimations. This can be used by companies to predict trends, control resources, and make informed judgments (Omol, 2024). NLP tools are used to read and analyse human speech and can be used to do sentiment analysis,

create chatbots, and provide voice-enabled services. The primary objective of RPA involves automating rule-based and repetitive tasks, eliminating the human error factor, and giving workers more time to focus on other high-value jobs. When combined with these tools, organisations can address both challenges associated with the industry and unlock new possibilities for operations (Kulkov et al. 2024).

When they are accustomed to working with an FTSE 250 company, they are likely to work together in a synchronised manner, thereby maximising efficiency. For example, Johnson Matthey, one of the world's leaders in sustainable technologies, is applying machine learning models to enhance catalyst design by analysing complex data on chemistry. Meanwhile, the firm also utilises NLP systems to organise technical publications and facilitate easier compliance reporting (Rajagopal et al., 2022). The combined approach demonstrates how AI-based technologies can be employed to supplement research and development without jeopardising regulatory demands. It is an illustration of how AI-based products can be applied to achieve not only innovation but also to enhance efficiency in a large-scale industrial environment. Similarly, Monzo Bank employs machine learning at the transaction risk scoring level, NLP to enable their customer service through a chatbot, and RPA in matching payment records across various platforms (Schneider & Kokshagina, 2021). The result is a smooth AI-driven environment that increases precision in fraud detection, customised user care and back-office operations. This is on a scale that allows the platform to support a high rate of growth in a competitive financial market (Imran *et al.* 2021).

Large-scale companies typically merge AI types to address complex, multi-layered procedures where accuracy, compliance, and creativity are of equal importance (Paleti, 2023). On the contrary, FinTech companies are more inclined to use them to achieve speed, scalability, and customer-focused service delivery. Finally, the fact that AI tools can be categorised into machine learning, NLP, and RPA offers a beneficial structure for encoding how organisations can utilise the technology. This is not a disconnected entity, but rather part and parcel of a more comprehensive digital transformation process (Teixeira & Pacione, 2024).

2.4 Impact of AI on business performance

AI has taken on a predominant role in determining organisational performance in industries. Its impact extends beyond the realm of technological improvement, catalysing change in operations, strategic flexibility, and sustainable development. Using the opportunities of AI, organisations can restructure their fundamental processes, discover new ways of value creation, and develop a competitive advantage in markets where the environment is extremely dynamic (Abrokwah-Larbi & Awuku-Larbi, 2024). The effects are mainly felt in three dimensions: operational efficiency, cost optimisation, and customer experience, which in turn lead to the realisation of measurable improvements in key performance indicators, including profitability, productivity, and innovation outcomes (Rubab, 2023).

Among the largest areas of business performance improvement that AI can enhance is operational efficiency. Automation of repetitive and labour-intensive activities shortens cycle times, minimises human error, and allows processes to run with minimal supervision. Predictive analytics from AI helps better distribute resources based on demand changes, allowing for just-in-time work, as well as facilitating the management of supply chains (Bharadiya 2023). In service functions, AI algorithms analyse and process large amounts of both structured and unstructured data at speeds that humans cannot operate. This also facilitates quicker decisions and operations that can be altered in real-time for improvement. There are still more efficiencies that are not only evident in the increased speed of turnaround but also in the enhancement of process consistency and scalability. These are essential in remaining responsive in the market (Kaggwa *et al.* 2024).

Simultaneously, AI is highly useful in terms of cost optimisation, helping to resolve inefficiencies, remove duplication of efforts, and improve asset utilisation. Such predictive maintenance can lower the cost of downtime because problems are identified before they occur (Anh, Anh, & Anh, 2025). Additionally, financial planning systems powered by AI can allocate budgets more efficiently as they constantly evaluate current spending behaviour and market trends. Moreover, inventory management supported by AI minimises the costs of holding inventory, as the quantity of stock is synchronised closer to the forecasted demand. Such cost savings could be reinvested in innovation, market expansion, or capacity building, thereby

strengthening the value creation cycle (Abrokwah-Larbi & Awuku-Larbi 2024). In addition to direct cost-cutting, AI also eliminates risk-related overheads by enabling the early identification of anomalies, proactive monitoring of compliance, and the avoidance of costly operational hiccups.

Another important area where AI leads to performance improvements is customer experience. AIs engage in consumer behaviour analysis to make products, services, and communications specific to the customer through advanced personalisation algorithms (Olan *et al.* 2022). NLP can make the customer experience effortless by allowing customers to interact with chatbots and virtual assistants, who offer prompt service, while human agents are reserved for handling more complex cases. Recommendation systems enhance the relevance of product offerings, thereby increasing engagement and conversion rates. The fact that tools used in sentiment analysis capture customer feedback in real-time also enables businesses to proactively adjust their product or service offerings, ensuring continued satisfaction and loyalty (Enholm et al., 2022). The outcome is a customer experience that is more conversational, receptive and helpful, reinforcing long-term relationships and raising customer lifetime value.

The connection between AI implementation and performance measurements which can be measured is becoming clear in empirical data. Organisations that utilise AI on a large scale tend to realise significant productivity gains, owing to a synergistic combination of process automation, augmented analytical capacity, and enhanced decision-making accuracy (Edilia & Larasati, 2023). The profitability gains are a result of higher operational throughput, as well as optimised cost structures, thus making better margins without compromising quality. The use of AI to encourage innovation is also well-established, and it has the capacity to detect emerging market trends. This contributes to the formulation of product ideas and the performance of rapid prototyping, which has increased the rate of introducing new offerings into the market. It is essential to note that the effects of AI on business performance extend beyond operational and financial benefits to include strategic agility. AI will help businesses predict market movements, react to emerging opportunities, and comply with regulations more efficiently and effectively (Perifanis & Kitsios, 2023). Market conditions, competitor actions, and customer emotions in real-time provide the intelligence needed to make proactive, data-driven strategic decisions.

2.5 Challenges and Limitations in AI Implementation

Although AI contributes significantly to business performance, the introduction of the organisational system is complemented by a complex set of challenges that encompass organisational, technical, and ethical areas. From an organisational perspective, a deficit in qualified personnel to design, implement, and support AI systems is one of the biggest obstacles from the organisation's viewpoint (Mohib et al., 2023). The skills required to undertake data engineering, including algorithm development and model management, are in high demand but in short supply, particularly within the competitive UK technology sector. Such a shortage may result in a lengthy implementation process, overdependence on third parties, and increased operational expenditures. Additionally, the organisational cultures that are established may impede the effective implementation of AI solutions due to their resistance to change (Mayo, 2023). Workers can perceive AI as a job threat, which may result in a low eagerness to adopt and possibly active resistance to its implementation. These human factors need to be managed, and change management plans are frequently required to overcome them; however, organisations often fail to appreciate the significant costs associated with communication, training, and adapting to culture (Aung, Wong & Ting 2021).

Technical issues are yet another significant restraint to the realisation of AI. One of the most influential aspects is the quality of the data, and AI models can be accurate and precise as the data that is used to collect it. Partial, unbalanced or outdated data can give flawed forecasts and poor choices. Also, siloed systems can be a clog when it comes to the integration of AI because the organisations face difficulties in building deep datasets that they can utilise in the appropriate modelling (Yang et al., 2023). Such concerns can be augmented by legacy IT platforms, which can be incompatible with the most up-to-date AI technology, leading to costly upgrades or redesign of systems. Algorithmic bias is one of the threats that would have technical and reputational consequences. Biases in training data can lead to discriminatory results in the case of customer interactions or hiring applications. Besides weakening the precision of the AI models, such biases can subject the organisations to legal and reputational repercussions (Cobanaj et al., 2024). An efficient way of dealing with bias

requires a representative and diverse dataset, frequent audits of the algorithms, and decision-making transparency. Such a strategy involves more resources and control.

The dearth of ethical considerations also prevents the adoption of AI, particularly with regard to data privacy, accountability and transparency. Collecting and handling huge amounts of data containing not only personal but also sensitive information poses doubts concerning compliance with the regulations, such as the UK General Data Protection Regulation (UK GDPR). The companies must make sure that their AI meets the strict privacy requirements, possesses a strong data handling process, and is trusted by its users (Rashid & Kausik, 2024). The question to be discussed is also that of accountability in AI-driven decision-making. In the case of opaque black box algorithms that produce results, it is challenging to identify who can be held responsible when mistakes occur or negative consequences arise. This inexplicability may undermine the confidence of stakeholders, especially in industries where decisions have high-stakes implications, such as the financial services industry or healthcare (Ahmed *et al.* 2023).

The high rate at which AI is evolving will also create a moving target for organisations, making it challenging to maintain the relevance of technology investments over time (Al-Surmi, Bashiri & Koliousis, 2022). The current deployed systems can rapidly become obsolete since more superior systems and tools are being developed. This has introduced the need to engage in constant upgrading and retraining, which is expensive and resource-demanding. Smaller companies may struggle to keep pace with these changes, resulting in an increasingly large gap between technology leaders and laggards (Otis *et al.* 2024).

The need for cross-functional cooperation also gives rise to integration issues. To implement AI solutions, it is common to organise the work of IT departments in collaboration with data scientists, heads of business units and compliance officers. Lack of alignment among them may result in duplication of efforts, underutilised and unused capabilities, and missed opportunities to optimise (Martins, 2024). Siloes in organisations, lack of clarity on governance and conflict priorities are some of the issues that may slow down the process or even halt the AI projects altogether. Another shortcoming is the potential for overdependence on AI, as decision-makers may have blind confidence in the automatic results without validating them. This has the potential

to lead to strategic mistakes when AI models are not frequently tested and revised to meet the new market conditions or realities on the ground. Human control is still necessary to ensure that AI does not replace informed judgment (Mishra, Ewing, & Cooper, 2022).

2.6 Strategic Approaches to AI Integration

Effective implementation of AI in business operations must do more than introduce sophisticated technologies; it must also drive meaningful improvements. This must demonstrate an integrated approach that aligns technical opportunities with organisational aspirations, culture, and governance systems (Aldoseri, Al-Khalifa & Hamouda 2023). Strategic approaches to AI integration centre around the strategy of realising that the technology not only serves providers as the means of operational improvements but also as a regular source of competitive advantages. It entails aligned planning in leadership, change management, digital culture, and cross-functional collaboration to have smooth adoption and long-term value creation (Saxena, Tripathi, & Jain, 2024).

Leadership is also a major force that guides AI integration. Top-level management will also need to create a vision regarding how AI can bring value to organisational goals (Al-Surmi, Bashiri & Koliousis 2022). This confirms that tether aligns with the technological initiatives and the overall business strategy. Leadership commitment will also facilitate the support of AI projects in terms of sufficient resources, including budget allocation, skilled staff, and infrastructure investments. Moreover, leaders should promote the use of AI across all organisational branches, and convey the message that AI is a tool that enables growth instead of replacing human abilities. Leadership can stay accountable by establishing quantifiable goals and tracking progress, thus keeping AI initiatives goal-oriented and focused on providing real results (Martins, 2024).

Managing change is just as important in the successful implementation of AI. The maintenance of AI often interferes with working routines, and employees must be prepared to use new tools, adapt to new decision-making processes, and even acquire entirely new sets of skills. Unorganised management of change means that such changes may result in opposition, misinterpretation, or poor usage of the AI systems

(Otis *et al.* 2024). A strategic approach to managing change includes open communication of the intention and the benefits of adopting AI. Specific training programmes to develop technical skills, and a means to collect employee feedback to improve the implementation. Additionally, setting up support systems, such as having internal AI champions or cross-departmental task forces, can further facilitate the transition and ensure active staff engagement (Bareis & Katzenbach, 2022).

Another form of foundation for embedding AI is the ability to develop a digital culture. A digital culture would reward data-driven decision-making, experimentation, and lifelong learning. It motivates employees to adopt an innovative mindset, question traditional ways of doing things, and experiment with the possibilities of new technologies (Radu, 2021). To achieve this, organisations should ensure that people have free access to relevant information, encourage employee teamwork to solve problems, and incorporate a digital literacy programme into the professional development process. The integration of AI into everyday business practices is more efficient when employees perceive it as a tool and an essential part of their toolkit, rather than as an outside influence or intrusion. Proper digital culture also contributes to making sure that the use of AI is not restricted to specific projects but becomes an organisational capacity (Rana *et al.* 2022).

Interfunctional communication will play a vital role in eliminating the siloed methods that usually prevent the use of AI. AI projects involve participation of various fields such as IT, data science, operations, marketing, finance, and compliance. In the absence of conscious coordination, work becomes siloed, standards are inconsistent, and duplication of effort and underutilisation of abilities occur (Martins, 2024). A strategic approach involves the development of a formalised collaboration, such as cross-functional steering committees, integrated project groups, or centralised AI governance entities. Such structures enable the sharing of knowledge, alignment of agendas, and ensure that AI solutions are developed through collaboration among all stakeholders, thereby making them more applicable and accepted at all levels of the business (Cobanaj *et al.* 2024).

Besides such organisational approaches, an efficient AI integration plan consists of constant review and optimisation. AI technologies are dynamic, hence require the model to be retrained, the data pipeline to be updated, and systems to be

upgraded regularly (Ore & Sposato, 2022). The development of a framework to monitor performance on an ongoing basis enables organisations to evaluate the value of their investment in AI projects and identify areas for improvement. Additionally, this also ensures that systems are still aligned with the business needs as they change. This entails the establishment of key performance indicators not only in operational outputs, namely the accuracy or speed of processing, but also with regard to the broader business impacts. The impacts actually include the satisfaction of customers, cost savings and the innovation potential (Omol, 2024).

The incorporation of ethical considerations into strategic approaches should also be done at the very beginning. Though the efficiency gains can be achieved through the technical implementation of AI, its long-term success is confined to stakeholder trust. The implementation of ethical principles into the governance of AI will provide the systems with transparency, accountability, and bias-free outcomes. This includes adopting practices in auditing of algorithms, protection of data privacy and rendering the process of making decisions explicable to internal and external customers (Bharadiya, Thomas & Ahmed 2023). Dealing with the concerns proactively minimises the chance of non-regulatory compliance and will help the organisation build the image of a responsible innovator. Finally, strategic planning has to take into consideration scalability in terms of the integration of AI. First implementations usually target pilot projects or small-scale applications, but a properly planned integration strategy should expect greater use of the integration throughout the organisation (Pearlson, Saunders & Galletta 2024).

2.7 Theoretical Underpinning

2.7.1 Diffusion of Innovation Theory
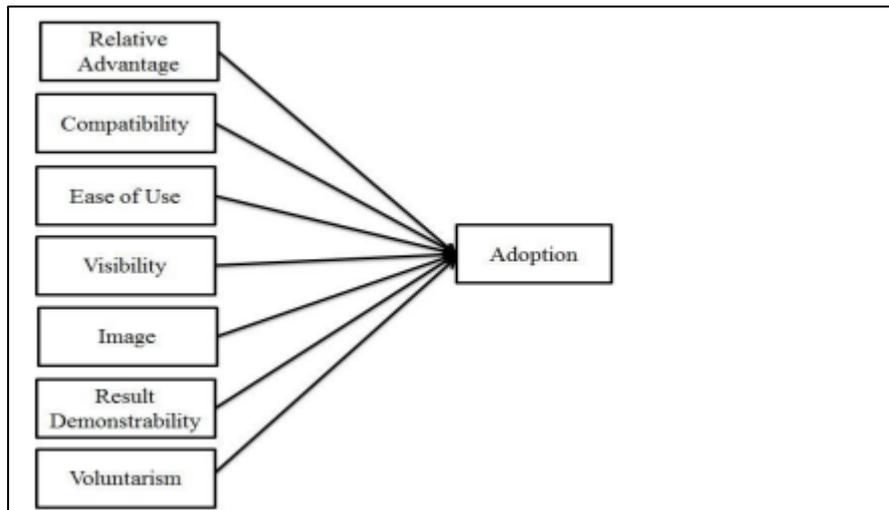
Figure 2.1: DOI Theory

(Source: Turan, Tunç & Zehir 2015)

Diffusion of Innovation (DOI) Theory offers an idea of the diffusion of innovation in an organisation and between organisations. This theory describes the mechanism through which AI innovation enters business organisations in the form of AI. This showcases how AI innovation goes through the stages of awareness to full integration of AI based on perceived benefits, compatibility with current IT systems, and complexity of implementation (Patnaik & Bakkar, 2024).

The theory divides the adopters into five categories, namely innovators, early adopters, early majority, late majority and laggards, who all have different characteristics that determine the adoption rate. In the case of FTSE 250 and FinTech companies, innovators and early adopters are the companies that frequently drive AI implementation, motivated by the chance of competitive advantage and operational efficiency (Lund, 2025). Since these early adopters prove their advantages, the early and late majority adhere and are driven by the decreases in uncertainty and formation of industry standards. On the other hand, laggards might not adopt because of the perceived risk, cost factors or organisational inertia (Govindan, 2022).

The relative advantage, compatibility, complexity, trialability, and observability are the key factors of DOI that are especially important in the context of the integration of AI. Relative advantage is connected with the performance of AI in increasing, improving productivity, improving cost optimisation, or customer relations compared to the current approaches (Faqihi & Miah, 2023). Compatibility is an indication of

compatibility with existing processes and corporate culture. Complexity relates to the difficulty perceived in using and learning to use AI tools, and this complexity may prevent implementation if systems are too technical. Trialability, as a feature that enables organisations to experiment, on a small scale, with AI, enables them to determine feasibility without making a full commitment to integration. Observability is the notion of AI benefits being visible, and it can speed up adoption when the outcomes are well visible and reported (Govindan, 2022).

2.7.2 Dynamic Capabilities Theory
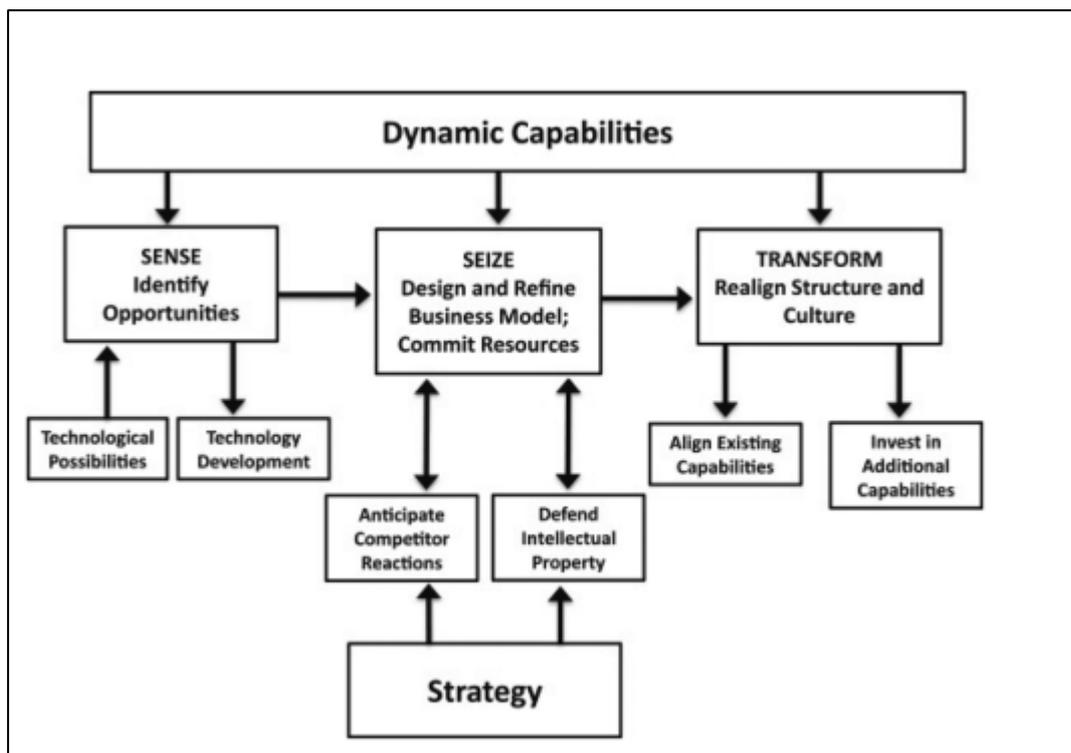
Figure 2.2: Dynamic Capabilities Theory
(Source: Shiferaw & Amentie Kero 2024)

The Dynamic Capabilities Theory focuses more on the capability of organisations to integrate, build and reconfigure the internal and external competences of the organisation in a changing and fast-moving environment. In the case of AI adoption, this theory offers an insightful perspective on how companies use their resources and transform processes to utilise the new technologies for a long-term competitive edge (Gao, Liu & Yang 2025). Dynamic capabilities include three coupled capacities, which are sensing opportunities and threats, seizing opportunities,

and transforming organisational assets. Sensing is a step in the process of AI integration, during which areas where AI can create value, namely efficiency of operations, cost reduction, and customer experience improvement, are identified. That would demand constant monitoring of technological direction, competitor action and changing consumer needs. The process of capturing opportunities by means of strategic decisions and investment in AI tools, infrastructure, and skills is called Seizing (Drydakis 2022). It also entails the business model and workflow designs to enable AI to give quantifiable advantages. Transforming is associated with rearranging what has been in existence, processes, structure, and cultures. This is to integrate AI as a fundamental ability, with the benefit being that its benefits are not limited to standalone projects but can be scaled throughout the organisation (Cimino *et al.* 2025).

In the case of FTSE 250 and FinTech firms, the dynamic capabilities framework demonstrates that agility becomes a crucial factor when implementing AI. Legacy systems and processes will have to be redesigned to support AI implementations in large companies. On the other hand, FinTech companies may also be keen on scaling AI solutions quickly in order to gain a market edge. They both entail the constant state of learning orientation, with AI capabilities being developed over a period of time to changes in technological progress and evolving regulatory demands (Drydakis 2022). When implementing the Dynamic Capabilities Theory to AI adoption, one should emphasise that the technological investment is not sufficient. However, long-term performance gains based on an organisation's capacity to reconfigure resources, adapt and develop in relation to the changing realities of the market and operational needs need to be prioritised (Drydakis 2022).

The combination of the Diffusion of Innovation Theory and the Dynamic Capabilities Theory provides a complete framework for comprehending the use of AI integration in business organisations (Patnaik & Bakkar, 2024). The Diffusion of Innovation Theory describes the routes that the technologies of AI tend to pass through, being introduced, tested, and adopted by various adopter groups. This also outlines several of the influencing factors, including relative advantage, compatibility, complexity, trialability, and observability, which affect adoption. This point of view is helpful in examining the progression of AI through early adopters in companies of the FTSE 250, FinTech, and into the broader organisational acceptance through

perceived value and risk reduction (Pearlson, Saunders & Galletta 2024). Alternatively, Dynamic Capabilities Theory pays attention to organisational capabilities that are necessary to leverage AI for a sustainable competitive advantage. It focuses on the ability to sense opportunities, exploit them with strategic investment and deployment, and transform structures and processes to instil AI as a scalable and adaptive capability (Cimino *et al.* 2025). This is most applicable in the evaluation of how businesses ensure they remain agile and adaptive in technological change and have their application of AI to match the market and regulatory conditions.

2.8 Conceptual Framework
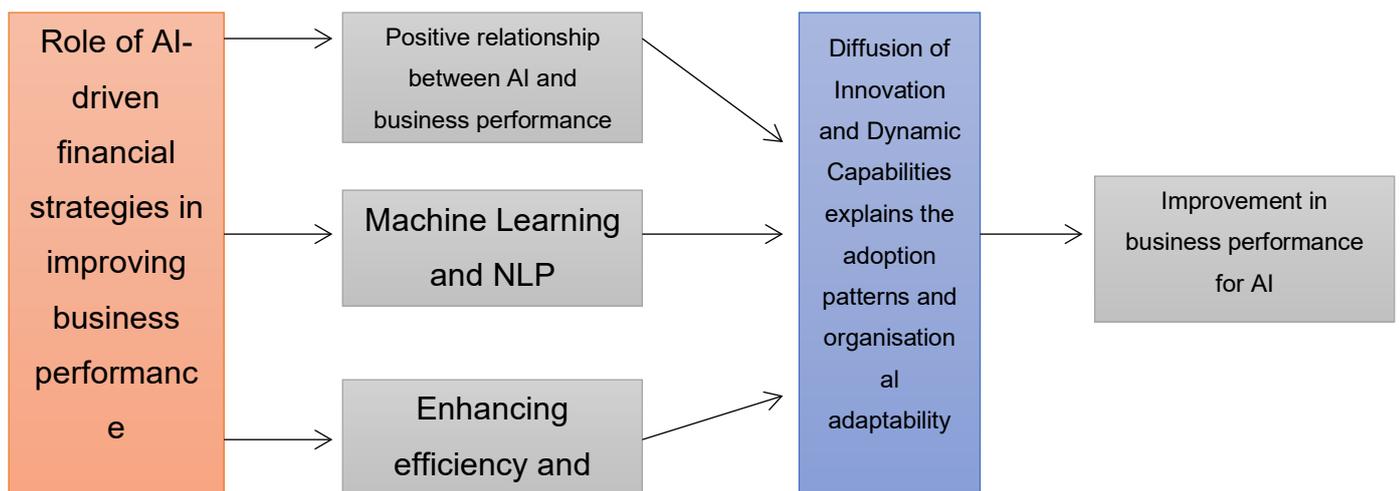
Figure 2.3: Conceptual Framework

(Source: Self-Developed)

The conceptual framework (shown in Figure 2.3) depicts how AI-based financial options can improve business results by means of a particular mechanism and theoretical perspective. Among the most important tools of AI that are identified by the model, there are Machine Learning and NLP, as well as the orientation on improving efficiency and cutting costs. These factors are connected to the positive correlation between AI implementation and better business results. The framework integrates Diffusion of Innovation with Dynamic Capabilities theories to describe the means and routes of adoption, as well as organisational flexibility that must support the

implementation of AI with a high degree of success. In a nutshell, the end result is increased operational efficiency, cost optimisation and general business performance.

2.9 Literature Gap

Although there is vast literature devoted to AI adoption and its effect on business performance, the prevailing journals mainly focus on MNCs and the specific technology sector (Radu, 2021; Mishra, Ewing & Cooper, 2022). The scholarly attention towards FTSE 250 companies and FinTech firms in the UK is lacking. The majority of research focuses on AI in the general sense of financial services or in the adoption of AI in leading corporations. However, these do not consider the specific operating entity, strategic planning, and market dynamics. Moreover, the current studies tend to approach AI implementation in conventional corporates and agile FinTechs as distinct disciplines and do not assume much comparative research of the respective approaches, methods, and success measures (Ahmed *et al.* 2023; Mishra, Ewing & Cooper 2022). This gap restricts the understanding of how AI can be effectively leveraged across different organisational models. This research focuses on addressing this gap.

2.10 Chapter Conclusion

There is no doubt that AI is reshaping business performance with its capacity to drive operational efficacy, optimise cost, and enhance customer experience. Fundamental tools such as machine learning and NPL allow organisations to process vast amounts of data, automate processes and deliver strategic insights. Successful integration actually depends on strong leadership, effective change management, and supporting digital culture. Even though there are challenges regarding the inclusion of this technology, in the near future, every FTSE 250 and FinTech firm will adopt AI technology.

Chapter 3: Research Methodology

3.1 Introduction of the Chapter

This section of this study identifies the essential strategies that need to be used to carry out the study on the relevance of AI-powered financial strategies regarding the improvement of business performance. It outlines the philosophy of research that would be used to relate the study to the objectives and the type of research that would be used in governing the whole process. The research strategy adopted allows a systematic form of studying the research problem, whereas the choice of research gives uniformity in the form of data used. An identified time frame is set so that it can contextualise the study. The keywords that concern the topic are developed to guide the search of the literature and the collection of the data. The inclusion criteria identify the literature and data sources to be used, whereas the exclusion criteria define the limits to exclude those irrelevant or not suitable. The approach used in data collection is also given together with the analysis procedures of the data in the methodology. Ethical issues are considered to maintain and provide the protection of the participant and the information. Lastly, research limitations are also noted to point to possible limitations and boundaries that influence the study results.

3.2 Research Philosophy

The research has used the Interpretivism philosophy, which considers research by focusing on the meanings that individuals or organisations give to phenomena. Through this philosophy, the concept of AI-driven financial strategies and the manner in which this kind of strategy is affecting business performance can be assessed in an appropriate manner. Interpretivism can be utilised by going into greater detail concerning the perception of decision-makers, their execution, and adaptations in the natural business environment. The merits of this method are seen in the ability of the method to reflect subjective experiences and contextual effects. Furthermore, the subtle interplay between technology and human judgment is not often reflected in quantitative evaluations (Junjie & Yingxin, 2022). Overall, Interpretivism is substantial in the sense that it encourages an in-depth, detailed understanding, as opposed to the restrictive findings of the numerical patterns (Ali, Shah, & Shah, 2021). It also accepts that a business environment is a socially constructed environment shaped by various

perspectives, which makes it helpful when analysing complex, changing technologies like AI in finance.

Other philosophies that would not have been chosen are those of Positivism, which concentrates more on measurable variables and statistical authentication. This may not be able to capture the requirements of this study, which concentrates more on contextual and human factors. Pragmatism has also been ruled out because the researcher would want a deeper understanding of the background rather than a combination of various approaches when addressing issues (Ikram & Kenayathulla, 2022). Using the concept of Interpretivism, the study will be in line with the goal of investigating the experience and perception of AI-enabled strategies instead of quantifying their effects.

3.3 Research Approach

In this study, an inductive research method will be used. Through which the study has been capable of developing the theories and reflections about the observed data, instead of confirming or rejecting the pre-determined hypothesis. The inductive approach is beneficial in the context of investigating AI-based financial strategies and their influence on the business performance of a particular business. This is because the patterns, relationships and concepts can freely appear as a result of the information gathered. This is especially helpful when applied to a rapidly growing industry such as AI in finance, where the practice remains somewhat nascent and not all driving forces are clearly defined in the literature available. The inductive approach is important since it fosters flexibility, adaptability, and discovery (Proudfoot, 2023).

It allows studies to react to new tendencies and find new points of view that can criticise or solidify the theoretical approaches (Vears & Gillam, 2022). It is vital in the investigation of innovative and swiftly evolving fields in which dogmatic pre-formed models can be ineffective in describing reality properly. The other methods, including the deductive method, were not chosen because they start with a predetermined theory. Also, then prove it, and this would shrink the scope of study in unravelling new findings in what is considered a relaxation area. The abductive method was also ruled out, which is a combination of deduction and induction. This is more appropriate for

refining a theory based on the previous ones instead of establishing new theoretical ideas based on empirical research.

3.4 Research Strategy

In this research, a case study strategy has been used, and it entails a detailed examination of a particular situation to establish detailed knowledge about intricate problems. When focusing on the research of the use of AI-driven financial strategies and associated changes in business performance, the case study method has been beneficial. This is due to the opportunity to study the practical use of the concept in the organisational environment. Also, it permits in-depth insights into the processes surrounding decisions, their implementation issues, and situational circumstances that could affect outcomes, which may be missed otherwise by more general and less specific methods (Lavarda & Bellucci, 2022). It may be especially active to research emergent technologies such as AI, and the real-world practice can be given as an example of how the theory is implemented and modified.

The use of other methods, like surveys, was not incorporated due to the tendency of such methods to reflect patterns on surface value. Also, surveys led to insufficient depth of information needed to comprehend the intertwining intricacies (Lim, 2025). The exclusion of interviews as an independent strategy was identified, despite its utility regarding the collection of personal views. Since it may not identify the entire organisational and contextual dynamics that may be identified with case studies, the case study therefore gives a more elaborate, nuanced insight into the topic under study.

3.5 Research Choice and Time Horizon

The present study makes the research decision to conduct a qualitative research study. This would allow quantitatively collecting and analysing data to determine trends between AI-driven financial playbooks and the business performance of an organisation. The merit here is that it can generate objective, valid findings that include evidence-based conclusions. In most cases, qualitative research is important in offering accuracy, repeatability, and generalisability of results (Mulisa, 2022). Other research options, including quantitative methods and mixed methods, were not considered since the research will involve measurable variables and not

subjective associations. Also, most likely, the combination is not necessary when trying to cover the scope and purposes of the proposed research.

The research uses a time-horizon (longitudinal), which allows monitoring any changes and tendencies of AI-powered financial strategies and their effect on the business performance over a long period. The strength here is the possibility to follow the changes, assess long-term outcomes and recognise emerging trends that inhabitants of short-term research can overlook (Neale, 2021). In most cases, a longitudinal approach is important in determining cause and effect as well as measuring the sustainability of the outcomes. The other time horizons, such as. Cross-sectional data were not taken into consideration since they only represent one instance of time, which would not offer the temporal analysis depth needed in this study.

3.6 Keywords

The keywords that have been used in this study are "AI-driven financial strategies", "business performance", "artificial intelligence in finance", "financial decision-making", "fintech innovation", "FTSE companies", and "organisational strategy". The importance of keywords is that they determine the focus and scope of a research and act as a guide to the research process and search for articles (Moran, 2021). They facilitate scholarly search ability in academic databases, hence making the work accessible to the appropriate people. The keywords which have been carefully selected are also helpful in structuring the research, ensuring thematic consistency, being indexed for future use, and are completely necessary in both academic visibility and direction of the research.

3.7 Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Language	Articles published in English	Articles published in other languages
Publication Date	Studies published after 2020	Studies published before 2020

Case Studies	3 case studies from FTSE-250 (Experian, Currys PLC, Keller Group) and 3 from Fintech (Revolut, Monzo, and Virgin Mobile)	Other case studies

Table 1.1: Inclusion and Exclusion Criteria

(Source: Self-developed)

3.8 Data Collection

In this research, a secondary qualitative data collection process has been used, which involves the collection of pre-existing non-numerical data by using publicly available, credible, and authoritative sources. This strategy is beneficial in the current case of studying AI-related financial strategies and their effect on business performance. This is due to it allowing the researcher to retrieve rich, detailed information without the limitations imposed by primary research, including the time and resource demands. The secondary qualitative data collection is important as, during its implementation, it allows one to access the wide range of currently existing information. This has minimised the possibility of duplicating the research efforts (Cheong et al., 2023). It is especially suitable when creating new or dynamically developing subjects, like AI in finance, in which there is already a high-quality analysis of the industry and reports.

To conduct the current research, information has been gathered on the basis of authentic sources and company reports across six identified case studies, three on FTSE-250 listed companies (Experian, Currys PLC, Keller Group) and three on Fintech companies (Revolut, Monzo, and Virgin Mobile). The source materials used include established websites like McKinsey & Company, Statista, BBC, and Forbes. This source material is credible as well as being relevant to the focus of the research (Taherdoost, 2021). Surveys or interviews were not considered as other methods, as they would take significant time in recruiting participants and collecting the corresponding data. Also, they might not be as representative or validated as

conclusions in industry reports. The selected approach, therefore, guarantees that the study can rely on quality, contextually informed, and analytically demanding data

3.9 Data Analysis

A content analysis tool has been introduced in this study, as it helps evaluate secondary qualitative data to find the application of AI-driven financial techniques in real scenarios in detail. This study has merit in that it can give an in-depth and contextual sense of the manner in which certain organisations use and change these strategies, exposing the practice constraints and success criteria. Content analysis has been useful in previous analyses in understanding a complex business phenomenon, and specifically, content analysis has been able to explain technology adoption (Vears & Gillam, 2022). It has been extensively employed to draw actionable knowledge to the stakeholders, both in the academic and industrial communities. Thematic analysis was not involved since it deals with specific situations, one case at a time, instead of determining patterns or themes in a large amount of qualitative data. This is to ensure that, where possible, the integrity of each case is kept and findings are not dissolved into generalised categories.

3.10 Ethical Consideration

Strict ethical considerations are observed in this study to ensure the quality, accountability, and reality of the research work. Since it is based on the secondary qualitative material, the sources are duly referenced to prevent cases of plagiarism and commend the integrity of the intellectual property rights. The collection of data includes credible and publicly available sources, and no intellectual rights or rights to use the data have been violated. The study cannot be full of lies since they report the results of the research in a clear and unbiased way. Any sensitive information about the company that might be encountered is managed confidentially, and no personal or confidential data of people is utilised. The research is also in accordance with the institutional research ethics provisions in the study; it is not secretive and so far as possible in its approach. The research will not bring any harm to organisations, individuals, or stakeholders because only verified open data from credible sources is used. All these act to maintain the integrity of academics and preserve the credibility of the research findings.

3.11 Research Limitation

The study has some limitations that ought to be identified. First, it contains only a representation of secondary qualitative data. It can be explained that the findings are resistant to the reliability, relevance, and completeness of already existing reports and publications. Therefore, there might have been a lack of information or a lack of access to proprietary insights, which might have helped broaden the analysis. Second, six selected case studies used in the research (three FTSE 250-listed firms and three Fintech firms) might restrict the generalisability of findings to other sectors or to other settings. Third, the changeable nature of an AI-based financial plan implies that certain data can supersede in the short term, which can impact the relevance of the conclusions in the long run. Lastly, the interview/surveys as a tool to collect primary data have been avoided, which limits firsthand opinions. Nonetheless, these limitations do not diminish the strength and validity of the study's research findings and recommendations, which are contextual considering the set objectives.

3.12 Chapter Conclusion

This chapter has described the research approach that has been used in undertaking the study, explaining its approaches to obtain the optimal results of the study. The approaches include philosophy, method, strategy, selection, time horizon, keywords, inclusion and exclusion issues, data acquisition, data analysis, ethical implications, and limitations. The approaches applied make the research of the AI-based financial strategies and their influence on the activities of companies more structured, credible, and context-related. The research took an alternative approach as it draws upon secondary qualitative information and uses case study analysis to capture real-time insights, avoiding any ethical compromises. As much as the given limitations apply, the methodology can be considered ideal to answer the research questions, and it offers a strong basis for the following analysis and discussion chapters.

Chapter 4: Findings and Results

4.1 Chapter Introduction

This section presents the findings and results of the research on how AI-driven financial strategies contribute to improving business performance, particularly among FTSE 250 and FinTech companies in the UK. The study relies on secondary data, which examines in detail how AI is transforming operations. The chapter begins with a summary of the research's key themes. This is followed by a thorough discussion of AI impact on business performance, the nature of tools used and their effectiveness related to efficiency and cost-optimisation. The cases analysed are Experian, Currys PLC, Keller Group, Revolut, Monzo, and Virgin Mobile.

4.2 Table of Themes

Themes	Sub-Themes	Description	Sources
1. AI as a Driver of Business Performance	Revenue Growth and Profitability Market Competitiveness Sectorial Disparities	The impact of AI directly increases revenue and the profit margin by accelerating model development, product innovation, and market capture. Through AI-first models and retail optimisation platforms, firms are able to gain a competitive advantage in the digital markets.	Experian (2025); Currys PLC (2025); Reuters (2025a); EIQ (2025)

2. Technological Deployment of AI Tools	Advanced Analytics and Fraud Detection	Examples of data platforms with predictive analytics and anomaly detection include Experian Ascend, Monzo Fraud Prevention, and Revolut systems. The tools, such as Redi (Virgin Money), automate client requests and make them more satisfied and less dependent on the call centres.	Experian (2025b, 2025c); Monzo (2025); Cryptonomist (2024)
	Customer Engagement & Conversational AI		
	Governance & Decision Support		
3. Operational Efficiency and Cost Optimisation	Process Automation & Time Savings	AI minimises the process cycles of operation, streamlines data processes, and speeds up approvals. Fraud AI systems help companies save hundreds of millions in fraud-related expenses as well as add security.	Experian (2025a); Currys PLC (2025) Revolut (2024); Monzo (2025); CFI (2025)
	Fraud Loss Reduction		
	Resource Utilisation & Cost Savings		

Table 4.1:Thematic Table

(Source: Self-Developed)

4.3 Secondary Data Analysis

4.3.1 The way Artificial Intelligence (AI) enhances business performance in UK FTSE 250 and FinTech companies

The analysis of secondary insights highlights how AI helps companies revise their corporate strategy and alter decision-making processes, enabling them to achieve higher profitability and efficiency rates than with conventional methods. The profitability level of Experian as a company demonstrates how AI-based programs can significantly contribute to an increase in revenues. By introducing the Experian Assistant, the firm reduced the development time frame for creating a model. The time dedicated to the development process is measured not in months but in hours, and the company is delivering its services more quickly, with the opportunity to serve many more clients. This acceleration led to 8% revenue growth and 11% EBIT growth in FY25, making Experian the leader in the industry in adopting AI to gain a competitive advantage (Reuters, 2025).

Statutory			
Revenue	7,523	7,097	6
Operating profit	1,793	1,694	6
Profit before tax	1,549	1,551	0

Figure 4.1: Experian Performance

(Source: Experian, 2025)

In addition to streamlining its operational workflows, the company's AI risk management system reduced internal approval time by up to 70% (Experian, 2025a). This not only limits the administrative overheads but also increases the customer acquisition capacity. As a result, Experian registered revenue of $7.52 billion and operating profit of $1.79 billion in 2025, as shown in Figure 4.1, which is directly correlated with its capacity to scale AI technologies (Experian, 2025).

With the conventional retail and distribution of technology, the implementation of AI can be seen through Currys PLC, which produces significant benefits in profitability (Pymnts, 2025). The company reported a 37% rise in adjusted pre-tax profit to £162 million and an exceptional rise of 300% in net income to £108 million (Currys PLC, 2025). This was accompanied by increased margin expansion to 1.2% compared to 0.3%, directly indicating how profitability measures are improving (Currys PLC, 2025). Currys is the market leader in AI-powered laptops, with a 75% market

share in the UK in this category, and is launching Action AI. This platform would optimise the selling process in stores and online (Currys PLC, 2025).

Figure 4.2: Revolut Performance

(Source: Experian, 2025)

In the context of the Fintech sector, Revolut boasted on revenue increase of 72% up to £3.1 billion and a 149% rise in pre-tax profit to £1.089 billion in 2024. The notional value of the net profit grew at a rate of 130%, which is the combined impact of AI on the functionality of the automated customer service for fraudulent detection and the financial processes (EIQ, 2025). The fraud prevention system implemented by Revolut has certainly prevented £600 million of fraudulent transactions, thereby protecting the customers' assets while maintaining the financial health of the business. Chatbot technology with AI also reduced customer resolutions by 80% and incurred less operational expenditure, while also satisfying the user more (EIQ, 2025). A combination of service efficiency and risk management indicates that the implementation of AI has more comprehensive financial returns than the general efficiency quotient.

Similarly, Monzo results are in line with an even broader trend across UK FinTechs of exponential AI-powered expansion. By 2025, the bank achieved its first billion-pound turnover, recording a 48% increase to £1.2 billion, while pre-tax profit rose to £60.5 million (Reuters, 2025a). The deposit made by customers increased by

48% to £16.6 billion, as customers have confidence in AI-supported security and operating facilities (Reuters, 2025a). The fraud detection framework developed by Monzo (four steps) demonstrates the complexity of the AI systems that contemporary FinTech companies use. With the implementation of AI in the selection of controls, loading of features, execution of controls, and application of actions, the company guarantees that the detection of fraud functions with precision and scalability (CFI, 2025).

The case of Virgin Money presents a slightly different scenario, where the initial decrease in profitability was caused by strategic investments in AI, which ultimately enabled the creation of competitive advantages in the long run. It invested £130 million in AI and cybersecurity, which temporarily resulted in a dip in profits to £345 million (Investing, 2023). Nonetheless, its human-like assistant, Redi, exhibited more than one million customer interactions in two years with a 57% containment rate of client queries (Financial IT, 2024).

	H1 2025 £m	H1 2024 £m	% change	Constant currency % change
Revenue	1,457.7	1,489.8	-2%	+1%
Underlying operating profit1	102.6	113.2	-9%	-6%
Underlying operating profit margin1	7.0%	7.6%	-60bps	n/a
Underlying diluted earnings per share1	98.1p	103.3p	-5%	

Figure 4.3: Keller Group Performance
(Source: Experian, 2025)

Keller Group is an example of how the application of AI in traditional FTSE 250 organisations is not as easy to implement as in some other organisations. Their revenues had decreased by 2% to £1.457 billion, and the operating profit had decreased by 10.34%, from £113.2 million to £102.6 million between 2025 (MS, 2025). However, its utilisation of Lucia, a board intelligence service based on AI, improves

governance and decision-making. Through the Question-Driven Insight methodology, Keller enhanced the speed and ease of its board papers in its 19 business units in 40 countries (BI, 2023).

Broader data across various sectors support the trends. A similar growth powered by AI was also achieved by another UK FinTech leader, Starling Bank, which suggests that such a positive experience was not limited to Revolut and Monzo. However, it represents a general tendency in the structural setting. According to sector-level data, 75% of UK financial services companies were already using AI by 2025, and 10% plan to include AI in the next 3 years (Tech UK, 2024). Additionally, technology budgets allocated to AI have also expanded, so by 2025, they are expected to comprise 16% of all technology budgets, up from 12% in 2024 (FinTech Magazine, 2025). This is yet another indicator of the growing significance of AI in financial strategy.

### 4.3.2 Different types of AI tools currently used within FTSE 250 and FinTech companies in the UK.

The implementation of AI in the UK's FTSE 250 and FinTech firms signifies a highly advanced environment of technological solutions, all of which are tailored to handle the requirements of various operations. Experian offers one of the prime examples of AI use in the FTSE 250. The centre of its system is the Experian Assistant, the GenAI-backed platform that connects with the broader Ascend infrastructure of the company. The Ascend Platform, with over 2,000 client solutions, incorporates embedded GenAI capabilities, in addition to a range of risk management solutions featuring Governance Manager modules, which are automated through risk control (Experian, 2025b). This enables Experian to supervise, certify, and clear credit models more effectively compared to conventional oversight frameworks.

(Source: NeuroID, 2025)

The incorporation of third-party AI APIs, including NeuroID, shown in Figure 4.4 for behavioural analytics and Fraud Sandbo for simulation and testing of new fraud detection algorithms, represents another layer of sophistication (NeuroID, 2025). In addition, Experian Cashflow attributes and scores utilise open banking data to further aid predictive analysis of borrower behaviour, helping practitioners make more accurate credit decisions based on a clearer picture of the borrower (Experian, 2025c).
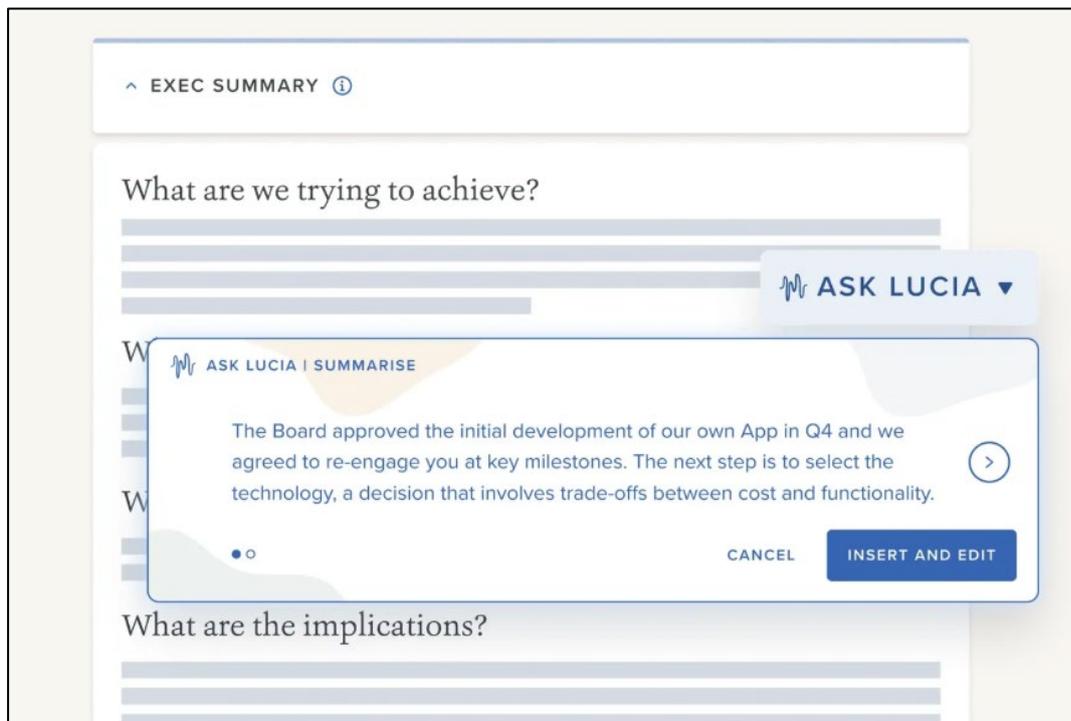
(Source: BI, 2025)

A stark contrast is provided by the Keller Group, where it is apparent that AI is utilised in corporate management rather than financial activities. The firm has also revolutionised its company decision-making processes across 19 business units functioning in more than 40 countries through the adoption of Lucia (BI, 2023). Lucia employs the Question-Driven Insight approach, whereby prompts and nudges are used to ensure that management reports are structured in a manner that enables strategic decisions. This can help the board process more complex information about operations more quickly and make informed decisions to govern their organisations

through AI-powered analysis (BI, 2025). Although one may not be able to see the direct financial impact of such a system immediately, the qualitative effect is evident, which concerns the efficiency of decision-making.

*Figure 4.6: Currys PLC's Electronic Shelf Edge Labelling technology*
(Source: RTIH, 2024)

Currys PLC provides another practical example of AI usage in an organisation dealing with retail. Its use of Action AI, built with Quorso, which is an innovative management platform that can analyse the data streams regarding sales, promotions, customer footfall and satisfaction (RTIH, 2024). The platform provides managers with real-time insights that they can utilise, thanks to the millions of calculations processed using a single dashboard. The system has been directly linked to the Currys Electronic Shelf Edge Labelling technology, which automates inventory management and dynamic pricing strategies (Currys PLC, 2024). This conglomeration signifies the integration of the analytical capabilities of AI technology and physical retail trade, a feature enhanced by the Next Level mechanism of website improvement. With over 200 bits of automation created for the digital platform of Currys, Next Level has also helped add 25 basis points to online conversion, further proving that these AI-powered retail tools have a real financial benefit (Currys PLC, 2025).
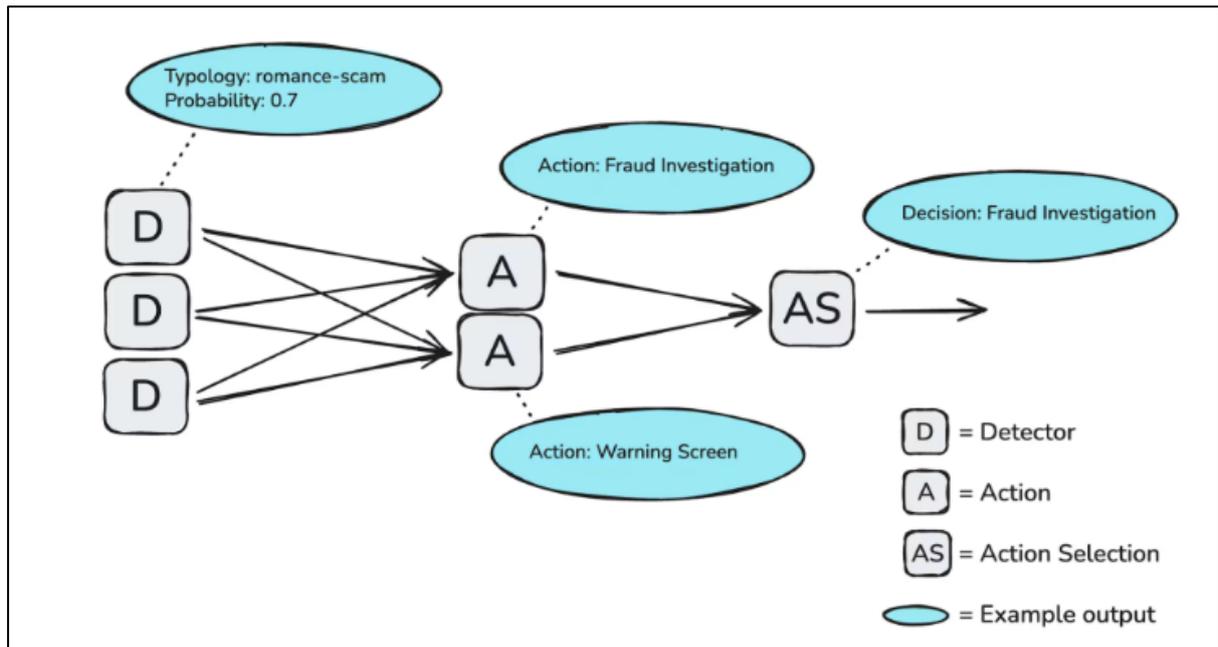
Figure 4.7: Fraud Prevention Platform of Monzo

(Source: Monzo, 2025)

On the other hand, the FinTech companies exhibit a higher dependency on customised AI architecture meant to support the essential banking functions. The example of such an approach is the Fraud Prevention Platform developed by Monzo, which implements the AI architecture based on four steps, including the Engine microservice used to coordinate the system. The detection of fraud is handled by three different types of controls, namely: Detectors, Action Controls, and Action Selection Controls (Monzo, 2025). These elements utilise machine learning formulas developed in Starlark, a dialect of Python, ensuring that fraud models are not fixed but dynamic and transparent. The feature loading is built with Directed Acyclic Graphs and calculates Just-in-Time, Near Real-Time and Batch features, allowing this system to trade off between real-time fraud detection and scalable performance (Monzo, 2025). The Action Applier subsequently imposes stateful actions and rate-limiting protocols that avoid overloads while maintaining the accuracy of detection.
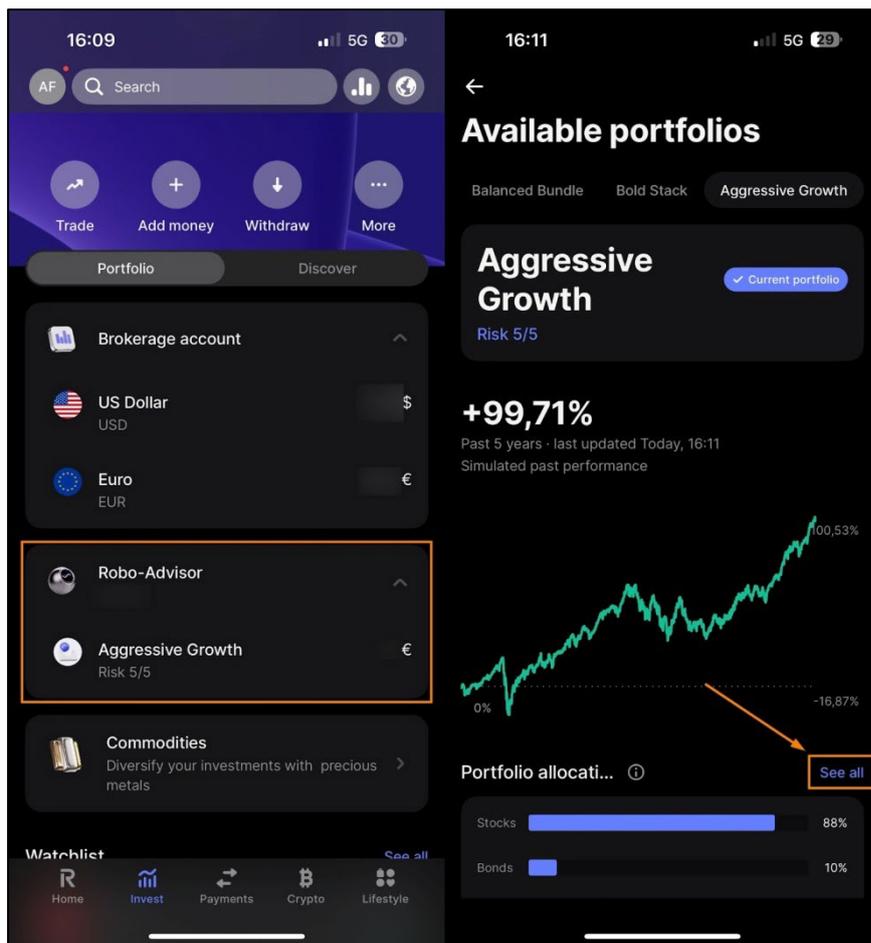
Figure 4.8: Revolut Robo-Advisor

(Source: IBS, 2024)

Revolut has an equally layered AI environment, with its applications in fraud detection preventing over 550 million euros of fraud in 2024 alone (Cryptonomist, 2024). Biometric authentication and proactive alerting, reinforced by these systems, enhance security throughout the customer journey. In addition to fraud detection, Revolut has also entered the AI-powered wealth management market through its Robo-Advisor, shown in Figure 4.8. This service applies machine learning concepts to create diversified portfolios tailored to a client's risk profile, allowing customers to start investing with as little as €100 (IBS, 2024). Another example is the planned launch of the Billpay platform by Revolut, which aims to automate accounts payable tasks in enterprises. This illustrates the growing focus of AI on infiltrating the domain of financial services among corporations. With the potential to save more than 80% of time on average in financial transactions, such entrants present the efficiency gains

that can be achieved by applying AI technology to high-volume administration (IBS, 2024).
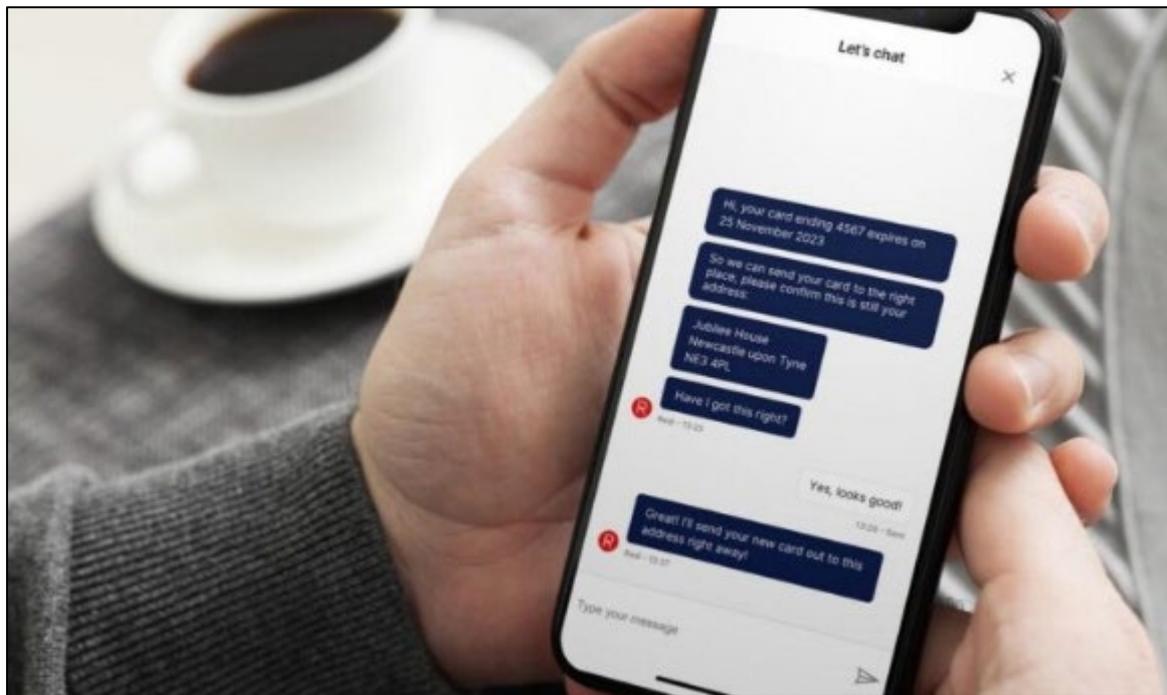
Figure 4.9: Redi by Virgin Mobile

(Source: Aigentel, 2025)

Virgin Money offers an emphasis on conversational AI-based customer service automation. Its Redi platform uses Microsoft Power Virtual Agents and Bot Framework Composer to show that the powerful toolsets typically found in the enterprise can be customised to apply to the financial services industry. Redi connects with over 50 APIs throughout the customer journey, enabling it to make immediate account changes and provide individualised customer support (Aigentel, 2025). With high levels of natural language understanding, Redi has managed to contain 57% of customer queries at peak, significantly reducing the burden on human call centre utilisation. Integration with core banking systems ensures Redi is not restricted to generic query processing and is free to interact at an account data level, which improves efficiency and customer satisfaction levels. The tool has been in use since its launch, with more than 2 million customer interactions across all lines of business (Aigentel, 2025).

A number of these AI tools rely on machine learning and predictive analytics. Experian credit risk models are constructed using predictive modelling, and Monzo's fraud prevention is primarily based on anomaly detection algorithms. Robo-Advisor is

adopted by Revolut and uses portfolio optimisation and risk modelling, whereas Redi is a natural language processing and intent recognition solution implemented by Virgin Money (Aigentel, 2025). Starling Bank can provide additional support for industry trends by monitoring transactions in real-time, optimising customer service with the help of machine learning. Integration of the tools is also important, and various organisations use different integration platforms. Ascend, provided by Experian, is a complete infrastructure which carries thousands of client-facing solutions. Monzo has the Engine microservice to coordinate several pieces of AI in fraud detection (Monzo, 2025).

4.3.3 Contribution of AI technologies to operational efficiency and cost optimisation in these organisations.

The use of AI in FTSE 250 and FinTech organisations in the UK proves to directly and quantifiably benefits operations and optimises costs. The process automation realised by Experian, with the help of AI, becomes a process that produces substantial efficiency gains in information-based financial services. The Experian Assistant reduces the time spent building models from a few months to hours, enabling data scientists to maximise throughput with a view to optimising analytical accuracy (Pymnts, 2025). Such acceleration is complemented by the risk management assistant of the corporation, which is driven by AI, which minimises the internal approval process by up to 70% (Pymnts, 2025). The operating cash flow conversion rate of 97% is the benchmark for the company, indicating the level of efficiency in capital utilisation spread under automation facilitated by AI. Such operational efficiencies are not merely hypothetical, but can be quantified, contributing to Experian's 8% rise in revenues and an 11% increase in EBIT in FY25 (Experian, 2025).

Retail-oriented activities portray equal efficiencies, especially those in Currys PLC. The Action AI platform runs millions of calculations on sales, footfall, promotions, and satisfaction data to provide succinct, actionable insights that inform the decision-making process on a store-by-store basis. The system enables managers to perform real-time analytics; hence, when underperforming categories are identified, they are rectified immediately, thereby reducing the opportunity cost of inaccurate inventory strategies (Currys PLC, 2025). The Next Level platform at Currys demonstrates the potential of automated optimisation further, which created over 200 improvements that

cumulatively changed conversion rates in the UK by 25 basis points. These productivity improvements are implemented in physical retail through Electronic Shelf Edge Labelling, which eliminates the labour-intensive task of manually updating prices across more than 100 stores (Currys PLC, 2025). The system enables dynamic pricing and automated inventory adjustments, saving personnel time and optimising revenue capture. The operational impact is further enhanced by the 15% growth, which enables the collection of revenue (Currys PLC, 2025). As a result, order and collect revenue now accounts for 34% of the group's online sales (Currys PLC, 2025).

The fraud prevention aspect of AI offers one of the most significant areas for cost reduction, particularly in FinTech companies. In 2024, Revolut stopped more than €550 million in fraud through its fraud detection systems, which directly decreases the company's financial exposure to such fraud (Cryptonomist, 2024). There was a 30% reduction in fraud losses related to card-related scams, indicating significant operational cost optimisation (Cryptonomist, 2024). This was backed up by AI-based chatbots that decreased the time it took to resolve customer issues by 80%, enabling Revolut to handle many more customer requests without similar increases in the figures analysing staffing (EIQ, 2025). The next-generation Billpay system is expected to bring another level of efficiency by saving enterprise accounts payable systems more than 80% of the time spent processing (EIQ, 2025). This highlights the role of AI systems in extending beyond fraud prevention to deliver administrative cost savings.

Monzo has also been efficient in its 4-step architecture, protecting against fraud with the aid of AI. Since the platform handles millions of transactions every day, it is able to easily spot fraudulent behaviour within the regular traffic —something that can be likened to finding a needle in a haystack. The modular design means that it is responsive to changing methods of fraud and has low-end payment processing latency (Monzo, 2025). Monzo also makes efficiency more effective by its usage of a Feature Loader, a Directed Acyclic Graph-based system that optimises the computation of Just-in-Time, Near Real-Time, and Batch features. This saves on the computational resources, and the accuracy in detecting the fraud is maximised. Action Applier will provide continuity because they have integrated facilities to prevent system overloads, thus reducing downtime and ensuring continuity in service delivery (Monzo, 2025). Collectively, the systems highlight how advanced AI designs enable companies to benefit from reducing both direct costs associated with fraud and
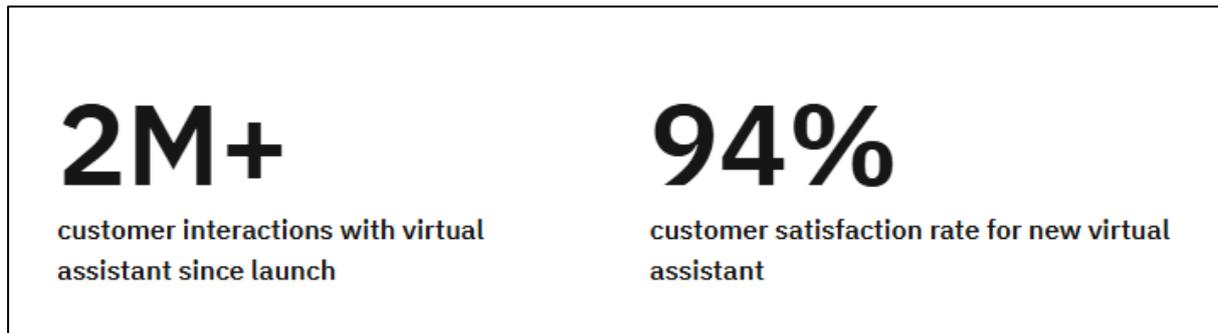
Figure 4.10: Virgin Mobile customer service automation

(Source: IBM, 2025)

Customer service automation is the other significant point of efficiency. AI assistant Redi, used by Virgin Money, has handled over two million customer interactions since its launch, which includes 57% of requests at an optimal performance level without human support (IBM, 2025). Real-time account changes are possible through Redi, as it integrates with more than 50 APIs and requires fewer call centre operations, thereby reducing staffing costs (IBM, 2025). Customer outcomes provide additional legitimacy to the system's efficiency, with a 94% satisfaction score, an 84% ease-of-use score, and a 91% success rate in answering intended queries (IBM, 2025). These results demonstrate that automation reduces certain costs while enhancing the customer experience, offering efficiencies that improve both operational and reputational performance. The sector-wide acknowledgement of these benefits of operations can also be equated to the award Virgin Money received for the use of AI in financial services (IBM, 2025).

The measurable cost optimisation of AI use is quite evident in financial indicators. The move of Currys to its Next Level platform in the Nordics saved the company an annual £2 million, resulting in improved performance at its sites (Currys PLC, 2025). Centralisation and economies of scale through marketing operating model improvements provided additional savings in the order of around £10 million annually (Currys PLC, 2025). These statistics represent the twofold ability of AI to increase revenue while reducing expenses. Equally, the twofold success of Revolut in minimising its losses through fraud and automating its customer service underscores how AI multiplies output, minimising exposure to operational risks, and streamlining costs in a single move. Virgin Money, with its query containment of 57%, is another

example of quantifiable savings in personnel budget, which gives a stable trend within the retail firms and finance technology companies (IBM, 2025).

4.4 Chapter Conclusion

The outcomes affirm that AI is one of the profound approaches to boosting business performance, operational efficiency, and cost optimisation of UK FTSE 250 and FinTech firms. Although FinTechs demonstrate swift profitability using AI-first frameworks, the more mature companies perform at a more moderate level with assisted implementations, which validates the idea of AI supporting a new competitive edge and sustainable strategy.

Chapter 5: Discussion

5.1 Chapter Introduction

This chapter aims to discuss the findings, critically interpreting them and linking them to the current literature and theoretical approaches. It reflects on the use of AI-led approaches in areas such as business performance, as well as operational and cost-cutting. The discussion also highlights differences in the sectors, scholarly implications, and practical contributions, which offer further insights into the transformational role of AI in organisations.

5.2 Discussion

5.2.1 The way Artificial Intelligence (AI) enhances business performance in UK FTSE 250 and FinTech companies

The results affirm that AI has become the leading business performance enabler in both FTSE 250 and FinTech firms in the UK. The literature suggests that the effects of AI on performance involve changing operations, enhancing strategic flexibility, and generating sustainable value (Abrokwah-Larbi & Awuku-Larbi, 2024). The example of Experian supports this, given that the Experian Assistant has reduced months of model development to hours, which translates to an increase in operational agility and the ability to undertake more services. The savings were reflected in an 8% growth in revenue and an 11% EBIT growth in FY25, which falls under the premise that automation reduces turnaround time and allows improvements to be made in real-time (Experian, 2025; Bharadiya, 2023).

Currys PLC reveals the use of AI in further transforming the indicators of profitability. The implementation of the Next Level platform and Action AI has led to reduced operational processes, both in-store and online, resulting in a 37% growth in adjusted pre-tax profit and an impressive increase in net income, triple its initial value or 300% (Currys PLC, 2025). Such consequences are strong indicators of the presence of relative advantage, as based on Diffusion of Innovation Theory, where AI provides tangible profitability solutions over outdated methods (Faqihi & Miah, 2023).

The debate that AI fosters strategic agility, which is the company's ability to stay competitive in dynamically changing market conditions, is also supported by the way AI can become an integral part of retail processes (Perifanis & Kitsios, 2023). The case of Currys' leadership in the AI-powered laptop market, with a 75% market share, illustrates the extent of its competitive advantage (Currys PLC, 2025). This can be achieved through early adoption of the DOI principle, which states that innovators define industry standards (Lund, 2025).

The most impressive effect can be seen in the FinTech sector, where deploying AI has led to a significant increase in profits. The operational efficiency, coupled with a risk management level, depicts the synergy between the two through the increase in the revenue and pre-tax profit that Revolut experienced in 2024 (Revolut, 2024). Moreover, a chatbot powered by AI in Revolut resulted in an 80% reduction in customer resolution time, due to the improved efficiency and customer experience (Revolut, 2024; Enholm *et al.,* 2022). These findings highlight the observability aspect of DOI theory, as substantial savings on fraud prevention make the benefits of AI palpable and spur the diffusion to the industry-wide level (Govindan, 2022).

Monzo will support this trend even further as revenue increases by 48% to reach £1.2 billion in 2025, along with deposits, which have risen by 13% to £16.6 billion in 2025 (Monzo, 2025). The compatibility of its four-step advanced AI fraud detection framework is an indication of the significance of compatibility in DOI, as the technology is well-suited to digital banking infrastructures, providing accuracy and scalability successfully (Patnaik & Bakkar, 2024). Through the lens of Dynamic Capabilities, Monzo demonstrates a high level of sensing and seizing capabilities by implementing anomaly detection algorithms and adaptive controls, which makes the company resilient to changing patterns of fraud (Gao, Liu & Yang, 2025). The profitability enhancements also validate the fact that the use of AI enhances key performance tenets, such as productivity and innovation results (Rubab, 2023).

The results also show that not every firm reaps immediate monetary rewards. A good example is Virgin Money, which invested £130 million in AI and cybersecurity, resulting in a decrease in profits to £345 million in the initial phase (Investing, 2023). However, its AI-enabled assistant, Redi, had the ability to handle over one million customer interactions and achieved a 57% customer retention rate (Financial IT,

2024). It contradicts the idea that customer experience is one of the crucial aspects of AI-driven improvements' performance, as Redi's 94% satisfaction rate and real-time account modification capacities are expected to generate customer loyalty over time (Olan et al., 2022). The trialability of DOI is also evident in the case of Virgin Money, as companies aim to explore the use of AI to check their potential viability and future worth (Govindan, 2022).

Overall, the results confirm the statements made in the literature regarding the positive influence of AI on business performance through efficiency, cost profiles, and customer experience (Rubab, 2023; Kaggwa *et al*., 2024). The DOI framework sheds light on the usage of innovation adoption trajectories in FTSE 250 and FinTech companies, separating between innovators, such as Experian and Revolut, and legacy firms that are not as liberated by legacy systems (Govindan, 2022). In the meantime, Dynamic Capabilities Theory provides the potential for long-term competitive advantage through an organisation's ability to sense opportunities, grasp them withhelp of strategic investments, and reform existing structures to make ithemthem AI-ready Ultimately, it is demonstrated to be not just an initiator of profitability, but also an enabler of organisational speed and responsiveness to a changing environment and dynamic markets and technologies.

5.2.2 Different types of AI tools currently used within FTSE 250 and FinTech companies in the UK

As the findings indicate, the implementation of AI in FTSE 250 and FinTech companies in the UK is characterised by an elaborate ecosystem of tools that deal specifically with the challenges of a particular sector. According to the literature, companies employ various types of AI technologies (Omol, 2024; Kulkov et al., 2024). The secondary data regarding Experian, Currys, Monzo, Revolut, Virgin Money, and Keller Group shows that different companies are using various types of AI tools according to their specific requirements. Machine learning systems are dominant in predictive analytics, risk assessment, and fraud detection. This is among the best demonstrations by Experian with its Experian Assistant built in the Ascend platform that has over 2,000 client solutions with embedded GenAI functions (Experian, 2025b). Other complementary tools include NeuroID and Fraud Sandbox, which extend the capabilities of behavioural analytics and fraud testing frameworks. Cashflow scores

leverage open banking data to analyse borrowers (NeuroID, 2025; Experian, 2025c). They are indicative of the stance taken in the literature that machine learning allows firms to forecast market conditions and maximise resource utilisation (Rajagopal et al., 2022). The fraud detection architecture developed by Monzo provides further evidence of the advanced application of machine learning.

Customer service automation involves the application of natural language processing. A prime example is Virgin Money Redi, which is powered by Microsoft Power Virtual Agents and Bot Framework Composer, and interacts with more than 50 APIs to support real-time changes in the account (Aigentel, 2025). With an almost 57% query containment, several million customer interactions have been recorded since its inception. This aligns with the literature, which suggests that Natural Language Processing enables sentiment analysis, chatbots, and customised interaction, thereby reducing costs and achieving customer delight (Olan *et al.,* 2022). The case also reflects the Dimensions of the Diffusion of Innovation Theory, as trialability and observability, as observed changes in query management and customer satisfaction, indicate adoption positivity (Govindan, 2022). The example of using Action AI integrated into Electronic Shelf Edge Labelling by Currys demonstrates how NLP-based analytics can also be applied to retail functions, enabling on-the-fly adjustments to pricing and inventory management (RTIH, 2024; Currys PLC, 2024). Such examples only strengthen the theoretical stance that NLP enables organisations to develop customer-centred plans while also ensuring operational enhancements (Teixeira & Pacione, 2024).

Another aspect of AI implementation that captures considerable attention is robotic process automation, which is often applied to high-volume administrative processes. Revolut is a good example, as the Billpay initiative aims to establish an enterprise accounts payable procedure, with a more than 80% time reduction anticipated (IBS, 2024). This aligns with the fact that RPA helps eliminate inefficiencies and reduce the number of human errors (Kulkov e*t al.,* 2024). Similarly, the Robo-Advisor of Revolut offers automated solutions to provide a diversified portfolio of investments that accommodates the risk levels of customers, allowing them to enter wealth management at a low level (Cryptonomist, 2024). These examples demonstrate how RPA can be combined with other AI applications to expand the range of possibilities in financial services and reduce their resource-intensive nature. The

Lucia platform, developed by the Keller Group, is not directly associated with RPA, but rather due to its ability to produce strategic board reports. It also reduces administrative inefficiency, which confirms that automation can facilitate governance processes (BI, 2023; BI, 2025).

5.2.3 Contribution of AI technologies to operational efficiency and cost optimisation in these organisations.

In the UK, AI has become a vital force in the drive for efficiency and cost optimisation in FTSE 250 organisations and FinTech organisations (Holmstrm, 2022). Automation of processes is also among the most evident contributions of AI. Experian has incorporated AI into many of its processes, whereby the Experian Assistant has reduced the time to create models (from 9 months to a few hours), freed up most of the data scientists, and ensured analytical accuracy (Pymnts, 2025). On top of that, the bank has cut down on its internal approval times by as much as 70% (Pymnts, 2025). This has been achieved through its risk management assistant, which is based on AI, simplifying operations and enabling faster market responses. Such integration efficiency is reflected in the operating cash flow turning rate at Experian of 97% in FY22, enabling an 8% improvement in revenues and an 11% increase in EBIT by FY25 (Experian, 2025). This is not only cost containment but a productivity dividend being delivered by AI-enabled automation.

Similar cases are observed in retail-oriented organisations. Currys PLC has unveiled the Action AI platform to process vast amounts of data on sales, foot traffic, and customer satisfaction, providing actionable insights in real-time (Currys PLC, 2025). The system minimises the drag that inventory strategies have on finances by empowering managers to reduce the poor categories in a single shot. For Currys PLC, not only did cost optimisation occur, but it also resulted in advancing revenues, with orders and collected revenue accounting for 34% of online sales (Currys PLC, 2025). These developments can be linked to the statement that AI systems cannot be ignored to remain competitive in the market and agile (Aakula, Saini, & Ahmad, 2024).

Fraud prevention is one of the most significant financial benefits that AI brings. By 2024, Revolut asserted to have blocked 550 million euros of fraudulent transactions (Cryptonomist, 2024). Its AI–based customer experience chatbots also reduce resolution times by 80% to increase customer satisfaction and control expenditures on

staffing (EIQ, 2025). A prime example demonstrates the integration of fraud prevention and administrative automation processes, leading to the creation of an efficient system in the case of the introduction of Billpay, which allegedly saves 80% of the payment processing time of enterprises (EIQ, 2025). The trend gains importance with the four-step AI fraud detection architecture designed by Monzo. This easily handles millions of transactions per day and offers minimal latency to maintain a continuous operation and limit the risk of financial losses (Monzo, 2025).

5.3 Academic and Practical Contribution

This research can be applied in both scholarly and professional contexts, as it discusses the use of the relatively underexplored intersection of AI, operational efficiency, and cost optimisation. Academically, it has the potential to expand upon the application of theories like the Resource-Based View (RBV) and Contingency Theory, as it demonstrates how AI is both a strategic capability and an adaptive mechanism. The findings contribute to current arguments by demonstrating that AI is actually dual-purpose. This enables companies to streamline their resources within an organisation and also remain responsive to changing external business conditions, especially regulations and competition.

Practically, the study highlights non-scientific pathways that organisations can utilise to access AI technologies, thereby achieving measurable performance improvements. The examples of companies such as Experian and Virgin Money demonstrate how AI can help minimise fraud, speed up the decision-making process, optimise customer service and provide high cost savings. Significantly, the research provides managers with insight into the balance between efficiency and innovation. The goal is to invest as a strategic approach towards long-term sustainability and competitive advantage within the digital economy.

5.4 Chapter Conclusion

This chapter showed how AI-based strategies can add value academically, as they can further the theoretical discussion and practically introduce the calculable value and cost reduction. The results affirm AI as a tool of resource optimisation and a strategic enabler with significant implications for the practical application to scholars and practitioners in fluid business environments.

Chapter 6: Conclusion

6.1 Summary of the Research

This study aimed to investigate the role of AI as a driver of business performance in UK FTSE 250 and FinTech firms. This is in terms of the improvements in business performance, the categories of AI tools in organic use today, their contributions to efficiency in operations, and cost optimisation.

The literature states that the integration of AI extends beyond technology implementations, and it needs robust leadership, effective change management, a digital culture and cross-functional teamwork. It improves profitability, efficiency, customer experience, innovation, and machine learning, natural language processing, and robotic process automation are the pillars of AI-driven transformation.

In this paper, the secondary data has been evaluated to give an anticipated result of the study.

As per the findings, Experian has boosted model development and tightened management of risks, resulting in an increase in revenues and a boost in operating efficiency. The profitability improvement and cost reduction were realised by Currys PLC in terms of action AI and automated inventory systems. With the chatbot, Revolut boosted earnings, enhanced fraud detection and cut down the cost of customer support. Monzo realised a substantial turnover increase via the implementation of the improved fraud detection systems, and Virgin Money was able to enhance the efficiency of its services. Keller Group has presented an example of the way AI may improve the governance and decision-making procedures. Together, the cases provide evidence of how AI has been involved in efficiency, cost optimisation, customer satisfaction and long-term competitiveness and can be termed as a transformative factor in business performance.

6.2 Linking With Objectives

6.2.1 The way (AI) enhances business performance in UK FTSE 250 and FinTech companies

Scholarly articles mention the ability of AI to increase business performance due to the operations efficiency, cost optimisation and customer experience (Abrokwah-Larbi & Awuku-Larbi, 2024; Rubab, 2023). Automation lowers error rates and cycle time, and predictive analytics guarantees resource optimisation (Bharadiya, 2023). These insights are confirmed by secondary data: Experian realised 8% revenue and 11% EBIT growth when it reduced months of work on a model to minutes (Experian, 2025a). Currys PLC experienced a 37 per cent increase in profits on its AI platform (Currys PLC, 2025). Also, Revolut established savings of 80 per cent of resolution times and 600 million pounds in savings by using AI to detect fraud (EIQ, 2025). A 48 per cent increase in deposits was observed by Monzo based on AI-propelled trust. So, the aim of presenting how AI can improve the performance of the UK FTSE 250 and FinTech is achieved.

6.2.2 Types of AI tools currently used within FTSE 250 and FinTech companies in the UK

In business, AI applications usually fall into three categories, namely, machine learning (ML), natural language processing (NLP), and robotic process automation (RPA) (Omol, 2024; Kulkov et al., 2024). It is described in the literature that ML can predict the trends, NLP allows interacting more easily with the help of the chatbots, and RPA automates the monotonous activities. This is confirmed by secondary data on UK companies: Experian utilises ML in credit risk modelling and governance (Experian, 2025b), Currys PLC combines the ML-based Action AI with inventory automation (Currys PLC, 2024). In the same manner, Revolut applies ML in its Robo-Advisor, and Redi is based on NLP by Virgin Money. Collectively, these examples show that the aim of determining the kinds of AI tools present among the UK FTSE 250 and FinTech firms has been achieved.

6.2.3 Contribution of AI technologies to operational efficiency and cost optimisation in these organisations

Literature points out that leadership vision, change management, digital culture, and cross-functional collaboration are needed to integrate AI into an occupation to provide measurable efficiency and cost improvements (Aldoseri et al., 2023; Saxena et al., 2024). Such principles are confirmed by the practice of FTSE 250 and FinTech companies. Experian minimised the build time of a model to less than a month, and it reduced the time taken to get an approval by 70% which led to an increase of EBIT by 11 per cent (Pymnts, 2025). Action AI and dynamic pricing helped Currys PLC to save 2m and increase conversion rates by using the former to gain a better understanding of the customer (Currys PLC, 2025). Revolut stopped 550 million fraudulent transactions and reduced the time it took to resolve cases by 80 per cent. Virgin Money had 57 per cent of queries, cutting down on staffing expenses. In this way, the purpose is achieved, the promotion of efficacy and cost optimisation of AI in the operations.

6.3 Recommendation

Building Organisational Readiness through Culture and Capability Development

The adoption of AI technologies requires organisations to have a digital-first culture, whereby adaptability, cooperation and the practice of ongoing learning are encouraged (Felemban, Sohail & Ruikar, 2024). Cultural preparedness is lacking. Therefore, the most advanced AI systems can be avoided or underutilised. The approach to training programmes includes upskilling on technical skills needed to handle an environment with AI. Also, create digital literacy procedures in both the workforce and the application of digital literacy staged across levels. This will help employees comprehend how AI can modify their jobs and the potential it has to boost value-creation. Creating cross-functional task forces enables the various departments, including operations, finance, marketing and compliance, to be part of the AI undertakings through conception and deployment. This is a deconstruction of silos and collective ownership.

Also, Employees need to feel a sense of contribution towards an AI system, and thus, it should be rewarded by encouraging innovation and experimentation, as employees are likely to have a more vested interest in the system that they have contributed towards and are willing to support and trust (Aliane, Gharbi & Semlali, 2023). Also, organisations must foster the internal AI champions, who serve as the

middlemen between the technology team and business departments and can guarantee the flow of communication, quicker troubleshooting, and increased engagement. Such cultural and ability change will assure long-term flexibility in fast-changing environments where technologies and consumer requirements change quickly.

Embedding Scalability, Optimisation, and Ethical Considerations

Effective implementation of AI is not a one-off program but an ongoing effort of perfection and expansion. Companies must begin with enterprise-specific pilot projects, and then incorporate them as enterprise-based solutions with business growth and customer value-driven efficiency and cost optimisation (Hammad & Abu-Zaid, 2024). Continuous monitoring and evaluation frameworks will have to be developed with a combination of operational and strategic key performance indicators to measure AI effectiveness. Since AI models have to be regularly retrained and recalibrated using additional data, it is important to invest in comprehensive data pipelines and cloud infrastructure in order to allow scaling.

Technical optimisation is just one part of it; ethical factors must also be integrated at all points of the AI life cycle (Wang, Li & Xu, 2025). Bias-reduction methods, privacy and explainable AI solutions protect the decision-making systems so that they are not only capable of delivering reliable results, but also do it in a way that can win public and regulatory confidence. These ethical practices, coupled with scalability, give organisations a competitive advantage, and through them, they can innovate in a responsible manner, as well as reduce the risks involved to a minimum. Finally, integrating AI into an adjustable, strategic, and reasonable-sized approach will allow companies to have better performances, striking the balance between efficiency and sustainable value.

6.4 Limitations and Future Research Scopes

The research has limitations in that the secondary data used does not fully reflect the insights of the challenges experienced by organisations during the implementation of AI. Success stories may be overrepresented in company reports and other industry sources because they may fail to report the failures, inefficiencies, or ethical dilemmas. A further limitation to the scope is the restriction to FTSE 250 and

UK FinTech companies. Therefore, the results cannot be generalised to smaller companies or to other geographic locales with varying regulatory and cultural backgrounds. Also, the high rate of AI development implies that the conclusions made might soon become obsolete with the further development of technologies and methods.

The studies on the topic could further be extended by collecting primary data using interviews and surveys of executives, managers, and employees at both FTSE-250 and FinTech companies. These would be more informative ways to explore, especially organisational preparedness, cultural inhibitors and attitude of employees towards adoption of AI, that cannot be reflected by secondary data. Attitudes toward the effect of AI on job roles, efficiency, and the accuracy of decision-making could be measured using surveys. However, the ideas, leadership strategies, ethics, and change management are to be discussed in more detail using interviews. The inclusion of regulators and customers' perspectives would also further enlighten on the position of AI in influencing trust, compliance, and competitiveness of the industry going forward.

References

Aakula, A., Saini, V., & Ahmad, T. (2024). The Impact of AI on Organizational Change in Digital Transformation. *Internet of Things and Edge Computing Journal*, *4*(1), 75-115. https://www.researchgate.net/profile/Tanzeem-Ahmad-3/publication/389650116_The_Impact_of_AI_on_Organizational_Change_in_Digital_Transformation/links/67cb1c09cc055043ce6f2de0/The-Impact-of-AI-on-Organizational-Change-in-Digital-Transformation.pdf

Abrokwah-Larbi, K., & Awuku-Larbi, Y. (2024). The impact of artificial intelligence in marketing on the performance of business organisations: evidence from SMEs in an emerging economy. *Journal of Entrepreneurship in Emerging Economies*, *16*(4), 1090-1117. https://www.emerald.com/insight/content/doi/10.1108/JEEE-07-2022-0207/full/html

Ahmed, M. I., Spooner, B., Isherwood, J., Lane, M., Orrock, E., & Dennison, A. (2023). A systematic review of the barriers to the implementation of artificial intelligence in healthcare. Cureus, 15(10). https://www.cureus.com/articles/170025-a-systematic-review-of-the-barriers-to-the-implementation-of-artificial-intelligence-in-healthcare.pdf

Aigentel, (2025). Virgin Money UK: Transforming Customer Experience with Redi, the AI Virtual Assistant. [Online]. Available at: https://aigentel.com/virgin-money-uk-transforming-customer-experience-with-redi-the-ai-virtual-assistant/ [Accessed on: 11th August, 2025]

Aldoseri, A., Al-Khalifa, K. N., & Hamouda, A. M. (2023). Re-thinking data strategy and integration for artificial intelligence: concepts, opportunities, and challenges. *Applied Sciences*, *13*(12), 7082. https://www.mdpi.com/2076-3417/13/12/7082?ref=blog.on-demand.io

Aldoseri, A., Al-Khalifa, K. N., & Hamouda, A. M. (2024). AI-powered innovation in digital transformation: Key pillars and industry impact. *Sustainability*, *16*(5), 1790. https://www.mdpi.com/2071-1050/16/5/1790

Ali, M., Shah, A.A. & Shah, S.A.A., (2021). Positivism and interpretivism. *Qlantic Journal of Social Sciences*, *2*(1), pp.20-26. https://qjss.com.pk/index.php/qjss/article/download/19/17

Aliane, N., Gharbi, H., & Semlali, Y. (2023). The role of artificial intelligence, digital capabilities and digital awareness on supply chain management: moderating role of organisational

readiness and digital organisational culture. *Transformations in Business and Economics*, *22*(3), 832-852. https://www.researchgate.net/profile/Yahdih-Semlali/publication/382254313_The_Role_of_Artificial_Intelligence_Digital_Capabiliti es_and_Digital_Awareness_on_Supply_Chain_Management_Moderating_Role_of_ Organizational_Readiness_and_Digital_Organizational_Culture/links/6694f3543e0ed b1e0fe4d000/The-Role-of-Artificial-Intelligence-Digital-Capabilities-and-Digital-Awareness-on-Supply-Chain-Management-Moderating-Role-of-Organizational-Readiness-and-Digital-Organizational-Culture.pdf

Al-Surmi, A., Bashiri, M. & Koliousis, I., (2022). AI based decision making: combining strategies to improve operational performance. *International Journal of Production Research*, *60*(14), pp.4464-4486. https://www.tandfonline.com/doi/pdf/10.1080/00207543.2021.1966540

Al-Surmi, A., Bashiri, M., & Koliousis, I. (2022). AI based decision making: combining strategies to improve operational performance. *International Journal of Production Research*, *60*(14), 4464-4486. https://www.tandfonline.com/doi/abs/10.1080/00207543.2021.1966540

Al-Surmi, A., Bashiri, M., & Koliousis, I. (2022). AI based decision making: combining strategies to improve operational performance. *International Journal of Production Research*, *60*(14), 4464-4486. https://www.tandfonline.com/doi/abs/10.1080/00207543.2021.1966540

Anh, B. D., Anh, H. P., & Anh, T. T. P. (2025). Impact of AI on Strategic Performance of Enterprises. *Cuestiones de Fisioterapia*, *54*(5), 370-384. https://cuestionesdefisioterapia.com/index.php/es/article/download/3064/2210

Atkinson, W. (2025). Artificial Intelligence as a Strategy in the British Economic Field. *The British Journal of Sociology*. https://onlinelibrary.wiley.com/doi/pdf/10.1111/1468-4446.13218

Aung, Y. Y., Wong, D. C., & Ting, D. S. (2021). The promise of artificial intelligence: a review of the opportunities and challenges of artificial intelligence in healthcare. *British medical bulletin*, *139*(1), 4-15. https://academic.oup.com/bmb/advance-article-pdf/doi/10.1093/bmb/ldab016/40343944/ldab016.pdf

Bank of England, (2024). Artificial intelligence in UK financial services - 2024. News. [Online] Available at: https://www.bankofengland.co.uk/report/2024/artificial-intelligence-in-uk-financial-services-2024#:~:text=75%25%20of%20firms%20are%20already,58%25%20and%2014%25%20respectively. [Accessed on: 13th August, 2025]

Bareis, J., & Katzenbach, C. (2022). Talking AI into being: The narratives and imaginaries of national AI strategies and their performative politics. *Science, Technology, & Human Values*, *47*(5), 855-881. https://journals.sagepub.com/doi/abs/10.1177/01622439211030007

Beauhurst, (2025). The Fintech Top 100 UK | 2025. News. [Online] Available at: https://www.beauhurst.com/blog/fintech-startup-companies/ [Accessed on: 13th August, 2025]

Bharadiya, J. (2023). The impact of artificial intelligence on business processes. *European journal of technology*, *7*(2), 15-25. https://www.academia.edu/download/123707086/1611.pdf

Bharadiya, J. P., Thomas, R. K., & Ahmed, F. (2023). Rise of artificial intelligence in business and industry. *Journal of Engineering Research and Reports*, *25*(3), 85-103. https://www.academia.edu/download/103844778/1776.pdf

BI, (2023). How Keller unlocked strategic conversations with shorter, sharper reports. [Online]. Available at: https://www.boardintelligence.com/clients/keller [Accessed on: 14th August, 2025]

BI, (2025). Lucia, AI-powered management reporting software.[Online]. Available at: https://www.boardintelligence.com/lucia [Accessed on: 14th August, 2025]

Binhammad, M., Alqaydi, S., Othman, A. & Abuljadayel, L.H., (2024). The role of AI in cyber security: Safeguarding digital identity. *Journal of Information Security*, *15*(2), pp.245-278. https://www.scirp.org/pdf/jis2024152_107801006.pdf

CFI, (2025). UK's Digital Bank Monzo Reports Steady Revenue Growth, Profitability. [Online]. Available at: https://www.crowdfundinsider.com/2025/06/241424-uks-digital-bank-monzo-reports-steady-revenue-growth-profitability/ [Accessed on: 14th August, 2025]

Cheong, H.I., 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*, p.16094069231180160. https://journals.sagepub.com/doi/pdf/10.1177/16094069231180160

Cimino, A., Corvello, V., Troise, C., Thomas, A., & Tani, M. (2025). Artificial Intelligence Adoption for Sustainable Growth in SMEs: An Extended Dynamic Capability Framework. *Corporate Social Responsibility and Environmental Management*. https://onlinelibrary.wiley.com/doi/abs/10.1002/csr.70019

Cobanaj, M., Corti, C., Dee, E. C., McCullum, L., Celi, L. A., Curigliano, G., & Criscitiello, C. (2024). Artificial intelligence in the oncology workflow: Applications, limitations, and future perspectives. In *Artificial Intelligence for Medicine* (pp. 91-111). Academic Press. https://www.sciencedirect.com/science/article/pii/B9780443136719000132

Cryptonomist, (2024). Revolut: the ML and AI-based system prevented scams for over €550 million. [Online]. Available at: https://en.cryptonomist.ch/2024/04/17/revolut-the-ml-and-ai-based-system-prevented-scams-for-over-e550-million/ [Accessed on: 12th August, 2025]

Currys PLC, (2024). Currys Powers Up Stores ahead of Peak. [Online]. Available at: https://www.currysplc.com/news-media/press-releases/2024/currys-powers-up-stores-ahead-of-peak/ [Accessed on: 12th August, 2025]

Currys PLC, (2025). Performance continues to strengthen. [Online]. Available at: https://www.currysplc.com/news-media/press-releases/2025/currys-full-year-results-2024-25/ [Accessed on: 16th August, 2025]

Drydakis, N. (2022). Artificial Intelligence and reduced SMEs' business risks. A dynamic capabilities analysis during the COVID-19 pandemic. *Information Systems Frontiers*, *24*(4), 1223-1247. https://link.springer.com/article/10.1007/s10796-022-10249-6

Edilia, S., & Larasati, N. D. (2023). Innovative approaches in business development strategies through artificial intelligence technology. *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, *5*(1), 84-90. https://aptikom-journal.id/itsdi/article/view/612

EIQ, (2025). Revolut Statistics By Diversity, Revenue And Facts (2025). [Online]. Available at: https://electroiq.com/stats/revolut-statistics/ [Accessed on: 15th August, 2025] Reuters, (2025a). British challenger bank Monzo's profit soars, revenue tops $1.35 billion. [Online]. Available at: https://www.reuters.com/business/finance/british-digital-

bank-monzos-annual-profit-surges-revenue-tops-135-billion-2025-06-02/ [Accessed on: 16th August, 2025]

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information systems frontiers*, *24*(5), 1709-1734. https://link.springer.com/article/10.1007/s10796-021-10186-w?trk=public_post_comment-text

Experian, (2025). Strong performance and excellent strategic progress in FY25. [Online]. Available at: https://www.experianplc.com/newsroom/press-releases/2025/full-year-results-fy25 [Accessed on: 16th August, 2025]

Experian, (2025a). Preliminary results for the year ended 31 March 2025. [Online]. Available at:
https://www.experianplc.com/content/dam/marketing/global/plc/en/assets/documents/results-and-presentations/2025/experian-fy25-full-year-results.pdf [Accessed on: 16th August, 2025]

Experian, (2025b). Experian Assistant Leading the Way in Financial Services: Wins Big Innovation Award. [Online]. Available at: https://www.experian.com/blogs/news/2025/01/30/experian-assistant-wins-big-innovation-award/ [Accessed on: 13th August, 2025]

Experian, (2025c). New GenAI solution Experian Assistant wins 2025 BIG Innovation Award. [Online]. Available at: https://www.experianplc.com/newsroom/press-releases/2025/new-genai-solution-experian-assistant-wins-2025-big-innovation-a [Accessed on: 13th August, 2025]

Faqihi, A., & Miah, S. J. (2023). Artificial intelligence-driven talent management system: Exploring the risks and options for constructing a theoretical foundation. *Journal of Risk and Financial Management*, *16*(1), 31. https://www.mdpi.com/1911-8074/16/1/31

Felemban, H., Sohail, M., & Ruikar, K. (2024). Exploring the readiness of organisations to adopt artificial intelligence. *Buildings*, *14*(8), 2460. https://www.mdpi.com/2075-5309/14/8/2460

Ferreira, M. K. M. (2024). *Finance & Artificial Intelligence* (Doctoral dissertation, Universidade Católica Portuguesa).

https://repositorio.ucp.pt/server/api/core/bitstreams/ae4b564d-ea61-428d-b06f-6debbadf2ea6/content

Financial IT, (2024). Virgin Money's AI-Powered Virtual Assistant, Redi, Now Available for Current Account Customers. [Online]. Available at: https://financialit.net/news/artificial-intelligence/virgin-moneys-ai-powered-virtual-assistant-redi-now-available-current [Accessed on: 14th August, 2025]

FinTech Magazine, (2025). UK Finance: AI Spend to Hit Record Levels in 2025. [Online]. Available at: https://fintechmagazine.com/articles/uk-finance-ai-spend-to-hit-record-levels-in-2025 [Accessed on: 14th August, 2025]

Fulton, R., Fulton, D., Hayes, N. & Kaplan, S., (2024). The Transformation Risk-Benefit Model of Artificial Intelligence: Balancing Risks and Benefits Through Practical Solutions and Use Cases. *arXiv preprint arXiv:2406.11863*. https://arxiv.org/pdf/2406.11863

Gao, Y., Liu, S., & Yang, L. (2025). Artificial intelligence and innovation capability: A dynamic capabilities perspective. *International Review of Economics & Finance*, *98*, 103923. https://www.sciencedirect.com/science/article/pii/S1059056025000863

Govindan, K. (2022). How artificial intelligence drives sustainable frugal innovation: A multitheoretical perspective. *IEEE Transactions on Engineering Management*, *71*, 638-655. https://ieeexplore.ieee.org/abstract/document/9669166/

Hammad, A., & Abu-Zaid, R. (2024). Applications of AI in decentralised computing systems: harnessing artificial intelligence for enhanced scalability, efficiency, and autonomous decision-making in distributed architectures. *Applied Research in Artificial Intelligence and Cloud Computing*, *7*(6), 161-187. https://core.ac.uk/download/pdf/620852567.pdf

Holmström, J. (2022). From AI to digital transformation: The AI readiness framework. *Business horizons*, *65*(3), 329-339. https://www.sciencedirect.com/science/article/pii/S0007681321000744

Huang, X. (2024). *Model Risk Management in the Era of Artificial Intelligence* (Master's thesis, Universidade NOVA de Lisboa (Portugal)). https://run.unl.pt/bitstream/10362/174368/1/TEGI3100.pdf

IBM, (2025). Redi, the AI-powered banking virtual assistant, boosts customer engagement. [Online]. Available at: https://www.ibm.com/case-studies/virgin-money [Accessed on: 10th August, 2025]

IBS, (2024). Revolut launches Robo-Advisor to automate investment processes. [Online]. Available at: https://ibsintelligence.com/ibsi-news/revolut-launches-robo-advisor-to-automate-investment-processes/ [Accessed on: 11th August, 2025]

Ikram, M. & Kenayathulla, H.B., (2022). Out of touch: comparing and contrasting positivism and interpretivism in social science. *Asian Journal of Research in Education and Social Sciences*, *4*(2), pp.39-49. https://www.researchgate.net/profile/Maryam-Ikram/publication/366810045_Out_of_Touch_Comparing_and_Contrasting_Positivism_and_Interpretivism_in_Social_Science/links/63b30f54097c7832ca84ccd3/Out-of-Touch-Comparing-and-Contrasting-Positivism-and-Interpretivism-in-Social-Science.pdf

Imran, F., Shahzad, K., Butt, A., & Kantola, J. (2021). Digital transformation of industrial organisations: Toward an integrated framework. *Journal of change management*, *21*(4), 451-479. https://www.tandfonline.com/doi/abs/10.1080/14697017.2021.1929406

Investing, (2023). Virgin Money to invest £130 million in AI and cybersecurity. [Online]. Available at: https://in.investing.com/news/virgin-money-to-invest-130-million-in-ai-and-cybersecurity-93CH-3911245 [Accessed on: 14th August, 2025]

Junjie, M. & Yingxin, M., (2022). The Discussions of Positivism and Interpretivism. *Online Submission*, *4*(1), pp.10-14. https://files.eric.ed.gov/fulltext/ED619359.pdf

Kaggwa, S., Eleogu, T. F., Okonkwo, F., Farayola, O. A., Uwaoma, P. U., & Akinoso, A. (2024). AI in decision making: transforming business strategies. *International Journal of Research and Scientific Innovation*, *10*(12), 423-444. https://www.researchgate.net/profile/Oluwatoyin-Farayola/publication/377345979_AI_in_Decision_Making_Transforming_Business_Strategies/links/6601fe2fa4857c796282c14e/AI-in-Decision-Making-Transforming-Business-Strategies.pdf

Kaggwa, S., Eleogu, T. F., Okonkwo, F., Farayola, O. A., Uwaoma, P. U., & Akinoso, A. (2024). AI in decision making: transforming business strategies. *International Journal of Research and Scientific Innovation*, *10*(12), 423-444.

https://www.researchgate.net/profile/Oluwatoyin-Farayola/publication/377345979_AI_in_Decision_Making_Transforming_Business_Strategies/links/6601fe2fa4857c796282c14e/AI-in-Decision-Making-Transforming-Business-Strategies.pdf

Khan, J., Oladosu, S.A., Ike, C.C., Adeyemo, P., Adepoju, A.I.A., Hamzah, F., Liang, W., John, B. & Oluwaferanmi, A., (2025). Data Science as a Strategic Asset: Leveraging Big Data and AI for Evidence-Based Policymaking and Public Sector Innovation. https://www.researchgate.net/profile/Aremu-Oluwaferanmi/publication/392693681_Data_Science_as_a_Strategic_Asset_Leveraging_Big_Data_and_AI_for_Evidence-Based_Policymaking_and_Public_Sector_Innovation/links/684d85ca26f43051a5809332/Data-Science-as-a-Strategic-Asset-Leveraging-Big-Data-and-AI-for-Evidence-Based-Policymaking-and-Public-Sector-Innovation.pdf

Kitsios, F., & Kamariotou, M. (2021). Artificial intelligence and business strategy towards digital transformation: A research agenda. *Sustainability*, *13*(4), 2025. https://www.sciencedirect.com/science/article/pii/S0160791X21001044

Kulkov, I. (2021). The role of artificial intelligence in business transformation: A case of pharmaceutical companies. *Technology in Society*, *66*, 101629. https://www.sciencedirect.com/science/article/pii/S0160791X21001044

Kulkov, I., Kulkova, J., Rohrbeck, R., Menvielle, L., Kaartemo, V., & Makkonen, H. (2024). Artificial intelligence-driven sustainable development: Examining organisational, technical, and processing approaches to achieving global goals. *Sustainable Development*, *32*(3), 2253-2267. https://onlinelibrary.wiley.com/doi/abs/10.1002/sd.2773

Kumar, S. & Ujire, D.K., (2024). Inductive and deductive approaches to qualitative research. *International Journal of Multidisciplinary Educational Research*, *13*(1), pp.58-63. http://ijmer.s3.amazonaws.com/pdf/volume13/volume13-issue1(4)/9.pdf

Lavarda, R. & Bellucci, C.F., (2022). Case study as a suitable method to research strategy as practice perspective. *The Qualitative Report*, *27*(2), pp.539-555. https://www.researchgate.net/profile/Christiane-Bellucci/publication/358711195_Case_Study_as_a_Suitable_Method_to_Research_Strategy_as_Practice_Perspective/links/624b59a921077329f2f210b4/Case-Study-as-a-Suitable-Method-to-Research-Strategy-as-Practice-Perspective.pdf

Lim, W. M. (2025). What is qualitative research? An overview and guidelines. *Australasian Marketing Journal*, *33*(2), 199-229. https://journals.sagepub.com/doi/pdf/10.1177/14413582241264619

Lund, B. (2025). Diffusion of innovations: still a relevant theory for studying library technology in the age of AI?. *Library Hi Tech News*, *42*(4), 9-11. https://www.emerald.com/insight/content/doi/10.1108/lhtn-12-2024-0209/full/html

Martins, M. R. (2024). Optimising business operations through artificial intelligence. *International Journal of Advanced Research and Interdisciplinary Scientific Endeavours*, *1*(4), 226-236. https://www.ijarise.org/index.php/ijarise/article/view/76

Mayo, S. M. (2023). Restrictions, Challenges and Opportunities for AI and ML. *International Journal of Innovations in Science & Technology*, *5*(2), 121-132. https://www.researchgate.net/profile/Ijist-Jr/publication/379897214_Restrictions_Challenges_and_Opportunities_for_AI_and_ML/links/6620a56966ba7e2359e63368/Restrictions-Challenges-and-Opportunities-for-AI-and-ML.pdf

Microsoft, (2024). Meet the Microsoft UK partners blazing a trail in the use of AI. News. [Online] Available at: https://ukstories.microsoft.com/features/meet-the-microsoft-uk-partners-blazing-a-trail-in-the-use-of-ai/ [Accessed on: 13th August, 2025]

Mishra, S., Ewing, M. T., & Cooper, H. B. (2022). Artificial intelligence focus and firm performance. *Journal of the Academy of Marketing Science*, *50*(6), 1176-1197. https://link.springer.com/article/10.1007/s11747-022-00876-5

Mitta, N. R. (2022). AI-Powered Chatbots for Financial Advisory Services: Developing Natural Language Processing and Machine Learning Models for Real-Time Customer Interaction and Personalised Recommendations. *Journal of Artificial Intelligence & Machine Learning Studies*, *6*, 28-65. https://jaimls.org/index.php/publication/article/view/17

Mohib, M., Khan, F. K., El Burari, E. R., & Ali, S. (2025). The Challenges and Limitations of Artificial Intelligence Adoption in Small and Medium-Sized Enterprises. *Review Journal of Social Psychology & Social Works*, *3*(1), 292-303. https://www.socialworksreview.com/index.php/Journal/article/view/99

Monzo, (2025). Building a reactive Fraud Prevention Platform. [Online]. Available at: https://monzo.com/blog/build-a-reactive-fraud-prevention-platform [Accessed on: 11th August, 2025]

Moran, M. (2021). Keywords as method. *European journal of Cultural studies*, *24*(4), 1021-1029. https://journals.sagepub.com/doi/pdf/10.1177/13675494211016858

MS, (2025). Keller : Interim Results Announcement for the six months ended 30 June 2025 Press Release. [Online]. Available at: https://uk.marketscreener.com/news/keller-interim-results-announcement-for-the-six-months-ended-30-june-2025-press-release-ce7c5edbda8df727 [Accessed on: 14th August, 2025]

Mulisa, F. (2022). When does a researcher choose a quantitative, qualitative, or mixed research approach?. *Interchange*, *53*(1), 113-131. https://www.researchgate.net/profile/Feyisa-Mulisa/publication/356567326_When_Does_a_Researcher_Choose_a_Quantitative_Qualitative_or_Mixed_Research_Approach/links/674965bb790d154bf9b386b0/When-Does-a-Researcher-Choose-a-Quantitative-Qualitative-or-Mixed-Research-Approach.pdf

Neale, B. (2021). Fluid enquiry, complex causality, policy processes: making a difference with qualitative longitudinal research. *Social Policy and Society*, *20*(4), 653-669. https://www.cambridge.org/core/services/aop-cambridge-core/content/view/324A6E3BF84910F62265A1471B2705EC/S1474746421000142a.pdf/fluid-enquiry-complex-causality-policy-processes-making-a-difference-with-qualitative-longitudinal-research.pdf

NeuroID, (2025). A New Era in Fraud Prevention: Experian Acquires NeuroID. [Online]. Available at: https://www.neuro-id.com/resource/blog/a-new-era-in-fraud-prevention-experian-acquires-neuroid/ [Accessed on: 14th August, 2025]

Nwabekee, U.S., Okpeke, F. & Onalaja, A.E., (2025). Modeling AI-enhanced customer experience: The role of chatbots and virtual assistants in contemporary marketing. *World Scientific News*, *203*, pp.54-77. https://worldscientificnews.com/wp-content/uploads/2025/05/WSN-203-2025-54-77-1.pdf

Olan, F., Arakpogun, E. O., Suklan, J., Nakpodia, F., Damij, N., & Jayawickrama, U. (2022). Artificial intelligence and knowledge sharing: Contributing factors to organisational performance. *Journal of Business Research*, *145*, 605-615. https://www.sciencedirect.com/science/article/pii/S0148296322002387

Omol, E. J. (2024). Organisational digital transformation: from evolution to future trends. *Digital Transformation and Society*, 3(3), 240-256. https://www.emerald.com/insight/content/doi/10.1108/dts-08-2023-0061/full/html

Omol, E. J. (2024). Organisational digital transformation: from evolution to future trends. *Digital Transformation and Society*, 3(3), 240-256. https://www.emerald.com/insight/content/doi/10.1108/dts-08-2023-0061/full/html

Ore, O., & Sposato, M. (2022). Opportunities and risks of artificial intelligence in recruitment and selection. *International Journal of Organizational Analysis*, 30(6), 1771-1782. https://www.emerald.com/insight/content/doi/10.1108/ijoa-07-2020-2291/full/html

Otis, N., Clarke, R., Delecourt, S., Holtz, D., & Koning, R. (2024). The uneven impact of generative AI on entrepreneurial performance. https://www.aeaweb.org/conference/2025/program/paper/Sa6tT4H3

Paleti, S. (2023). Trust Layers: AI-Augmented Multi-Layer Risk Compliance Engines for Next-Gen Banking Infrastructure. *Available at SSRN 5221895*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5221895

Patnaik, P., & Bakkar, M. (2024). Exploring determinants influencing artificial intelligence adoption, reference to diffusion of innovation theory. *Technology in Society*, 79, 102750. https://www.sciencedirect.com/science/article/pii/S0160791X24002987

Pearlson, K. E., Saunders, C. S., & Galletta, D. F. (2024). *Managing and using information systems: A strategic approach*. John Wiley & Sons. https://books.google.com/books?hl=en&lr=&id=1bzmEAAAQBAJ&oi=fnd&pg=PR1&dq=Strategic+Approaches+to+AI+Integration+in+business&ots=w2itW85anU&sig=Yalmi1aBXC643lDx8QtQaoFYBQY

Perifanis, N. A., & Kitsios, F. (2023). Investigating the influence of artificial intelligence on business value in the digital era of strategy: A literature review. *Information*, 14(2), 85. https://www.mdpi.com/2078-2489/14/2/85

Proudfoot, K. (2023). Inductive/deductive hybrid thematic analysis in mixed methods research. *Journal of mixed methods research*, 17(3), 308-326. https://journals.sagepub.com/doi/pdf/10.1177/15586898221126816

Pymnts, (2025). Experian Unveils New AI Tool for Managing Credit and Risk Models. [Online]. Available at: https://www.pymnts.com/news/artificial-

intelligence/2025/experian-unveils-new-ai-tool-managing-credit-risk-models/
[Accessed on: 15th August, 2025]

Radu, R. (2021). Steering the governance of artificial intelligence: national strategies in perspective. *Policy and society*, *40*(2), 178-193. https://academic.oup.com/policyandsociety/article-abstract/40/2/178/6509308

Rajagopal, N. K., Qureshi, N. I., Durga, S., Ramirez Asis, E. H., Huerta Soto, R. M., Gupta, S. K., & Deepak, S. (2022). Future of business culture: An artificial intelligence-driven digital framework for organisation decision-making process. *Complexity*, *2022*(1), 7796507. https://onlinelibrary.wiley.com/doi/abs/10.1155/2022/7796507

Rana, N. P., Chatterjee, S., Dwivedi, Y. K., & Akter, S. (2022). Understanding dark side of artificial intelligence (AI) integrated business analytics: assessing firm's operational inefficiency and competitiveness. *European Journal of Information Systems*, *31*(3), 364-387. https://www.tandfonline.com/doi/abs/10.1080/0960085X.2021.1955628

Rane, N.L., Paramesha, M., Choudhary, S.P. & Rane, J., (2024). Artificial intelligence, machine learning, and deep learning for advanced business strategies: a review. *Partners Universal International Innovation Journal*, *2*(3), pp.147-171. https://puiij.com/index.php/research/article/download/143/114

Rashid, A. B., & Kausik, M. A. K. (2024). AI revolutionising industries worldwide: A comprehensive overview of its diverse applications. *Hybrid Advances*, 7, 100277. https://www.sciencedirect.com/science/article/pii/S2773207X24001386

Reuters, (2025). Credit data firm Experian forecasts 6% to 8% annual organic revenue growth. [Online]. Available at: https://www.reuters.com/markets/europe/uks-experian-forecasts-fiscal-year-2026-revenue-growth-expanded-product-2025-05-14/
[Accessed on: 16th August, 2025]

RTIH, (2024). Currys upgrades stores including switch to ESELs and digital queuing system alongside back of house improvements. [Online]. Available at: https://retailtechinnovationhub.com/home/2024/11/22/currys-upgrades-stores-including-switch-to-esels-and-digital-queuing-system-alongside-back-of-house-improvements [Accessed on: 12th August, 2025]

Rubab, S. A. (2023). Impact of AI on business growth. *The Business and Management Review*, *14*(2), 229-236. https://cberuk.com/cdn/conference_proceedings/2023-09-13-16-29-12-PM.pdf

Rudko, I., Bashirpour Bonab, A., & Bellini, F. (2021). Organisational structure and artificial intelligence. Modeling the intraorganizational response to the AI contingency. Journal of Theoretical and Applied Electronic Commerce Research, 16(6), 2341-2364. https://www.mdpi.com/0718-1876/16/6/129

Saxena, T., Tripathi, D. R., & Jain, R. (2024). Evaluating The Opportunities and Risks of Artificial Intelligence In Strategic Management and Business Integration. *International Journal of Innovations in Science, Engineering And Management*, 19-24. https://ijisem.com/journal/index.php/ijisem/article/view/132

Schneider, S., & Kokshagina, O. (2021). Digital transformation: What we have learned (thus far) and what is next. *Creativity and innovation management*, *30*(2), 384-411. https://onlinelibrary.wiley.com/doi/abs/10.1111/caim.12414

Şen, Y. (2023). Auditors' Perceptions of Artificial Intelligence: Evidence From Global Audit Companies (Master's thesis, İzmir Ekonomi Üniversitesi). https://gcris.ieu.edu.tr/bitstream/20.500.14365/156/1/1560.pdf

Shiferaw, R. M., & Amentie Kero, C. (2024). Dynamic capabilities view practices of business firms: a systematic literature review. *Cogent Business & Management*, *11*(1), 2336309. https://www.tandfonline.com/doi/abs/10.1080/23311975.2024.2336309

Siddiqui, N. A. (2025). Optimising Business Decision-Making Through AI-Enhanced Business Intelligence Systems: A Systematic Review of Data-Driven Insights in Financial And Strategic Planning. *Strategic Data Management and Innovation*, *2*(1), 202-223. https://www.researchgate.net/profile/Noor-Siddiqui-7/publication/392079877_Optimizing_Business_Decision-Making_Through_Ai-Enhanced_Business_Intelligence_Systems_A_Systematic_Review_Of_Data-Driven_Insights_In_Financial_And_Strategic_Planning/links/68333a92be1b507dce90e229/Optimizing-Business-Decision-Making-Through-Ai-Enhanced-Business-Intelligence-Systems-A-Systematic-Review-Of-Data-Driven-Insights-In-Financial-And-Strategic-Planning.pdf

Taherdoost, H. (2021). Data collection methods and tools for research; a step-by-step guide to choose data collection technique for academic and business research projects. *International Journal of Academic Research in Management (IJARM)*, *10*(1), 10-38. https://hal.science/hal-03741847v1/file/Data%20Collection%20Methods%20and%20Tools%20for%20Research%20.pdf

Tech UK, (2024). New findings from BoE and FCA survey on AI adoption in UK financial services. [Online]. Available at: https://www.techuk.org/resource/new-findings-from-boe-and-fca-survey-on-ai-adoption-in-uk-financial-services.html [Accessed on: 14th August, 2025]

Teixeira, N., & Pacione, M. (2024). Implications of artificial intelligence on leadership in complex organisations: An exploration of the near future. https://openresearch.ocadu.ca/id/eprint/4190/

Turan, A., Tunç, A. Ö., & Zehir, C. (2015). A theoretical model proposal: Personal innovativeness and user involvement as antecedents of unified theory of acceptance and use of technology. *Procedia-Social and Behavioral Sciences*, *210*, 43-51. https://www.sciencedirect.com/science/article/pii/S1877042815056748

Vears, D.F. & Gillam, L., (2022). Inductive content analysis: A guide for beginning qualitative researchers. *Focus on Health Professional Education: A Multi-Professional Journal*, *23*(1), pp.111-127. https://search.informit.org/doi/pdf/10.3316/informit.455663644555599

Wang, Y., Li, Y., & Xu, C. (2025). Position: AI Scaling: From Up to Down and Out. *arXiv preprint arXiv:2502.01677*. https://arxiv.org/pdf/2502.01677

Yang, W., Wei, Y., Wei, H., Chen, Y., Huang, G., Li, X., ... & Kang, B. (2023). Survey on explainable AI: From approaches, limitations and applications aspects. *Human-Centric Intelligent Systems*, *3*(3), 161-188. https://link.springer.com/article/10.1007/s44230-023-00038-y