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Leveraging Artificial Intelligence: Exploratory Case Study of AI Adoption in Business Administration

A study of benefits, success factors and associated risks of adopting Artificial Intelligence (AI) for competitive advantage in business.

1. Abstract

Artificial Intelligence (AI) has profoundly changed numerous industries and is increasingly recognised as a pivotal subject in management discourse. The advent of modern generative AI (GAI) tools, such as DeepSeek, has fundamentally transformed the nature of human and machine interaction. Contemporary discussions on AI frequently encompass both the significant benefits associated with AI adoption and the necessity for effective management strategies. There exist multiple drivers facilitating AI integration, alongside important considerations that warrant cautious implementation.

This aim of this study is an exploratory case studies of AI adoption in various sized organisations to critically examine the primary enablers and obstacles to AI adoption, including an analysis of critical success factors for effective implementation. The study will purposely not be limited to a particular sector or industry to enable the identification of common success factors, while also appreciating peculiarities of certain industries. This research reviews relevant literature and assesses the current and prospective roles of AI in business applications, especially amid ongoing technological advancements and the proliferation of generative AI tools like DeepSeek and ChatGPT. The study will employ a rigorous exploratory case study methodology to evaluate how different size firms maintain competitiveness during widespread AI adoption, it will also explore whether firms should

pursue early adoption or adopt more measured strategies, and explore the implications of increased AI reliance against a backdrop of competition and employment trends.

Additionally, ethical considerations will be addressed throughout the study. By examining present applications, analysing established research, and proposing a novel adoption framework, this research intends to offer a comprehensive perspective on utilising AI for competitive advantage in the business sector.

Keywords: Critical Success Factors, GenAI, AI Adoption, Benefits of AI adoption, Competitive Advantage, Barriers to AI Adoption.

2. Introduction

Artificial Intelligence (AI) is expected to drive exponential growth in economic output worldwide with productivity also set to increase by over 40% by 2030 (Accenture, 2019). AI is also anticipated to generate economic gains in excess of \$13 trillion US dollars for the global economy by 2030 (McKinsey Institute, 2018). The transformative impact of AI is already evident across nearly every industry, with its adoption recognised as a key priority for management (Hutzschenreuter and Lämmermann, 2025). Moreover, research indicates that the majority of global organisations surveyed (more than 85%) believe failure to successfully leverage AI tools will result in commercial disadvantages, including loss of market share and diminished competitive advantage, underscoring the importance placed on effective AI integration (Chatterjee, Rana and Dwivedi, 2024).

This research proposal will explore and examine the implementation of AI within organisations, across a section of small and medium, and large firms. The study will investigate the drivers, principal barriers, and critical success factors influencing AI adoption. Key objectives include reviewing existing literature, analysing core conceptual elements of AI, and evaluating both current and potential risks and opportunities associated with its

application. The study will also identify some of the critical ethical issues that most organisations will inevitably be faced with when considering their approach to AI adoption.

Many organisations are incorporating AI into their operations to enhance efficiency by fostering innovation, which enables them to reduce costs and deliver quicker for their clients, which in turn will strengthen their competitive positioning (Rane, 2023).

Modern AI technology enable organisations to undertake the processing of vast datasets, delivering results that offer strategic advantages, which results in improved productivity, operational efficiency, and ultimately, profitability (Black and Van Esch, 2020).

AI enables practitioners to allocate more time to higher-value analytical tasks that currently remain beyond the scope of even the most advanced AI systems (Donahue, 2018).

AI is being leveraged by businesses across many frontiers, be that in front end customer services, such as the use of bots by banks and online shops. In engineering with predictive maintenance monitoring for trains and planes, or in the recruitment process by human resource departments to automatically scan and filter resumes to match job descriptions. The top 10 industries leveraging AI comprise the following: education, housing and nutrition, construction, wholesale and retail trade, healthcare, agriculture, social services, transport, manufacturing, financial services (Svetlana *et al.*, 2022).

2.1 Research Significance

Insights from a 2019 Accenture survey, revealed that the majority of senior executives (84%) recognised the importance of AI adoption for organisational success but 79% of the same executives lacked the necessary knowledge and strategies to adopt AI initiatives.

This study aims to provide credible insights in order to significantly address the current gap in knowledge for successful AI adoption.

Furthermore, a review of the literature can readily identify a list of the advantages of adopting artificial intelligence (AI), however, organisations also encounter challenges in defining clear pathways to widespread implementation. The current body of literature on technology adoption and AI adoption strategies remains fragmented and frequently fails to consider context-specific factors (Hutzschenreuter and Lämmermann, 2025). Existing technology adoption models are largely outdated or inadequate for contemporary AI systems, underscoring the necessity for new frameworks to support modern organisations (Matt, Hess and Benlian, 2015).

Although AI *is* increasingly utilised across various professions and industries (Atallah *et al.*, 2023), comprehensive research on its strategic implications in business are what are the crucial consideration prioritised by companies when adopting the technology is limited. This study aims to address this gap by presenting a framework and practical strategies for successful AI integration. The goal of the study is to enable business professionals to increase their competitive advantage and achieve better returns on their AI investment through informed and proficient AI adoption.

2.2 Search Criteria

Various academic search engines were used to undertake the research for the literature review, including, Google Scholar, Scopus, JSTOR, and EBSCOhost. Key search words and phrases used included “Business and AI use,” “Strategies for AI adoption in business”, “Critical Success Factors”, “AI Adoption” and “Benefits and Risks to AI adoption”. Priority was given to articles published in top-tier journals that were focused on the critical issues and had high citations. Further relevant works were identified by examining references in respected business publications, such as, Forbes, advancing the research process.

Additionally, searches were made using Google to source current materials from reputable

organisations in the technology space, including the likes of IBM and the Massachusetts Institute of Technology (MIT) and like organisations recognised for their leadership in technology, education and business.

3. Literature Review

3.1 Defining AI

Despite the amount of AI investment, the experts have yet to agree on a unified definition of AI (Russell and Norvig, 2022; MIT, 2024). Although various definitions have been proposed, most centre on the idea of machine intelligence that mirrors aspects of human cognition. An early articulation by McCarthy et al. (1955) describes AI as “making a machine behave in ways that would be called intelligent if a human were so behaving.” In accordance with this perspective, AI can be defined as machines with intelligence capable of performing cognitive functions (Radhakrishnan and Chattopadhyay, 2020). In the computer science realm, the Massachusetts Institute of Technology (MIT) has its own definition, where AI as a collection of technologies capable of accomplishing tasks considered intelligent by people (MIT, 2024).

3.2 How to Map Artificial Intelligence

Peifer, Jeske and Hille (2022) classify machine intelligence into the following three categories, in order of intelligence: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI). While artificial intelligence has made substantial progress, its current capabilities remain at the ANI stage, which does not reach the level of human cognitive abilities. AGI, defined as intelligence surpassing that of humans, represents a significant anticipated development in the field. Currently, experts have yet to predict with any certainty when AGI will be achieved (Peifer, Jeske and Hille, 2022).

Historically, "machine intelligence" bore little resemblance to human cognition. However, recent advancements in AI technologies including systems such as Chat-GPT and Deep Seek demonstrate increasingly sophisticated abilities that approach characteristics of genuine intelligence (Peifer, Jeske and Hille, 2022). Although AI remains at the Artificial Narrow Intelligence stage, the pursuit of Artificial General Intelligence where machines possess cognitive capacities comparable to humans, constitutes a major forthcoming objective. Despite uncertainty regarding the exact timeline, some experts suggest AGI could materialise within this century (Müller and Bostrom, 2016).

3.3 Forms of AI

AI is a broad spectrum of machine-driven methodologies and specialized disciplines. The principal categories within AI comprise Machine Learning, Big Data, Deep Learning, and Large Language Models (LLM) including examples such as DeepSeek, Qwen, and Moonshot. These components are often interconnected, functioning collectively to facilitate the advanced capabilities attributed to contemporary AI systems. For example, DeepSeek is a LLM that leverages both Deep Learning and machine learning. They are trained on expansive datasets representative of Big Data. Notably, ChatGPT-3 was developed with billions of parameters (Atallah and Atallah, 2021). Natural Language Processing (NLP), which employs machine learning strategies to enable computers to comprehend and interact effectively with human users, is another important component of AI technology (IBM, 2021).

3.6 Drivers of AI Adoption

Here are some key drivers of AI adoption in business.

3.6.1 Reduction of Costs

According to Accenture, the implementation of artificial intelligence produces average cost savings of approximately 25% across various sectors including information technology, banking, and operations (Accenture, 2017). Factoring in initial investment, AI-driven automation and efficiency at scale contribute to reduced operational costs and enhanced productivity.

3.6.2 Increase in Productivity

AI automates tasks that are repetitive or administratively taxing, allowing employees to allocate effort towards higher value-added activities, thereby increasing efficiency and reducing operational costs (LexisNexis, 2023). Take for example, in the legal sector, where AI is enabling lawyers to focus on matters requiring professional expertise by managing routine processes. In a Thomson Reuters (2025) survey, it was revealed that more than 50% of legal professionals expect productivity to be enhanced as a result of AI use. AI has the ability to process vast amounts of documents, which notably augments the effectiveness and speed of doing research and interrogation of documents (Donahue, 2018). Furthermore, unlike human practitioners, AI systems function continuously without the need for rest, executing their tasks efficiently and in substantially less time than would be required by a human employee (Kar, Kar and Gupta, 2021).

3.6.3 Decision Making and Data Analysis

Modern AI systems are capable of analysing extensive datasets to uncover patterns and insights that may not be readily identified by their human counterparts (Solaimani and Swaak, 2023). This capability facilitates strategic decision making in real-time and proves invaluable in complex issues where the data is vast. AI is capable of developing novel strategies providing unprecedented value in decision making.

3.6.4 Enhanced Client Care

Companies are increasingly using AI-powered chatbots and associated systems to enhance customer servicing and client interactions (Rane, 2023). By managing initial client consultations, AI enables business professionals to dedicate their attention to higher-priority tasks that increase value. These technologies streamline the delivery of services, improve operational efficiency, provide data-driven insights, and support informed decision-making, thereby benefitting clients (Mukherjee, 2020). In a 2025 survey by Thomson Reuters, nearly half of the participants expressed the belief that AI could lead to better quality outcomes and better client response times.

3.7 Barriers to AI Adoption

Artificial intelligence, while offering significant benefits, can also introduce some complex risks and challenges. These include job displacement, data privacy concerns, and other societal implications (Bostrom and Yudkowsky, 2014; Kar, Kar and Gupta, 2021). Therefore, companies will need to understand these issues and plan accordingly around them so that measures can be put in place to manage these issues with due diligence to ensure the effective management of such risks (Floridi *et al.*, 2018). Available studies suggest that many early adopters have faced difficulties integrating AI into their operations. In many instances, these initiatives have not met expectations, frequently falling short of anticipated outcomes or failing to achieve the projected ROI (Browder *et al.*, 2022).

Barriers to adoption are also attributed to variables that include industry type, organisational size, business structure, appetite for change, management organisation, and investment in technology (Lee *et al.*, 2019).

3.7.1 The Cost of AI Implementation

There are significant costs associated with AI adoption that both tangible and intangible, which is an obstacle to the implementation of AI technologies for some law firms. Such cost considerations extend beyond the initial investment costs, such as, software, security, storage, and IT infrastructure investment, to maintenance, system upgrades, substantial commitments to both current and near-term training for front-line staff, support staff, and management staff, to improve AI skills throughout the organisation. However, with increasing adoption rates and improving economies of scale being realised, the expenses related to AI software and security are gradually decreasing (Lee and Shin, 2020).

3.7.2 Displacement of Jobs

Based on research by the International Monetary Fund (IMF, 2024), we are experiencing a technological transformation unlike anything in the history of humanity that has the potential to stimulate global economic growth while also posing risks such as job displacement and increased inequality. Artificial intelligence is significantly redefining the way we work and fundamentally disrupting employment (Clio, 2024). Although, some positions may be reduced or even eliminated, it's not all negative, since the integration of AI will generate opportunities. The key is in reskilling, to facilitate the shift in knowledge within the workforce, which will invariably become more pronounced (Sharma and Reddy, 2024).

3.7.3 Security and Confidentiality

As artificial intelligence continues to gain traction, firms are expected to face growing challenges in information security, particularly in light of their rigorous confidentiality requirements. It is essential for firms to strategically leverage AI while implementing comprehensive governance measures to ensure compliance and to mitigate risks associated with the storage of sensitive data to avoid data breaches (Clio, 2024).

3.7.4 Accuracy and Lack of Transparency

Maintaining accuracy is critical, because without accuracy the system would be fundamentally flawed. This sentiment was corroborated by more than 40% of respondents in a Thomson Reuters (2024) study, which identified AI data accuracy to be of prime concern. Accordingly, substantial human oversight is still currently required to validate AI-generated results. To address these concerns, comprehensive AI training will be necessary to facilitate thorough evaluation of outputs. Going forward, both human knowledge and advanced AI augmentation are expected to play increasingly integral roles (Clio, 2024). At present, many AI solutions face criticism regarding their lack of transparency, often being described as “black boxes” because only the inputs and outputs can be examined and the exact methodology used to derive a result is unknown (IBM, 2024).

3.7.5 AI Hallucinations

GAI technologies, despite their impressive abilities, possess an inherently dangerous and critical flaw, often referred to as AI "hallucinations" (Emsley, 2023). This phenomenon refers to instances where generative AI systems produce false or incorrect information that may appear credible to users, despite being entirely fabricated by the technology (Emsley, 2023). Research into the accuracy and authenticity of a sample of references generated by such AI found that less than 8% were authentic and accurate, 44% was entirely inaccurate, and approximately 48% of the references were fabricated (Bhattacharyya *et al.*, 2023).

3.7.6 Ethics

Some key ethical considerations in the adoption and use of artificial intelligence technology include transparency, trust, fairness, privacy, bias, accountability, human rights, integrity, moral agency, and discrimination, among others (IBM, 2021; Cumming *et al.*, 2024). AI

systems may manifest biases originating from their training datasets or inherent within their system architecture (IBM, 2024).

More extreme risks include the very threat to humanity itself posed by the risk associated with a form of AI that decides coexistence with humans is not the way forward. Whilst this is a more extreme view, it is a real concern, none the less (McLean *et al.*, 2023).

3.7.7 AI Emotional Intelligence

On a spectrum of intelligence, current artificial intelligence technology is identified as Artificial Narrow Intelligence (ANI), with the next level of intelligence referred to as Artificial General Intelligence (AGI) (Peifer, Jeske and Hille, 2022). Meanwhile, virtual reality technologies continue to progress at a significant pace. Recent research conducted by Ovsyannikova, de Mello and Inzlicht (2025) indicates that AI has outperformed humans in crafting messages designed to express compassion, contrary to the common conception that AI lacks the ability to express such an emotion.

3.8 Critical Success Factors

A primary element of this study is premised on the understanding of the factors that determine success, more often referred to as critical success factors (CSF). In this context, the research will explore the specific elements that enabled the organisation to successfully incorporate AI into its business and how it was achieved. Analysing CSFs is a recognised academic method for understanding the main contributors to success within a specific domain (Duan, Edwards and Dwivedi, 2019). Identifying and comprehending these factors is critical for any business seeking to implement AI, as they underpin a successful deployment strategy, which can mean the difference between success and failure. Failure to achieve successful implementation will invariably mean that the anticipated benefits of AI have not been realised, which will have a direct negative impact to its competitive advantage (Merhi, 2023).

The CSFs below explore some of the principal success factors highlighted from the review of the literature.

3.8.1 Project Lead Champion

Given the complex challenges involved in integrating and adopting AI within established organisations, in addition to numerous other factors that must be addressed, it is essential to appoint an accountable and empowered individual to lead the project from inception through to completion. Concurrently, success in AI adoption depends on developing a comprehensive plan with clearly defined objectives. The objectives should also be aligned with the key goals of the organisation, which helps to focus and align the AI adoption (Grebe, Franke and Heinzl, 2023). Many projects do not succeed due to the absence of effective planning and execution strategies (Merhi, 2023).

3.8.2 Executive Management Support

Support from the top is frequently regarded as an important factor for the success of AI adoption strategies, as noted by several studies on this subject (Merhi, 2023; Solaimani and Swaak, 2023). Since adopting AI technology is complicated, requires changes to the existing practices, typically involving high costs, complex privacy and data considerations, and integration issues, the probability of successful implementation is increased considerably with resources and support from senior management. In some cases, only with approval from the top can such projects even get off the ground (Merhi, 2023).

3.8.3 Ease of Use - Perception

The perception of ease of use is a significant consideration when introducing any new system, as it considerably influences user acceptance and the eventual adoption of technology (Solaimani and Swaak, 2023). The opacity or “black box” perception often associated with

AI systems amplifies the relevance of this success factor. If users regard the system as complex or challenging to operate, the likelihood of successful implementation diminishes due to negative user perceptions, which may proliferate throughout an organization, sometimes acting as a deterrent to would-be users (Lee *et al.*, 2019).

3.8.4 Technical Competence and Skill

This concept of technical skill and competence encompasses the necessary skills and competencies required for effective AI adoption within an organisation, including considerations related to information systems infrastructure. Without the proper skills in place, successful AI adoption will be hindered or may not be possible at all. Organisations will likely encounter difficult challenges during the adoption process and will need to decide as part of their AI adoption plan whether to hire skilled staff in house or at least on a short-term basis to support their adoption journey (Solaimani and Swaak, 2023). Additionally, established organisations often face difficulties integrating AI solutions with existing infrastructure, while newer organisations have greater flexibility to implement new systems but may lack sufficient IT expertise to plan and deploy these technologies (Lee *et al.*, 2019).

4. AI Adoption and Existing Frameworks

4.1 Existing Theoretical Frameworks

Various frameworks exist in relation to technology adoption, many of which are considered seminal as they have stood the test of time.

Several frameworks are often referenced when examining technology adoption: the Technology Adoption Model (TAM), the Technology Organization Environment (TOE) model (Tornatzky, 1990), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Benefits, Organizational Readiness, and External Pressure (BOE) model

(Iacovou, Benbasat and Dexter, 1995), the Diffusion of Innovation (DOI) model (*Diffusion of Innovations, 4th Edition*, 2010), and the Functionality, Availability, Complexity, Cost (FACC) model (Wendler and Dasgupta, 2019).

While these models differ in methodology, they collectively offer valuable perspectives on key considerations for technology adoption and highlight the diversity of available frameworks.

4.2 DOI – TOE – BOE – FACC

The Diffusion of Innovation (DOI) model primarily examines the temporal dynamics of technology uptake, Technology, Organisation, Environment (TOE) centres on external influences such as regulatory requirements and market forces, whereas BOE provides a more holistic perspective by addressing external pressure, organisational readiness, and perceived benefits. Initially developed for electronic data interchange (EDI) adoption, Benefits, Organisational Readiness, External Pressure (BOE) has since become a general framework for technology implementation. Additionally, the Functionality, Availability, Complexity, Cost (FACC) model applies distinct criteria, focusing primarily on determining optimal timing for adoption (Wendler and Dasgupta, 2019). Although these models may appear straightforward, they possess significant potential for generating meaningful insights. Nevertheless, their value is limited, as they tend to inform early-stage decisions, such as the rationale and timing of adoption, while insufficiently addressing implementation strategies. This underscores the necessity for a tailored framework, particularly regarding AI adoption within the legal sector.

4.3 TAM

The Technology Acceptance Model (TAM) has been around since 1987 and is focused on the user experience in relation to technology adoption (Davis, 1987). Its research was premised

on how users perceive the technology, measured by perceived ease of use, i.e. the amount of effort required, and usefulness of the technology, i.e. how does it improves the users' job performance (Mugo *et al.*, 2017).

4.4 UTAUT

The Unified Theory of Acceptance and Use of Technology (UTAUT) draws upon eight prominent and competing models within the literature at the time, consisting of: the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), a combined model of TAM and TPB (C-TAM-TPB), the Model of PC Utilization, the Motivational Model (MM), the Social Cognitive Theory (SCT), the Theory of Reasoned Action (TRA), and the Innovation Diffusion Theory (IDT) (Ahmad, 2014)

The UTAUT model is premised on four core constructs that is focused on determining intention to use or usage behaviour. The constructs include Effort Expectancy, Performance Expectancy, Social Influence and Facilitating Conditions. Additionally, moderating variables, namely Age, Gender, Experience, and Voluntariness of Use are incorporated to account for their influence on the relationships between various factors and the intention to use (Ahmad, 2014).

4.5 AI and Business Strategies

Hutzschenreuter and Lämmermann (2025) explore the systematic incorporation of transformative technologies, such as AI systems to enhance the competitive advantage of businesses from a strategic level. Their research explores both unsupervised and supervised self-learning technology systems, including generative and predictive models. The study also introduces and explores the concepts of “black-box perception” and “AI task superiority” in relation to AI technologies. Furthermore, the authors present a framework intended to guide business leaders in developing effective AI adoption strategies, organized around five key

questions to support organizational decision-making. Although the theoretical foundations of the framework are sound, a closer examination indicates that its depth is somewhat limited, potentially reducing its value for leaders seeking thorough guidance on both macro and micro dimensions to support their AI adoption strategies.

Abuzaid (2024) conducted a study that explored the integration of artificial intelligence within corporate decision-making, providing valuable insights into corporate engagement with AI technologies. The research introduced a framework that prioritises ethics and data security, positioning these considerations as paramount compared to other business factors. Thus demonstrating the author's philosophical approach to the study, emphasising their ontological, epistemology and axiological approach. Conversely, the framework established by Hutzschenreuter and Lämmermann (2025) places greater emphasis on practical business concerns and omits reference to ethics or data security. These contrasting approaches offer insights into differing leadership priorities among organisations (and is also revealing of the researchers' different philosophical approaches). The comparison between the two studies highlights ongoing discussions regarding the prioritisation of elements in AI adoption, particularly concerning the inclusion of ethics and data security. For this proposed study, the author also attaches weight to ethical considerations and data integrity, as they are essential when formulating effective strategies for AI implementation, including applications within the legal sector.

4.6 AI and Strategic Management

Strategic management involves formulating and executing long-term plans designed to achieve organisational objectives. AI enhances strategic management by providing data-driven insights, enabling market trend forecasting, and optimising resource allocation (Porter and Heppelmann, 2014). We understand from research, which suggests that organisations

integrating AI into their strategy development may observe positive variations in performance outcomes compared to those not utilising AI (Brynjolfsson & McAfee, 2017).

According to Hutzschenreuter and Lämmermann (2025), five key questions can help guide organisations as they develop an AI strategy. These questions are arranged into three categories outlined by the researchers, providing a structured framework for considering AI adoption. The first consideration concerns determining areas within an organisation where AI implementation may be appropriate, acknowledging that universal deployment may not be practical due to constraints such as emerging technology and limited resources. Organisations are encouraged to start by identifying a specific problem that AI could address and to focus on achieving measurable results with that area of focus in mind.

Once an organisation is able to effectively identify its initial objectives and challenges, it can systematically identify further areas for AI implementation, adopting an iterative approach. The subsequent priority is to assess how AI delivers value and strengthens the organisation's competitive position. Additionally, it is crucial to evaluate the role of AI in driving the company's financial performance. These core "why" questions should be thoroughly considered during the development of any AI strategy. Addressing them will logically lead to technical considerations, such as identifying the Information Technology (IT) resources and human resources required to meet the organisation's AI objectives.

5. Research Aims, Questions and Hypotheses

5.1 Aims

1. To provide a multi-stage strategic framework for AI adoption in business
2. To understand what the contemporaneous drivers and barriers are for scalable AI adoption in business

3. To uncover and understand the critical success factors for AI adoption in business

5.2 Research Questions

- Q1. What are the factors that influence AI adoption in organisations?
- Q2. What are the challenges associated with AI adoption in organisations?
- Q3. What are the factors that contribute to successful AI implementation?
- Q4. How can organisations address both facilitating and hindering factors to enhance competitiveness?
- Q5. What approaches can organisations take to develop successful AI adoption strategies?

5.3 Research Hypotheses

The following hypotheses are listing below for ease of reference, further details on the development of these hypotheses can be found in sections six and seven of this research proposal.

H1. Organizations that define a clear AI development objective and select a focused operational domain will achieve more effective outcomes in AI implementation, measurable by ROI, KPI metrics, and cost efficiency compared with organisations that pursue broad, organization-wide AI strategies.

H2. A good AI adoption strategy is be based on a thorough understanding of the drivers, barriers, and critical success factors that are relevant to the organisation and must align with its core values and mission statement, in order to provide maximum value.

H3a. Larger companies have more financial resources, enabling them to scale AI adoption more readily than small companies.

H3b. Larger companies have more human resources, enabling them to scale AI adoption more readily than small companies.

H3c. Larger companies have more technology systems, enabling them to scale AI adoption more readily than small companies.

H4a. Small companies with less financial resources at their disposal and therefore have to be more focused in their AI strategy, which may limit the scale of their AI adoption

H4b. Small companies with less human resources at their disposal and therefore have to be more focused in their AI strategy, which may limit the scale of their AI adoption

H4c. Small companies with less technology resources at their disposal and therefore have to be more focused in their AI strategy, which may limit the scale of their AI adoption

6. Discussion on AI Adoption

The literature review covers diverse concepts and theories on AI adoption, with authors agreeing on its potential benefits and risks. Despite exploring new theoretical approaches, no comprehensive or systematic method for AI adoption was identified.

Developing effective strategies necessitates thorough evaluation of factors such as the industry, culture, business landscape, workforce characteristics, and organisational size. The framework introduced by Hutzschenreuter and Lämmermann (2025) is designed to be versatile in its support of business AI integration. However, the current model demonstrates limited granularity and depth in its scope. The primary investigator believes its overall effectiveness could be substantially improved by expanding and developing the model.

Establishing a clear objective and selecting a well-defined "playing field" enables an organisation to focus efforts within a targeted domain of AI development that is relevant to the organisation (Hutzschenreuter and Lämmermann, 2025). Such a concentrated strategy is more likely to produce effective results than pursuing broad AI implementation across the entire organisation. By limiting scope, organisations can more effectively manage costs, assess return on investment (ROI), and monitor key performance indicators (KPIs), thereby facilitating alignment between outcomes and strategic expectations. A systematic evaluation of each segment within their framework supports the identification of departments or sub-departments best positioned to benefit from AI adoption. Although this methodology provides a practical foundation, its inherent simplicity constrains its utility beyond the initial phase. Accordingly, the principal investigator advocates for the development of a comprehensive framework to address these identified limitations.

H1. Organizations that define a clear AI development objective and select a focused operational domain will achieve more effective outcomes in AI implementation, measurable by ROI, KPI metrics, and cost efficiency compared with organisations that pursue broad, organization-wide AI strategies.

H2. A good AI adoption strategy is based on a thorough understanding of the drivers, barriers, and critical success factors that are relevant to the organisation and must align with its core values and mission statement, in order to provide maximum value.

7. Methodology

7.1 Research Design

The study will adopt a mixed methods approach, combining a quantitative questionnaire with an exploratory case study that will feature 3-5 companies that have adopted AI technologies

as part of a structured strategic approach. Case study research is based on a postpositivist paradigm, which is premised on an ultimate reality that we cannot entirely understand (Schoch, 2020) and is well suited for understanding the phenomenon of AI and business.

Given the nascent nature of AI adoption, the lead investigator believes that an exploratory case study will provide quality insights and is very appropriate for this research proposal, which is attempting to address the how and the why of the phenomenon of AI adoption. The researcher has limited influence over the events, and the focus is on examining the complex contemporary phenomena of AI adoption in real-life contexts. The case studies can yield both confirmatory (deductive) and explanatory (inductive) insights (Yin, 2009). The case study method is appropriate for single or multiple cases and may utilize a combination of qualitative and/or quantitative data. This approach facilitates a comprehensive analysis of organizational dynamics, decision-making processes, and stakeholder viewpoints (Yin, 2009).

7.2 Case Selection

This study will adopt an exploratory case study approach. A purposive sampling strategy will be employed to select three to five organizations that meet the following criteria:

- (1) Of varying company size
- (2) Have undergone a strategy of AI adoption within the past 3 years
- (3) Are willing to provide access to key informants and internal documentation

- (1) Of varying company size:

The aim is to have a mixture of large, medium and small company to form a diverse cross section, which can provide insights into differences in approach based on company size and resources. The reason for this design is to provide additional insight into how

companies of varying size may approach AI adoption. Some hypotheses that can be tested include:

H3a. Larger companies have more financial resources, enabling them to scale AI adoption more readily than small companies.

H3b. Larger companies have more human resources, enabling them to scale AI adoption more readily than small companies.

H3c. Larger companies have more technology systems, enabling them to scale AI adoption more readily than small companies.

Larger companies have more resources in terms of financial resources, human resources, and technological systems, enabling them to scale AI adoption more readily than small companies. Specifically, greater financial resources allow these enterprises to invest in AI technologies, fund pilot projects, and absorb initial implementation costs with less risk. Their larger pools of skilled employees, including data scientists, IT professionals, and project managers, facilitate the development, customization, and ongoing support of AI solutions. Additionally, advanced technological systems and established IT infrastructures streamline the integration of AI tools into existing workflows and enable efficient management of complex data environments. Together, these advantages position larger companies to adopt and expand AI initiatives on a broader scale and at a faster pace than their smaller counterparts (Muminova *et al.*, 2024).

H4a. Small companies have less financial resources at their disposal and therefore have to be more focused in their AI strategy, which may limit the scale of their AI adoption

H4b. Small companies have less human resources at their disposal and therefore have to be more focused in their AI strategy, which may limit the scale of their AI adoption

H4c. Small companies have less technology resources at their disposal and therefore have to be more focused in their AI strategy, which may limit the scale of their AI adoption

Small companies, constrained by limited funding and a shortage of specialized talent, must focus their AI strategies on projects with the most immediate impact. Unlike larger enterprises that can allocate resources to multiple initiatives, smaller firms are often compelled to prioritize essential deployments, such as automating customer service over more ambitious implementations like organization-wide predictive analytics. For instance, a startup might invest in chatbots to streamline client interactions but lack the capital or expertise to develop advanced data-driven solutions across all departments. This necessity for prioritization can slow the pace and limit the scope of AI adoption. The research supports a reoccurring theme of SMEs struggling with limited budgets for investment in technology (Muminova *et al.*, 2024). Thus underscoring how financial limitations fundamentally shape their strategic decisions and overall adoption trajectory.

Enterprises can be categorized by size using various criteria, with the number of employees being one of the most common. Small and medium-sized enterprises (SMEs) are defined as those employing fewer than 250 people, small enterprises (10 to 49 employees), and medium-sized enterprises (50 to 249 employees). Large enterprises are classified as those with 250 or more employees (OECD, 2023).

The selected cases will serve as instrumental cases to illuminate broader theoretical constructs rather than to generalize findings.

7.3 Data Collection Methods

Multiple sources of evidence will be triangulated to enhance the validity of the findings, including the following methods.

Semi-structured interviews: some open-ended questions will be prepared in advance, and the interview will be conducted with key stakeholders, such as, executives, managers and frontline staff. Actual interview questions will be determined later and will be guided by a flexible protocol and audio recorded with the express consent of participants.

Document analysis: will include the review internal reports, meeting minutes, strategic plans, and other relevant organisational artifacts relevant to the research.

Survey: these can be structured questionnaires administered to a select group of participants who were involved in a specific case under study. The survey questions will be designed with the research objectives in mind. The survey results will be analysed with software to identify findings. Surveys can further inform the study by gathering quantitative data to complement or support the qualitative findings.

Observations: if practical and can add value to the research, the researcher will observe meetings or work processes in order to capture contextual nuances (Schoch, 2020).

All data will be collected over a period of 6–12 months.

7.4 Data Analysis

7.4.1 Thematic Analysis and Coding

The process of conducting a thematic analysis can be very subjective, and can vary considerably depending on the perspective of the researcher, however, it is a very useful way of processing, organising and analysing qualitative data (Boyatzis, 1998).

The data collected will be analysed by categorising into various themes that will become apparent from the identified data, which will help the researcher to prepare the data for further analysis, and will also inform how the results are coordinated and presented.

Thematic analysis will be used to identify patterns and insights across the data. The process will follow the six-phase framework by Bruan and Clarke (2006):

1. Familiarisation with data
2. Generating initial codes
3. Searching for themes
4. Reviewing themes
5. Defining and deciding theme names
6. Producing the report

NVivo software will be used to assist with coding and organizing qualitative data. The software enables researchers to manage and analyse unstructured data, such as audio, images, video, and text. NVivo is widely used in especially for the analysis of interview data (Phillips and Lu, 2018)

7.5 Research Plan Timetable

	Activity	Duration
1	Literature review: detailed review	3-4 months
2	Qualitative – exploratory case study – review of documents and interview preparation	6-8 months
3	Conduct interviews	3-4 months
4	Data analysis: Qualitative	3-4 months

5	Design of the Survey	1-2 months
6	Participants – Recruitment Phase	1-2 months
7	Participants - Conduct surveys	3 months
8	Data analysis: Quantitative	6 months
9	Findings – Write up	8-9 months

7.6 Ethical Considerations

Ethical approval will be sought from the UWTSD before proceeding. Participants will be provided with informed consent forms outlining the purpose of the study, their rights, and data confidentiality measures. All data will be anonymized and securely stored in compliance with GDPR and institutional guidelines.

7.7 Discussion on Research Design

The design of the research based is on mixed methods combining quantitative research with a qualitative exploratory case study approach, which will aim to address the research questions and test the hypotheses proposed in this research. Additionally, the research design will elicit deep insights into how companies have successfully approached AI adoption. The results will be of interest and add value to companies that are about to embark on their AI adoption strategies, providing practical and tangible guidance that will inform their approach. The exploratory nature of the case study will address the how and the why those companies approached their AI strategies in the way that they did, what challenges they overcame and how they aligned their approach with their business priorities.

7.8 Limitations

Qualitative methods lend themselves to the risk of projections by the researcher where there are gaps in the research or the data that may not be readily explainable (Boyatzis, 1998). The principal investigator is mindful of this and will try to remain cognisant of this fact throughout the process of data gathering and synthesis of the information. The nascent nature of the research proposal is subject to constant change and is an ever-evolving topic of discussion and research with few established experts. Whilst this lends itself to the exploratory case study approach, there will likely be factors at play that extend beyond the boundaries of the research, which future researchers may decide to pick up upon for further research and analysis. The design of the study is deliberately broad to provide insights and elucidate nuances in strategies by various companies. Some may find this too broad and may wish to hone in for future studies. While this study does not address all of the nuanced interconnecting elements in detail, future research could explore those areas further and may focus on how a particular phenomenon impacts a company's AI trajectory and overall strategy.

8. Conclusion

This research proposal is focused on the significant impact of artificial intelligence within the business sector and will provide a structured framework for integrating AI as part of a business strategy. Its primary goals include the establishment of the critical factors for success along with research on the barriers and drivers of AI adoption. The mixed method approach will produce quantitative data combined with an exploratory case study approach for in depth insights and learnings into how companies design and implement their AI strategies. The literature review demonstrates that, despite a growing body of work on AI, there is a distinct gap in studies directly addressing the focal topics of this proposal. The

interplay between incentives and challenges relating to AI implementation within organisations necessitates thorough case by case evaluation to determine effective strategies that can be leveraged for competitive advantage. The case studies will test the proposed hypotheses and address the research questions. Furthermore, the critical success factors influencing AI adoption will differ depending on organisational characteristics and their particular core values. This research seeks to generate additional insights from the exploratory case studies in order to articulate and contextualise different strategies. By methodically examining the core elements of AI adoption, the study aims to make substantive contributions to the body of literature on AI and adoption strategies. The knowledge will benefit academics, practitioners, students, and anyone with an interest in the intersection of AI and business.

References

- Abuzaid, A.N. (2024) 'Strategic AI Integration: Examining the Role of Artificial Intelligence in Corporate Decision-Making', in *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS)*. *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS)*, pp. 1–6. Available at: <https://doi.org/10.1109/ICKECS61492.2024.10616871>.
- Accenture (2017) *Redefine Banking with Artificial Intelligence*. Available at: <https://dl.icdst.org/pdfs/files3/586bb16c395d33fa2cdc64dbcf5b4f27.pdf> (Accessed: 10 February 2025).
- Accenture (2019) *Scaling AI: From Experimental to Exponential*. Available at: <https://www.accenture.com/us-en/insights/artificial-intelligence/ai-investments> (Accessed: 15 February 2025).
- Ahmad, M.I. (2014) 'Unified Theory of Acceptance and Use of Technology (UTAUT)'.
- Atallah, A.B. and Atallah, S. (2021) 'Cloud Computing for Robotics and Surgery', in S. Atallah (ed.) *Digital Surgery*. Cham: Springer International Publishing, pp. 37–58. Available at: https://doi.org/10.1007/978-3-030-49100-0_4 (Accessed: 3 February 2025).

Atallah, S.B. et al. (2023) 'How large language models including generative pre-trained transformer (GPT) 3 and 4 will impact medicine and surgery', *Techniques in Coloproctology*, 27(8), pp. 609–614. Available at: <https://doi.org/10.1007/s10151-023-02837-8>.

Bhattacharyya, M. et al. (2023) 'High Rates of Fabricated and Inaccurate References in ChatGPT-Generated Medical Content', *Cureus* [Preprint]. Available at: <https://doi.org/10.7759/cureus.39238>.

Black, J.S. and Van Esch, P. (2020) 'AI-enabled recruiting: What is it and how should a manager use it?', *Business Horizons*, 63(2), pp. 215–226. Available at: <https://doi.org/10.1016/j.bushor.2019.12.001>.

Bostrom, N. and Yudkowsky, E. (2014) 'The Ethics of Artificial Intelligence', *The Cambridge Handbook of Artificial Intelligence*, pp. 316–334.

Boyatzis, R.E. (1998) *Transforming Qualitative Information: Thematic Analysis and Code Development*. SAGE.

Browder, R.E. et al. (2022) 'Learning to Innovate with Big Data Analytics in Interorganizational Relationships', *Academy of Management Discoveries*, 8(1), pp. 139–166. Available at: <https://doi.org/10.5465/amd.2019.0048>.

Bruan, V. and Clarke, V. (2006) 'Using thematic analysis in psychology', *Qualitative Research in Psychology* [Preprint]. Available at: <https://doi.org/10.1191/1478088706qp063oa>.

Brynjolfsson & McAfee (2017) *The Business of Artificial Intelligence*. Available at: <https://hbr.org/2017/07/the-business-of-artificial-intelligence> (Accessed: 13 February 2025).

Chatterjee, S., Rana, N.P. and Dwivedi, Y.K. (2024) 'How does business analytics contribute to organisational performance and business value? A resource-based view', *Information Technology & People*, 37(2), pp. 874–894. Available at: <https://doi.org/10.1108/ITP-08-2020-0603>.

Clio (2024) *Legal Innovation and AI: Risks and Opportunities*. Available at: https://www.americanbar.org/groups/law_practice/resources/law-technology-today/2024/legal-innovation-and-ai-risks-and-opportunities/ (Accessed: 10 February 2025).

Cumming, D. et al. (2024) 'Towards AI ethics-led sustainability frameworks and toolkits: Review and research agenda', *Journal of Sustainable Finance and Accounting*, 1, p. 100003. Available at: <https://doi.org/10.1016/j.josfa.2024.100003>.

Davis, F. (1987) 'TAM'. Available at:
<https://quod.lib.umich.edu/b/busadwp/images/b/1/4/b1409190.0001.001.pdf>
(Accessed: 8 September 2025).

Diffusion of Innovations, 4th Edition (2010). Available at:
<https://www.simonandschuster.com/books/Diffusion-of-Innovations-4th-Edition/Everett-M-Rogers/9781451602470> (Accessed: 7 April 2025).

Donahue, L. (2018) *A Primer on Using Artificial Intelligence in the Legal Profession*, *Harvard Journal of Law & Technology*. Available at: <https://jolt.law.harvard.edu/digest/a-primer-on-using-artificial-intelligence-in-the-legal-profession> (Accessed: 28 January 2025).

Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2019) 'Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda', *International Journal of Information Management*, 48, pp. 63–71. Available at:
<https://doi.org/10.1016/j.ijinfomgt.2019.01.021>.

Emsley, R. (2023) 'ChatGPT: these are not hallucinations – they're fabrications and falsifications', *Schizophrenia*, 9(1), pp. 1–2. Available at:
<https://doi.org/10.1038/s41537-023-00379-4>.

Floridi, L. *et al.* (2018) 'AI4People—An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations', *Minds and Machines*, 28(4), pp. 689–707. Available at: <https://doi.org/10.1007/s11023-018-9482-5>.

Grebe, M., Franke, M.R. and Heinzl, A. (2023) 'Artificial intelligence: how leading companies define use cases, scale-up utilization, and realize value', *Informatik Spektrum*, 46(4), pp. 197–209. Available at: <https://doi.org/10.1007/s00287-023-01548-6>.

Hutzschenreuter, T. and Lämmermann, T. (2025) 'What Is Your AI Strategy? Systematically Integrating Self-Learning Technologies into Your Business Strategy', *Academy of Management Perspectives*, p. amp.2023.0243. Available at:
<https://doi.org/10.5465/amp.2023.0243>.

Iacovou, C.L., Benbasat, I. and Dexter, A.S. (1995) 'Electronic Data Interchange and Small Organizations: Adoption and Impact of Technology', *MIS Quarterly*, 19(4), pp. 465–485. Available at: <https://doi.org/10.2307/249629>.

IBM (2021) *What is AI Ethics?* | IBM. Available at: <https://www.ibm.com/think/topics/ai-ethics> (Accessed: 12 February 2025).

IBM (2024) *What Is Black Box AI and How Does It Work?* | IBM. Available at:
<https://www.ibm.com/think/topics/black-box-ai> (Accessed: 12 February 2025).

IMF (2024) *AI Will Transform the Global Economy. Let's Make Sure It Benefits Humanity.*, IMF. Available at: <https://www.imf.org/en/Blogs/Articles/2024/01/14/ai-will-transform-the-global-economy-lets-make-sure-it-benefits-humanity> (Accessed: 20 July 2025).

Kar, S., Kar, A.K. and Gupta, M.P. (2021) 'Modeling Drivers and Barriers of Artificial Intelligence Adoption: Insights from a Strategic Management Perspective', *Intelligent Systems in Accounting, Finance and Management*, 28(4), pp. 217–238. Available at: <https://doi.org/10.1002/isaf.1503>.

Lee, I. and Shin, Y.J. (2020) 'Machine learning for enterprises: Applications, algorithm selection, and challenges', *Business Horizons*, 63(2), pp. 157–170. Available at: <https://doi.org/10.1016/j.bushor.2019.10.005>.

Lee, J. et al. (2019) 'Emerging Technology and Business Model Innovation: The Case of Artificial Intelligence', *Journal of Open Innovation: Technology, Market, and Complexity*, 5(3), p. 44. Available at: <https://doi.org/10.3390/joitmc5030044>.

LexisNexis (2023) *The Use of Artificial Intelligence in the Legal Profession*. Available at: <https://www.lexisnexis.com/community/insights/legal/practical-guidance-journal/b/pa/posts/the-use-of-artificial-intelligence-in-the-legal-profession> (Accessed: 15 February 2025).

Matt, C., Hess, T. and Benlian, A. (2015) 'Digital Transformation Strategies', *Business & Information Systems Engineering*, 57(5), pp. 339–343. Available at: <https://doi.org/10.1007/s12599-015-0401-5>.

McKinsey Institute (2018) *MGI-Notes-from-the-AI-frontier-Modeling-the-impact-of-AI-on-the-world-economy-September-2018*, McKinsey Global Institute. Available at: https://www.mckinsey.com/~/_media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Notes%20from%20the%20frontier%20Modeling%20the%20impact%20of%20AI%20on%20the%20world%20economy/MGI-Notes-from-the-AI-frontier-Modeling-the-impact-of-AI-on-the-world-economy-September-2018.pdf (Accessed: 20 July 2025).

McLean, S. et al. (2023) 'The risks associated with Artificial General Intelligence: A systematic review', *Journal of Experimental & Theoretical Artificial Intelligence*, 35(5), pp. 649–663. Available at: <https://doi.org/10.1080/0952813X.2021.1964003>.

Merhi, M.I. (2023) 'An evaluation of the critical success factors impacting artificial intelligence implementation', *International Journal of Information Management*, 69, p. 102545. Available at: <https://doi.org/10.1016/j.ijinfomgt.2022.102545>.

MIT (2024) *What is AI?*, MIT Technology Review. Available at: <https://www.technologyreview.com/2024/07/10/1094475/what-is-artificial-intelligence-ai-definitive-guide/> (Accessed: 8 February 2025).

Mugo, D. et al. (2017) 'The Technology Acceptance Model (TAM) and its Application to the Utilization of Mobile Learning Technologies', *British Journal of Mathematics & Computer Science*, 20(4), pp. 1–8. Available at: <https://doi.org/10.9734/BJMCS/2017/29015>.

Mukherjee, S. (2020) 'Emerging Frontiers in Smart Environment and Healthcare – A Vision', *Information Systems Frontiers*, 22(1), pp. 23–27. Available at: <https://doi.org/10.1007/s10796-019-09965-3>.

Müller, V.C. and Bostrom, N. (2016) 'Future Progress in Artificial Intelligence: A Survey of Expert Opinion', in V.C. Müller (ed.) *Fundamental Issues of Artificial Intelligence*. Cham: Springer International Publishing (Synthese Library), pp. 555–572. Available at: https://doi.org/10.1007/978-3-319-26485-1_33.

Muminova, E. et al. (2024) 'AI in Small and Medium Enterprises: Assessing the Barriers, Benefits, and Socioeconomic Impacts', in *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS)*. *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS)*, pp. 1–6. Available at: <https://doi.org/10.1109/ICKECS61492.2024.10616816>.

OECD (2023) *Enterprises by business size*, OECD. Available at: <https://www.oecd.org/en/data/indicators/enterprises-by-business-size.html> (Accessed: 10 September 2025).

Ovsyannikova, D., de Mello, V.O. and Inzlicht, M. (2025) 'Third-party evaluators perceive AI as more compassionate than expert humans', *Communications Psychology*, 3(1), pp. 1–11. Available at: <https://doi.org/10.1038/s44271-024-00182-6>.

Peifer, Y., Jeske, T. and Hille, S. (2022) 'Artificial Intelligence and its Impact on Leaders and Leadership', *Procedia Computer Science*, 200, pp. 1024–1030. Available at: <https://doi.org/10.1016/j.procs.2022.01.301>.

Phillips, M. and Lu, J. (2018) 'A quick look at NVivo', *Journal of Electronic Resources Librarianship*, 30(2), pp. 104–106. Available at: <https://doi.org/10.1080/1941126X.2018.1465535>.

Radhakrishnan, J. and Chattopadhyay, M. (2020) 'Determinants and Barriers of Artificial Intelligence Adoption – A Literature Review', in S.K. Sharma et al. (eds) *Re-imagining Diffusion and Adoption of Information Technology and Systems: A Continuing Conversation*. Cham: Springer International Publishing, pp. 89–99. Available at: https://doi.org/10.1007/978-3-030-64849-7_9.

Rane, N. (2023) 'Role and Challenges of ChatGPT and Similar Generative Artificial Intelligence in Business Management', *SSRN Electronic Journal* [Preprint]. Available at: <https://doi.org/10.2139/ssrn.4603227>.

Russell, S.J. and Norvig, P. (2022) *Artificial intelligence: a modern approach*. Fourth edition, global edition. Boston: Pearson (Prentice Hall series in artificial intelligence).

Schoch, K. (2020) 'Case Study Research', in *Research Design and Methods: An Applied Guide for the Scholar-Practitioner*. SAGE Publications Ltd, pp. 245–258. Available at: <https://uk.sagepub.com/en-gb/asi/research-design-and-methods/book262895> (Accessed: 14 September 2025).

Sharma, R. and Reddy, B. (2024) 'Strategic Approaches to AI Integration in Organizations: Managing Change and Maximizing Benefits', in *2024 4th Asian Conference on Innovation in Technology (ASIANCON)*. *2024 4th Asian Conference on Innovation in Technology (ASIANCON)*, pp. 1–5. Available at: <https://doi.org/10.1109/ASIANCON62057.2024.10838046>.

Solaimani, S. and Swaak, L. (2023) 'Critical Success Factors in a multi-stage adoption of Artificial Intelligence: A Necessary Condition Analysis', *Journal of Engineering and Technology Management*, 69, p. 101760. Available at: <https://doi.org/10.1016/j.jengtecman.2023.101760>.

Svetlana, N. et al. (2022) 'Artificial intelligence as a driver of business process transformation', *Procedia Computer Science*, 213, pp. 276–284. Available at: <https://doi.org/10.1016/j.procs.2022.11.067>.

Thomson Reuters (2025) *How AI is transforming the legal profession (2025) | Legal Blog*, Thomson Reuters. Available at: <https://legal.thomsonreuters.com/blog/how-ai-is-transforming-the-legal-profession/> (Accessed: 15 February 2025).

Tornatzky, L.G. (1990) *The processes of technological innovation*. Lexington, Mass. : Lexington Books. Available at: <http://archive.org/details/processesoftechn0000torn> (Accessed: 7 April 2025).

Wendler, S. and Dasgupta, A. (2019) 'AI Adoption Strategies', *Postdoctoral Research Fellow, Artificial Intelligence Centre for Technology and Global Affairs, University of Oxford* [Preprint].

Yin, R.K. (2009) *Case Study Research: Design and Methods*. SAGE.