Artificial Intelligence Adoption Under the Influence of Top Team Management Background and AI Knowledge Spillover Effects in UK SMSs

by

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Contents

Page

Abstract

This study applies upper echelons theory and the social capital theoretical frameworks to observe the determinants of AI adoption in UK-based SMEs. The study focuses on core competencies of SMEs, such as top management's AI literacy and innovativeness through social capital values for AI adoption. To investigate these relationships, data from 209 companies were collected through websites and social network platform. Findings suggest that top management's AI literacy positively impacts firm-level AI adoption and that external factors, such as regional influences, moderate the relationship between top management AI literacy and AI adoption. Furthermore, this research suffers from robustness checks, limited cross-sectional data, and contingencies that arose unexpectedly, thus providing empirical arguments for further research. By highlighting AI diffusion this study gives the importance of further research on SMEs' interconnections with other firms and the transmission of AI knowledge focusing on top management's AI skills. Considered as an early stage of AI adoption, this research offers insights for SMEs and policymakers to embrace AI by identifying potential beneficial factors such as AI literacy, access, and exposure to AI knowledge, thereby gaining a competitive advantage and deriving value from AI.

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Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction

1.1 Introduction

In the VUCA (volatile, uncertain, complex, and ambiguous) business world, traditional business strategies may not be effective for navigating these challenges. Instead, it is essential for business leadership to foster dynamic capabilities to leverage innovative business models (Schoemaker, Heaton and Teece, 2018). As a disruptive innovation, artificial intelligence (AI) has the potential to transform business models by enhancing human decision-making, optimizing business processes, improving operational efficiency, and driving innovation (Davenport *et al.*, 2020). Currently, most businesses are integrating AI into their processes. However, due to the early stage of widespread AI adoption and the initial emergence of AI benefits in business, there are risks associated with applying and aligning AI with business goals (McKinsey, 2024). Therefore, it is necessary for forthcoming AI adopters to be literate about AI's benefits and limitations. This AI literacy tailors AI deployment by contextualizing the benefits and limitations, encouraging dialogues among various stakeholders, and addressing ethics and risks issues (World Economic Forum, 2022). Moreover, when innovative technology emerges, it renders the old technology obsolete and forces firms to adopt new technology (Rothaermel and Hill, 2005). This shift further accelerates the obsolescence of outdated technological knowledge if firms have access to AI knowledge sources (Liu *et al.*, 2024).

1.1 Background

The term "artificial intelligence" was first used by John McCarthy and his research colleagues in 1955 (McCarthy *et al.*, 2006). They described it as machine functionality that mimics human-like intelligence. Davenport et al. (2020) structured the conceptualization of AI around three key dimensions: the level of intelligence, AI task type, and AI in robotics. They defined AI as technology with advanced computational capabilities to perform human-like cognitive tasks. The intelligence level enhances responses to context-specificity and the ability to analyse different task types, regardless of whether the data are structured or unstructured, and the dimension of robotic systems can provide a tangible element to the experience. These factors of AI fundamentally transform the business model by exceptionally creating business value for organizational success (Enholm et al., 2022). This transformation enables businesses to gain a unique competitive advantage through the generation of innovative products or services. Moreover, to sustain and survive, the value proposition must meet the challenges of a competitive business environment. It is possible for businesses to significantly improve their competitiveness by effectively utilizing the knowledge-related and transformative capabilities of AI (Zebec and Indihar Štemberger, 2024). This overcomes the limitations of conventional information technology, making it possible to gain continuous competitive advantages.

However, to maximize the benefits of AI, firms should invest in AI training and knowledge development and management possesses AI capabilities (Alekseeva *et al.*, 2020). Unlike conventional IT, AI possesses capabilities such as learning, adaptability, and autonomy (Bawack, Wamba and Carillo, 2019). This emphasizes the importance of management's strategic roles in facilitating organizational change towards businesses aligned with AI. Organizations preparing for AI adoption should consider this because AI sometimes operates in unexplainable ways. To mitigate this, the top management's ability to discover patterns in data and logically compare these with AI models can avoid unforeseen circumstances (Nagahisarchoghaei *et al.*, 2023). This Human-AI complementing strategic perspective and incremental implementation of AI are vital for AI adoption, which reduces those AI deployment challenges(Davenport, 2018). By examining the pragmatic side of AI adoption, top management equipped with AI skills is better positioned to leverage AI technologies to drive strategic decisions that align with the firm's growth objectives (Alekseeva et al., 2020). Moreover, top managers' decisions on AI adoption are influenced by learning from experimentation, imitation of previous implementers' practices, and geographical and cultural variations, which can potentially increase the success of AI integration (Kolbjørnsrud, Amico and Thomas, 2017).

1.2 Problem Statement

The UK has approximately 5.5 million small and medium-sized enterprises (SMEs) (Hutton, 2024). Overall, SMEs contribute 61% to employment and are a driving force for innovation in the UK economy (*Small to medium sized enterprise (SME) action plan*, 2022). The British Chamber of Commerce found that 59% of businesses identified skills such as technical and managerial abilities as crucial for enhancing productivity, yet only 25% of businesses have adopted AI, according to a survey conducted predominantly among SMEs (BCC, 2024). The survey concludes that the majority of SMEs experience difficulty in adopting AI. Masood et al. (2020)noted that lack of financial resources, knowledge constraints, awareness of new technology, managerial practices, and resistance to change significantly affect the adoption process in the UK. Another study also found that significant invest in skill development hindering AI adoption among SMEs (Tawil *et al.*, 2024). Therefore, understanding how SME firms face challenges in AI adoption is vital because AI offers tremendous opportunities for businesses (Alekseeva *et al.*, 2020; BCC, 2024).

The term AI literacy refers to the knowledge and proficiency in artificial intelligence, encompassing both technical and non-technical aspects, and the ability to effectively communicate and collaborate with AI systems (Long and Magerko, 2020; Heyder and Posegga, 2021) . AI literacy for a firm's top executives is vital because it fosters learning and adaptability for making strategic decisions in an AI-driven business environment. It involves understanding how AI can be integrated into the business (Gordon, 2022). Insufficient AI literacy could lead to difficulties in AI-related initiatives that hinder a firm's AI adoption (Yang, Blount and Amrollahi, 2021). The AI literacy characteristics of top management teams (TMT) positively influence AI adoption (Pinski, Hofmann and Benlian, 2024). Especially, TMT members' attributes strongly influence the organization's decision outcomes in SMEs because the lack of these traits impacts openness, and firms might choose more conservative strategy (Xie, Nozawa and Managi, 2023) (Xie, Nozawa and Managi, 2023). It is necessary to for an organization to have AI strategy for AI adoption for determining the potential values of AI (Davenport, 2018; Nagahisarchoghaei *et al.*, 2023). These strategies equip organizations to meet the challenges of configuring existing AI systems and developing new AI capabilities by offering solutions to address the unique challenges faced by a firm (Weber *et al.*, 2023). Thus, first research question (RQ1) is: How does a firm's TMT AI literacy affect its AI adoption?

This study extends this area of research by providing a social capital perspective to examine how social relationships impact AI adoption in SMEs. SMEs face challenges due to limited resources, and to mitigate these limitations TMT's relationships with external parties bring in diverse knowledge, thereby enabling the firm to achieve exploratory innovations (Li, Lin and Huang, 2014). These ties enrich industry-specific knowledge and enhances the TMT's ability to manage challenges more effectively. From the perspective of social capital theory, external ties with external firms stakeholders bring valuable resources and information from outside the firm, contributing to better organizational performance (Kim and Cannella Jr., 2008). Moreover, the social network structure can facilitate or hinder the flow of new ideas by providing access to diverse, non-redundant information (Borgatti and Foster, 2003). This information can be considered a resource and the interconnections between firms such as direct and indirect influences the access to this information. The knowledge dynamics in SMEs are also significant (Simmie, 2002). For example, those linked with educational institutions and situated in urban areas demonstrate knowledge levels are different. Since social capital influences exposure to sources of stimulation and knowledge, it acts as a crucial resource to the AI adoption process (Dahlke *et al.*, 2024). Oldemeyer et al. (2024) argue that most frequently mentioned AI adoption barriers are knowledge gaps, high costs, and insufficient digital maturity in SMEs. By exploring the social context of firms' exposure to AI knowledge and the role of the TMT in network relationships, it is expected to have significant importance. Thus, the second research question (RQ2) is: How does knowledge spillover affect the relationship between the TMT AI literacy and AI adoption?

1.3 Conceptual Framework

To address the first research question, Upper Echelons Theory (UET) significantly enhances our understanding of how a firm's business strategy is developed. UET posits that top executives' decision-making processes are shaped by their personalities, experiences, and backgrounds collectively referred to as upper echelons which influence the organization's overall direction and business outcomes (Porter, 1985). Previous research has predominantly focused on UET, particularly examining how the knowledge and experience of top management teams (TMT) positively impact AI adoption. These studies have found that TMT AI competencies influence the use of AI technologies and capabilities within firms (Li *et al.*, 2021; Xu and Zhang, 2023; Pinski, Hofmann and Benlian, 2024). TMT AI literacy is considered an upper echelon factor, and examining TMTs with AI literacy shows that they are more likely to adopt AI because this literacy provides the technological knowledge and understanding necessary to align AI with strategic business objectives. The second research question is examined based on Social Capital Theory, which suggests that the exchange of knowledge among firms is a vital aspect of innovation and technology adoption (Bozeman, Dietz and Gaughan, 2001). This study argues that TMT AI literacy, combined with exposure to AI, increases the likelihood of AI adoption in firms because the assimilation of AI knowledge in SMEs primarily occurs through social interactions. This exposure provides opportunities for firms to learn from each other, share resources, and collectively overcome challenges related to technology adoption (Li, Lin and Huang, 2014; Bettoni *et al.*, 2021; Dahlke *et al.*, 2024). The hypotheses were tested using a generalized linear model, specifically a binary logit, on a sample size of 209 UK SME firms. The hypothesis testing report supports the hypothesis for research question one; however, the hypothesis for research question two is not fully supported.

1.4 Research Contribution

Theoretically, far less attention has been paid to AI literacy, access to AI knowledge sources, and exposure to AI, all of which are critical for promoting AI adoption. This research offers a comprehensive explanation of AI adoption by uniquely integrating UET and social capital theoretical frameworks. UET elucidates the influence of individual-level (internal) characteristics on strategic choices, while theories of social capital emphasize external characteristics. These perspectives are complemented by highlighting the impact of the business environment on firm level and vice versa. The integration of these theories provides a comprehensive understanding of the factors influencing AI adoption at the top management level, firm level, and macro level facilitated by the UET and direct and indirect influences described by social capital theory. Additionally, UET's endogeneity problem relates to contingencies and contextual factors are influencing the relationship between TMTs characteristics (upper echelons) and firm outcomes (Neely *et al.*, 2020). This research would allow for an understanding of the dynamic nature of how contextual factors impact decision-making for AI, considering the diverse levels of dynamics that influence AI adoption.

Methodologically, this research follows Dahlke et al. (2024) in utilizing econometric methods for empirical analysis and normalizing data distribution behaviours. Adding the variable of TMT AI literacy introduces new combinational perspectives for the empirical analysis. Moreover, data collection techniques, especially those identifying companies, company websites, and top executives highlight the replicability of this study's data collection technique for other similar studies.

Practically, there is a significant research gap in identifying determinants of AI adoption in SMEs compared to large businesses (Oldemeyer, Jede and Teuteberg, 2024). This research focuses on SMEs and establishes relationships between various determinants of AI adoption, analysed using quantitative techniques. However, the robustness of these determinants was not verified through other methods. These determinants offer SMEs and interest stakeholders valuable insights for adopting AI.

Chapter 2: Literature Review

2.1 AI Adoption in SMEs

Artificial intelligence differs notably from conventional information technologies regarding its abilities and functionalities. AI systems are deliberately engineered to carry out intricate tasks, like constructing predictions and making selections under continuously changing conditions (Faraj, Pachidi and Sayegh, 2018). AI systems, unlike preceding technologies, are not confined by fixed rule-based algorithms and have the capacity to adjust to current circumstances. This innate discrepancy clarifies the groundbreaking potential of AI, like its capability to automate processes, anticipate events, grasp and generate natural language, and better procedures (Enholm *et al.*, 2022). For small and medium-sized businesses, AI is not simply an innovative technology, but additionally an essential necessity to maintain competitiveness. AI allows these companies to enhance operational efficiency, decrease costs, stimulate sales growth, and improve accuracy in diverse business operations (Enholm *et al.*, 2022). AI systems enhance decision-making by proficiently examining information, recognizing patterns, comprehending contextual subtleties, and swiftly making decisions in real time. These abilities allow more knowledgeable and timely actions and choices (Campbell *et al.*, 2020; Davenport *et al.*, 2020; Åström, Reim and Parida, 2022). The ability to successfully take advantage of data is particularly important for businesses, as they regularly operate with restricted resources and must maximize each opportunity to maintain competitiveness (Alsheibani, Cheung and Messom, 2018). However, the decision to include AI into an organization necessitates a profound comprehension of its aptitude to not just exchange existing processes but in addition improve and optimize them .The administration must have a thorough grasp of both the potential and limitation of AI. It is also crucial to acknowledge that integrating AI into operational processes leads to a significant shift in business culture and strategy (Nagahisarchoghaei *et al.*, 2023). AI systems sometimes lack transparency, which presents notable technical and human-centred challenges, unlike conventional digital technologies (Nagahisarchoghaei et al., 2023). If the absence of clarity caused by the opaqueness of AI algorithms is not effectively regulated, it could result in significant issues. Organisations should give priority to tackling these difficulties by ensuring that AI systems are created and deployed in a way that is clear and controllable.

AI creates new business opportunities and challenges, necessitating balanced approaches within the context of agile AI development, which emphasises continuous learning and adaptability (Caner and Bhatti, 2020). This necessitates a shift towards more strategic, technology-driven practices to address issues such as overcoming organisational culture, managing the expectations of a multigenerational workforce, and retaining new-age talent (Rana and Sharma, 2019). Bhalerao et al. (2022)conducted a study in SMEs that highlighted the disadvantages of AI adaptation, such as technical competencies and a lack of awareness of data quality. Bettoni et al (2021) propose a conceptual framework for AI adoption in small and medium-sized businesses. They claim that encouraging continuous learning and collaboration with external entities can help businesses prepare for AI adoption by reducing the challenges that come with being a small business, such as a lack of finances and talent. According to the Unified Theory of Acceptance and Use of Technology (UTAUT) process, social influence and available support resources serve an important role in determining technology acceptance, with expected performance benefits becoming more significant over time (Venkatesh *et al.*, 2003). The theoretical model of Chaudhuri et al. (2022) is also comparable to the UTAUT in that the successful deployment of AI in SMEs requires a combination of technological and leadership support, individual competencies, and competitive pressure. Technological and leadership support are needed to encourage AI adoption and resolve technical issues quickly. Learning skills and trust in AI technologies affect AI integration effectiveness. Competitive pressure emphasises the need for firms and SMEs, especially in fast-changing technological contexts, to adopt AI to stay ahead. These factors clearly indicate that SMEs can improve their sustainability and long-term success by taking a balanced approach to AI adoption (Chaudhuri *et al.*, 2022).

Open innovation is the practice of firms actively seeking and using knowledge from external sources instead of depending primarily on their own research and development activities (Chesbrough, 2003, 2012). When comparing SMEs with large enterprises, SMEs generally possess restricted resources and competencies as due to of their smaller size. Nevertheless, SMEs frequently exhibit enhanced flexibility and promptness, enabling them to rapidly adjust to fresh knowledge and prospects in open innovation. This includes promptly establishing new collaborations or speedily venturing into new marketplaces (Gassmann, Enkel and Chesbrough, 2010). The way SMEs use Industry 4.0 technologies exemplifies their agility, large corporations leverage their absorptive capacity to implement exploratory strategies aimed at developing innovative business models focused on novelty and they employ exploitative strategies to enhance efficiency-centred models. On the other hand, small and medium-sized enterprises primarily rely on exploratory strategies to achieve both innovation and efficiency in their business models (Müller, Buliga and Voigt, 2021). This illustrates that small and medium-sized enterprises possess a notable ability to effectively utilise their capacity to absorb knowledge and skills, enabling them to promote innovation and embrace novel and transformative technologies in order to sustain a competitive advantage within their respective sectors. Furthermore, the ability of small and medium-sized enterprises to effectively adopt and utilise digital technologies is affected by factors such as the nature of the business, the type of innovation, and the level of support provided by management. The Study that utilises the Technology-Organization-Environment (TOE) paradigm indicates that the commitment of senior management and the readiness of the organisation are crucial factors in enhancing the outcomes of AI adoption (Lada *et al.*, 2023). The significance of managerial assistance and organisational preparedness in improving SMEs' capacity to embrace and get advantages from innovative technology is emphasised by this research.

2.2 Upper Echelons Theory and Top Management Teams (TMT)

The upper echelons hypothesis, proposed by Hambrick and Mason(1984), contends that the attributes of an organization's top management team shapes its strategic decisions and overall performance. This notion originally focused on the impact of individual executive qualities, but in 2007 , Hambrick expanded the concept to emphasize the importance of TMTs' group characteristics. These features, known as upper-echelon characteristics, involve a diversity of observable elements including educational background, professional experiences, abilities, socioeconomic status, and the level of sway that individual team members hold within the group (Hambrick and Mason, 1984; Hambrick, 2007). These upper-echelon characteristics have an effect that transcends representation, influencing the TMT's internal dynamics and interactions. These dynamics can significantly impact a company's strategic decisions and outcomes, such as its ability to pioneer, respond to competitive pressures, and adapt in rapidly changing markets (Carpenter, Geletkanycz and Sanders, 2004). For instance, in the context of AI implementation, the collective technological knowledge and experience within the TMT become pivotal. Executives with restricted knowledge of AI may encounter confusion, uncertainty, or anxiety when considering the execution of these technologies. This can lead to reliance on TMT members with technological expertise, affecting decision-making and the overall direction of the organization's AI strategy (Brock and von Wangenheim, 2019). While diversity in the composition of the TMT can promote innovative and comprehensive decision-making, it also poses challenges. Varied perspectives and expertise may result in conflicts and decreased effectiveness if not properly handled (Bromiley and Rau, 2016). These challenges could be circumvented by appropriately combining TMTs with diverse backgrounds and adequate functional expertise. This strategic structuring can assist organisations in overcoming growth obstacles and achieving long-term expansion by ensuring that diverse viewpoints positively contribute to the firm's strategic trajectory (Chen, Kang and Butler, 2019).

Talke and Salomo (2010), within the framework of Upper Echelons Theory, argue that diversity in top management teams (TMTs) enhances decision-making by incorporating a wide range of perspectives and reducing conformity, which in turn supports a firm's innovation strategy and positively impacts its market performance. Decision-making is further influenced by external factors, including industry conditions, regulatory and cultural contexts, internal organizational settings, and broader national-level influences, which can be moderated by TMTs to shape these conditions indirectly (Abatecola and Cristofaro, 2020). Li et al. (2021)highlight that in large organizations, TMT characteristics such as educational diversity, R&D experience, and AI experience significantly affect the success of a Chief Information Officer's (CIO) AI initiatives. These attributes enable CIOs to secure board support, align strategies effectively, and achieve the organization's overall AI strategy. Importantly, the impact of executives' attributes on firm strategies and outcomes is greater in SMEs than in large corporations. This is consistent with the UET view that managerial discretion and the influence of top executives are more pronounced in environments with less rigid structures and greater freedom to shape strategies (Xie, Nozawa and Managi, 2023) . Similarly, In SMEs, CEOs with academic backgrounds are more likely to make AI implementation decisions due to their rigorous training and innovative thinking developed through academic experience. Overall, the AI trajectory of SMEs can be determined by the characteristics of their TMT and contextual conditions such as socioeconomic factors.

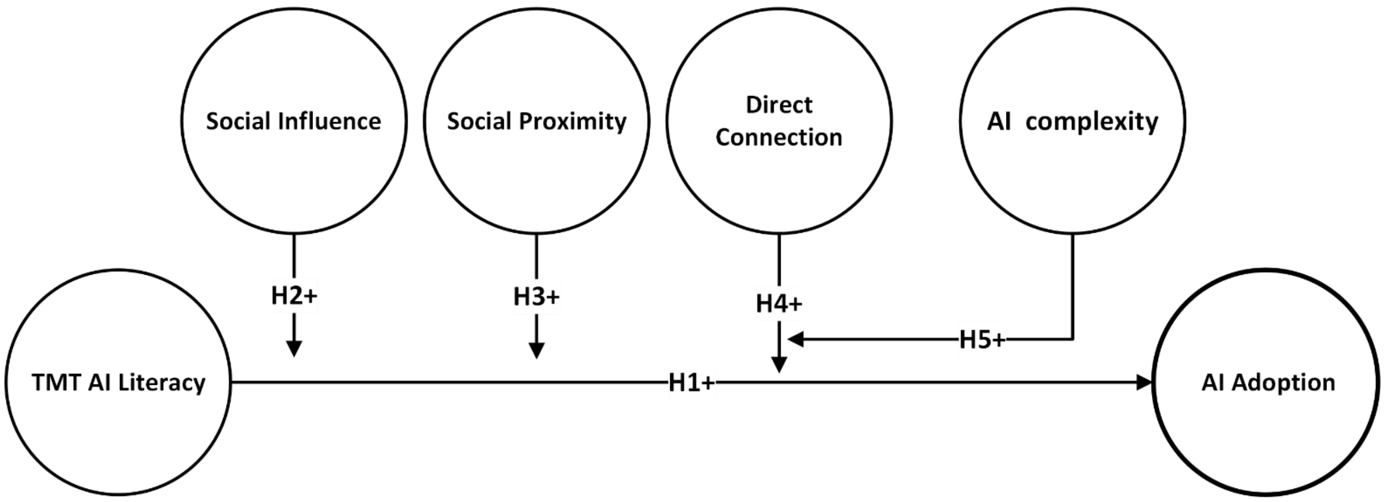
2.2.1 TMT and AI Literacy

The primary driver linking the top management team's (TMT's) comprehension of artificial intelligence (AI), through the lens of upper echelons theory (UET), is the effect of executives with expertise in AI, which immediately affects strategic decision-making involving AI (Pinski, Hofmann and Benlian, 2024). Prior studies applying UET have focused on the role-oriented viewpoint, stressing how the inherent skills in specific executive roles impact organizational outcomes. For example, Li et al. (2021) applied UET to analyse the connection between an organization's orientation toward AI and the presence of Chief Information Officers (CIOs), highlighting how their technological know-how and strategic functions guide initiatives to implement AI. Likewise, another investigation into UET explored how executives with specialized domain knowledge, for instance Chief Sustainability Officers (CSOs), influence corporate performance, particularly in areas such as corporate social responsibility (Fu, Tang and Chen, 2020). The role-oriented outlook suggests that TMT individuals with AI expertise can leverage their diverse understanding to shape of the progression of developing an AI strategy, influencing other TMT individuals in the method (Li *et al.*, 2021). Regardless of the varying roles and focal points, the common thread across these viewpoints is the emphasis on the significance of skills, aligning with the upper echelons qualities that expertise is rooted in learning. This research, therefore, proposes the hypothesis that AI literacy among TMT members positively impacts adoption of AI, particularly considering more diverse groups are shown to make better judgments (Yaniv, 2011). Furthermore, having AI-literate TMT members can streamline decision-making processes relating to AI, as the effect in decision-making increases with a higher level of shared knowledge among TMT members (Hambrick, 2007; Pinski, Hofmann and Benlian, 2024).Moreover, AI literacy encompasses the ability to communicate and team up effectively with AI systems across various circumstances, fostering informed and accountable participation (Long and Magerko, 2020). This capability can lead to a greater reliance on TMT individuals with know-how about AI, thereby affecting both decision-making and the overall direction of the organization's AI adoption (Brock and von Wangenheim, 2019).

Therefore, this research proposes the first hypothesis:

H1: TMT AI literacy positively influences firm-level AI adoption

Figure 1 Research Model



2.3 Knowledge Spillover and AI adoption

Rogers (1983) points to that the individual-level acceptance of new ideas, products, behaviours, or technologies is influenced by social values and networks. The theory has identified the process of adopting an innovation as the innovation-decision process. This involved five distinct stages: learning about the innovation, creating an attitude towards the new technology, determining whether to adopt or reject the innovation, implementing the innovation, and evaluating its use based on experience. The five stages mentioned are ongoing and interconnected. The pace at which the spread happens is controlled by various factors, such as the perceived relative advantage, compatibility with existing practices, simplicity, testability, and visibility of the technology. Karshenas et al. (1993) assert that the adoption of new technology at the individual level is impacted by social networks. They claim that enterprises are more likely to accept new technology when they have the chance to acquire knowledge from others within the same industry. Rogers (2003) elaborated on the significance of engaging with mass media and interpersonal contact in facilitating companies' acquisition of innovative information. The impacts highlighted can be observed in prosperous companies that have embraced AI technology and are facing intense competition. In such cases, the spread of innovation is influenced by the surrounding social context (Chen, Li and Chen, 2021). Moreover, the presence of a social context that encompasses businesses dependent on cognitive tasks confers a distinct benefit in the acquisition of human capital, hence facilitating rapid adaption to AI (Felten, Raj and Seamans, 2021).The adoption of AI is linked to Rogers' theory and supported by a study conducted in the UK, which shows that collaborating with external enterprises, both directly and indirectly, as well as benefiting from local knowledge, can boost innovation efforts. The primary reason for this is the advantages of interactive knowledge search, which enables the sharing of knowledge while reducing the potential for heightened competitiveness and imitation (Roper, Love and Bonner, 2017) .

2.3.1 Social Influence

A firm’s industrial social network, along with geographic agglomeration, significantly impacts its ability to acquire knowledge, which in turn enhances the firm's innovative performance (Sorenson, Rivkin and Fleming, 2006). This concentration of businesses provides cost advantages and benefits from the socio-economic factors of the environment. Gruber et al. (2013)suggest that technological adoption is influenced by the knowledge sources available in the local environment, as well as the educational background and cognitive abilities of a firm’s inventors, which contribute to innovation. A firm’s social factors are crucial because it facilitates informed decision-making, provides access to resources, and supports technology adoption, thereby fostering an environment conducive to innovation (Abaddi, 2024). Consequently, socio-economic factors and industrial characteristics are key determinants of AI adoption (Dahlke et al., 2024).

Therefore, this research proposes the second hypothesis:

H2. The likelihood of a firm implementing AI positively moderated by the diffusion of AI in its local region and sector.

2.3.2 Social Proximity

Social proximity can divide in two, geographical proximity and cognitive proximity. Geographic proximity refers to the close physical distance between businesses, which might impact their awareness of risks and opportunities of innovation (Krueger, Sautner and Starks, 2019). Similarly the cognitive identifies firm collaboration facilitates the exchange of intricate and tacit knowledge, as individuals with similar cognitive frameworks or areas of expertise are more adept at comprehending widely accessible knowledge (Glückler, 2013; Krueger, Sautner and Starks, 2019). In the context of SMEs, geographical proximity and open innovation are indeed relevant and interconnected, particularly for small and medium-sized enterprises, where open innovation is essential (Kapetaniou and Lee, 2019). Geographical proximity influences innovation indirectly by providing easier access to cognitive proximity, which facilitates knowledge acquisition (Molina-Morales, García-Villaverde and Parra-Requena, 2014). These proximities moderate the effects of AI diffusion, as shown in a study on German-based firms, firms located near each other, particularly in regional or industrial, are more likely to observe AI adoption among their neighbours, creating indirect mimetic pressure that influences their decision to adopt AI (Dahlke *et al.*, 2024).

Therefore, this research proposes the third hypothesis:

H3. AI adoption is positively moderated by the average proximity between the firm and prospective sources of AI knowledge.

2.3.3 Direct Connection

In contrast to acquiring knowledge through observation of the environment, tacit knowledge gained from an external party offers the firm a better chance of effectively using that knowledge (Roper, Love and Bonner, 2017). This collaboration is essential for leveraging new technology by fostering effective knowledge sharing and exchange (Borgatti and Halgin, 2011). The process of sharing collective knowledge improves creative activities by making them more methodical and uniform. Collaboration fosters trust through open communication, so enhancing the effectiveness of these initiatives (Huang and Li, 2009). Knowledge can be transmitted directly through structural and relational means, or by sharing a common perspective. These connections moderately influence the innovation progress of a firm (Zheng, 2010). A study conducted on SMEs in the UK emphasises that collaboration is an essential method for these organisations to acquire knowledge and skills. This enables them to stimulate innovation and overcome the constraints of their internal resources. Those SMEs greatly increased their capabilities, expedite product development, and bolster their competitive position in both local and international markets by establishing relationships with external entities such as suppliers, customers, universities, and competitors (Audretsch *et al.*, 2023) (Audretsch *et al.*, 2023). However, Bozeman et al. (2004)argue that transmission of tacit knowledge requires direct interaction with individuals or institutions possessing relevant technical skills, resources, and professional network ties, rather than relying solely on firms’ interactions.

Therefore, this research proposes the fourth hypothesis:

H4: Firms with a higher share of connections to other AI-adopted firms experience positive moderated effects in AI adoption.

Likewise, the process of gaining knowledge can also be influenced by the level of complexity of the knowledge itself. When knowledge is basic, it is simpler to spread, but it becomes more challenging to communicate when it is complicated, especially when there is no clear link between the source and the recipient (Sorenson, Rivkin and Fleming, 2006). Dahlke et al. (2024) found that the degree of complexity in adopting AI is greatly impacted by the presence of direct linkages between companies. More specifically, corporations that have stronger connections to other firms possessing sophisticated AI expertise are more capable of effectively implementing intricate AI technology. This act of sharing knowledge collectively improves innovative endeavours by making them more organised and reliable because of this collaboration fosters trust through communication (Huang and Li, 2009). This knowledge sharing can be transmitted directly through structural and relational means, or by sharing a common perspective.

Therefore, this research proposes the fifth hypothesis:

H5: The complexity of AI amplifies the impact of direct connections on TMT AI literacy, such that the effect of direct connections is stronger when the AI type is more complex on AI adoption.

Chapter 3: Data and Methodology

The initial sample is based on data gathered from 9,610 company websites. Web-scraped data was used to identify textual content associated with AI-related keywords and semantic similarity. Additionally, hyperlinks on the websites of 3,549 companies were used to map inter-firm relationships. Furthermore, a sample of 1,433 LinkedIn profiles was analysed to identify keywords related to AI literacy. This study focused on analysing the UK SME industry, with particular emphasis on the ICT and financial sectors, as these firms typically highlight the importance of AI adoption in business. To test the hypothesis, data from 209 companies were examined after constructing interconnections through hyperlink analysis. This primary data is cross-sectional, as it relates to the establishment of AI adoption by firms, using various objective data points to determine AI adoption.

3.1 Data Source

3.1.1 Web-scraped data

Websites serve as a comprehensive communication tool for firms, allowing them to convey their organizational identity to a diverse range of stakeholders and emphasize different aspects to various audiences (Oertel and Thommes, 2018). By prioritizing accessibility and navigation, websites incorporate interactive features, such as search engines and feedback links, which facilitate engagement with diverse audiences, including peer companies, and help manage the firm’s identity (Esrock and Leichty, 2000). In this study, websites are considered a measure of organizational identity, particularly in defining AI-adoptive firms, as the presence of AI-related keywords in the textual content of websites indicates a firm's orientation toward AI. This identification is based on a set of keywords derived from relevant literature (Enholm *et al.*, 2022). A study conducted on UK SMEs for identify innovation activities found that web mining is the most accessible source of information, although it presents challenges related to handling unstructured data (Gök, Waterworth and Shapira, 2015). A similar UK-based web scraping study found a link between regional digital technology adoptions and regional productivity and tested the robustness of the data, considering it reliable (Tranos, Kitsos and Ortega-Argilés, 2021). This study's hypothesis heavily relies on web-based data to understand knowledge sharing and innovation processes. Websites are considered communication tools that act as correspondents between firms, while traditional innovation indicators, such as patents and R&D spending, are too limited to recognize new trends(Feser, 2023). Therefore, considering AI is still in its early stages, website data collection plays a key role in recognizing current AI adoption scenarios in the UK SMEs.

3.1.2 UK SMEs Sample

The UK has approximately 5.5 million small and medium-sized businesses (Hutton, 2024). For this study, 13,544 companies were selected, excluding non-SMEs based on their Companies House account type. According to the UK government, an SME is defined as having a turnover of less than €50 million (*Small to medium sized enterprise (SME) action plan*, 2022). The first stage of sampling involved identifying SMEs in the UK. The Companies House website includes a list of active companies and their account types. For this study, small, medium, and abridged accounts were classified as SMEs. According to Companies House account guidance, companies with a small account must have an annual turnover of no more than £10.2 million and fewer than 50 employees. Companies with a medium account must have an annual revenue of no more than £36 million and an average employee count of no more than 250. Abridged accounts show a turnover of no more than £10.2 million and an average employee count of no more than 50 (*Companies House accounts guidance*, 2023). Based on this classification, companies that did not meet the SME criteria were filtered out, and companies primarily engaged in ICT and financial services were purposively selected, as these industries are more likely to use websites, thereby increasing the likelihood of website identification. From the filtered dataset, companies were then randomly selected for this study. Data was also collected from other types of industries, but the majority were from the ICT and financial services sectors. This allows for the validation of sectors and the proportion of AI-adopting firms.

3.1.3 Website Identification

As one of the main sources of data, website identification plays a crucial role in this research. AI adopters and non-adopters were classified based on AI-related keywords found on their websites. A major challenge in data collection was identifying websites from the sample of 13,544 companies. Initially, trade association websites were used to identify these firms; however, only approximately 900 company websites were identified through trade associations. The trade associations mainly comprised SMEs, such as TechUK, UKspace SMEs, and the Engineering Industries Association. Due to the insufficient number of identified websites, Microsoft Azure's Bing Web Search API was utilized to identify the remaining websites by querying company names. The Bing Web Search API searches based on company names and returns the most relevant result (*Web Search API | Microsoft Bing*, 2024). To enhance the accuracy of search results, websites that only mentioned the company name without relevant content were excluded. A Python algorithm was developed to filter out such websites, including corporate databases, government registries, and social networking platforms. Simultaneously, if the API failed to find an accurate result, it returned a null value. To ensure precision, a random validation was conducted, confirming that the API correctly identified 96.80% of the company websites, verified by examining a random sample of 250 companies. As a student, Microsoft Azure provided $200 worth of credit for this search API, which was sufficient for identifying the websites.

3.1.4 Web Scraping Procedure

This study used Python algorithms to extract text from webpages, considering the ethical and legal aspects of web scraping. Robots.txt files and other proxy tools were not utilized in the web scraping process. As robots.txt files specify permissions for web scraping, websites that restricted scraping were not included (Glez-Peña *et al.*, 2014). Today, most webpages are dynamically constructed, which adds complexity to scraping the main content and subpages of websites. Selenium and BeautifulSoup were employed to address this; Selenium is useful for dynamic webpages and executing JavaScript, while BeautifulSoup was used to extract text (Khder, 2021). A maximum of 30 pages per company were collected, and to mitigate server overload, the request rate was limited to 5 requests per second in a responsible manner. The collected web texts could be stored in various formats such as CSV, SQL, or text files. A text file was chosen because the data collected contained a large volume of words, hyperlinks, and other unspecified characters, which are not suitable for storage in a database. A total of 13,544 company websites were examined. Due to careful implementation, web text from 9,639 companies was retrieved, resulting in 11 GB of data in folders as multiple text files. Text files are named after their registered company numbers and reflect each company. Cleaning text files without deleting hyperlinks and alphanumeric characters reduced data size to 6 GB.

Figure 2. Web Data Collection and Analysis Procedure

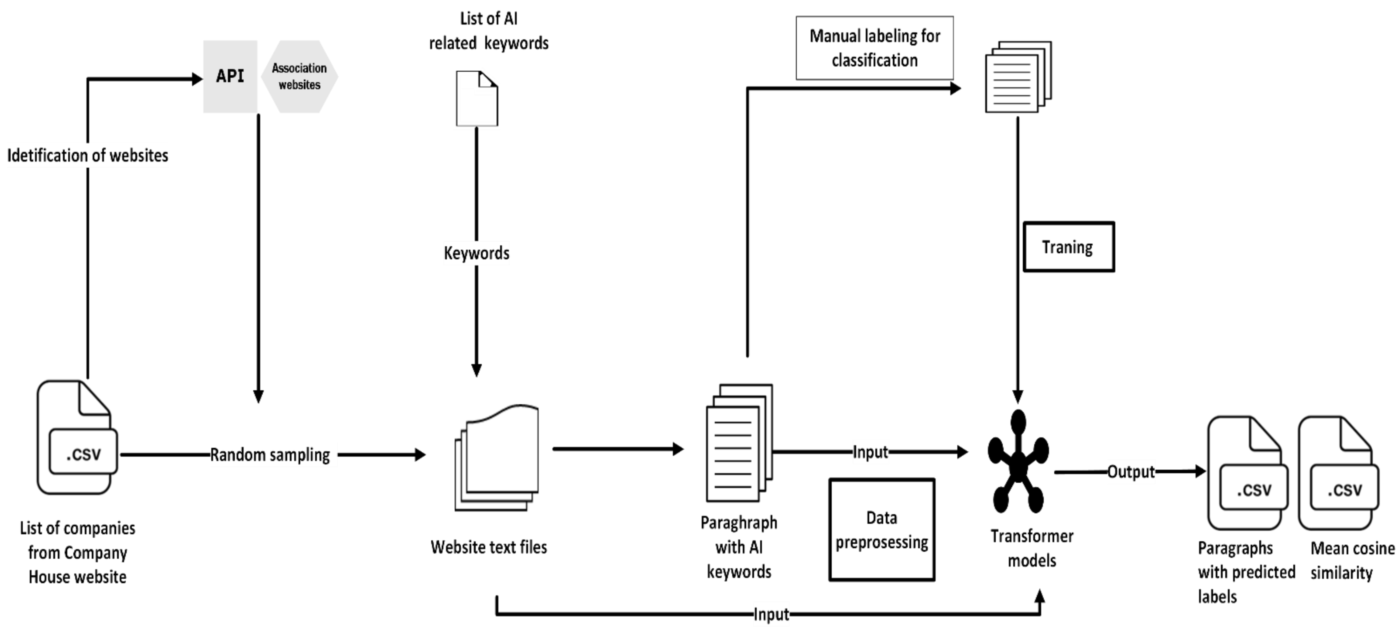


Figure 1. Analysis procedure replicated from Dahlke *et al.*, (2024).

3.1.5 Hyperlink Extraction Procedure

The hypothesis of the study involves the direct transmission of knowledge between two firms. Interconnected hyperlinks between two firms were considered as links connecting them (Krüger *et al.*, 2020). The domain names of hyperlinks are used as nodes for network analysis, and shared nodes between firms are considered as edges. To simplify network analysis and account for time constraints, only unidirectional connections were identified. 2,397 unique unidirectional company relationships shared at least one domain name on their websites. Dahlke et al. (2024) provided the method for sophisticated network analysis in this study. Dahlke et al. (2024) deleted duplicate nodes from the same company to improve webpage content extraction and simplify the node-edge relationship structure. Before deleting duplicates, 24,839 node-edge combinations were found. After filtering out the unique nodes and edges, 728 node (firm provided the domine) and 1,669 edges (firm uses the domine) were found. NetworkX Python library was utilised for analysis because to its accuracy and programming convenience. To reduce computational time, the hyperlinks from each text file were separately extracted and stored in a CSV file, which was collected from the earlier web scraping process. According to the documentation for the NetworkX package, the company number (source) and the hyperlink (target) were provided as separate columns in the CSV file. This data processing reduced processing time and enhanced accuracy. The code for the network analysis is provided in Appendix A.

3.1.6 Top Team Management (TMT) Data.

Another crucial data point in this study is the observable characteristics of top team management. Following the approach of Pinski et al. (2024), LinkedIn was utilized to gather information on top management teams from the list of companies. The names and designations of company officers were collected using the Companies House API. The Companies House API provides a free REST API for retrieving company data, including officer names and office addresses (‘Developer Hub Home’). Using this API in a Python environment, the list of all officers, excluding resigned officers, was collected. After this step, LinkedIn was searched for 927 companies and 2,738 top managers using both the company names and officer names. If both the company name and officer name matched a LinkedIn profile, the profile was considered to belong to the same person listed in the Companies House data. After reviewing the profiles, 1,433 reliable top manager profiles were identified for 640 companies. These profiles were then manually classified to determine whether the top managers had AI literacy by searching for AI-related keywords in their education, skills, and experience sections.

3.1.7 Geographical Proximity and Region Data

The hypothesis included analysing the geographical proximity between two firms and the socio- economic region of the firms. Initially the companies’ postcodes were collected using the Companies House API. Then the Postcodes.io API was used to gather longitude, latitude, and International Territorial Level 3 (ITL-3) data for specific socio-economic regions (*Postcodes.io*). To find the distance in kilometres between two firms, their longitude and latitude coordinates are used with the help of the Geopy Python library (‘geopy: Python Geocoding Toolbox’, 2023), and the Euclidean distance formula is implemented as a function in Python. For regional data collection, this study used the geographical dataset provided by the Office for National Statistics under the UK government (*LAD ITL*, 2023). The International Territorial Levels (ITL) 3, 2, and 1 were matched through this dataset to ensure accurate regional classification.

3.1.8 AI Identification in The Web Data

Prominent literature uses keyword analysis to examine AI adoption (Alsheibani, Cheung and Messom, 2018; Li *et al.*, 2021; Dahlke *et al.*, 2024; Pinski, Hofmann and Benlian, 2024) . Dahlke et al. (2024) used a similar procedure in this study for analysing keywords to identify AI. A Python dictionary of AI-related keywords was developed for text mining from the scraped website text files. To improve identification, the Natural Language Toolkit (NLTK) library, specifically the PorterStemmer module, was used to identify AI-related text snippets (a total of 50 words per AI keyword) in the text data. The identified text snippets were then saved in a CSV file along with the corresponding company number. PorterStemmer is a rule-based algorithm that automatically identifies word suffixes (*NLTK :: Python Module Index*). For example, if the keyword given is "AI," the algorithm can identify variations, such as "AI's," in the text file. Additionally, the algorithm was written to ensure keywords were not misinterpreted or partially identified. For instance, if the keyword "ml" is given, it should return results related to "machine learning" rather than unrelated terms like "millilitre." Careful consideration was given in programming to avoid such ambiguities. Appendix B provides the AI-related keywords used dictionary for AI adoption identification.

3.1.9 Classification of AI paragraphs

Figure 3. Paragraph Classification Model Accuracy

```
Model Accuracy: 89.31%
Classification Report:
              precision    recall  f1-score   support

       supAI       0.88      0.95      0.91       189
      deepAI       0.92      0.81      0.86       129

    accuracy                           0.89       318
   macro avg       0.90      0.88      0.89       318
weighted avg       0.90      0.89      0.89       318
```

This study hypothesizes that the complexity of AI may affect AI adoption. For this reason, the AI adoption status of 2,397 hyperlink-sharing firms was checked. If the AI adoption status was confirmed, those firms' AI-related keyword-containing text snippets were analysed to determine whether they pertained to simple or complex AI. A total of 61,264 text snippets were required to be classified as either simple or complex AI. To perform this classification, TF-IDF (Term Frequency-Inverse Document Frequency) was utilized. Initially, approximately 1,500 text snippets were manually labelled, classifying the text as complex AI if the main content mentioned people, business processes, or products, and simple AI if it contained general information about the use and importance of AI. The Sklearn Python package was used to train the TF-IDF model. Figure illustrates the model accuracy report, where supAI refers to simple AI information and deepAI refers to text snippets containing complex AI knowledge. The model achieved 89% accuracy, with 68% accuracy being the cutoff for classification acceptance, according to Chicco and Jurman (2020).

3.1.10 Final Sample Size

The data collection was conducted in a way of multi-stage. Initially, potential companies were identified, from which firms that had adopted AI and those connected via hyperlinks were selected. For the top management teams, data from LinkedIn profiles were collected, and team members were classified according to their AI background. Ultimately, only 209 companies contained all the necessary data points. Given that the study's purpose is not suited to analysing all variables with missing data points, statistical techniques such as metadata analysis and normalization were not further conducted. Appendix C provides the statistics of all data

3.2 Methodology

Dependent Variable: AI Adoption

Definition: The AI adoption process in organizations is complex and multidimensional. Related research suggests that AI adoption requires readiness in people, processes, technology, and data, as exemplified by more favourable performance through cognitive process automation, innovation, and learning (Uren and Edwards, 2023). Cost-effectiveness, relative advantage, top management support, HR readiness, competitive pressure, and external support are the significant factors affecting the AI adoption process (Zebec and Indihar Štemberger, 2020).

Measurement: AI orientation is measured as a binary outcome variable: a value of 1 indicates that the firm has adopted AI, while a value of 0 indicates that the firm has not adopted AI. A text-mining Python algorithm was developed, and AI-related keywords were identified from the firm's website content (Dahlke et al., 2024; Pinski, Hofmann and Benlian, 2024).

Independent: TMT AI Share

Definition: Top management team AI literacy refers to the knowledge and proficiency in artificial intelligence, encompassing both technical and non-technical aspects, and the ability to effectively communicate and collaborate with AI systems (Heyder and Posegga, 2021; Pinski, Hofmann and Benlian, 2024).

Measurement: To measure TMT AI literacy, the procedures outlined by Pinski et al. (2024) were followed. The LinkedIn profiles of top managers were analysed for AI-related keywords to check for AI-related education, skills, and experience. The score ranges from 0 to 1, where 0 indicates no AI competency in the TMT, and 1 indicates that all executives in the TMT possess AI competency. This score is determined by the proportion of AI-related keywords to the total number of words.

Moderating Variable: Geographical Proximity

Definition: A firms geographical distance to connected firms, the closer the firms are, the more it facilitates the transmission of innovative knowledge, as firms that are geographically closer are more likely to collaborate and share the new knowledge effectively (Glückler, 2013; Krüger *et al.*, 2020).

Measurement: Krueger et al. (2019) used empirical methods to analyse geographical proximity. They measured it using the average minimum distance to AI-adopting firms. They utilize Euclidean distance formula for finding the proximity, represent average minimum distance the firms have to AI adopted firm. In this study, latitude and longitude difference of the firms were used to measure distance, and the normalized values range from 0 to 1, where 1 indicates that the connected firm is closer, and values closer to 0 indicate greater distances. The following equation (Eq.1) calculates the geographical proximity.

$geo\ mean_i = \frac{1}{K_i}\sum_{K=1}^{K_i}\left(1 - \frac{d_{i,k}}{d_{max}}\right)$ (Krueger, Sautner and Starks, 2019) Eq. 1

Where:

- $d_{i,k}$ is the Euclidean distance between i and its connected firm
- d_{max} is the maximum possible distance between any two firms in the dataset
- $1 - \frac{d_{i,k}}{d_{max}}$ is the normalizes and inverts the distance, so that closer distances give higher values (closer to 1).

Moderating Variable: Cognitive proximity

Definition: Cognitive proximity refers to the difference between a firm's knowledge and that of another. This shared or common knowledge facilitates collaboration between the two connected firms (Boschma and Frenken, 2009) .

Measurement: The resemblance of webpage content among connected firms is examined with a transformer model in Python, wherein the text is initially vectorised to numerically denote the content. A score of 0 signifies that the content of the firms' webpages is analogous, whereas a value of 1 denotes dissimilarity (Dahlke et al., 2024). The BRETopic model employs vectorisation throughout its processing pipeline to analyse similarity. This topic model is more employs advanced vector embeddings for subject extraction (Grootendorst, 2022). This study employs the all-MiniLM-L6-v2 module for vectorization. Since this transformation model is computationally intensive, the web content was analysed in 355 batches. Cosine similarity, using the Python function from sklearn.metrics.pairwise, was applied to evaluate the text embeddings between connected firms. Cosine similarity measures the average value of web content similarity between firms. For normalization to a range of 0 to 1, the following equation was used.

$cogn\ mean_i = \frac{1}{K_i}\sum_{K=1}^{K_i}\left(1 - \frac{u_i \cdot u_k}{\|u_i\|_2 \|u_k\|_2}\right)$ (Dahlke *et al.*, 2024) Eq. 2

- u_i is the vector representing the website text of firm i
- u_k is the vector representing the website text of firm k, which is connected to firm i
- $u_i \cdot u_k$ is the dot product of the vectors, representing the similarity between the two
- $\|u_i\|_2 \|u_k\|_2$ are the Euclidean norms (lengths) of the respective vectors
- k_i is the number of linked firms for firm

Moderating Variable: Region

Definition: The local environment of a firm contributes to and enhances knowledge transfer, as the socio-economic region provides essential resources to firms, such as talent (Dahl and Pedersen, 2004). Therefore, this local environment influences the diffusion of new technology (Keller, 2002).

Measurement: The socio-economic regions in the UK considered for the measurement, particularly the ITL-3 regions, are more localized clusters and environments. The equation depicted by Dahlke et al. (2024) is used to measure the influence of regional factors on AI adoption.

$AI\ region_{i,r} = \frac{|X_{AI,reg}| - X_{AI,i,reg}}{|X_{reg}| - 1}$ (Dahlke *et al.*, 2024) Eq. 3

- $X_{AI,reg}$ is the set of companies in region $r$eg adopting AI.
- $X_{AI,i,reg}$ is the AI-adopting companies in region reg , excluding the focal firm i
- X_{reg} is the total set of companies in region reg

Moderating Variable: Sector

Definition: Firms within the same sector significant due to the cognitive similarity shared among them (Woerter et al., 2017) (Woerter *et al.*, 2017). This cognitive similarity facilitates the exchange of intricate and tacit knowledge, as individuals with similar cognitive frameworks or areas of expertise are more adept at comprehending and utilizing widely accessible knowledge (Glückler, 2013; Krueger, Sautner, and Starks, 2019).

Measurement: The Standard Industrial Classification (SIC), used in the Companies House company list, categorizes firms by sector. This SIC classification is employed to categorize each firm by its respective sector. Dahlke et al. (2024) operationalized the measurement of sectoral influence using an equation to determine the rate of deviation of a firm's characteristics from common industrial norms. This study follows that equation.

$AI\ sector_{i,sec} = \frac{|X_{AI,sec}| - X_{AI,i,sec}}{|X_{sec}| - 1}$ (Dahlke *et al.*, 2024) Eq. 4

- $X_{AI,sec}$ is the set of AI-adopting companies in sector
- $X_{AI,i,sec}$ is the total set of companies in the sector

Moderating Variable: AI Share

Definition: The transmission innovative knowledge requires sharing direct connections with individuals or entities that possess pertinent technical expertise, resources, and professional connections, rather than depending exclusively on indirectly. (Bozeman and Corley, 2004). Therefore, stronger direct connection with a firm that has adopted AI enhances the likelihood of AI adoption (Dahlke et al., 2024).

Measurement: A firm's number of hyperlink connections with AI adopted were used to measure (Kinne and Axenbeck, 2020). The share of hyperlinks with AI-adopting firms was measured to analyse and normalize the number of shared hyperlinks (Dahlke *et al.*, 2024). A value closer to 1 indicates a strong connection with AI-adopting firms The firms considered for analysis are those that have received (edge) unidirectional hyperlinks. For example, if firm C has a unidirectional link with firms A and B, then firms A and B are included in the analysis. The firm C must have adopted of advance level of AI, while firms A and B may or may not have adopted AI.

Mediating Variable: AI complexity

Definition: For successful implementation of the complex knowledge is not possible without the possibility to access the expert guides. Without the access to the guides and method used in previously, it would be highly problematic for a firm to pursing complex technologies (Winter, 1995). If the knowledge is simple, diffusion of ides or technology would easier, but it becomes more difficult to transmit if it is complex, especially when there is no direct connection between the source and the recipient (Sorenson, Rivkin and Fleming, 2006). (Dahlke et al., 2024) expanded the concept to AI adoption and found that the adoption of complex AI requires direct connections with firms that have already adopted AI.

Measurement: (Dahlke et al., 2024) classified the level of AI complexity based on the context in which AI-related keywords were used. If the keywords were used to provide general information about AI, the text was classified as offering only general information. However, if the text mentioned people, business processes, or products, it was considered to represent more complex AI content. The proportion of complex AI is calculated by dividing the number of complex AI instances by the total number of both simple AI and complex AI instances.

Chapter 4: Analysis and Result

This study utilized IBM SPSS for data analysis, specifically for analysing the interaction effect. This chapter is intended to report the statistical techniques employed and the probability results. The subsection on descriptive statistics provides an overview of the distribution behaviour, which then leads to the selection of the generalized linear model, as well as the estimation and interpretation of the results. Finally, this chapter presents the interaction effects between the independent and moderating and mediating variables and limitations of this study.

4.1 Descriptive Statistics

To study the phenomenon of firm AI adoption, the empirical strategy used for testing the hypothesis involved various mathematical tools. The goal of this study's empirical analysis is to identify the likelihood of AI adoption. The table (Table1) below summarizes the different measurement techniques used for analysis and represents the variables and their measurements.

Table 1.Variables and Measurement

Variable	Hypothesis	Unit of Measurement	Description
Firm AI adoption	H1	Binary	Dummy: 1 represents the presence of AI-related keywords 0 represents the absence of AI-related keywords
TMT AI share (TMT AI literacy)	H1	Proportion	0 to 1, closer to 1 indicates stronger AI literacy within TMT
Geographical mean	H3	Similarity	0 to 1, closer to 1 indicates stronger AI similarity in the region the firm
Cognitive mean	H3	Similarity	0 to 1, closer to 1 indicates stronger cosign similarity with the connected firm
Region	H2	Deviation	0 to 1, with values closer to 1 indicating closer alignment with AI firms in the region
Sector	H2	Deviation	0 to 1, with values closer to 1 indicating closer alignment with the sector
Complex AI	H5	Proportion	0 to 1, closer to 1 indicates stronger complex AI
AI share	H4	Proportion	0 to 1, closer to 1 indicates stronger AI share

Firstly, this study analyses central tendency and variance in the distribution to provide significant insights into the data for developing the selection of appropriate methods for analysis. The following table (Table 2) illustrate descriptive statistics of the data.

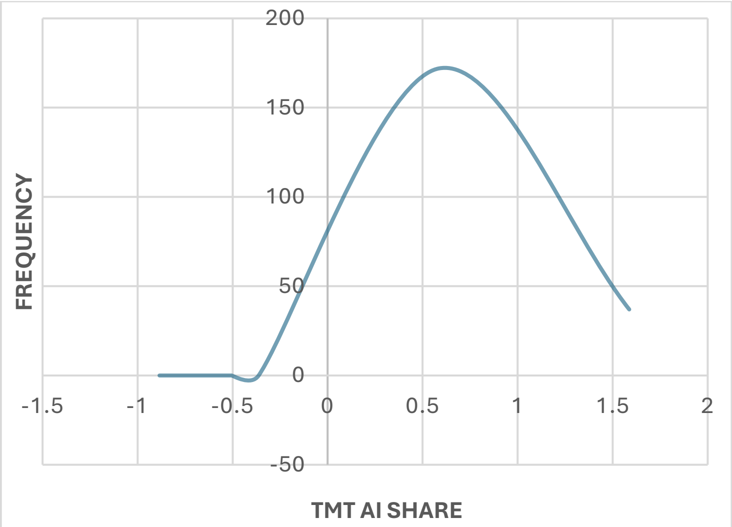
Table 2. Descriptive Statistics

Variable	N	Minimum	Maximum	Mean	Std. Deviation
TMT AI share	209	0	1	0.25	0.38
Geographical mean	209	0	1	0.83	0.21
Cognitive mean	209	0	0.98	0.46	0.29
Region	209	0.2	1	0.75	0.21
Sector	209	0.59	1	0.60	0.04
Complex AI	209	0	1	0.64	0.36
AI share	209	0.03	1	0.46	0.35

This descriptive statistics can be described in a variety of ways (Martinez and Bartholomew, 2017). The constant and prevalent variables are geographical mean and region, which both have a low standard deviation. Sector is another variable that may exhibit average consistency. The variable may have a moderate prevalence due to its moderate mean and high variance. Variables that may have substantial similarity and prevalence include cognitive mean and AI share in the case of considerable divergence. Complex AI have a high mean but a high deviation. There may be both low and high prevalence. TMT AI share is an example of low prevalence and large variability. A detailed interpretation of this descriptive statistics is provided in Appendix D.

Secondly, to analyse the distributional behaviour of the dataset, this study examines skewness and kurtosis to assess the symmetry and outliners of the distribution, respectively.

Figure 4. TMT AI Literacy Data Skewness



This study focuses on the independent variable, TMT AI literacy, which significantly impacts the results. In the dataset, 77 firms' TMTs have AI literacy out of the 87 AI-adopting firms. The figure below visualizes the dataset, indicating roughly symmetrical behaviour, with a skew to the right. The curve appears positively skewed, but at the same time, the left tail is longer than the right. This suggests that outliers are present in the TMT AI literacy, and the mean being less than the median indicates that in some cases AI literacy is lower. This clearly shows a significant gap in the distribution of TMT AI literacy data.

This study requires multivariate statistical analysis to examine the relationship between the independent variable and the moderating and mediating variables. The distribution's skewness and kurtosis can be easily understood through their respective values. To calculate the skewness and kurtosis, Microsoft Excel's “skew ()” and “kurt ()” functions were used. The table (Table 3) below illustrates the distribution's behaviour and classifies it according to the accepted norms, as depicted by Jagdeesh (2023).

Table 3. Data Distribution's Skewness and Kurtosis

Variable	Skewness	Kurtosis	Skewness Type	Kurtosis Type
TMT AI share	1.1747633	-0.22466	Highly positively skewed	Mesokurtic (moderate kurtosis)
Geographical mean	-1.1752387	0.263145	Highly negatively skewed	Mesokurtic (moderate kurtosis)
Cognitive mean	0.5291272	-0.95499	Moderately positively skewed	Mesokurtic (moderate kurtosis)
Region	-0.3831684	-0.90966	Slightly negatively skewed	Mesokurtic (moderate kurtosis)
Sector	9.6513173	95.09475	Highly positively skewed	Leptokurtic (high kurtosis)
Complex AI	-0.5059734	-1.25212	Moderately negatively skewed	Platykurtic (low kurtosis)
AI share	0.40285764	-1.50495	Slightly positively skewed	Platykurtic (low kurtosis)

In case of Kurtosis analysis, most variables are characterized by moderate kurtosis because they have a kurtosis closer to three. It means that they have distributions that are not too peaked but not too flat, and the tails resemble those of a normal distribution. However, Sector has a high kurtosis value, and it is leptokurtic. It means that the peak is sharp, and the tails are fatter, indicating the presence of outliers. Besides, TMT AI Share and AI Share have a kurtosis value of less than 3, indicating platykurtic distributions, they are flatter and contain fewer extreme values. In other words, all the variables are not mesokurtic and they exhibit non-normal distribution characteristics.

Considering the analysis of skewness, it is evident that the TMT AI literacy is positively skewed because most data are close to the extreme. It is likely that some of the firms have a high proportion of AI-literate managers at the top, but they are quite few. In turn, the Geographical Mean is highly negatively skewed. It is important to note that the variable sector is positively skewed by an exceptionally high value of 9.65. It is evident that most organizations are concentrated only in specific sector. In overall of skewness, no variable has a skewness of zero, which indicating mixed distribution patterns.

In overall, choosing a method is critical because the following implications must be considered during the descriptive statistics analysis:

1.As there are non-normal distributions: as clearly shown by the varying skewness and kurtosis, most of the variables seem not to be normally distributed. This will certainly affect the kind of test that should be used, non-parametric assuming tests will be betters, robust methods should be the order of statistical method.

2. Misleading interpretations: the skewness indicates that the dataset is complex, and relying on certain measures could be misleading. For instance, the mean may not accurately represent the central tendency due to substantial skewness or multimodality.

3. Outliers and extreme values: importantly, sector variable given the high co-efficient of kurtosis will be responsible for having a number of outliers and extreme values that may be crucial for this analysis. Scrutiny and necessary treatment will be applied on them.

4. Data transformation: as there is extreme skewedness in the variables, like TMT AI share and Geographical mean, in this case there will be transformations needed to be made, say log transformations that will be needed to meet assumptions of certain statistical techniques.

4.2 Model Selection and Assumptions

The dataset shows a non-normal distribution with skewness and potential outliers, making a linear approach unsuitable for predicting the dependent variable. A linear method is also inappropriate for assessing firm AI adoption, as the dependent variable is categorical. Therefore, identifying interactions between variables is challenging. Generalized Linear Models (GLMs) with a link function address this issue, as they handle various response distributions without data transformations, and data points (responses) are considers as independent (Hastie and Pregibon, 1992).

Key assumptions for GLMs (Hastie and Pregibon, 1992) include:

- The dependent variable must be binary.
- Predictor and response variables have linear relationships (the logit link function ensures that the relationship between the log-odds of success and the predictors is linear)
- Data points are independent, a critical assumption for model fitting.
- The choice of distribution defines the variance and likelihood, impacting inference.
- Each response type has a corresponding variance and link function.
- Parameters are estimated using maximum-likelihood methods, assuming the model is correctly specified.
- Predictor variables should not be perfectly collinear.

These assumptions are met for the generalized linear model (GLM), and the next question is whether using binary logit or binary probit would be best for the analysis. Logit model is preferred over the probit model due to the dataset's heavy tails (Mize, 2019). The logit model's flexibility, ease of interpretation, and robustness to outliers make it suitable. Tests in SPSS confirm non-normality (p-value = 0.05) and no multicollinearity (VIF values below the threshold) in the dataset's distribution behaviour. Test results for normality and collinearity are in Appendix E.

4.2.1 SPSS Features Selection for GLM

IBM SPSS was used for the GLM, focusing on binary logit. A generalized linear model feature was selected from the mixed model in SPSS for this analysis. For accurate calculations, variables were first defined as nominal and scale. In the first step, the Firm AI adoption variable was defined as nominal and set as the target due to its binary outcome and role as the dependent variable. TMT AI share, geographical mean, cognitive mean, region, sector, complex AI, and AI share were defined as scale variables and entered as inputs in SPSS because they are continuous and represent independent and moderating and mediating variables for the analysis. To improve accuracy, region and sector names were added as nominal variables rather than calculated values, with these variables treated as subjects in the data structure. In the Field and Effect tabs, firm AI adoption (DV) was selected as the target, and its relationship and distribution were linked with the linear model. Specifically, the binary logistic function was chosen. From the same tab, fixed effects, main effects, and interaction effects were selected. Interaction effects were calculated using multilevel modelling, as this is vital for cross-sectional prediction. In the building options, the sorting order for categorical and non-categorical variables was set to descending, and the model option was set with the link function transformation.

4.3 Result

Results of the hypothesis testing are presented in the table (Table 4) below. Model 1 is the baseline model. Models 2 and 3 are testing H3, Models 4 and 5 are testing H2, Model 7 is testing H4, and Model 8 is testing H5. Model 9 is testing the independent variable together with all other variables. Overall significance of the models could be judged by examining the Pseudo R Square values at the bottom of the table. The Pseudo R Square values across all models varied between 0.370 and 0.474, supporting the notion that the effect of explanatory variables on the dependent variable responded for a moderate and mediate proportion of the variation in the firm AI Adoption. Model 7, which included the interaction between TMT AI literacy and AI Share, had the highest pseudo R square value at 0.474. It is also essential to pay attention to the incremental changes of the Pseudo R Square values when introducing additional interactions, which indicated that these more complex interactions with AI Share were capturing additional variation in AI adoption.

This analysis examined the variables influencing firm AI adoption and tested hypotheses related to constructs such as TMT AI literacy, regional and sectoral AI diffusion, proximity to AI knowledge sources, connections to AI-adopted firms, and AI knowledge complexity. The baseline model (Model 1) shows that TMT AI share ($\beta = 2.76$, $p < 0.001$), geographical mean ($\beta = 1.95$, $p < 0.05$), cognitive mean ($\beta = 2.42$, $p < 0.001$), region ($\beta = 3.28$, $p < 0.001$), and AI share ($\beta = 1.68$, $p < 0.01$) are all significant predictors of firm AI adoption. This indicates that these factors play important roles in a firm's decision to adopt AI technologies.

Table 4. Regression Models Statistical Report

Dependent Variable: Firm AI Adoption
Probability distribution: Binomial
Link function: Logit

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
TMT AI share	2.76*** (0.57)	2.84 (1.78)	3.43*** (0.94)	-2.74 (2.06)	-31.06 (30.79)	2.95*** (0.87)	5.78*** (0.99)	3.56** (1.07)	3.39** (1.12)
Geographical mean	1.95* (0.94)	1.99 (1.35)	2.07* (0.94)	1.97* (0.97)	2.19* (0.98)	1.89* (0.96)	1.59 (1.00)	1.50 (1.22)	2.20 (1.35)
Cognitive mean	2.42*** (0.60)	2.43*** (0.61)	2.89*** (0.80)	2.22*** (0.61)	2.55*** (0.62)	2.41*** (.60)	2.06** (0.63)	2.17*** (0.61)	2.92*** (0.71)
Region	3.28*** (0.87)	3.28*** (0.87)	3.41*** (0.89)	1.52 (1.03)	3.37*** (0.89)	3.27*** (0.87)	2.49** (0.90)	2.97** (0.93)	3.64*** (0.92)
Sector	1.15 (4.28)	1.13 (4.29)	1.09 (4.48)	0.64 (3.97)	0.43 (4.37)	1.22 (4.28)	-0.07 (4.19)	1.07 (2.55)	1.07 (2.56)
AI Complexity	0.59 (0.49)	0.58 (0.49)	0.56 (0.49)	0.64 (0.50)	0.51 (0.49)	0.69 (0.61)	0.69 (0.52)	1.02 (0.61)	0.88 (0.63)
AI Share	1.68** (0.50)	1.67** (0.51)	1.61 (0.51)	2.02*** (0.53)	1.67** (0.51)	1.68** (0.51)	3.22*** (0.65)	2.13*** (0.51)	1.85*** (0.49)
TMT AI share x Geographical Mean		2.21 (1.96)							
TMT AI share x Cognitive Mean			1.49 (1.62)						
TMT AI share x Region				7.64** (2.85)					
TMT AI share x Sector					56.45 (51.47)				
TMT AI share x AI Complexity						-0.38 (1.28)			
TMT AI share x AI Share							-7.16*** (1.70)		
TMT AI share x Complex AI x AI share								-3.51* (1.58)	
TMT AI share x Geographical Mean x Cognitive Mean x Region x Sector x AI Complexity x AI Share									-13.9* (5.79)
Pseudo R Square	0.371	0.371	0.371	0.433	0.391	0.370	0.474	0.384	0.397

Note:
Robust standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Before interpreting the interaction effect, first examine TMT AI literacy and AI adoption. The results of the baseline model (Table 4, Model 1) confirm the first hypothesis that TMT AI literacy positively influences firm-level AI adoption. This study hypothesizes that TMT AI literacy is shaped by observable factors such as education, skills, and experience. The construct and results align with prior studies suggesting that TMT AI literacy positively influences firm-level AI adoption (Pinski, Hofmann, and Benlian, 2024). This claim is further supported by another study, using upper echelons theory from a role-oriented perspective, which found that the presence of a Chief Information Officer positively impacts AI adoption (Li et al., 2021). These findings, highlight the importance of AI adoption as a strategic decision, requiring deliberate actions from decision-makers. This is attributed to the judgment, experience, and contextual knowledge of decision-makers in AI implementation (Li *et al.*, 2021; Shollo *et al.*, 2022). Therefore, based on upper echelons theory, the H1 test results explain the positive effect of TMT AI literacy on a firm's AI adoption.

Below present a detailed interpretation of the hypothesis testing results.

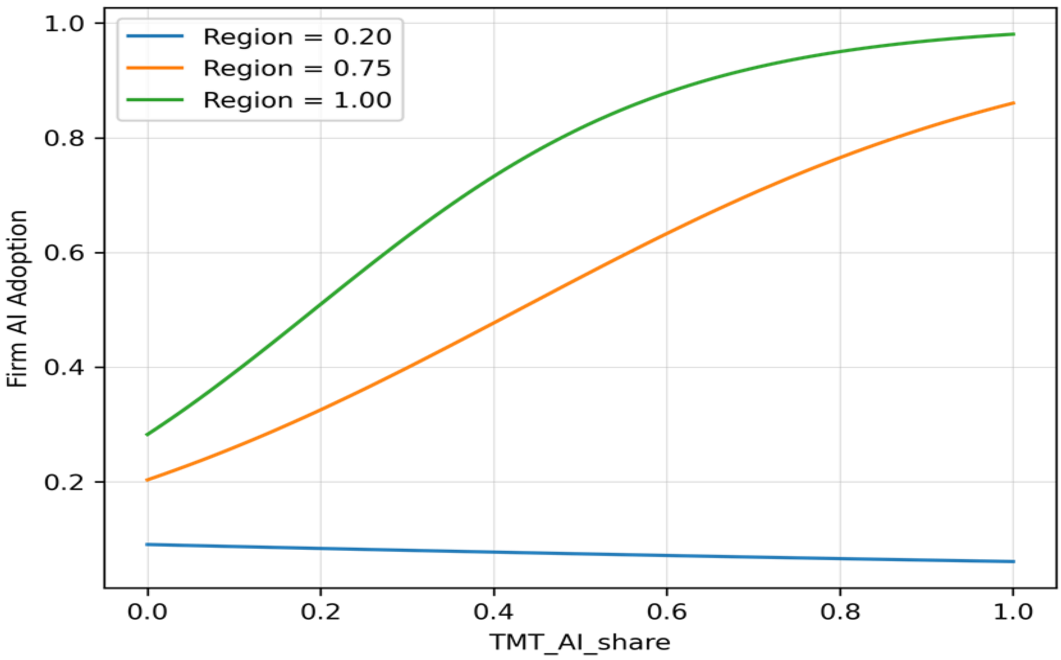
4.4 Interpretation of Interaction Effect

This study utilized upper echelons theory to explain the effect of TMT AI literacy on a firm's AI adoption and also examined the interaction roles of contingencies such as regional and sectoral AI diffusion, proximity to AI knowledge sources, connections to AI-adopted firms, and AI knowledge complexity. The results of the analysis indicate that most such variables do not influence the relationship between TMT AI literacy and AI adoption. However, these variables except sector and AI complexity shows significances in independently on AI adoption. Therefore, a detailed examination of these variables' coefficients and significance is necessary because interpreting interaction results solely based on coefficients reduces the meaningfulness and reliability of interaction effects (Mize, 2019). To address this issue, this study presents the interaction effects through graphical representation, where the binary logit predicted probabilities of the interaction variables are illustrated as line graphs.

4.4.1 Social Influence

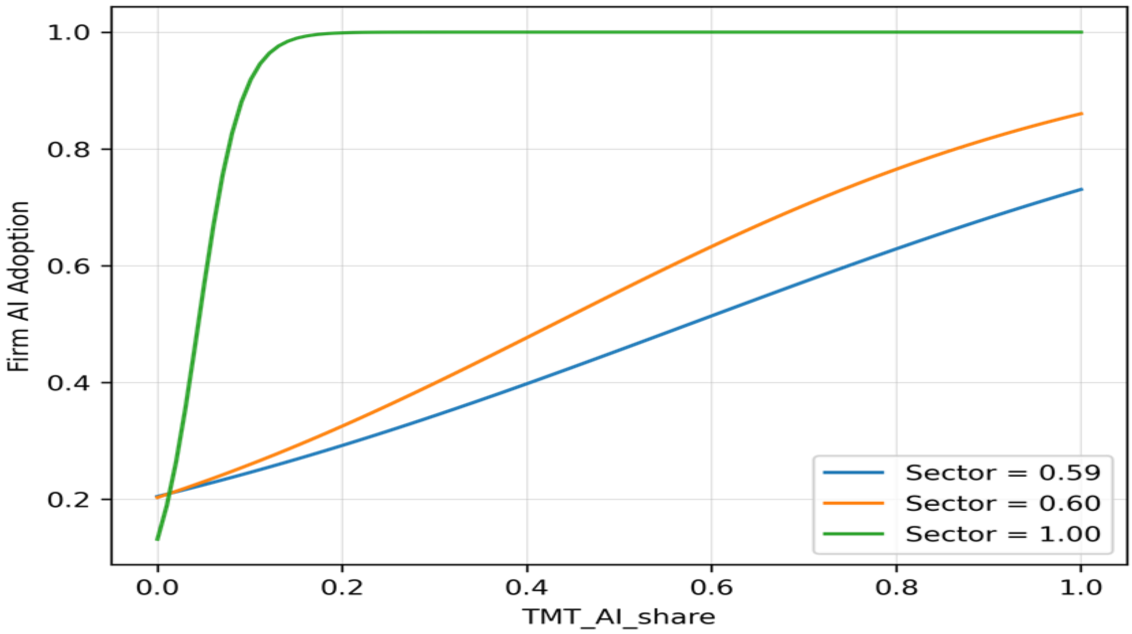
Firstly, regression models 4 and 5 were used to test the hypothesis 2, the likelihood of a firm implementing AI is moderated by the diffusion of AI in its local region and sector. Examining model 4 clearly indicates that the moderating effect of region and TMT AI literacy is positive and significant ($\beta = 7.64$, $p < 0.01$). For a reliable interpretation of this relationship, the predicted probabilities are visualized in the graph. The graph (Figure 5) illustrates the moderating effect of region (represented by different lines) on the relationship between TMT AI literacy (x-axis) and Firm AI Adoption (y-axis). The different lines represent the minimum (blue line), mean (orange line), and maximum (green line) of the region's predicted probability of AI adoption. The relationship between TMT AI literacy and Firm AI Adoption is slightly negative and almost flat at the minimum regional value. At the mean regional value (0.75), there is a strong positive relationship between TMT AI literacy and Firm AI Adoption. For the maximum regional value, the relationship is strongly positive and non-linear, with increasing TMT AI literacy corresponding to higher AI adoption. It can be concluded that the effect of TMT AI literacy on Firm AI Adoption is significantly enhanced in regions with higher AI diffusion.

Figure 5. Region Moderating Effect



Compared with other research, Gao et al.(2019) identified that regions with higher socioeconomic levels tend to have greater connectivity and communication density. This finding aligns with the positive relationship between regions and AI adoption found in this study. Some regions have more AI-adopting firms, particularly in urban areas. This suggests that urban regions, which are already technologically advanced, may benefit more from AI due to the easier diffusion of technological knowledge through local interactions and collaborations (Felten, Raj and Seamans, 2021). In such regions, advanced infrastructure, high levels of education, and strong industries better position them to leverage AI technologies. These regions with greater exposure to AI are also more likely to generate tacit knowledge on how to effectively work with and benefit from AI (Felten, Raj, and Seamans, 2021). In contrast, economically weaker regions face challenges in developing new strategies due to economic disparities, which can hinder entrepreneurs' ability to innovate and grow (Hassink and Gong, 2019). These socioeconomic factors are significant for SMEs, as their innovation implementation relies heavily on knowledge acquisition from the local environment, despite resource limitations (McAdam, Reid and Shevlin, 2014). Therefore, the hypothesis that the likelihood of a firm implementing AI is moderated by the diffusion of AI in its local region can be validated by the results from the analysis and previous research papers. Appendix F provides regions ITL data

Figure 6. Sector Moderating Effect

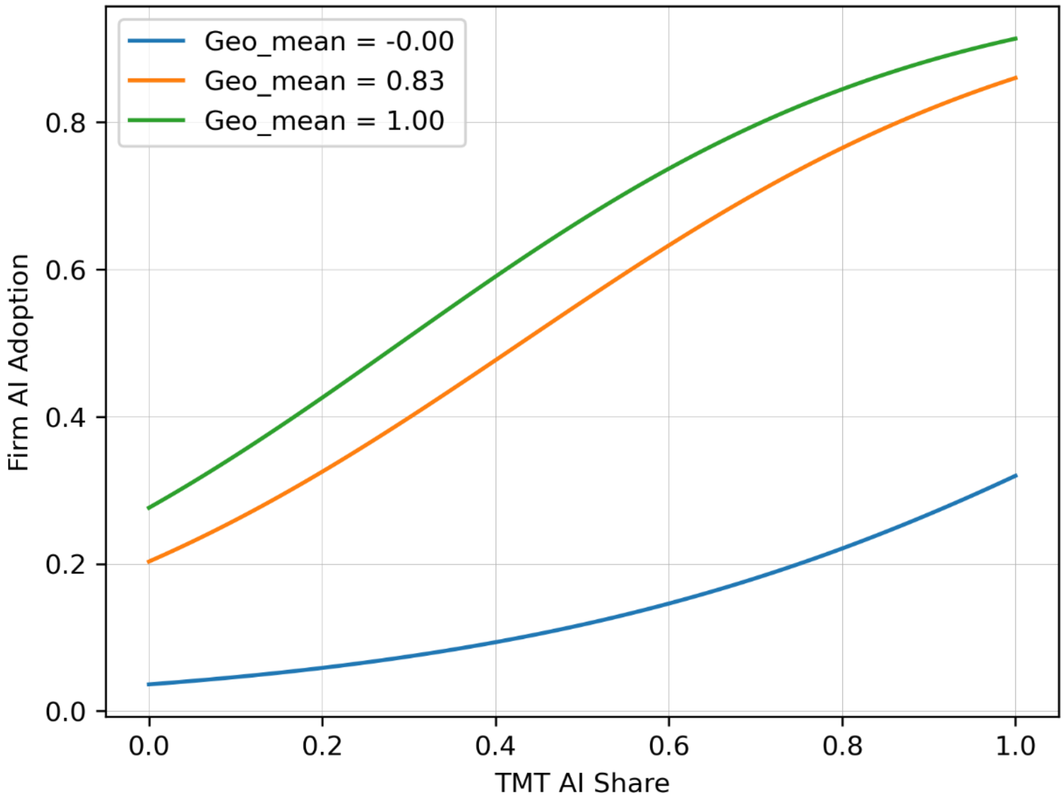


In the case of sector influence, the graph (Figure 6) shows an interaction between TMT AI Share and sector in their effect on Firm AI Adoption. For all sector values, increasing TMT AI Share generally leads to Firm AI Adoption, supporting H2, which states that TMT AI literacy positively influences firm-level AI adoption. However, this probability prediction contrasts with the results of model 5 ($\beta = 56.45$, $p \geq 0.05$). This discrepancy is likely due to the two types of sectors such as ICT and financial services represented in the dataset, where the proportion of AI-adopting firms and TMT AI literacy is approximately similar. Therefore, this conflicting result may reflect false positives and false negatives, rendering both results inappropriate to support H2's partial claim that the likelihood of a firm implementing AI is moderated by the diffusion of AI within the sector. Appendix G depicts the ROC analysis for variable fit for prediction.

An examination on why the ICT and financial services sectors has a proportional number of AI-adopted firms found that the readiness of these firms for AI adoption is a key factor. These industries benefit from high market competition, social influences, and strong IT skills, which enable them to implement AI more effectively (Rajak, Dey and Sahu, 2022). In sectors like IT and finance, leadership is often more tech-savvy, and the presence of robust data infrastructure facilitates AI adoption. As a result, firms in these sectors tend to be more AI-ready and face fewer compatibility challenges (Yang, Blount and Amrollahi, 2024). However, studying sectors beyond professional services could increase the significance of sector type as a moderating variable. Dahlke et al. (2024) analysed AI adoption across multiple sectors and found that the sector has a significant influence on AI adoption, with the majority of AI-adopting firms coming from ICT and financial services. Therefore, the sample size diversity for predicting AI adoption by sector is inadequate, and the sector variable does not support the hypothesis

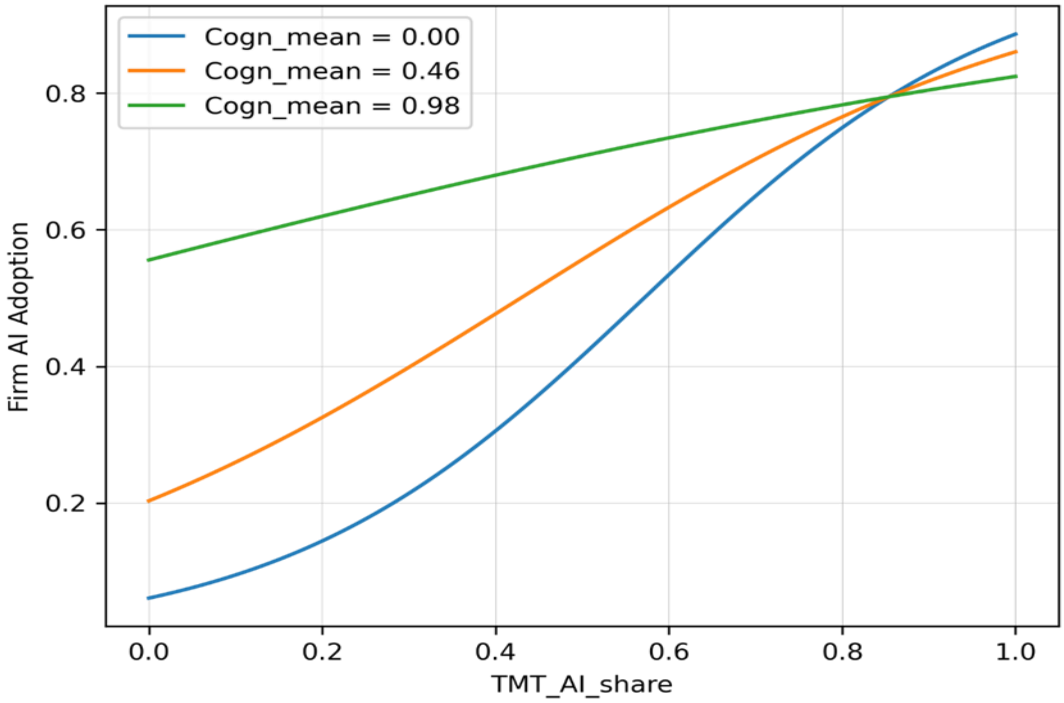
4.4.2 Social Proximity

Figure 7. Geographical Proximity Moderating Effect



The graph (Figure 7) shows that the interaction effect between TMT AI literacy and geographical proximity (geographical mean) on AI adoption. As TMT AI literacy increases (moving right on the x-axis), firm AI adoption increases for all levels of geographical proximity. The effect of TMT AI literacy on firm AI adoption becomes stronger (with a steeper slope) as geographical proximity increases. Geographical proximity decreases, and AI adoption reaches its lowest point. The moderate relationship between TMT AI literacy and firm AI adoption remains positive but relatively weak. However, the mean (orange line) and maximum (green line) demonstrate that the positive relationship between TMT AI literacy and firm AI adoption is stronger than at the minimum level. Even though the graph and a coefficient of 2.21 (model 2) show a positive trend, the standard error of 1.96 indicates that the moderating effect of geographical proximity is insignificant.

Figure 8. Cognitive Proximity Moderating Effect



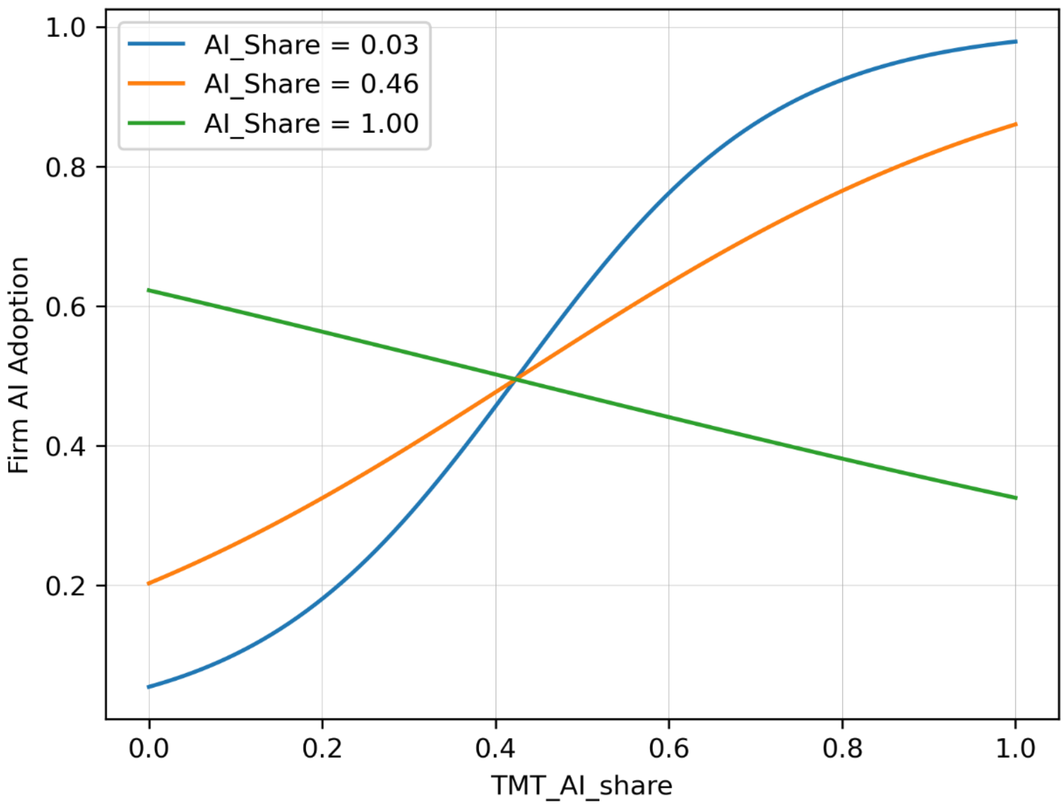
The graph (Figure 8) shows the interaction effect between TMT AI literacy and cognitive proximity on firm AI adoption. At a low Cognitive mean (0.00), the relationship is positive and non-linear. As the Cognitive mean increases to the average (0.46), the relationship becomes more linear while remaining positive. At a high Cognitive mean (0.98), the relationship remains positive but with a more gradual slope, indicating a reduced impact of TMT AI Share on firm AI adoption. The coefficient also indicates a positive effect (β =1.49). Similar to geographical proximity, cognitive proximity has a high standard error (1.62), suggesting that the moderating effect of this variable is insignificant.

Neither geographical proximity nor cognitive proximity has a significant moderating effect on AI adoption. However, these variables show main effects in the baseline model, and the trend in the graph indicates positive relationships. Previous studies found that geographical proximity influences SMEs' open innovation (Kapetaniou and Lee, 2019). Geographically closer firms engage in knowledge sharing more cost-effectively, which enables efficient knowledge acquisition (Molina-Morales, García-Villaverde, and Parra-Requena, 2014). However, the results of this study found no significant effect of geographical proximity, which may be due to the impact of digitalization, which might reduce the importance of geographical proximity (Stucki and Woerter, 2019). Dahlke et al. (2024) also found that geographical proximity is insignificant in the AI adoption process. A possible explanation for this is that, in SMEs, regardless of geographical distance (whether they are close or far apart), the direct influence of the three dimensions (structural, relational, and cognitive) on knowledge sharing remains unchanged (Chumnangoon, Chiralaksanakul and Chintakananda, 2023).

Dahlke et al. (2024) found that cognitive proximity is significant in AI implementation, however, in this study, cognitive proximity does not have a significant moderating effect. For innovative performance in SMEs, connections with similar knowledge base firms enhance the adoption of innovation and facilitate a firm's absorptive capacity (Sánchez-García *et al.*, 2023). Similarly, studies indicate that cognitive proximity is more prevalent than geographical proximity, which enhances collaboration with partners that have a similar AI knowledge base (Koopmann *et al.*, 2021). The results of this study may not be suitable for predicting the interaction between TMT AI literacy and cognitive proximity on AI adoption. Since neither variable's result is significant in this study, H3 (the diffusion of AI-related knowledge and a firm's likelihood to adopt AI are moderated by the average proximity between the firm and prospective sources of AI knowledge) not supported by the hypothesis testing.

4.4.3 Direct Connection

Figure 9. AI Share Moderating Effect

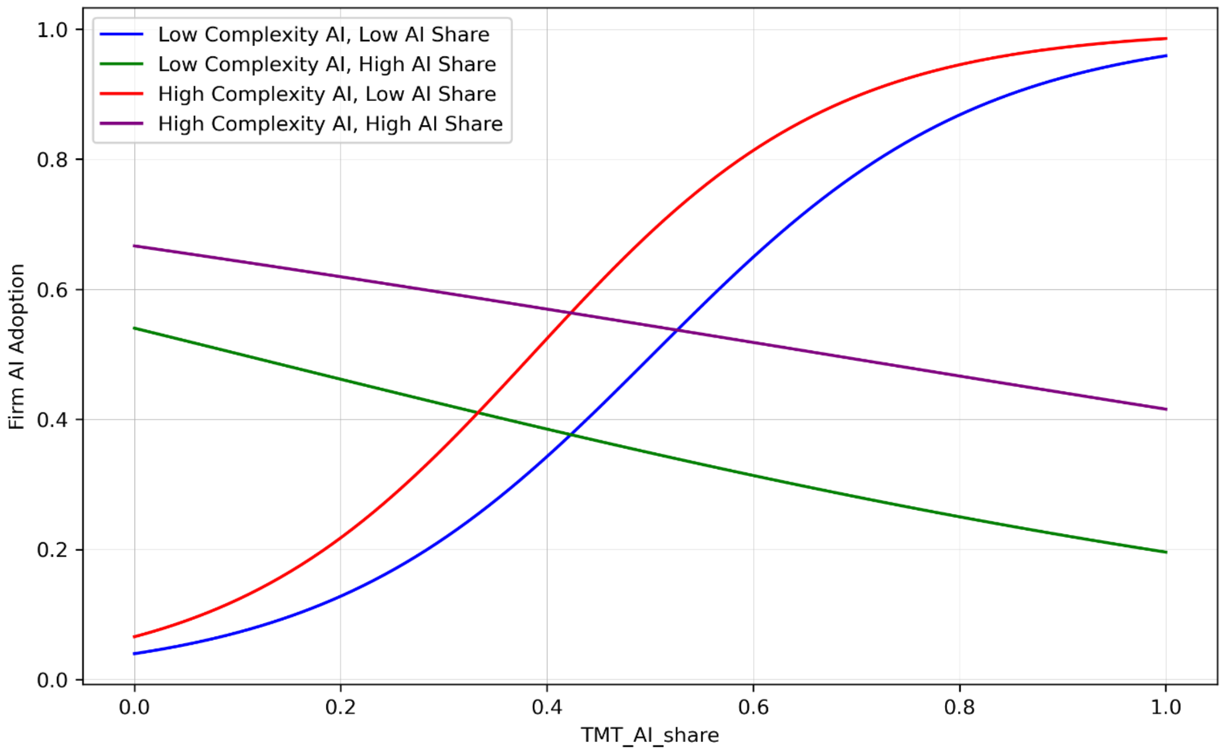


This graph (Figure 9) illustrates the complex interaction between TMT AI literacy (x-axis), AI share (represented by different lines), and firm AI adoption (y-axis). The graph shows a strong and complex interaction between TMT AI Share and AI share in their effect on firm AI Adoption. For the minimum (blue line) and mean (orange line) AI share values, there is a positive nonlinear relationship. In contrast, for the maximum AI share value, there is a negative relationship. This can be interpreted as follows:

- At low levels of TMT AI literacy requires higher AI share with other AI adopted firms leads to higher firm AI adoption.
- However, when TMT AI literacy is high, the relationship inverts, with a lower AI share leading to higher firm AI adoption.

Evaluating this predicted probability visualization alongside the results of model 7 (β = -7.16, $p < 0.01$) clearly indicates why the coefficient becomes negative. The relationship between a firm's connections to AI-adopting firms (AI Share) and firms own AI adoption is more complex than initially hypothesized. At low levels of TMT AI literacy, having more connections to AI-adopting firms does increase the likelihood of AI adoption, supporting the network effect aspect of H4. However, as TMT AI literacy increases, the effect of connections to AI-adopting firms diminishes and even becomes negative. This suggests that TMT AI literacy may be overtaking the influence of connections to AI-adopting firms. Therefore, the 4^{th} hypothesis that firm with a higher share of connections to other AI-adopting firms experience moderated effects in adopting AI is not supported by the hypothesis testing.

Figure 10. Mediating Effect



The graph (Figure 10) shows significant 3-way interactions between TMT AI literacy, AI complexity, and AI share in their effects on Firm AI Adoption. This can be interpreted as follows:

- For low complexity AI with both low and high AI share, increasing TMT AI literacy increases firm AI adoption (blue and red lines).
- For high complexity AI, increasing TMT AI literacy decreases firm AI adoption (green and purple lines).
- At low TMT AI literacy, high complexity AI leads to higher adoption than low complexity AI.
- As TMT AI literacy increases, this relationship inverts, with low complexity AI leading to higher adoption rates.
- For low complexity AI, higher AI share (red line) leads to higher adoption rates compared to low AI share (blue line).

- For high complexity AI, the effect of AI Share is less pronounced, with high AI share (purple line) only slightly higher than low AI share (green line) at low TMT AI literacy levels

In overall the 5th hypothesis, the complexity of AI knowledge enhances AI adoption through TMT AI literacy and a higher number of connections to AI-adopting firms, is not supported by hypothesis. Similarly, the model 8 indicates complex AI, and AI share is negative and significant (β = -3.51, $p < 0.05$). This suggests that AI knowledge complexity does mediating the relationship between TMT AI literacy, connections to AI-adopting firms, and AI adoption, but not in the hypothesized direction. The complexity of AI knowledge appears to weaken the positive effects of TMT AI literacy and connections to AI-adopting firms on AI adoption.

Both hypotheses (H4 and H5) are not supported by the hypothesis testing. For H4, the reason for the lack of support is that TMT AI literacy and connections with AI-adopting firms appear to substitute for each other in influencing AI adoption. In H5, the direction of the effect is negative instead of the hypothesized positive direction. The direct connection construct is more complex than initially hypothesized. However, both hypotheses provide insight into how network effects operate in AI adoption. As TMT AI literacy increases, the reliance on connections with AI-adopting firms decreases. When it comes to more complex AI technologies, firms with low TMT AI literacy become more dependent on other firms. At the same time, as the complexity of AI increases, the connection with AI-adopting firms tends to decrease. Previous research on complex AI and AI share suggests that firms with more connections to companies that have adopted complex AI are more likely to adopt complex AI themselves (Dahlke et al., 2024). These connections facilitate the sharing and exchange of information about new technologies (Borgatti and Halgin, 2011). This study also incorporated the construct of TMT AI literacy, as knowledge transmission requires the receiver to possess the relevant skills to acquire and utilize the knowledge (Bozeman and Corley, 2004). Hypotheses H4 and H5 require further research to understand why high TMT AI literacy appears to decrease connections with AI firms, while simultaneously increasing the likelihood of adopting complex AI. The Technology-Organization-Environment (TOE) framework or other AI readiness frameworks may be relevant in identifying the underlying causes.

4.5 Limitations

This study has several limitations due to cross-sectional data and multidimensional approach used to study AI adoption in SMEs. Firstly, although the research model assesses internal factors such as TMT AI literacy, complex AI usage, and AI technological knowledge acquisition capability, as well as external factors like interconnections with other firms and socio-economic influences, it does not identify different types of business orientations towards AI. These AI orientations could significantly influence AI adoption because these factors identify firm-level strategic biases for AI adoption (Li et al., 2021). Secondly, the research model assumes that communication between firms occurs when they share hyperlinks, even though previous research conducted in the UK has ascertained innovativeness of a firm can analysis by examining websites (Gök, Waterworth, and Shapira, 2015; Tranos, Kitsos, and Ortega-Argilés, 2021). However, this research deliberately analysed interconnections between firms through hyperlinks unidirectionally only, whereas previous prominent research conducted hyperlink analyses bidirectionally and unidirectionally (Dahlke et al., 2024). Thirdly, the TMT observable characteristics such as skill, education, and experience are only analysed for their personal traits to adopt innovation and do not identify entrepreneurial orientation traits such as proactiveness, risk-taking, and innovativeness of TMT, which might be significant as the SME's business strategy is more exploratory in adopting new technology (Matsuno, Mentzer, and Özsomer, 2002; Müller, Buliga, and Voigt, 2021). Previous research also find that entrepreneurial orientation significantly increases the AI adoption (Baldegger, Caon and Sadiku, 2020; Pinski, Hofmann and Benlian, 2024)

Fourthly, the regression results indicate that variables have a nexus relationship with each other, and the research model does not map out the ambiguity of the regression results. This is mainly due to companying the variables of TMT AI literacy and relationships with other partnered firms. The model predicts that a lack of experience might increase partnerships with other firms for AI knowledge acquisition, but this was not significant in this study's regression model. A robustness check is required for the results because generally, previous papers suggest that if a firm lacks expertise, it may seek partnerships with other firms for knowledge exchange, and these papers do not evaluate the upper echelons' characteristics of AI (Sorenson, Rivkin, and Fleming, 2006; Felten, Raj, and Seamans, 2021; Dahlke et al., 2024). Additionally, for accurate regression testing, a diverse and large sample size is needed, especially since variables such as sectors show less diversity, rendering the results of the regression insignificant. Fifthly, a Python dictionary for finding AI adoption and AI literacy involves broad terms such as Artificial Intelligence and Deep Learning, but these key terms alone may not adequately indicate the degree of AI adoption or AI literacy. Sixthly, the regression model results suggest the presence of inverse direction and substitute relationships, which create doubts about endogeneity. Another reason for this concern is that although the main effects are present in the baseline model for most variables, many variables have not interaction effects on AI adoption. This limitation was primarily due to the data being cross-sectional, and control variables such as time were not included in this study to help identify the causes of inverse and substitute relationships of variables.

Chapter 5: Conclusion

The research focuses on how technology adoption determinants variables affect a firm's decision-making process regarding AI adoption. AI adoption can be described as a strategic process that involves eliminating unnecessary AI models, enabling human-AI collaboration, and understanding the benefits of AI (Bawack, Wamba, and Carillo, 2019; Li et al., 2021; Nagahisarchoghaei et al., 2023). The identified AI adoption determinants in this research provide insights into factors that would be helpful for AI customization in SMEs. The research identified that SMEs face resource constraints such as talent acquisition, financial limitations, skill gaps, and knowledge disparities comparing to large firms, as well as they possess strategic perspectives like exploratory and open innovations (Gassmann, Enkel and Chesbrough, 2010; Masood and Sonntag, 2020; Müller, Buliga and Voigt, 2021; Bhalerao, Kumar and Pujari, 2022; Gordon, 2022; Tawil *et al.*, 2024). Considering the strategic perspectives of SMEs, this research argues that mitigating resource limitations through TMT skill sets and leveraging values gained from social capital enhances AI adoption. Moreover, considering previous papers' arguments of AI adoption differs from traditional IT adoption (Bawack, Wamba and Carillo, 2019), integrating key research variables such as AI literacy and AI complexity has enhanced the prevalence of the identified AI adoption determinants.

Overall, this study examined the influence of Top Management Team (TMT) AI literacy on firm-level AI adoption, incorporating constructs such as socio-economic influences, social proximities, and direct connections as interaction variables of the relationship between TMT AI literacy and AI adoption. The findings substantiate the hypothesis that TMT AI literacy significantly enhances AI adoption, aligning with theoretical predictions from upper echelons theory. This positive correlation demonstrates that the educational background, skills, and experiences of TMTs lead to firm-level adoption of AI. This study also examined the interaction effects using a generalized linear model focusing on binary logit. The results indicate that TMT AI literacy, moderated by regional variability has a significant impact on AI adoption. Therefore, constructs of social influences partially supported by these variables result. Other outcome variables, such as sector, geographical proximity, and cognitive proximity, did not support the hypothesis and were insignificant in the results. While the variable AI share (connected with other AI adopted company) and complexity AI was significant, but the results depict a negative effect on AI adoption; hence, this variable's construct, direct connections, also not supported. Therefore, hypothesis one is fully supported and hypotheses two partially supported, while other hypotheses are not supported by the hypothesis test.

The regional moderating effect and TMT AI literacy on AI adoption is this research's most plausible explanation for AI adoption in SMEs. Higher levels of AI literacy within TMTs directly contribute to a higher likelihood of AI adoption. The TMT AI literacy variable specifically considers the diversity within the TMT. The analysis of TMT AI literacy specifically accounts for the importance of this diversity and empirically measures this variable in proportion to AI-literate members in the top team. Therefore, the results encompass the possibility of power dynamics that might occur within the TMT. Previous research also suggests that increasing TMT AI literacy positively impacts AI adoption (Pinski, Hofmann and Benlian, 2024). Similarly, the region acts as a significant moderating factor in the relationship between TMT AI literacy and AI adoption. This implies that the impact of TMT AI literacy on AI adoption can vary depending on the region in which the SME operates. It can be concluded that TMT AI literacy is a key enabler of AI adoption in SMEs, but its effectiveness is contingent on the regional context. This dual focus on both internal capabilities (TMT AI literacy) and external factors (region) offers a nuanced view of the dynamics influencing technology adoption in businesses.

Even though the variables AI share and complex AI showed significance in mediating the impact of TMT AI literacy on AI adoption, the hypotheses were not supported. Analysing why they appeared importantly in the regression model; it can be understood that knowledge gaps significantly influence the connection between firms. The complex structure of this relationship varies depending on TMT AI literacy. The relationship cannot be defined linearly, especially when considering the higher AI adoption at low levels of TMT AI literacy with less complex AI. Moreover, the presence of AI in a firm's AI share generally supports adoption, but its impact varies with the complexity of the AI technology and the level of TMT AI literacy. With less support from previous papers, substitute effects of these variable, and not supporting the hypothesis, these findings can be considered as inconclusive estimates and highly valuable for future research.

5.1 Recommendations

Firstly, as discussed, the customization of AI plays an important role in AI adoption. The positive influence of TMT AI literacy on AI adoption provides insight that management skills in AI should be developed for strategic decision-making in AI adoption. This research clearly indicates the significance of AI literacy, but the research did not explore cause and effect with other variables. For example, it considered the region's moderating effect on TMT AI literacy and AI adoption rather than exploring why some regions adopt AI more than others. Previous research frameworks on this moderating effect might not be valid in the context of AI because they are less explored by these variables in UK SMEs.

Secondly, analysing the complex AI and AI share variables revealed unexpected patterns, leading to insights about the specific characteristics and size of TMTs that are most conducive to successful AI adoption. Future research on certain types of AI literacy, and classifying technical and non-technical, executive and non-executive (power dynamics) aspects of TMT and business objectives will enhance the understanding of AI adoption. It is understood that there is a knowledge gap in AI literacy balance in SME TMTs; however, this study did not given results for suggesting the absence and presence of specific factors impacting the variance in this mediating effect of complex AI on AI share and the moderating effect of AI share on TMT AI literacy.

Thirdly, AI readiness frameworks coupled with upper echelons theory (UET) would be suitable for future understanding of the unique challenges faced by SMEs. This approach allows for the study of the organization's goals, culture, and the technological challenges it encounters. Despite levels of TMT AI literacy in top management, other barriers such as the ability to manage the firm's data production and redefining organizational structures to align with the AI strategy might be considered critical in the AI adoption process. Weber et al. (2023) argue that communication among stakeholders and AI model selection require AI knowledge, skills, and an organizational culture that supports such activities. They utilized a qualitative research approach, which enabled a deep understanding of the organizational capabilities necessary for AI implementation. Considering the limitations of this research model, such as the collection of subjective data, incorporating qualitative techniques might improve understanding of the AI adoption process.

Fourth, variables such as geographical proximity and cognitive proximity are significant in the baseline model of regression analysis, and at the same time, the probability prediction in their direction is positive. However, in their moderating role, they do not support the hypothesis. One possible explanation for the inconsistency is that the data size might be limited for differentiating and recognizing hidden patterns. Similarly, the sector variable only exhibits limited diversity in the dataset. This indicates that a larger dataset and future studies using binary logit for analysis should consider this type of behaviour in the dataset distribution. Moreover, future studies could investigate the progress of AI adoption using a longitudinal research approach, which might enable variance in AI literacy and the interaction of these variables' effects on AI adoption.

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Appendix

Appendix A: The code for the network analysis

Appendix B: AI related keyword python dictionary

Appendix C: Main sample data statistics

Appendix D: Detailed interpretation of descriptive statistics

Appendix E: Normality and Collinearity test

Appendix F: Regions and ITL data

Appendix G: ROC Analysis

Appendix A: The code for the network analysis

The following code is done for the network analysis (‘networkx: Python package for creating and manipulating graphs and networks’),

Edge= (Company Number of Source, Target, Wight=1.0)

Here,

Edge: Connection between 2 firms

Company Number of Source: Node represents the company that contains the hyperlink pointing to another company (in other words, the hosts the hyperlink).

Target: Node is the company that the hyperlink points to. This is the destination of the edge. It is the domine parsed from original hyperlink.

Wight: Numerical value that represents the strength or significance of the edge.

Appendix B: AI related keyword python dictionary

keywords = [

"Deep Learning", "Machine Learning", "Neural Networks", "Natural Language Processing", "Computer Vision", "Reinforcement Learning", "Supervised Learning", "Unsupervised Learning", "Semi-Supervised Learning", "Artificial Neural Networks", "Convolutional Neural Networks", "Recurrent Neural Networks", "Generative Adversarial Networks", "Robotics", "Cognitive Computing", "Support Vector Machines", "Artificial General Intelligence", "Chatbots", "Bayesian Networks", "Quantum Computing", "Ethics in AI", "AI Governance", "Explainable AI", "AI Safety", "Autonomous Vehicles ", "Data Augmentation, "Hyperparameter Tuning", "Model Evaluation", "Robotics Process Automation", "Automated Machine Learning", "Cognitive Robotics", "Text-to-Speech", "Speech-to-Text", "Contextual AI", "Robot Learning", "Genetic Algorithms", "Particle Swarm Optimization", "Artificial Life", "Cognitive Architectures", "Hierarchical Learning", "Hierarchical", "Semiotic AI", "Neural Turing Machines", "Capsule Networks", "Spiking Neural Networks", "Sparse Coding", "Boltzmann Machines", "Hopfield Networks", "Echo State Networks", "Liquid State Machines", "WaveNet", "Transformer Networks", "Attention Mechanisms", "Seq2Seq Models", "BERT", "GPT", "XLNet", "RoBERTa", "ALBERT", "T5", "ELMo", "Neuromorphic Computing", "Emotional AI", "Affectiva", "Human-in-the-Loop", "Transparent AI", "Responsible AI", "Trustworthy AI", "Privacy-Preserving AI", "AI Fairness", "AI Bias", "AI Regulations", "AI Standards", "AI Auditing", "Data Governance", "Data Ethics", "NLP", "ANN", "CNN", "RNN", "GAN", "SVM", "AGI", "NLU", "XAI", "HCI", "NAS", "MDP", "RPA", "AutoML", "NLG", "TTS", "STT", "HRI", "PSO", "ALife", "VQA", "NLI", "NTM", "SNN", "Bidirectional Encoder Representations from Transformers", "Advanced AI", "AI Moderation", "Artificial Neural Network", "AI Analytics", "Algorithmic Trading ", "AI Algorithm", "AI Chip", "Deepfake", "AI Driven", ""AI Expert", "Text Generation", "Image Labelling", "ML Model", "Autonomous Weapon", "Artificial Intelligence", "AI Facilitated", "Virtual Assistant", "Neural Network", "Self-Driving ", "AI Models", "AI Startup", "Text Analysis", "Text Recognition", "AI Traffic", "AI-Powered", "AI/ML", "Artificial Creativity", ""Probabilistic Neural Network", "Extreme Learning Machine", "Cutting Edge AI", "Supervised Machine Learning", "Deep "Innovative AI", "Deep Neural Networks", "Back-propagation Neural Network", "AI Strategy", "AI Implementation", "AI Innovation", "AI Collaboration", "AI Transformation", "AI Integration", "AI Research", "Machine Perception", "AI Simulation", "Computational Intelligence", "AI Infrastructure", "AI Modelling", "AI Optimization", "Swarm Robotics", "AI Diagnostics", "Learning Algorithms", "AI Systems", "Distributed AI", "AI Training", "AI Tuning", "AI Ecosystems", "AI Implementations", "Hybrid AI", "Intelligent Assistants", "Machine Cognition", "Model Compression", "Neuroimaging", "Reinforcement Algorithms", "Speech Processing", "Predictive AI", "Prescriptive Analytics", "Robotic Process Automation", "Semi-Supervised Learning", "Smart Sensors", "Speech Interface", "Transfer Reinforcement Learning", "Uncertainty Estimation", "User-Adaptive AI", "Utility Computing", "AI-enhanced IoT", "Biometric Recognition", "Cognitive Agents", "Context-aware Computing", "Deep Reinforcement Learning", "Intelligent Control Systems", "Lifelong Learning Algorithms", "Multi-agent Learning", "Neuro-fuzzy Systems", "Robust AI Systems" , "llm", "LLM", "Large language model", "IoT", "Internet of Things", ""Black box AI"]

Appendix C: Main sample data statistics

Descriptive Statistics

1. **For binary variable outcomes:**

TMT AI Literacy and Firm Level AI Adoption

Particulars	Value
Number TMT members	1432
Average TMT size	3
Min TMT size	2
Max TMT size	26
Number of Firms	646
AI Adopted firms	360
Number of TMT member possess AI Literacy	252
Both Firm and TMT member have AI	109

2. **For continuous variable outcomes:**

Variable	Observation	Mean	Std	min	max
Complex AI Knowledge	2700	0.42	0.35	0	1
Simple AI	2700	0.57	0.34	0	1
Cognitive mean	7548	0.73	0.60	0.58	0.97
Geographical mean	9589	0.97	0.40	0	1
Closeness Centrality	2414	0.026247	0.024820	0.069256	0.813954

3. **Categorical variable outcomes**

Top 10 ITL3 regions by AI-oriented firm count

ITL3 Region name	count of AI - oriented firm
Camden and City of London	575
Westminster	338
Berkshire	132
Haringey and Islington	116
Oxfordshire CC	100
Tower Hamlets	81
West Surrey	79
Cambridgeshire CC	77
Hertfordshire CC	70
Manchester	69

Industry wise AI-oriented firms and total number of firms studied

Sector	Number of AI oriented firms	Total number of firms
ICT	2664	6142
Financial services	726	2815
Hospitality	94	491
Manufacturing	25	54
Education	2	4
Retail	2	33
Healthcare	1	35
Construction	0	7
Transportation	0	31
Utilities	0	1
Grand Total	*3514*	*9613*

Appendix D: Detailed interpretation of descriptive statistics

Variable	N	Minimum	Maximum	Mean	Std. Deviation
TMT AI share	209	0	1	0.25	0.38
Geographical mean	209	0	1	0.83	0.21
Cognitive mean	209	0	0.98	0.46	0.29
Region	209	0.2	1	0.75	0.21
Sector	209	0.59	1	0.60	0.04
Complex AI	209	0	1	0.64	0.36
AI share	209	0.03	1	0.46	0.35

- TMT AI Share: A mean of 0.25 and a maximum of 1 indicate that, on average, 25% of top management teams (TMT) are AI-literate. Some observations show no AI-literate members in the TMT, while others have all members with AI literacy. The standard deviation of 0.38 reflects a considerable amount of variance among different firms in terms of AI literacy within their TMTs.
- Geographical mean: The geographic distance variation among organisations is important, as evidenced by the mean of 0.83. This influence suggests that most enterprises sustained a substantial physical presence in the geographical location. Observations demonstrated significant consistency, as evidenced by a standard deviation of 0.21, indicating a low variation from the mean.
- Cognitive mean: the cognitive mean of 0.46 among firms signifies a moderate level of similarity. However, the standard deviation of 0.29 reveals substantial disparities vary between firms, depending on their distinct circumstances.

- Region: Region: A mean of 0.75 indicates that, on average, firms have a moderate tendency to focus their operations within a specific region. However, the standard deviation of 0.21 reveals that some firms dispersed their business in a different region, while others concentrated in a specific region.
- Sector: The mean of 0.60 indicates a moderate level of significance. However, the low standard deviation of 0.04 suggests low variation across sectors, indicating that the dataset is quite homogeneous rather than heterogeneous.
- Complex AI: A mean of 0.64 signifies a moderate degree of significance. A standard deviation of 0.35 indicates a moderately significant amount of variance, indicating that certain firms have characteristics that deviate from the average of other firms.
- AI share: A mean of 0.46 indicates a somewhat significant level of firm AI adoption. Similarly, the standard deviation of 0.35 suggests that the number of firms fluctuates moderately due to the AI shares variation in the dataset.

Appendix E: Normality and Collinearity test

Tests of Normality

Variable	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
TMT AI share	.378	209	<.001	.662	209	<.001
Geographical mean	.257	209	<.001	.767	209	<.001
Cognitive mean	.137	209	<.001	.908	209	<.001
Region	.132	209	<.001	.916	209	<.001
Sector	.417	209	<.001	.161	209	<.001
Complex AI	.228	209	<.001	.833	209	<.001
AI share	.160	209	<.001	.847	209	<.001
a. Lilliefors Significance Correction						

- Normality test significance indicates none of the variables data distribution are normal distribution.
- Collinearity test VIF values are lesser than threshold 5, it indicates no multicollinearity.

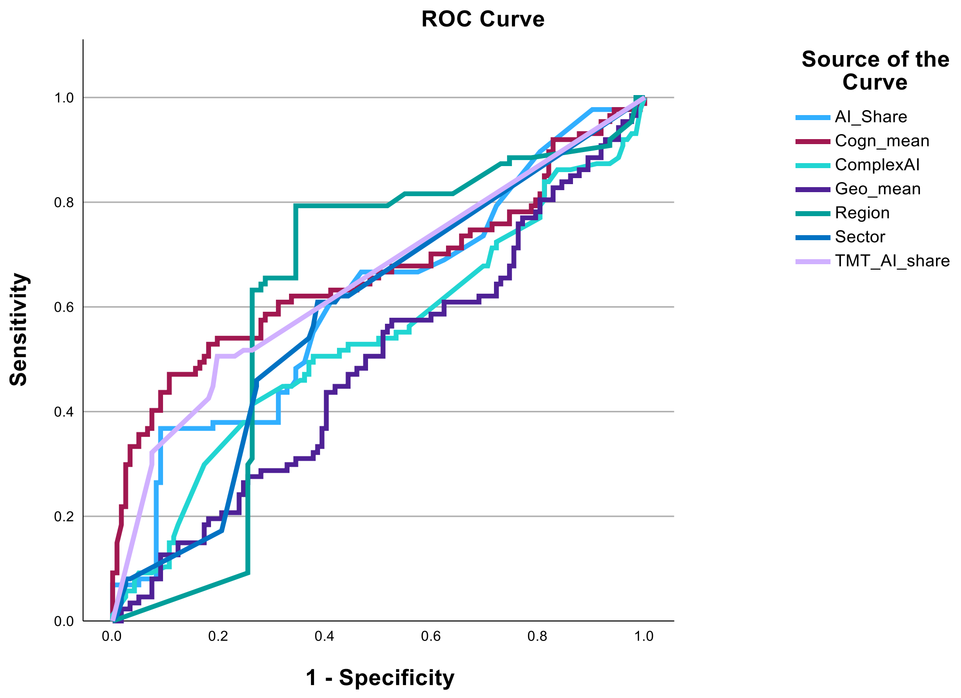
Collinearity Test

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	-0.88	0.474		-1.855	0		
TMT AI share	0.49	0.087	0.376	5.662	<.001	0.781	1.28
Geographical mean	0.296	0.149	0.126	1.98	0	0.853	1.172
Cognitive mean	0.454	0.102	0.265	4.439	<.001	0.961	1.04
Region	0.547	0.139	0.232	3.937	<.001	0.994	1.006
Sector	0.176	0.728	0.014	0.241	1	0.986	1.014
Complex AI	0.103	0.082	0.075	1.25	0	0.963	1.038
AI share	0.308	0.086	0.216	3.569	<.001	0.938	1.067

Appendix F: Regions and ITL Data

ITL3_x	ITL3_Name
TLC22	Tyneside
TLD33	Manchester
TLD34	Greater Manchester South West
TLD35	Greater Manchester South East
TLD36	Greater Manchester North West
TLD37	Greater Manchester North East
TLD62	Cheshire East
TLD72	Liverpool
TLD74	Wirral
TLE22	North Yorkshire CC
TLE31	Barnsley, Doncaster and Rotherham
TLE42	Leeds
TLE44	Calderdale and Kirklees
TLF14	Nottingham
TLF16	South Nottinghamshire
TLF22	Leicestershire CC and Rutland
TLF25	North Northamptonshire
TLG12	Worcestershire CC
TLG13	Warwickshire CC
TLG24	Staffordshire CC
TLG31	Birmingham
TLG32	Solihull
TLH11	Peterborough
TLH12	Cambridgeshire CC
TLH14	Suffolk CC
TLH15	Norwich and East Norfolk
TLH21	Luton
TLH23	Hertfordshire CC
TLH25	Central Bedfordshire
TLH35	West Essex
TLI31	Camden and City of London
TLI32	Westminster
TLI33	Kensington & Chelsea and Hammersmith & Fulham
TLI41	Hackney and Newham
TLI42	Tower Hamlets
TLI43	Haringey and Islington
TLI44	Lewisham and Southwark
TLI45	Lambeth
TLI53	Redbridge and Waltham Forest
TLI54	Enfield
TLI61	Bromley
TLI63	Merton, Kingston upon Thames and Sutton
TLI71	Barnet
TLI72	Brent
TLI74	Harrow and Hillingdon
TLI75	Hounslow and Richmond upon Thames
TLJ11	Berkshire
TLJ12	Milton Keynes
TLJ13	Buckinghamshire
TLJ14	Oxfordshire CC
TLJ22	East Sussex CC
TLJ25	West Surrey
TLJ27	West Sussex (South West)
TLJ32	Southampton
TLJ36	Central Hampshire
TLJ37	North Hampshire
TLK11	Bristol, City of
TLK12	Bath and North East Somerset, North Somerset and
TLK13	Gloucestershire CC
TLK24	Bournemouth, Christchurch and Poole
TLK43	Devon CC
TLL15	Central Valleys
TLL22	Cardiff and Vale of Glamorgan
TLL23	Flintshire and Wrexham
TLN06	Belfast
TLN08	Newry, Mourne and Down

Appendix G: ROC Analysis



Area Under the ROC Curve

Test Result Variable(s)	Area
TMT_AI_share	.651
Geo_mean	.487
Cogn_mean	.664
Region	.626
Sector	.589
ComplexAI	.538
AI_Share	.611

- TMT AI Share, AI Share and Region are closer to 1. It indicates these variables are more suitable for prediction.