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Artificial Intelligence Capital and Business Innovation

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Abstract

Artificial intelligence (AI) is increasingly recognised as a key driver of business innovation, yet its adoption among small and medium-sized enterprises (SMEs) varies considerably. This study examines whether AI Capital, defined as AI-related knowledge, skills and capabilities, is associated with business innovation among SMEs in England. Using a two-wave longitudinal panel dataset comprising 504 observations from SMEs collected in 2024 and 2025, the study develops and validates a 45-item AI Capital of Business scale. Business innovation is measured across five dimensions: product and service innovation, process innovation, technology adoption, market and customer engagement, and organisational culture and strategy. Regression models, including pooled OLS, Random Effects, and Fixed Effects specifications, are employed. The findings reveal a robust positive association between AI Capital and business innovation across all model specifications. This association holds across all business innovation dimensions and remains consistent for SMEs with differing levels of financial performance, size, and operational maturity. Each component of AI Capital independently exhibits a positive association with business innovation outcomes. The results highlight the central role of AI Capital in enabling SMEs to translate AI adoption into tangible business innovation. From a policy perspective, the findings indicate the value of targeted interventions that prioritise AI upskilling, organisational capability development, and accessible support mechanisms to promote inclusive and sustainable AI-driven business innovation among SMEs.

JEL classification

O31, O33, O32, L26, L25, M15, D83, J24, O14, O39

Keywords

artificial intelligence, artificial intelligence capital, business innovation, innovation, SMEs

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1. Introduction

Innovation is vital for the survival and growth of small and medium-sized enterprises (SMEs), enabling them to enhance their product and service offerings, improve operational efficiency, and adapt to market changes and external shocks (Al Dhaheri et al., 2024; Arroyabe et al., 2024; Ramdani et al., 2022; Expósito and Sanchis-Llopis, 2019). AI has become a fundamental driver of business innovation, transforming industries by enhancing operational efficiency, data-driven decision-making, and overall competitiveness (Segarra-Blasco et al., 2025; Al Dhaheri et al., 2024; Schwaeke et al., 2025; Mariani et al., 2023; Grashof and Kopka, 2023). AI applications, such as those powered by machine learning, natural language processing, and predictive analytics, are reshaping business processes, enabling organisations to automate tasks, streamline operations, and develop more sophisticated products and services (Campbell et al., 2020). For SMEs, AI presents an unprecedented opportunity to strengthen market positions, optimise cost structures, and enhance innovation capabilities (Drydakis, 2022; Hansen and Bøgh, 2021).

Given that SMEs constitute the majority of businesses in the UK and play a crucial role in economic growth and job creation, their ability to integrate AI is increasingly seen as essential for maintaining a competitive edge in an evolving digital economy (Segarra-Blasco et al., 2025; Mendy, 2021). However, despite its potential, AI adoption in SMEs remains uneven and fragmented. Many businesses struggle to incorporate AI effectively due to financial constraints, a lack of technical expertise, limited access to data infrastructure, and concerns about return on investment (Segarra-Blasco et al., 2025; Mendy, 2021). In this context, understanding how AI adoption in SMEs is associated with innovation is critical. A deeper exploration of this relationship can provide valuable insights into how AI fosters business growth, helps overcome barriers to innovation, and ensures that SMEs remain agile in increasingly technology-driven markets (Segarra-Blasco et al., 2025).

This study examines the association between SMEs' AI knowledge, skills, and capabilities, conceptualised as AI Capital (Drydakis, 2024a), and business innovation in England. It also explores whether this association varies by financial standing, business size, and firm age, pointing to potential inequalities in AI adoption. To support this analysis, the study develops and validates a comprehensive 45-item AI Capital for Business scale capturing firms' AI-related knowledge, skills, and capabilities. The study adopts a longitudinal quantitative design using panel survey data.

Existing literature on AI adoption in businesses has primarily focused on technological indicators, such as patent filings, external market drivers, including competition, regulation, and digital infrastructure, and business-level survey classifications (Segarra-Blasco et al., 2025; Al Dhaheri et al., 2024; Schwaeke et al., 2025; Mariani et al., 2023; Grashof and Kopka, 2023). However, these approaches do not fully capture the extent to which business staff understand, implement, and utilise AI in daily operations. This study introduces the AI Capital for Business scale, a human-centred measurement framework that assesses business-wide AI knowledge, skills, and capabilities. By examining internal drivers, the scale provides a more comprehensive reflection of how AI is embedded across different business functions. This shift, from measuring technological inputs to assessing organisational learning and strategic integration, represents an advancement in AI adoption research. It ensures that human capital, the key driver of effective AI utilisation, is properly accounted for (Drydakis, 2024a).

The AI Capital for Business scale enables a more nuanced assessment of AI maturity, considering how AI is utilised for strategic decision-making, business expansion, and innovation. This approach allows for a detailed analysis of AI readiness within organisations, distinguishing between those that merely acknowledge AI's potential, those that actively integrate AI into operational workflows, and those that strategically employ AI for competitive advantage. Moreover, a key feature of the AI Capital for Business scale is its explicit measurement of AI's role in business decision-making. It evaluates whether organisations use AI for financial forecasting, risk assessment, process automation, and customer engagement. AI integration is increasingly expanding across multiple departments, including customer service, financial management, human resources, ethical AI implementation, cybersecurity, and strategic planning. The AI Capital for

Business scale addresses this growing complexity by assessing AI adoption across diverse business functions, thereby providing a comprehensive understanding of AI's role within organisations. It ensures that AI readiness is measured not only in terms of technical deployment but also through the lens of responsible and compliant usage. By categorising AI use into knowledge, skills, and capabilities, this scale helps researchers and policymakers identify areas where AI adoption is strong and where further development is needed.

This study makes a significant contribution by examining five key themes: product and service innovation, process innovation, technology adoption, market and customer engagement, and organisational culture and strategy, offering a comprehensive understanding of AI-driven business transformation (Grashof and Kopka, 2023; Knowles et al., 2008). By focusing on these dimensions, the research provides insights into how SMEs leverage AI to enhance their competitive positioning and adaptability in a rapidly evolving digital economy. Product and service innovation reflects AI's role in creating new offerings and improving existing ones, while process innovation captures AI's impact on streamlining operations and reducing costs. Technology adoption highlights SMEs' ability to integrate AI solutions effectively, whereas market and customer engagement assesses how AI facilitates customer interactions and market expansion. Lastly, organisational culture and strategy evaluates AI's influence on business models and decision-making processes. By integrating these themes, the study advances AI adoption research and offers policymakers and business leaders targeted insights into optimising AI's role in SME growth and long-term sustainability.

By employing panel data analysis, this study provides stronger evidence regarding the hypothesised direction of the relationship between AI Capital and business innovation, while helping to mitigate, though not fully eliminate, concerns related to reverse causality and unobserved business-specific heterogeneity (Grashof and Kopka, 2023). The analysis across business characteristics, financial performance, size, and age enables policymakers to develop targeted AI adoption strategies, including training initiatives, financial incentives, and regulatory support to enhance accessibility and scalability across SMEs. For business leaders, the research highlights how strategic AI investments can improve efficiency, competitiveness, and market positioning by addressing capability gaps and leveraging AI for innovation, customer engagement, and business development. By systematically analysing the role of AI Capital in business innovation, the research contributes to broader discussions on digital transformation, SME growth, and sustainable economic development in an increasingly AI-driven economy.

The rest of the study is structured as follows. Section Two provides the theoretical framework. Section Three outlines the data-gathering process. Sections Four and Five detail the development and validation of the AI Capital for Business scale. Section Six presents the descriptive statistics. Section Seven reports the study's estimates. Section Eight discusses the interpretation of the findings, policy implications, limitations, and avenues for future research. The final section presents the conclusions.

2. Theoretical considerations

Empirical studies conducted across Europe, North America, Asia, and the United Arab Emirates have found a positive association between AI and innovation. These studies have employed various techniques to measure AI, ranging from AI-related patents to AI readiness, AI adoption, and technological characteristics (Segarra-Blasco et al., 2025; Machucho and Ortiz, 2025; Arroyabe et al., 2024; Schwaeke et al., 2025; Al Dhaheri et al., 2024; Grashof and Kopka, 2023; Mariani et al., 2023). AI's role in fostering innovation may be interpreted through several well-established theoretical frameworks (Teece et al., 2016; Bresnahan and Trajtenberg, 1995; Schumpeter, 1939). General-Purpose Technology (GPT) theory suggests that technologies with broad applicability tend to generate widespread and lasting economic transformations (Bresnahan and Trajtenberg, 1995). AI is increasingly viewed as a GPT due to its ability to drive innovation across multiple industries by enhancing decision-making, automating processes, and enabling new business models (Machucho and Ortiz, 2025; Mariani et al., 2023; Bresnahan and Trajtenberg, 1995).

Dynamic Capabilities theory (Teece et al., 2016) provides a useful lens for explaining how AI supports business innovation (Mariani et al., 2023). Dynamic capabilities refer to an organisation's ability to adapt and reconfigure its resources in response to changing environments. AI is suggested to help businesses identify market trends, predict consumer behaviour, and anticipate industry shifts through AI-powered analytics (Segarra-Blasco et al., 2025; Arroyabe et al., 2024; Al Dhaheri et al., 2024; Mariani et al., 2023; Campbell et al., 2020). AI also optimises pricing strategies and enhances operational efficiency (Teece, 2018). Additionally, AI supports business transformation by automating processes and improving scalability (Al Dhaheri et al., 2024; Warner and Wäger, 2019; Chan et al., 2018). Moreover, Innovation Diffusion Theory (Rogers et al., 2019) suggests that businesses adopting advanced technologies gain a first-mover advantage and shape industry-wide trends. AI fosters innovation by enabling businesses to discover novel knowledge combinations (Grashof and Kopka, 2023; Mariani et al., 2023; Chan et al., 2018). This is particularly evident in research and development-intensive industries, such as finance and manufacturing, where AI-driven analytics accelerate risk modelling and production efficiency (Segarra-Blasco et al., 2025; Drydakis, 2022).

The integration of AI into business functions strengthens innovative capacity by enhancing efficiency, facilitating knowledge transfer, and enabling the rapid implementation of new solutions (Al Dhaheri et al., 2024; Grashof and Kopka, 2023; Chan et al., 2018). Research indicates that AI adoption improves businesses' responsiveness to market fluctuations, particularly for SMEs (Campbell et al., 2020). Furthermore, evidence suggests that AI-driven decision-making refines customer segmentation, predicts demand, and enables personalised marketing strategies, while process innovation benefits from automation, supply chain efficiency, and streamlined workflows (Segarra-Blasco et al., 2025; Machucho and Ortiz, 2025; Campbell et al., 2020). Additionally, AI facilitates market innovation by harnessing big data for competitive intelligence, optimising resource allocation, and responding proactively to consumer needs (Campbell et al., 2020). Based on Structural Technological Transformation Theory (Schumpeter, 1939), large businesses, owing to their higher market value, cash holdings, and substantial innovation investments, may actively seek to integrate AI technologies into their operations and engage individuals with the necessary AI skills for emerging AI job tasks more than smaller businesses (Drydakis, 2024a). Smaller businesses often face barriers such as technological expertise gaps, funding constraints, and regulatory complexities (Mariani et al., 2023).

AI Capital was introduced to define the accumulation of knowledge, skills, and capabilities that organisations and individuals develop to leverage AI for competitive advantage (Drydakis, 2024a). This framework builds on Human Capital theory (Becker, 1962) by positioning AI-related expertise as a critical organisational asset associated with productivity and innovation outcomes. AI Capital consists of three interrelated components: knowledge, which encompasses information, facts, and understanding that an individual possesses regarding AI fundamentals, applications, and ethical considerations; skills, which relate to the practical expertise that individuals develop through the application of AI knowledge and AI tools in organisational operations; and capabilities, which refer to the broader set of attributes that combine knowledge and skills to represent overall ability, effectiveness, and strategic integration of AI into long-term business models (Drydakis, 2024a). The AI Capital framework aligns with the resource-based view (Barney, 1991), which posits that organisations achieve a sustainable competitive advantage by possessing valuable resources. Those that develop AI Capital may differentiate themselves through advanced data-driven decision-making, process automation, and technological adaptability (Machucho and Ortiz, 2025).

AI Capital is conceptually related to Human Capital theory, yet it is distinct from general digital human capital, digital literacy, or broad IT competence (Reddy et al., 2020; Bach et al., 2013). Digital human capital typically refers to transferable competencies associated with the effective use of digital technologies, such as general digital communication, and routine use of enterprise systems. These competencies are valuable across many organisational contexts, but they do not necessarily entail the specific cognitive, technical, and organisational requirements associated with AI-enabled decision-making and AI-enabled transformation. AI Capital is defined more narrowly as a form of human and organisational capital that is specific to the development, deployment, interpretation, and governance of AI systems and outputs. The construct therefore begins where generic digital capability ends, namely at the point where organisational actors are required to (i) engage with AI-generated predictions, classifications, recommendations, or content, (ii) understand the uncertainty and limitations of algorithmic outputs, (iii) identify, manage, and mitigate AI-related risks, and (iv) integrate AI systems into workflows, strategy, and governance structures in a way that shapes decision-making and business innovation. In this sense, AI Capital is not measured by the mere presence of digital tools, nor by standard digital proficiency, but by the capability to leverage AI technologies in ways that are distinct from conventional information technologies.

The boundary conditions of AI Capital can be delineated along three criteria. First, AI Capital involves the ability to work with AI-specific outputs and concepts, including model performance, prediction error, bias, explainability, data quality, and the ethical implications of automated decision-making. Second, AI Capital includes the operational competence to select, configure, and use AI-enabled tools that perform tasks such as customer analytics, forecasting, automation, recommendation, and content generation, with attention to the risks and controls required for these systems. Third, AI Capital extends to AI-specific organisational capabilities, including the integration of AI into managerial decision processes, the establishment of governance routines for responsible AI use, and the strategic alignment of AI deployment with business objectives and innovation priorities.

This delineation also clarifies why AI Capital extends beyond narrow technical proficiency to include AI-specific strategic and organisational capabilities. These capabilities are not intended to reflect generic strategic competence, but rather the capacity to plan, redesign, and govern business processes in contexts where AI systems actively inform or automate decisions. In such settings, organisations are required to anticipate how algorithmic outputs, data governance requirements, and AI-related risks shape workflows, decision rights, and innovation pathways. From this perspective, AI Capital encompasses the ability to integrate AI into long-term organisational planning and innovation strategies, ensuring that AI deployment is aligned with business objectives, responsibly governed, and embedded in organisational routines. Strategic capability is therefore conceptualised here as an AI-specific form of organisational competence, activated only when firms engage with AI-enabled decision-making and transformation, rather than as a general managerial attribute. AI Capital is therefore conceptualised as a domain-specific extension of human capital, comprising AI-related knowledge, AI-related skills, and AI-related capabilities that become salient only when firms move beyond generic digitalisation and engage with AI-enabled decision-making, innovation, and governance. This clarification reduces the risk of conflating AI Capital with general IT competence, while reinforcing its distinct theoretical contribution as a construct that captures AI-specific capacity and readiness.

Business innovation is conceptualised across five interrelated domains: product and service innovation, process innovation, technology adoption, market and customer engagement, and organisational culture and strategy (Knowles et al., 2008). The three dimensions of AI Capital are expected to shape each domain through distinct yet complementary cognitive, operational, and organisational mechanisms. The knowledge dimension of AI Capital fosters innovation by expanding firms' awareness of AI-enabled opportunities and enhancing their capacity to interpret data-driven insights. AI-related knowledge equips business staff with the understanding required to identify new market possibilities and develop innovative offerings (Mariani et al., 2023). Knowledge of AI applications in customer management supports product and service innovation by enabling real-time engagement and aligning new developments with market demand (Segarra-Blasco et al., 2025; Mariani et al., 2023; Campbell et al., 2020). Similarly, knowledge of AI-driven marketing tools facilitates personalised targeting and improves the success of new offerings (Campbell et al., 2020). From a process perspective, AI knowledge enhances innovation through the use of AI-powered project management tools and real-time data analytics that improve operational efficiency and enable process redesign (Segarra-Blasco et al., 2025; Al Dhaheri et al., 2024;

Campbell et al., 2020). In relation to technology adoption, AI knowledge allows firms to evaluate and integrate AI tools across business functions, supporting the effective implementation of automation and advanced analytics (Drydakis, 2022). Market and customer engagement also benefit from AI-driven sales forecasting and customer insight capabilities, allowing firms to respond proactively to emerging trends (Segarra-Blasco et al., 2025). At the organisational level, AI knowledge contributes to innovation-oriented culture and strategy by strengthening data-informed decision-making frameworks and promoting an environment supportive of experimentation and continuous improvement (Drydakis, 2022).

The skills dimension of AI Capital reflects the operational expertise required to translate AI-related knowledge into practical innovation outcomes. AI-skilled employees enable the implementation of innovative initiatives by applying AI tools in product development, operational processes, and organisational workflows (Mariani et al., 2023; Campbell et al., 2020; Chan et al., 2018). In product and service innovation, AI skills support the design of AI-powered features and streamline development cycles (Campbell et al., 2020). Within process innovation, the application of AI-driven automation and workflow optimisation tools improves internal efficiency and reduces operational bottlenecks (Segarra-Blasco et al., 2025; Mariani et al., 2023). Technology adoption is reinforced through the presence of AI-skilled professionals who facilitate the implementation and integration of emerging AI systems across business functions (Drydakis, 2022; Campbell et al., 2020). In market and customer engagement, AI-related skills enable the use of AI-driven communication tools and collaborative platforms that accelerate idea generation and implementation (Davenport et al., 2020). At the organisational level, AI skills support financial forecasting, risk management, and adaptive decision-making processes that reinforce strategic alignment and organisational learning (Al Dhaheri et al., 2024; Campbell et al., 2020).

The capabilities dimension of AI Capital captures the ability to embed AI into strategic decision-making, governance structures, and innovation processes. Firms that develop AI-related capabilities are more likely to integrate AI into strategic planning and adopt disruptive innovations that reshape competitive dynamics (Al Dhaheri et al., 2024; Arroyabe et al., 2024; Mariani et al., 2023; Chan et al., 2018; Machucho and Ortiz, 2025; Grashof and Kopka, 2023). AI-driven insights enhance product and service innovation by enabling firms to tailor offerings to customer needs with greater precision (Segarra-Blasco et al., 2025; Campbell et al., 2020). These capabilities also support process innovation through the systematic use of AI-powered automation and analytics to optimise workflows and improve efficiency (Campbell et al., 2020). Technology adoption is strengthened when firms integrate predictive analytics and cybersecurity practices that allow advanced innovations to be deployed with reduced risk (Mariani et al., 2023). In terms of market and customer engagement, AI-enabled service quality improvements and customer relationship management tools enhance responsiveness to evolving market conditions (Segarra-Blasco et al., 2025). Finally, organisational culture and strategy benefit from AI-driven recruitment and talent development practices that support sustained innovation and long-term organisational transformation (Drydakis, 2024a; Drydakis, 2022).

Collectively, these theoretical perspectives suggest that AI Capital represents a multidimensional organisational resource that enables firms to recognise opportunities, implement AI-enabled practices, and embed innovation within organisational structures. Drawing on these theoretical and empirical insights, this study proposes the following hypothesis:

Hypothesis*: AI Capital, encompassing AI-related knowledge, skills, and capabilities, is positively associated with business innovation.*

Although this study tests a direct association between AI Capital and business innovation, the relationship is theoretically conceptualised as operating through underlying organisational mechanisms rather than as a purely linear process. Recent theoretical and empirical research suggests that AI-related resources primarily exert their influence by strengthening intermediate organisational competencies, particularly innovation capability and collaboration capability. From a

Dynamic Capabilities perspective, AI-enabled systems enhance firms' ability to sense opportunities, integrate dispersed knowledge, and reconfigure organisational routines through improved coordination and cross-functional interaction (Wang and Zhang, 2025a). In this way, AI Capital supports not only the adoption of advanced technologies but also the development of organisational processes that enable systematic innovation and proactive strategic behaviour. Emerging evidence further indicates that AI technologies facilitate collaboration within and across organisational boundaries by improving information sharing, aligning decision-making, and supporting real-time coordination among teams, suppliers, and partners. AI-adaptive operations strengthen both innovation capability and collaboration capability, particularly when embedded within proactive strategic frameworks (Wang and Zhang, 2024). These intermediate capabilities enable firms to transform AI-related knowledge and skills into collective learning, joint problem-solving, and coordinated experimentation, which are central to sustained innovation outcomes.

This perspective is especially relevant for the skills and capabilities dimensions of AI Capital. AI-related skills enhance employees' ability to collaborate using data-driven tools, communicate insights across functions, and integrate AI outputs into shared workflows. AI-related capabilities extend this process by embedding collaboration and innovation routines into organisational strategy, governance structures, and decision-making practices. Rather than functioning as a stand-alone technological input, AI Capital contributes to business innovation by strengthening firms' capacity to collaborate effectively and innovate proactively. This theoretical framing indicates that AI Capital is associated with organisational processes that underpin innovation outcomes, even where the study's hypothesis focuses on the direct association between AI Capital and business innovation.

In Figure 1, the relationship between AI Capital of Business and innovation is illustrated, forming the so-called AI Capital and Business Innovation model. AI Capital consists of three key components: AI knowledge, AI skills, and AI capabilities, which collectively represent an organisation's ability to understand, apply, and leverage AI technologies. This AI Capital positively contributes to business innovation across several dimensions, such as, product and service innovation, process innovation, technology adoption, market and customer engagement, and organisational culture and strategy.

[**Figure 1**]

3. Data gathering

This study employed a structured survey methodology to collect longitudinal data from SMEs operating in England. SMEs were identified using commercial business databases and organisational listings that provide sectoral classification and contact details for registered businesses. From these sources, firms were randomly selected and contacted across twelve sectors: manufacturing; construction; wholesale and retail trade; financial and insurance services; information and communication; transportation and storage; real estate; professional, scientific and technical services; administrative and support services; education; health and social work services; and leisure, hospitality, and tourism. This sectoral coverage was intended to reflect the heterogeneity of AI adoption and innovation practices across the UK SME population, rather than to target AI-intensive industries exclusively.

The survey was distributed electronically to key personnel within these organisations, primarily via email-based e-surveys that directed participants to a dedicated online survey platform. The questionnaire covered business characteristics, such as revenue growth rate, number of employees, and years of operation, alongside technical questions on AI and innovation. Given the nature of the study, certain sections were designed for finance personnel and general managers or directors, while others were intended for information and technology personnel. The opening letter invited recipients to forward the survey to the relevant departments or individuals, ensuring that responses were provided by those responsible for potential AI-related decision-making, including senior management, IT specialists, innovation managers, and R&D personnel. The survey structure was designed to capture insights from individuals directly involved in AI adoption and implementation.

The study adopted a longitudinal research design consisting of two survey waves to track developments over time. The first wave of data collection took place between January and February 2024, followed by a second wave one year later, between January and February 2025. In the first wave, the response rate was 12.8%, yielding 287 SME responses. In the second wave, the retention rate was 88%, resulting in 252 SME responses. The longitudinal nature of the survey was explained in the participant information sheets, and each questionnaire required participants to provide their official email addresses and roles within the business for follow-up contact. Firms were matched across survey waves using organisational identifiers and verified contact information to ensure longitudinal consistency. The participant information sheets specified that data would be pooled to ensure anonymity. The study adhered to standard ethical approval procedures and maintained strict confidentiality measures to protect participant identities. Confidentiality assurances were explicitly stated, emphasising that responses would be anonymised and aggregated for research purposes. Follow-up emails and reminders were systematically sent to businesses that had not yet completed the survey, ensuring a higher response rate and robust data collection.

The one-year interval between the two survey waves reflects a deliberate balance between the dynamics of AI capital formation and the pace of observable innovation outcomes in SMEs. While some forms of technological innovation may unfold over longer horizons, AI Capital can evolve relatively quickly through targeted training, learning-by-doing, and the incremental integration of AI tools into existing business processes. Prior research on digital and AI-related capabilities suggests that meaningful changes in managerial understanding, employee skills, and the applied use of digital technologies can emerge within a 12-month period, particularly in environments characterised by rapid technological diffusion and active upskilling (Drydakis, 2025a).

At the same time, a one-year lag allows sufficient time for newly acquired AI-related competencies to be translated into early-stage innovation outcomes, such as process improvements, product adaptations, or enhanced decision-making, while limiting the risk that longer intervals could confound effects through broader structural or market changes (Drydakis, 2025a). Given the fast pace of AI development, longer lags may also capture shifts across different technological generations rather than the effects of capability accumulation per se. The chosen time frame therefore aligns with the study's focus on short- to medium-term capability formation and its association with business innovation, while remaining sensitive to the rapid evolution of AI technologies and practices.

4. Scales

4.1 AI Capital of Business scale

Expanding upon the concept of AI Capital (Drydakis, 2024a), this study develops the AI Capital of Business scale to measure the level of AI Capital within firms. The development of this scale follows DeVellis's (2003) eight-step framework for creating new measurement instruments, ensuring reliability and validity in assessing businesses' AI knowledge, skills, and capabilities. The first step in this framework involved defining the purpose of the AI Capital of Business scale. Guided by the AI Capital framework, the aim of the scale was to measure the level of AI-related knowledge, skills, and capabilities among SMEs. This measurement enables the assessment of a firm's integration of AI into its operations and the level of maturity in AI adoption.

Following this, the second step involved generating an initial item pool designed to capture the scale's objectives. This was achieved through a literature review comprising both theoretical and empirical studies on AI adoption in business (Grashof and Kopka, 2023; Mariani et al., 2023; Igna and Venturini, 2023; Acemoglu et al., 2022; Drydakis, 2022; Hansen and Bøgh, 2021; Ng et al., 2021; Xu and Babaian, 2021; Alekseeva et al., 2021; Davenport et al., 2020; Akpan et al., 2020; Campbell et al., 2020; Canhoto and Clear, 2020; Cubric, 2020; Chan et al., 2018). A comprehensive list of 83 items was developed to reflect the core dimensions of AI Capital in business settings. The literature review informed the inclusion of these items across key themes: AI knowledge, skills, and capabilities. The third step focused on determining the measurement format. Based on the literature review, a five-point Likert scale was selected to assess the extent to which business personnel agreed with each statement, aligning with standard measurement practices in the social sciences (DeVellis, 2003). This format ensures standardisation, ease of interpretation, and the ability to capture variability in AI adoption across firms.

The fourth step involved an expert review and refinement of the scale. A panel of AI and business experts, consisting of six AI business specialists, six IT and technology strategists, and four business executives, reviewed the initial pool of 83 items for relevance, clarity, and representativeness. These expert profiles were deliberately selected to reflect the distributed and multi-layered nature of AI adoption in business, where AI-related knowledge, skills, and capabilities span strategic decision-making, technological implementation, and operational execution rather than being concentrated within a single organisational function. AI business specialists contributed expertise on the conceptual foundations of AI applications, data-driven decision-making, and emerging AI use cases across business functions, ensuring alignment between the scale items and contemporary AI practices. IT and technology strategists provided insight into systems integration, data infrastructure, cybersecurity, and implementation constraints, enabling an assessment of whether items reflected the technical and organisational realities of AI deployment within firms. Business executives contributed a strategic and managerial perspective, assessing whether items captured decision-making processes, investment considerations, and longer-term capability development associated with AI adoption in SMEs. All participants held roles involving regular engagement across strategy, technology, and operations, ensuring that items were evaluated not only in isolation but also in terms of how AI-related knowledge, skills, and capabilities interact across organisational levels.

During the review process, feedback was systematically logged and analysed to refine the measurement of AI Capital and its three constituent dimensions. Items were removed where they were judged to be redundant, insufficiently specific to AI-enabled activity, or weakly aligned with the intended dimension of AI Capital. Where interpretation varied across participants, items were reworded to improve clarity and ensure that responses reflected engagement with AI systems rather than general digitalisation or managerial intent. Conceptually adjacent items were separated where necessary to distinguish awareness of AI's potential from its applied use and integration within organisational processes. In several cases, items initially framed at the level of strategic intention or policy commitment were revised to require evidence of AI-enabled operational practice, such as the use of AI tools in decision-making, automation, or forecasting. Other items were refined to improve precision regarding responsibility for AI-related activities, organisational scope, and the conditions under which AI-related capabilities could be considered present. To reduce the risk that variation in responses reflected linguistic ambiguity rather than substantive differences in AI Capital, selected items were pre-tested with expert participants prior to pilot testing. This iterative refinement ensured that the final scale captured operational AI use, organisational readiness, and strategic integration in a manner consistent with the theoretical structure of the AI Capital of Business framework. The process resulted in a reduced and theoretically coherent set of 45 items reflecting how AI-related knowledge, skills, and capabilities are developed, combined, and mobilised within SMEs, while remaining applicable across sectors and accessible to non-technical business respondents.

As shown in Appendix Table A.I, the Knowledge theme comprises 15 items, evaluating a business's understanding of AI's role across various business functions. This includes an understanding of AI fundamentals, its contribution to improved decision-making, and its applications in customer management, financial management, and marketing, as well as an awareness of data privacy, cybersecurity, and ethical risks. Moreover, the Skills theme, which comprises 15 items, focuses on the actual use of AI applications within business operations. It evaluates the use of AI in communication, customer relationship management, marketing, sales, financial operations, workflow management, and human resources. The Capabilities theme, which also comprises 15 items, assesses a business's ability to integrate AI into long-term strategies, enabling the scaling of operations, enhancing customer engagement, and ensuring compliance with regulatory frameworks. This theme also examines a business's ability to leverage AI to gain competitive advantages through service quality improvements and targeted marketing.

[Appendix, Table A.I]

The fifth step involved conducting a validity assessment through pilot testing with 20 SME personnel, following DeVellis (2003). This stage evaluated face validity, content validity, construct validity, criterion validity, convergent validity and discriminant validity and using structured respondent feedback alongside preliminary quantitative checks. Face validity was assessed by asking SME participants whether individual items appeared to measure AI-related business practices in a clear and understandable manner. For example, respondents were asked whether the item "We understand how AI collects information on customers' purchase history, transactions, and digital footprints" clearly reflected AI-related knowledge within a business context rather than general data handling. Participants indicated that the item was clear, relevant, and appropriately framed. Content validity was evaluated by asking participants whether the item adequately captured an important aspect of AI use and understanding within their business operations. Respondents confirmed that awareness of how AI processes customer data represents a relevant and meaningful component of AI-related knowledge for businesses, supporting its inclusion within the knowledge dimension of the scale. Construct validity was assessed by examining whether participants consistently interpreted the item as reflecting AI-related knowledge rather than AI use or strategic capability. Feedback indicated that respondents associated the item with understanding AI systems and data processes rather than operational deployment or strategic integration, aligning with its theoretical placement within the knowledge construct. Moreover, criterion validity was examined by assessing whether higher agreement with the item was associated with related self-reported indicators, such as the use of AI-driven customer analytics or customer relationship management tools within the business. Responses indicated that firms reporting greater understanding of AI data collection processes were also more likely to report AI use in customer-facing activities. Convergent validity was assessed by examining whether the item was perceived as closely related to other items measuring AI-related knowledge, such as understanding AI-supported decision-making or data governance. Also, discriminant validity was assessed by confirming that the item was viewed as conceptually distinct from items measuring AI skills and AI capabilities, indicating that it captured knowledge rather than application or strategic integration.

In addition to these validity checks, the pilot phase provided insight into how respondents engaged with the scale as a whole. Discussions explored whether items were interpreted consistently across managerial, technical, and operational roles, whether response options were appropriate for the range of AI adoption observed among SMEs, and whether the instrument enabled respondents to reflect on both formal arrangements and everyday AI-related practices. Particular attention was given to whether items prompted respondents to consider concrete evidence of AI engagement, such as the routine use of AI tools, staff training activities, data governance practices, and the integration of AI outputs into decision-making, rather than relying solely on stated intentions or high-level commitments. Feedback from the pilot indicated that the items functioned as intended: respondents reported that the questions were clear, relevant to their business responsibilities, and feasible to answer based on available organisational knowledge.

In the sixth step, as outlined in the section 'Data gathering', the scale was administered in 2024 to a sample of 287 SMEs. A follow-up survey was conducted in 2025, with 252 SMEs providing follow-up information. The seventh step involved evaluating item performance using confirmatory factor analysis (DeVellis, 2003) to assess the scale's internal consistency and model fit, with the results of this evaluation presented in the section 'Scales validation'. Finally, the eighth step focused on scale optimisation to ensure efficiency, testing alternative scale specifications. At this stage, the scale's consistency was assessed both as a complete 45-item scale and as a scale consisting of the three identified themes: knowledge, skills, and capabilities. The findings of this evaluation are presented in the section 'Scales validation'.

4.2 Conceptual and Interpretative Clarification of AI Measurement

Given the breadth and heterogeneity of AI technologies used by SMEs, careful clarification of how AI was defined and operationalised within the survey instrument is necessary to ensure measurement validity and interpretative consistency. In survey-based research, variation in respondents' understanding of "AI" can introduce measurement error, particularly where some respondents interpret AI as advanced algorithmic systems while others associate it with basic automation or general digital tools. Accordingly, this subsection outlines the definitional guidance and instructional design used to standardise respondents' interpretation of AI applications across firms. It clarifies how participants were instructed to understand AI, how broadly framed items were intended to be interpreted, and how capability-oriented items were designed to capture AI-specific organisational readiness rather than hypothetical intention or general managerial competence.

To reduce ambiguity, the survey instrument provided an explicit and standardised definition of AI at the outset of the questionnaire. Participants were instructed to interpret AI applications as software-based systems that use data-driven algorithms to generate predictions, recommendations, classifications, content, or automated decisions that extend beyond fixed-rule automation. The definition explicitly distinguished AI-enabled tools from basic digitalisation or rule-based automation. The survey instructions further clarified that AI applications included, but were not limited to, machine learning-based analytics, forecasting tools, recommendation systems, natural language processing applications, computer vision technologies, and generative AI tools used for tasks such as content creation, customer engagement, decision support, and workflow optimisation. Respondents were informed that both internally developed and externally sourced AI tools should be considered, provided that these systems relied on algorithmic learning or data-driven inference.

To further minimise interpretative heterogeneity, concrete examples of AI use cases across business functions were embedded throughout the questionnaire. These examples covered areas such as customer analytics, marketing personalisation, financial forecasting, process automation, and decision support. This design choice was intended to anchor respondents' understanding of AI in specific operational contexts rather than abstract technological labels. Broadly framed items referring to the use or adoption of AI applications in business operations were therefore designed to capture the presence and integration of AI-enabled systems rather than eliciting hypothetical or aspirational responses. Respondents were instructed to answer these items based on their firm's actual use of AI at the time of the survey, rather than planned or anticipated adoption. The scale intentionally focuses on current and realised AI Capital rather than future intentions, enabling analysis of how existing AI-related knowledge, skills, and capabilities are associated with innovation outcomes. Moreover, this approach reflects the heterogeneity of AI implementation across SMEs, where AI is often embedded within third-party platforms or bundled software solutions rather than deployed as standalone technologies. These design features reduce the risk that respondents interpret AI as basic automation or general digital tools, while preserving sufficient breadth to capture variation in AI use across sectors and business models. As a result, the AI Capital of Business scale measures AI-specific knowledge, skills, and capabilities rather than generic digitalisation or IT maturity.

Several items in the Capabilities theme are intentionally phrased using formulations such as "we can" (for example, "we can plan long-term business processes using AI" or "we can adopt new AI applications"). This wording is designed to capture demonstrated organisational capability in the present and organisational readiness rather than hypothetical intention or aspirational planning. Consistent with Dynamic Capabilities theory, these items assess whether firms possess the routines, governance structures, skills, and decision-making processes required to deploy, integrate, and scale AI-enabled systems when needed. Respondents were instructed to answer capability-oriented items based on their organisation's current operational and strategic capacity, drawing on existing experience with AI tools, established processes, and organisational arrangements. The use of "can" therefore reflects the presence of enabling conditions for AI integration, such as internal expertise, managerial oversight, data governance practices, and strategic alignment, rather than speculative future adoption. Importantly, capability-oriented items are not intended to capture generic strategic competence. Instead, they measure AI-specific organisational capabilities that become salient only when AI systems inform or automate decisions, shape workflows, introduce algorithmic risks, or require responsible governance. For example, the current ability to plan long-term business processes using AI refers to the capacity to anticipate and manage AI-enabled workflows, data dependencies, compliance requirements, and innovation trajectories, rather than general long-term planning skills.

More broadly, some items across the knowledge, skills, and capabilities themes are intentionally formulated at a relatively high level of abstraction. During the expert meetings, it was agreed that while such items may appear general when read in isolation, they are designed to be interpreted conditionally on the AI-specific definition and contextual guidance provided throughout the survey. Respondents were explicitly instructed to evaluate these items in relation to AI-enabled systems and practices rather than general managerial competence, digital literacy, or organisational performance. This design choice reflects the nature of AI adoption in SMEs, where AI is frequently embedded within integrated platforms and workflows rather than deployed as discrete or easily separable technologies. In such contexts, AI-related knowledge, skills, and capabilities are manifested through broader organisational processes such as decision-making, planning, coordination, and governance, but only insofar as these processes are shaped by, reliant on, or transformed through AI-enabled tools. From a measurement perspective, this approach aligns with established practices in capability-based constructs, where higher-level items capture latent organisational capabilities that cannot be reduced to narrow technical tasks alone. By anchoring respondents' interpretations to AI-specific definitions, examples, and use cases, the AI Capital of Business scale preserves construct validity while remaining sufficiently flexible to capture heterogeneous modes of AI implementation across sectors, technologies, and business models. This ensures that the scale measures AI-specific organisational capability and readiness rather than broader strategic capacity or general IT maturity.

4.2 Business Innovation scale

To measure SMEs' level of innovation, the Knowles et al. (2008) index was amended to reflect business realities across diverse sectors. The Knowles et al. (2008) scale focuses on the manufacturing sector in North America. The scale, which consists of twenty-five items, is structured around themes that measure the extent to which a business develops and adopts new products, evaluates its ability to develop and implement new manufacturing processes, and assesses its approach to adopting and implementing new business systems. It serves as a comprehensive measure of business innovativeness, examining how businesses innovate across products, processes, and business systems while also considering their performance outcomes.

Informed by the Knowles et al. (2008) scale, this study developed the Business Innovation scale to measure business innovation in SMEs by assessing various dimensions of innovative behaviour (Grashof and Kopka, 2023; Mariani et al., 2023; Expósito and Sanchis-Llopis, 2019; Lukes and Stephan, 2017; Saunila, 2016; Bayarçelik et al., 2014; Heimonen, 2012). The scale is designed to reflect business realities across diverse sectors. It consists of twenty-five items, each evaluated using a five-point Likert scale ranging from 'Strongly Disagree' to 'Strongly Agree'.

As observed in Appendix Table A.II, the scale is structured around five key themes that comprehensively evaluate different aspects of innovation. The Product and Service Innovation theme assesses the extent to which businesses develop and implement new or improved products and services. It examines the significance of product innovation for business success and competitive positioning, while also evaluating businesses' ability to encourage and utilise internal ideas for product and service improvement. The Process Innovation theme measures how businesses enhance their production or service delivery methods. It evaluates the importance of operational improvements in maintaining competitiveness and assesses businesses' approach to evaluating and implementing process efficiencies based on industry benchmarks and employee suggestions.

Moreover, the Technology Adoption theme evaluates businesses' openness to adopting new technologies that enhance efficiency and operations. It measures the extent to which businesses integrate digital tools and technological advancements and assesses how they maintain and upgrade their technological infrastructure. The Market and Customer Engagement theme assesses businesses' responsiveness to customer feedback and market trends. It measures how businesses leverage market research to identify opportunities and evaluates their ability to adapt offerings based on evolving market conditions and customer needs. Finally, the Organisational Culture and Strategy theme examines the role of innovation in strategic planning and resource allocation. It measures the extent to which businesses foster a culture that encourages creativity and continuous learning and assesses how they manage risks associated with innovation.

[Appendix, Table A.II]

The Business Innovation scale provides a structured and multi-dimensional measure of SMEs' innovation levels. By capturing changes across multiple dimensions, it allows for the identification of strengths and areas requiring further development. The validation of the Business Innovation scale is presented in the 'Scales Validation' section.

5. Scales validation

In the Appendix, Table A.III presents the confirmatory factor analysis (CFA) validation results of the AI Capital of Business scale, structured into two panels. Panel I examines the entire scale (45 items), while Panel II assesses the scale based on its three thematic components: Knowledge (15 items), Skills (15 items), and Capabilities (15 items).

[Appendix Table A.III]

In Panel I, it is observed that the overall scale exhibits internal consistency, with a Cronbach's Alpha (α) of 0.98, indicating that the scale items are highly correlated. The H Index for the full scale is 0.80, suggesting that the subcomponents of the scale are well-defined. The chi-squared to degrees of freedom ratio (χ^2/df) is 2.0, indicating an acceptable model fit. The Root Mean Square Error of Approximation (RMSEA) is 0.045, suggesting a good fit. The same applies to the Standardised Root Mean Square Residual score (SRMR = 0.013). The Normed Fit Index (NFI = 0.942), Relative Noncentrality Index (RNI = 0.970), Comparative Fit Index (CFI = 0.970), and Incremental Fit Index (IFI = 0.970) support the validity of the scale's structure (Hu and Bentler, 1999).

In Panel II, it is found that within the thematic subscales, Knowledge (Theme A) has a Cronbach's Alpha value of $\alpha = 0.98$, reflecting very high reliability. The same applies to Skills (Theme B, $\alpha = 0.98$) and Capabilities (Theme C, $\alpha = 0.98$). Across the subscales, the H Index values are H = 0.80 for Knowledge, H = 0.81 for Skills, and H = 0.79 for Capabilities. These values suggest good scalability, with the Skills theme showing slightly stronger structural consistency. Moreover, the chi-squared to degrees of freedom ratio (χ^2/df) is 2.0, suggesting an acceptable model fit. The Root Mean Square Error of Approximation is 0.045, indicating a good fit. The Standardised Root Mean Square Residual (SRMR) score is 0.013, suggesting an excellent fit. Furthermore, the Normed Fit Index (NFI = 0.943), Relative Noncentrality Index (RNI = 0.971), Comparative Fit Index (CFI = 0.971), and Incremental Fit Index (IFI = 0.971) indicate a strong model fit. The validation results for the full scale and the theme-oriented model are very similar, indicating that the subscales hold together well and align with the overall construct. The outcomes confirm that the AI Capital of Business scale is a reliable and valid instrument for assessing AI-related knowledge, skills, and capabilities in a business context.

Moreover, in the Appendix, Table A.IV presents the CFA validation results of the Business Innovation scale, structured into two panels. Panel I examines the entire scale (25 items), while Panel II assesses the scale based on its five thematic components: Product and Service Innovation (5 items), Process Innovation (5 items), Technology Adoption (5 items), Market and Customer Engagement (5 items), and Organizational Culture and Strategy (5 items). In Panel I, the overall scale exhibits very high internal consistency (Cronbach's Alpha, $\alpha = 0.97$). The H Index for the full scale is 0.86, suggesting that the subcomponents of the scale are well-defined. The chi-squared to degrees of freedom ratio (χ^2/df) is 2.1, indicating an acceptable model fit. The Root Mean Square Error of Approximation (RMSEA) is 0.048, suggesting a good fit. The same applies to the Standardised Root Mean Square Residual score (SRMR = 0.024). The Normed Fit Index (NFI = 0.942), Relative Noncentrality Index (RNI = 0.968), Comparative Fit Index (CFI = 0.968), and Incremental Fit Index (IFI = 0.968) support the validity of the scale's structure.

In Panel II, it is found that within the thematic subscales, Product and Service Innovation (Theme A) has a Cronbach's Alpha value of α = 0.89, reflecting strong reliability. The same applies to Process Innovation (Theme B, α = 0.89), Technology Adoption (Theme C, α = 0.87), Market and Customer Engagement (Theme D, α = 0.88), and Organizational Culture and Strategy (Theme E, α = 0.85). Across the subscales, the H Index values are H = 0.64 for Product and Service Innovation, H = 0.64 for Process Innovation, H = 0.60 for Technology Adoption, H = 0.63 for Market and Customer Engagement, and H = 0.63 for Organizational Culture and Strategy. These values suggest good scalability. Moreover, the chi-squared to degrees of freedom ratio (χ^2/df) is 2.2, suggesting an acceptable model fit. The Root Mean Square Error of Approximation is 0.048, indicating a good fit. The Standardised Root Mean Square Residual (SRMR) score is 0.023, suggesting a good fit. Furthermore, the Normed Fit Index (NFI = 0.943), Relative Noncentrality Index (RNI = 0.969), Comparative Fit Index (CFI = 0.969), and Incremental Fit Index (IFI = 0.969) indicate a strong model fit. The validation results for the full scale and the theme-oriented model are very similar, suggesting that the subscales hold together well and align with the overall construct. In addition, the results indicate that the Business Innovation scale is a reliable and valid instrument for assessing innovation-related knowledge, processes, and strategies in a business context.

[Appendix Table A.IV]

6. Descriptive statistics

Table 1 presents the descriptive statistics for the study's key variables, distinguishing between the total sample (Panel I, *n* = 539) and the paired observations sample (Panel II, *n* = 504). The focus here is on the outcomes observed in Panel I, which includes all available data from businesses that participated in either Wave I (2024, *n* = 287) or Wave II (2025, *n* = 252). The proportion of businesses experiencing a revenue growth rate greater than 5% is 38.96%. Additionally, 45.26% of businesses employ more than 50 employees, and 51.76% have been operating for more than 10 years. Businesses are distributed across multiple sectors, with notable proportions in Health and Social Work (9.83%), and Professional, Scientific and Technical Services (9.09%).

The AI Capital of Business scale has a mean score of 149.09 (out of 225) (Std. Dev. = 49.01). Within this category, the Knowledge theme has a mean score of 49.83 (out of 75) (Std. Dev. = 16.50), the Skills theme has a mean score of 49.77 (out of 75) (Std. Dev. = 16.62), and the Capabilities theme has a mean score of 49.48 (out of 75) (Std. Dev. = 16.15). Furthermore, the overall Business Innovation scale has a mean score of 90.35 (out of 125) (Std. Dev. = 19.15). Within this category, the Product and Service Innovation theme has a mean score of 17.99 (out of 25) (Std. Dev. = 4.14), the Process Innovation theme has a mean score of 18.11 (out of 25) (Std. Dev. = 4.16), and the Technology Adoption theme has a mean score of 18.03 (out of 25) (Std. Dev. = 3.90). Additionally, the Market and Customer Engagement theme has a mean score of 18.09 (out of 25) (Std. Dev. = 4.01), and the Organisational Culture and Strategy theme has a mean score of 18.12 (out of 25) (Std. Dev. = 3.86).

In Panel III, the difference test results indicate that differences between the total sample (Panel I) and the paired observations sample (Panel II) are not statistically significant across all variables. This suggests that the subsample used in Panel II remains representative of the total sample. Given the longitudinal nature of the study, the paired observations sample (Panel II) is more appropriate for analysis than the total sample (Panel I). While 287 businesses participated in Wave I (2024), only 252 of these took part in Wave II (2025), resulting in 35 missing observations in Wave II. Using the paired observations ensures that changes over time are measured accurately, as the same businesses are compared across both waves (Bell et al., 2019). Longitudinal studies benefit from paired data because they control for business-specific unobserved heterogeneity, allowing for a clearer interpretation of changes in revenue growth, business innovation, and AI Capital. Analysing only the total sample, which includes businesses with missing values in Wave II, could introduce bias and distort findings. Therefore, this study will prioritise the paired observations sample in Panel II for robust longitudinal comparisons while acknowledging that no significant differences exist between the two panels. However, in the regression stage, robustness checks will also utilise the full sample.

[Table 1]

In the Appendix, Table A.I presents the AI Capital of Business scale, displaying the mean scores and standard deviations for various AI-related competencies across two waves (2024 and 2025). The table captures business professionals' self-reported knowledge, skills, and capabilities across multiple AI themes. For instance, item 4 of the scale examined businesses' understanding of how AI can improve decision-making through data analysis. The results showed a modest increase in mean scores between 2024 and 2025 (3.26 vs 3.42, $t = 1.38$, $p > 0.10$), suggesting a slight but statistically insignificant improvement in businesses' confidence in leveraging AI for data-driven decisions. Moreover, item 18 assessed businesses' use of AI applications for managing customer information and interactions. The mean scores increased slightly from 3.22 in 2024 to 3.32 in 2025 ($t = 0.84$, $p > 0.10$), indicating a minor improvement in AI-driven customer management skills. In addition, item 35 of the scale measured businesses' ability to make strategic decisions based on AI-driven financial forecasting. The mean score rose from 3.12 in 2024 to 3.27 in 2025 ($t = 1.28$, $p > 0.10$), indicating a small, non-significant increase.

In addition, in the Appendix, Table A.II presents the Business Innovation scale, displaying the mean scores and standard deviations for various innovation-related competencies across two waves (2024 and 2025). The results highlight changes in businesses' innovation practices and their strategic integration of new technologies. For instance, item 1 of the scale assessed businesses' engagement in developing new or improved products or services to meet customer needs. The mean score increased from 3.45 in 2024 to 3.64 in 2025 ($t = 2.18$, $p < 0.05$), indicating a statistically significant improvement. Moreover, item 11 examined businesses' openness to adopting new technologies that enhance operations. The mean scores showed only a minor increase from 3.57 in 2024 to 3.60 in 2025 ($t = 0.35$, $p > 0.10$), indicating no statistically significant change. In addition, item 21 of the scale measured the extent to which businesses foster a culture that encourages creativity and innovation among employees. The mean score slightly increased from 3.59 in 2024 to 3.62 in 2025 ($t = 0.33$, $p > 0.10$), but this change was not statistically significant.

Table 2 presents the tabulation analysis for key business characteristics, comparing the AI Capital of Business scale and the Business Innovation scale across different business segments in Panel I. The analysis is based on paired observations. The results highlight significant differences in AI Capital and innovation scores across revenue growth, business size, operational longevity, and period. For instance, businesses experiencing a revenue growth rate greater than 5% report significantly higher scores in both AI Capital of Business scale score (192.83, Std. Dev. = 16.56) and Business Innovation scale score (107.72, Std. Dev. = 9.20). In contrast, businesses with a revenue growth rate lower than 5% have notably lower scores in AI Capital of Business scale score (121.54, Std. Dev. = 41.85) and Business Innovation scale score (79.02, Std. Dev. = 14.73). The difference tests are highly significant ($p < 0.01$).

Similarly, businesses with more than 50 employees report an AI Capital of Business scale score of 183.96 (Std. Dev. = 22.69) and a Business Innovation scale score of 104.79 (Std. Dev. = 11.33). Conversely, businesses with fewer than 50 employees exhibit lower scores in AI Capital of Business scale score (120.89, Std. Dev. = 44.38) and Business Innovation scale score (78.24, Std. Dev. = 15.34). The difference tests ($p < 0.01$) confirm that these differences are statistically significant. Additionally, businesses in Wave I (2024) report an AI Capital of Business scale score of 147.57 (Std. Dev. = 49.91) and a Business Innovation scale score of 89.00 (Std. Dev. = 19.02), while businesses in Wave II (2025) show slightly higher scores in AI Capital of Business scale score (151.52, Std. Dev. = 47.74) and Business Innovation scale score (91.59, Std. Dev. = 18.96).

However, the difference tests ($p > 0.10$) suggest that these changes are not statistically significant, indicating that AI Capital and innovation levels remained relatively stable over the observed period.

[Table 2]

Table 3 presents the correlation matrix for key business characteristics, with a focus on the AI Capital of Business scale and the Business Innovation scale. The AI Capital of Business scale is strongly correlated with the Business Innovation scale ($r = 0.948$, $p < 0.01$). This indicates that businesses with higher AI Capital tend to be more innovative, reinforcing the idea that AI Capital plays a crucial role in fostering innovation across businesses. Moreover, businesses experiencing a revenue growth rate greater than 5% exhibit a strong positive correlation with both AI Capital of Business scale score ($r = 0.713$, $p < 0.01$) and Business Innovation scale score ($r = 0.737$, $p < 0.01$). Similarly, businesses with more than 50 employees show positive correlations with both AI Capital of Business scale score ($r = 0.643$, $p < 0.01$) and Business Innovation scale score ($r = 0.695$, $p < 0.01$). Likewise, businesses operating for more than 10 years exhibit moderately strong correlations with both AI Capital of Business scale score ($r = 0.631$, $p < 0.01$) and Business Innovation scale score ($r = 0.631$, $p < 0.01$).

[Table 3]

7. Estimates

7.1 Estimation strategy

The empirical strategy involves estimating a set of regression models with different specifications to examine the relationship between the AI Capital of Business scale and the Business Innovation scale. Given the longitudinal nature of the data, the study employs three empirical specifications: Pooled Ordinary Least Squares (OLS) estimates, Random Effects estimates, and Fixed Effects estimates (Bell et al., 2019). The use of alternative models allows for a comprehensive understanding of the AI Capital–Innovation relationship under different econometric assumptions. Specifically, panel specifications are more appropriate than cross-sectional specifications for capturing within-entity variation over time. However, the study recognises that omitted factors may be correlated with key predictors in Random Effects models, potentially biasing the estimates. In contrast, Fixed Effects models address potential omitted variable bias by removing time-invariant unobserved heterogeneity (Vaisey and Miles, 2017). To determine the most appropriate empirical specification, Breusch and Pagan Lagrangian Multiplier and Hausman tests are conducted. By employing these three approaches, the analysis ensures robustness and offers insights into the dynamic interplay between AI Capital and innovation levels across businesses.

To mitigate potential endogeneity and omitted variable bias in examining the relationship between AI Capital and business innovation, the regression analysis includes controls for financial performance, business size, and business age (Grashof and Kopka, 2023; Clarke, 2005). Financial performance is a critical factor, as businesses with stronger financial health are more likely to invest in AI technologies and engage in innovation activities, potentially creating an endogeneity bias if not accounted for. Business size is also essential to control, given that larger businesses often have greater financial, human, and technological resources, which can influence both AI adoption and innovation outcomes. Without controlling for business size, the estimated AI–Innovation relationship may capture resource-driven advantages rather than AI's direct effect. Similarly, business age is included as it shapes businesses' experience with technology adoption and innovation processes, with older businesses potentially benefiting from established R&D structures, while younger businesses may be more flexible in adopting AI but constrained in innovation capacity. By incorporating these controls, the analysis ensures that the estimated association between AI Capital and innovation more accurately reflects AI's role, rather than being influenced by broader business-specific characteristics (Drydakis, 2022).

The robustness assessment extends beyond the aggregate AI Capital–Innovation relationship by disaggregating innovation into key themes and examining the independent contributions of AI-related knowledge, skills, and capabilities. In addition, the analysis explores how the AI Capital–Innovation link varies across business characteristics, including financial performance, business size, and age, ensuring that the estimated effects are not driven by specific business segments. A full-sample analysis is also conducted to validate the findings across all businesses in the dataset, thereby reinforcing the consistency of the association between AI Capital and innovation. Finally, an additional robustness check examines whether a more parsimonious version of the AI Capital of Business scale yields substantively equivalent results to the full 45-item instrument. All scale validation procedures, panel regressions, and robustness tests were conducted using Stata 19.

7.2 Full collinearity assessment

To assess whether common method bias materially affects the estimated relationships, a full collinearity assessment was conducted using variance inflation factors (VIFs). The results show that all VIFs remain well below commonly used cut-offs, with the highest VIF equal to 2.76 and a mean VIF of 1.88. These values fall comfortably below the conservative threshold of 3.3 often applied in assessments of common method bias, as well as the traditional econometric threshold of 5. This indicates that multicollinearity among the explanatory variables is limited and that no single latent factor dominates the regression model (Shrestha, 2020; Thompson et al., 2017). These findings suggest that, although common method variance may be present at the measurement level, it is unlikely to materially distort the estimated association between AI Capital and business innovation in the regression analyses.

7.3 Main estimates: The association between AI Capital and Business Innovation

In Table 4, Model I presents the Pooled OLS estimates. AI Capital is positively and significantly associated with business innovation, indicating that businesses with higher AI knowledge, skills and capabilities tend to be more innovative ($b = 0.315$, $p < 0.01$). In practical terms, this coefficient implies that a one-unit increase in AI Capital is associated with a 0.315-point increase in the Business Innovation scale; given the observed standard deviation of AI Capital (approximately 49), a one standard deviation increase corresponds to an increase of around 15 points in business innovation, which is sizeable relative to the sample mean of approximately 90, equivalent to roughly a 17 per cent increase relative to the mean level of business innovation. Therefore, the study's hypothesis is supported.

Moreover, businesses experiencing a revenue growth rate greater than 5% exhibit significantly higher innovation levels ($b = 2.687$, $p < 0.01$). This difference corresponds to a meaningful increase in business innovation performance compared with the average firm, rather than a marginal effect. In addition, businesses with more than 50 employees also demonstrate significantly higher innovation ($b = 4.802$, $p < 0.01$). The magnitude of this coefficient indicates a sizeable gap in innovation outcomes between larger and smaller firms.

Model II presents the Random Effects estimates. The relationship between AI Capital and business innovation remains strong and statistically significant ($b = 0.316$, $p < 0.01$). The near-identical magnitude relative to the Pooled OLS estimate suggests that the economic relevance of AI Capital is not sensitive to the treatment of unobserved heterogeneity. Model III offers the Fixed Effects estimates, indicating that AI Capital continues to show a strong and statistically significant relationship with business innovation ($b = 0.322$, $p < 0.01$). This estimate implies that within-firm increases in AI Capital are associated with economically meaningful changes in innovation over time. The Breusch and Pagan Lagrangian Multiplier test (chibar2 = 135.09, $p < 0.01$) confirms that Random Effects is preferable over Pooled OLS. Moreover, the Hausman test (chi2 = 1.53, $p > 0.10$) suggests that Random Effects is preferable over Fixed Effects.

A comparison across the three estimation strategies further strengthens the interpretation of the results. The similarity of the AI Capital coefficients across the Pooled OLS, Random Effects, and Fixed Effects models indicates that the positive association between AI Capital and business innovation is not driven by a particular set of econometric assumptions. In the Pooled OLS specification, the estimate reflects both between-firm and within-firm variation, capturing cross-sectional differences in AI Capital across businesses. The Random Effects estimates, which exploit both sources of variation while accounting for unobserved firm-level heterogeneity, yield an almost identical coefficient, suggesting that unobserved time-invariant business characteristics do not materially bias the estimated association. The Fixed Effects model, which isolates within-firm changes over time, produces a slightly larger coefficient, indicating that increases in AI Capital within the same business are associated with subsequent increases in innovation. The magnitude and stability of the coefficients suggest that the association is economically relevant across firms and over time, rather than reflecting small or transitory differences. These comparisons suggest that AI Capital is not merely a proxy for stable firm attributes such as managerial quality, organisational culture, or sectoral positioning, but is meaningfully associated with innovation both across firms and within firms over time.

[Table 4]

7.4 Robustness estimates: The association between AI Capital and Business Innovation themes

In Table 4, Models IV–VIII further disaggregate business innovation into its five key themes, using Random Effects models to explore how AI Capital affects specific dimensions of business innovation. In each model, the Breusch and Pagan Lagrangian Multiplier and Hausman tests are conducted, demonstrating the appropriateness of the Random Effects estimates. The analysis is based on paired observations.

The findings indicate that AI Capital is positively and significantly associated with product and service innovation (Model IV, $b = 0.066$, $p < 0.01$), process innovation (Model V, $b = 0.059$, $p < 0.01$), technology adoption (Model VI, $b = 0.061$, $p < 0.01$), market and customer engagement (Model VII, $b = 0.064$, $p < 0.01$), and organisational culture and strategy (Model VIII, $b = 0.063$, $p < 0.01$). Although the coefficients are smaller in absolute terms than those for the aggregate business innovation scale, they remain economically meaningful when evaluated relative to the means of the respective sub-scales, indicating non-trivial improvements across each innovation dimension. These estimates provide deeper insights into how AI Capital relates to distinct dimensions of business innovation, with consistently positive associations observed across all categories. Across the various models, businesses experiencing higher revenue growth, larger businesses in terms of employee numbers, and businesses with a longer operational history tend to exhibit higher innovation rates. The persistence of these patterns across dimensions suggests that the observed associations are not confined to a narrow subset of innovative activities.

A comparison across the five business innovation dimensions further clarifies how AI Capital is associated with distinct innovation processes rather than a single aggregated outcome. While the estimated coefficients are positive and statistically significant across all themes, their relative magnitudes reveal a consistent but differentiated pattern. The strongest associations are observed for product and service innovation and market and customer engagement, suggesting that AI Capital is particularly salient in domains where data-driven insights, customer analytics, and adaptive decision-making directly inform value creation and market responsiveness. In practical terms, these magnitudes suggest that AI Capital is particularly relevant for innovation activities that are outward-facing and closely linked to market interactions. Slightly smaller, though still robust, coefficients are observed for process innovation and technology adoption, indicating that AI Capital also supports internal efficiency and technological upgrading, but that these dimensions may be more incremental or constrained by existing organisational structures. This pattern suggests economically meaningful but more gradual changes in internal processes compared with customer-facing innovation outcomes. The association with organisational culture and strategy is comparable in magnitude to the customer-facing dimensions, underscoring the role of AI Capital in shaping broader decision-making routines, strategic alignment, and innovation-oriented cultures. The size of this coefficient indicates that AI Capital is not only linked to operational or technical change but also to organisational and strategic transformation. These comparisons suggest that AI Capital exerts a broad-based influence across innovation domains, while being particularly consequential for externally oriented and strategically embedded forms of innovation. This pattern is consistent with the view that AI-related knowledge, skills, and capabilities enhance firms' ability to translate data and analytics into market-facing innovation and strategic adaptation, rather than operating solely as a tool for narrow operational efficiency gains.

7.5 Robustness estimates: The association between AI Capital themes and Business Innovation

In Table 5, Models I–III examine the relationship between different components of AI Capital and business innovation. The three models present Fixed Effects estimates, as these have been found to better fit the data based on the Breusch and Pagan Lagrangian Multiplier and Hausman tests. Each model isolates a specific aspect of AI Capital, i.e., knowledge, skills, and capabilities, to determine their independent contributions to innovation. The analysis is based on paired observations.

The findings indicate that business innovation is positively and significantly associated with AI Capital's Knowledge theme (Model I, $b = 0.700$, $p < 0.01$), Skills theme (Model II, $b = 0.613$, $p < 0.01$), and Capabilities theme (Model III, $b = 0.622$, $p < 0.01$). In practical terms, these coefficients imply that within-firm improvements in each AI Capital component are associated with sizeable increases in business innovation relative to the observed variation in the innovation scale, indicating economically meaningful changes rather than marginal effects. These results suggest that knowledge acquisition, AI-related skills, and business-wide AI capabilities each play a crucial role in fostering innovation.

A comparison across the three components of AI Capital provides further insight into the mechanisms through which AI-related resources are associated with business innovation. While all three components exhibit positive and statistically significant associations with innovation, the relative magnitudes of the coefficients indicate meaningful differences in their roles. The knowledge component displays the largest coefficient, suggesting that improvements in firms' understanding of AI concepts, applications, and risks are particularly important for enabling innovation within the same business over time. The size of this coefficient indicates that changes in AI-related knowledge are associated with especially pronounced shifts in innovation outcomes, highlighting its economic relevance among the AI Capital dimensions. This finding implies that foundational AI knowledge may act as a prerequisite that allows firms to recognise innovation opportunities, interpret AI outputs, and make informed strategic decisions.

The coefficients for skills and capabilities are slightly smaller but remain comparable in magnitude, indicating that the applied use of AI tools and the organisational capability to integrate AI into workflows and strategic processes are also central to innovation outcomes. The similar magnitudes of these coefficients suggest that skills development and organisational integration contribute in complementary and quantitatively comparable ways to innovation performance. The similarity between the skills and capabilities coefficients suggests a complementary relationship, where hands-on AI use and broader organisational integration jointly support innovation rather than operating in isolation. These comparisons reinforce the conceptualisation of AI Capital as a multi-dimensional construct in which knowledge, skills, and capabilities perform distinct but mutually reinforcing functions, with knowledge providing the cognitive foundation and skills and capabilities enabling its translation into sustained innovative activity.

[Table 5]

7.6 Robustness estimates: The association between AI Capital and Business Innovation across business characteristics

In Table 5, Models IV–IX extend the analysis by examining the relationship between AI Capital and business innovation across different business characteristics. These models use Random Effects estimates, as indicated by the Breusch and Pagan Lagrangian Multiplier and Hausman tests. The analysis is based on paired observations.

The findings indicate that AI Capital is positively and significantly associated with innovation across all business characteristics, but the strength of the association varies. Specifically, businesses experiencing a revenue growth rate lower than 5% (Model IV, $b = 0.306$, $p < 0.01$) and those with a revenue growth rate greater than 5% (Model V, $b = 0.408$, $p < 0.01$) both exhibit a significant link between AI Capital and innovation, though the relationship appears stronger for higher-growth businesses. The difference in coefficient magnitude indicates that increases in AI Capital are associated with more pronounced innovation gains among faster-growing firms, suggesting economically meaningful heterogeneity across growth profiles.

Similarly, businesses with fewer than 50 employees (Model VI, $b = 0.311$, $p < 0.01$) and those with more than 50 employees (Model VII, $b = 0.340$, $p < 0.01$) also show a strong association between AI Capital and innovation, suggesting that both smaller and larger businesses benefit from AI, though larger businesses experience slightly stronger effects. These magnitudes indicate that the innovation-related benefits of AI Capital are not confined to firm size, but that scale may amplify their economic relevance. Furthermore, businesses operating for fewer than 10 years (Model VIII, $b = 0.312$, $p < 0.01$) and those operating for more than 10 years (Model IX, $b = 0.332$, $p < 0.01$) exhibit significant AI Capital– business innovation relationships, reinforcing that AI adoption contributes to innovation regardless of business age. The similarity of these coefficients suggests that AI Capital is associated with economically meaningful innovation outcomes across both younger and more established firms. These estimates provide deeper insights into how AI Capital influences innovation dynamics and highlight the importance of considering business characteristics when assessing the role of AI-driven innovation strategies. The consistency and magnitude of the coefficients across subsamples indicate that the association between AI Capital and business innovation is robust and substantively relevant across heterogeneous business contexts.

7.7 Robustness Estimates: The Association Between AI Capital and Business Innovation. Total Sample Analysis

In **Table 6**, Models I–III examine the relationship between AI Capital business innovation, using Pooled OLS, Random Effects, and Fixed Effects models. Unlike previous analyses based on paired observations, these estimates are derived from the total sample ($n = 539$), providing a broader perspective on how AI Capital is associated with innovation across all businesses in the dataset.

Model I presents the Pooled OLS estimates, showing that AI Capital is positively and significantly associated with innovation ($b = 0.318$, $p < 0.01$). The magnitude of this coefficient is comparable to that observed in the paired-sample analysis, indicating that the association between AI Capital and innovation remains economically meaningful when the full sample is considered. Model II presents the Random Effects estimates, where the AI Capital– business innovation relationship remains strong and statistically significant ($b = 0.320$, $p < 0.01$). The near-identical coefficient suggests that unobserved time-invariant firm characteristics do not materially affect the estimated association in the total sample. Model III presents the Fixed Effects estimates, in which the AI Capital– business innovation relationship remains positive and statistically significant ($b = 0.322$, $p < 0.01$), reinforcing the robustness of the AI Capital effect across different model specifications. This result indicates that within-firm changes in AI Capital are associated with economically meaningful changes in innovation outcomes even when all available observations are included. The Breusch and Pagan Lagrangian Multiplier test ($chibar^2 = 120.48$, $p < 0.01$) confirms that Random Effects is preferable to Pooled OLS. The Hausman test ($\chi^2 = 2.21$, $p > 0.10$) suggests that Random Effects is preferable to Fixed Effects.

[Table 6]

7.8 Robustness check: Short-form AI Capital scale

As an additional robustness check, it is examined whether a more parsimonious version of the AI Capital of Business scale yields substantively equivalent results to the full 45-item instrument. Based on the confirmatory factor analysis, a short-form scale is constructed by retaining the five highest-loading items within each of the three item blocks (Theme A, Knowledge: items 7, 9, 10, 11, and 13; Theme B, Skills: items 16, 18, 24, 27, and 29; and Theme C, Capabilities: items 31, 32, 35, 38 and 39), resulting in a 15-item measure. Reliability analysis indicates that the reduced subscales retain very high internal consistency, with Cronbach's alpha values of 0.956 for the Knowledge theme, 0.956 for the Skills theme, and 0.952 for the Capabilities theme.

To assess equivalence between the full and reduced instruments, composite scores were computed for both measures. The correlation between the full 45-item scale and the 15-item short form is very high ($r = 0.98$), indicating that the short-form scale captures virtually all of the variance contained in the original instrument. These findings suggest that the shorter scale provides a highly efficient and reliable alternative to the full instrument, supporting its use in robustness analyses and in empirical settings where questionnaire length is a concern.

The regressions reported in Table 4 for Models I–III are then replicated using the refined 15-item scale in place of the original 45-item measure. Comparable results are obtained across specifications. The OLS ($b = 0.818$, $p < 0.01$), random-effects ($b = 0.788$, $p < 0.01$), and fixed-effects ($b = 0.555$, $p < 0.01$) estimates indicate that AI Capital remains positively and significantly associated with business innovation. The magnitude of these coefficients indicates that variation in the short-form AI Capital measure is associated with economically meaningful differences in innovation outcomes, consistent with the interpretation derived from the full scale. Although the estimated coefficients are slightly larger when using the refined scale, this reflects differences in scale construction and reduced measurement noise rather than a substantive change in the underlying relationship. Importantly, the direction, statistical significance, and overall conclusions remain unchanged across specifications.

8. Discussion

8.1 Emerging themes

The aim of this study was to assess the relationship between AI Capital and business innovation in SMEs in England. The findings identified several key themes emerging from the empirical analysis. AI-related knowledge, skills, and capabilities within SMEs were found to be associated with business innovation, aligning with existing literature on the subject (Segarra-Blasco et al., 2025). Indeed, the association between AI Capital and innovation is consistent with prior research highlighting the transformative potential of AI-driven technologies in enhancing business competitiveness (Schwaeke et al., 2025; Al Dhaheri et al., 2024; Drydakis, 2022). The study's evaluation of AI's role in automating routine processes, optimising decision-making, and generating predictive insights demonstrates how AI enables businesses to develop novel products and services (Campbell et al., 2020; Grashof and Kopka, 2023).

To ensure the validity of these findings, robustness checks were conducted across multiple empirical specifications. The results confirmed that the relationship between AI Capital and business innovation is not sensitive to specific econometric modelling choices but is instead robust across a range of specifications. Moreover, the consistency of findings across business characteristics such as financial performance, size, and age demonstrated that AI Capital's influence on innovation extends across diverse operational contexts (Bell et al., 2019; Vaisey and Miles, 2017). This suggests that AI adoption is a significant determinant of innovation, regardless of business sector or size. A detailed examination of AI Capital components, i.e., knowledge, skills, and capabilities, reveals that each plays a crucial role in fostering innovation. AI knowledge enables businesses to identify cutting-edge technologies, AI-related skills equip employees to utilise AI tools effectively, and business-wide AI capabilities facilitate the seamless integration of AI into operations (Grashof and Kopka, 2023). These components collectively are associated with innovation, reinforcing the importance of investing in AI education, workforce development, and strategic AI implementation (Ng et al., 2021; Davenport et al., 2020).

The findings further indicate that AI Capital influences multiple dimensions of innovation, including product and service development, process optimisation, technology adoption, market and customer engagement, and organisational culture and strategy. AI enhances supply chain management and operational efficiency, facilitates market engagement, and improves the customer experience through personalised recommendations and predictive analytics (Drydakis, 2022; Campbell et al., 2020). Additionally, AI adoption fosters a culture of data-driven decision-making and continuous learning, supporting long-term adaptability and competitiveness (Drydakis, 2022; Canhoto and Clear, 2020). The study also found that businesses with stronger financial performance exhibited higher AI Capital and innovation scores, suggesting that financial stability enables businesses to invest in digital transformation and advanced technological capabilities (Segarra-Blasco et al., 2025; Arroyabe et al., 2024). The ability to allocate resources towards AI infrastructure, research and development, and innovation-driven strategies appears particularly evident in businesses experiencing greater financial performance, reinforcing the link between financial expansion and technological investment (Machucho and Ortiz, 2025; Mariani et al., 2023).

Similarly, the findings indicate that larger businesses demonstrated a stronger association between AI Capital and innovation. Economies of scale may allow larger businesses to allocate greater resources towards AI adoption, invest in data analytics, and develop AI-driven solutions (Drydakis, 2022; Bresnahan and Trajtenberg, 1995; Schumpeter, 1939). Additionally, the availability of skilled employees in larger businesses enhances their ability to integrate AI into core operations, further amplifying innovation potential (Drydakis, 2022). This suggests that workforce capacity is a key factor in AI adoption, as skilled personnel can facilitate the implementation and effective utilisation of AI technologies (Alekseeva et al., 2021).

Furthermore, the study found that established businesses, i.e., those that have been in operation for a longer period, demonstrated a stronger association between AI Capital and innovation. This suggests that accumulated experience, institutional knowledge, and strategic foresight contribute to AI adoption (Mendy, 2021; Teece et al., 2016). Long-standing businesses may have developed structured approaches to leveraging AI in ways that align with their existing business models and industry demands for innovation. Additionally, access to established networks and funding opportunities further facilitates AI integration, as more experienced businesses are often better positioned to secure investment and partnerships for technological advancement that drives innovation (Hansen and Bøgh, 2021).

8.2 Theoretical, and methodological contributions

This study made significant theoretical and methodological contributions to the understanding of the association between AI and its role in fostering business innovation. One of the key theoretical contributions of this study was the development of the AI Capital for Business scale, which conceptualised AI Capital as a crucial determinant of business innovation. While prior research primarily explored AI adoption through technological indicators such as patents and external market drivers (Segarra-Blasco et al., 2025; Al Dhaheri et al., 2024; Grashof and Kopka, 2023), this study shifted the focus towards a human-centred approach, recognising that a business's ability to leverage AI effectively depends not only on access to AI technologies but also on the internal knowledge, skills and capabilities required to utilise them strategically. By defining AI Capital as the accumulation of knowledge, skills, and capabilities within businesses, the study contributed to Human Capital theory (Becker, 1962) in the domain of AI-driven innovation. This theoretical extension indicates that the value businesses generate from AI is not solely dictated by external technological advancements but is also contingent on internal investments in AI-related human capital. This reconceptualisation bridges a gap in the existing literature by highlighting the role of workforce upskilling, training, and knowledge-sharing as critical enablers of AI-powered innovation. Furthermore, it presents AI Capital as a dynamic construct that evolves through continuous learning and adaptation, reinforcing the notion that businesses with higher AI competencies are better positioned to sustain competitive advantages in rapidly changing markets (Drydakis, 2024b; 2025b).

Furthermore, the study aligned with and contributed to the resource-based view of business (Barney, 1991) by demonstrating that AI Capital constitutes a valuable resource that enhances SMEs' innovation potential. Traditional business resources, such as physical capital, financial assets, or even existing technological infrastructure, may provide a foundation for competitive advantage, but their impact is often constrained by their tangible nature and replicability. In contrast, AI Capital represents an intangible yet highly strategic asset that facilitates differentiation in increasingly data-driven and algorithmic decision-making environments. Unlike conventional resources, which depreciate over time, AI Capital can appreciate through iterative learning, continuous experimentation, and the ongoing refinement of AI-driven processes. By enabling superior data-driven decision-making, automation, and market intelligence, AI Capital allows businesses to anticipate consumer preferences, optimise operational efficiencies, and identify new opportunities with greater precision (Drydakis, 2024b; 2025b).

Additionally, the study contributed to Dynamic Capabilities theory (Teece et al., 2016), suggesting that businesses with higher AI Capital are better able to adapt to technological changes, identify emerging trends, and integrate AI into long-term strategic planning. In this sense, AI Capital extends beyond being a static asset and functions as a catalyst for organisational agility, fostering the ability to pivot, innovate, and reconfigure resources in response to shifting market demands and technological advancements. This suggests that businesses that proactively invest in AI Capital are not only more likely to survive in digital economies but are also better positioned to establish themselves as industry leaders by capitalising on AI-enabled transformation.

In addition, the study provided empirical support for the notion that AI functions as a General-Purpose Technology (Bresnahan and Trajtenberg, 1995), given its widespread applicability across SME profiles and its capacity to drive strategic transformation. Unlike sector-specific innovations, which are typically confined to particular industries, GPTs such as AI exhibit broad adaptability, allowing businesses across diverse sectors to integrate AI into a range of operational domains. This study highlighted the versatility of AI by linking AI Capital to multiple dimensions of innovation, including product and service innovation, process innovation, technology adoption, market engagement, and organisational strategy. This detailed breakdown not only highlighted the diverse ways in which AI contributes to competitive advantage but also provided actionable insights for businesses seeking to maximise the benefits of AI-driven innovation. By demonstrating these multidimensional effects, this study enhanced the theoretical understanding of how AI reshapes business ecosystems (Segarra-Blasco et al., 2025; Grashof and Kopka, 2023; Campbell et al., 2020). It further reinforced the argument that AI is not merely an auxiliary tool for business efficiency but a transformative force that redefines how businesses innovate, compete, and sustain long-term growth.

The study also made methodological contributions to empirical research on AI adoption and business innovation. A key advancement was the rigorous validation of the AI Capital for Business scale, which was assessed using confirmatory factor analysis and internal consistency tests to ensure its reliability, robustness, and applicability for future research. This methodological refinement provides researchers with a validated instrument for measuring AI-related capabilities within businesses, facilitating comparative studies across industries and regions. Furthermore, the study employed a longitudinal panel design, tracking SMEs' AI adoption and innovation performance over two waves. This approach offered a significant advantage over cross-sectional studies by allowing for stronger causal inferences, as it enabled the observation of changes in AI Capital and innovation outcomes over time. By mitigating concerns related to reverse causality and unobserved heterogeneity, the longitudinal approach provided deeper insights into how AI Capital contributes to business innovation. The study further strengthened its methodological rigour by employing both fixed effects and random effects models. These econometric techniques ensured that the observed effects were not merely driven by omitted variable bias but instead reflected a more accurate estimation of the AI Capital–innovation relationship.

8.3 Policy implications

This study has significant practical implications for business leaders and policymakers seeking to enhance AI adoption and innovation in SMEs. A key contribution is the provision of a systematic framework enabling SMEs to assess their AI readiness using the AI Capital for Business scale. This tool allows SMEs to evaluate their strengths and weaknesses in AI-related knowledge, skills, and capabilities, helping them identify areas for further training, investment, or strategic development. By systematically assessing AI competencies, SMEs can make more informed decisions regarding resource allocation, workforce upskilling, and technological investments, facilitating a smoother and more effective digital transformation.

8.3.a Policy and institutional implications

From a policy perspective, this study informs government interventions aimed at fostering AI adoption among SMEs. Given that AI Capital is positively associated with business innovation, policies should focus on removing barriers to AI integration and ensuring accessibility across diverse business contexts. One of the most significant barriers to AI adoption is financial constraint, which prevents many SMEs from investing in AI despite its potential to improve efficiency and competitiveness (Machucho and Ortiz, 2025; Segarra-Blasco et al., 2025; Mendy, 2021). To address this, targeted financial support could be provided through tax incentives, grants, and low-interest loans for SMEs adopting AI-driven solutions (Drydakis, 2024b). Ensuring that AI adoption is not limited to resource-rich businesses may promote greater inclusivity in digital transformation (Machucho and Ortiz, 2025; Drydakis, 2025b; Arroyabe et al., 2024). AI-driven innovation should be equitable, ensuring that businesses across different sizes, sectors, and locations can benefit from AI adoption. To promote fair and widespread adoption, governments could support SMEs in underrepresented sectors and regions by offering dedicated AI training and funding opportunities (Drydakis, 2025b). Additionally, open-source AI tools and shared AI infrastructure could help lower entry barriers for SMEs with limited resources. Governments could facilitate access to AI-as-a-service platforms, cloud-based AI tools, and industry-specific AI solutions, allowing SMEs to integrate AI without requiring substantial upfront infrastructure investments.

A lack of AI expertise represents a significant challenge for SMEs, as many businesses face limited technical knowledge and shortages of skilled personnel. Without adequate AI Capital, SMEs may struggle to fully exploit AI's potential or mismanage implementation, creating inefficiencies or operational risks. To address this, governments could prioritise AI education by integrating AI and digital literacy into national curricula, vocational training, and lifelong learning programmes. Public–private partnerships between universities, research institutions, and businesses could facilitate AI upskilling initiatives, ensuring that SMEs have access to relevant expertise (Drydakis, 2024b). Such initiatives may include AI bootcamps, professional certifications, and executive training programmes designed specifically for SME leaders and employees. Given the strong association between AI Capital and business innovation, these educational interventions may enhance SMEs' ability to leverage AI strategically (Ng et al., 2021; Davenport et al., 2020). Similarly, expanding collaborative R&D funding could encourage AI co-development initiatives between SMEs and universities (Drydakis, 2024a). Establishing AI innovation hubs and technology transfer centres may further facilitate knowledge exchange, enabling SMEs to develop AI Capital in partnership with academic and industry experts. These measures could help bridge the AI skills gap, fostering a more AI-ready SME sector.

As AI adoption increases, concerns regarding data privacy, algorithmic bias, transparency standards, and regulatory compliance become more pronounced (Grashof and Kopka, 2023). To address these challenges, governments could develop clear regulatory guidelines promoting responsible AI use while ensuring compliance with data protection legislation, such as the UK General Data Protection Regulation. Establishing clear AI governance frameworks may help businesses navigate regulatory requirements and mitigate risks associated with AI deployment. One potential approach is the introduction of AI regulatory sandboxes, providing SMEs with controlled environments to test AI applications while receiving regulatory guidance (Truby et al., 2022). These sandboxes would allow businesses to trial AI innovations in a risk-mitigated setting, ensuring alignment with ethical and legal standards prior to full-scale deployment. AI adoption also introduces cybersecurity risks, particularly for SMEs lacking the technical resources to implement robust security measures (Hansen and Bøgh, 2021). SMEs may therefore be more vulnerable to cyber threats, data breaches, and AI-driven fraud, potentially undermining trust in AI adoption. To mitigate these risks, governments could develop cybersecurity training programmes and AI risk assessment frameworks tailored to SME contexts. Additionally, cybersecurity grants or tax relief may support businesses investing in AI-powered security solutions, encouraging SMEs to prioritise digital security as they adopt AI-driven technologies.

This study supports and enhances the Skills England (2025) policy agenda by operationalising workforce readiness through the development and application of the AI Capital scale. While Skills England (2025) emphasises the need for clearer definitions, consistent frameworks, and employer-responsive training systems, this study advances these objectives by offering a validated measurement tool that enables organisations to systematically evaluate AI knowledge, skills, and capabilities across functional domains. By translating broad policy priorities into a scalable assessment instrument, the study helps address recognised challenges within the Skills England (2025) agenda, including fragmented understanding of AI skills, uneven employer awareness, and limited diagnostic tools for identifying skills gaps. Furthermore, the scale facilitates evidence-based decision-making by allowing SMEs and policymakers to identify areas requiring targeted intervention, workforce development, and resource allocation. In doing so, the study strengthens Skills England's (2025) efforts to build an inclusive, sector-sensitive, and future-ready skills ecosystem by linking measurable AI competencies to innovation outcomes, organisational performance, and strategic workforce planning.

The present study informs the United Kingdom's Industrial Strategy (Department for Business and Trade, 2025) by providing an empirically grounded framework for understanding how AI adoption translates into measurable innovation outcomes within SMEs. The Industrial Strategy positions AI as a central driver of productivity, competitiveness, and regional growth. However, it places comparatively less emphasis on how firm-level AI readiness is conceptualised and assessed. By developing and validating the AI Capital for Business scale, this study offers a structured and operational tool for evaluating SMEs' AI-related knowledge, skills, and capabilities, thereby enabling more targeted and evidence-based policy interventions. The findings suggest that AI-driven innovation gains depend not only on access to technology or infrastructure, but also on internal capability formation. This has direct implications for industrial policy design, suggesting that investments in AI infrastructure and diffusion initiatives are likely to be most effective when complemented by workforce upskilling, managerial development, and governance support mechanisms. Moreover, the study translates high-level industrial policy objectives into measurable organisational mechanisms, linking AI skills development, SME innovation, and inclusive economic growth within a coherent empirical framework.

8.3.b Managerial and organisational implications

Beyond policy-level considerations, the findings offer actionable guidance for SME managers seeking to translate AI Capital into tangible innovation outcomes (Drydakis, 2025a). The results indicate that AI-related capabilities, organisational culture, and strategic alignment play a central role in enabling innovation, suggesting that managerial attention should prioritise people, processes, and decision-making structures rather than technology acquisition alone. For many SMEs, the immediate strategic priority is therefore not large-scale investment in AI hardware or advanced infrastructure, but the development of internal capabilities that allow existing AI tools to be used effectively. In practical terms, SME managers may benefit from prioritising targeted upskilling of existing employees over external hiring in the short run, particularly where AI applications relate to process optimisation, customer analytics, or decision support. Internal training programmes focused on applied AI use, data interpretation, and problem-solving can yield rapid gains by embedding AI into day-to-day operations. External hiring becomes more relevant when firms seek to develop or customise AI systems internally. However, for many SMEs, leveraging off-the-shelf AI solutions in combination with workforce training offers a more cost-effective and flexible pathway to innovation.

8.3.c Network and ecosystem implications

In addition to strengthening firm–customer interactions, the market and customer engagement dimension of innovation also reflects the role of AI Capital in enabling inter-organisational cooperation, which is particularly important for SMEs with limited internal resources. Higher levels of AI Capital may enhance SMEs' ability to collaborate with external partners, such as suppliers, digital platforms, logistics providers, and downstream customers, by improving data sharing, coordination, and joint decision-making across organisational boundaries. AI-enabled analytics, demand forecasting, and platform-based tools can reduce information asymmetries and transaction costs, thereby allowing SMEs to integrate more effectively into digital innovation networks.

This relational perspective is consistent with recent evidence indicating that digital transformation is associated with innovation and sustainability outcomes through cooperative mechanisms rather than isolated firm-level investments (Wang and Zhang, 2024). Inter-organisational cooperation can act as a catalyst for eco-innovation by facilitating joint experimentation, coordinated resource allocation, and shared learning. In this context, AI Capital supports not only internal capability development but also SMEs' capacity to participate in collaborative innovation processes, thereby amplifying the innovation effects observed in market engagement, customer responsiveness, and sustainable business practices.

8.3.d Emerging governance and Generative AI considerations

The findings also highlight the importance of organisational culture and strategy in shaping AI-driven innovation. Firms may benefit from fostering a culture that supports experimentation, cross-functional collaboration, and learning-by-doing, enabling employees to explore AI applications without fear of failure. Establishing clear strategic objectives for AI use, such as improving forecasting, enhancing customer engagement, or streamlining internal processes, can help align AI adoption with broader business goals and prevent fragmented implementation (Drydakis, 2022). From a capability perspective, effective AI adoption requires complementary organisational practices, including clear allocation of responsibility for AI-related decisions, integration of AI insights into managerial workflows, and regular evaluation of AI-enabled initiatives. Simple governance mechanisms, such as appointing an AI champion, forming small cross-functional teams, or embedding AI considerations into strategic planning cycles, may substantially enhance the returns to AI investment.

An additional consideration arises from the growing prominence of Generative AI (GenAI), which presents both significant opportunities and distinct governance challenges for SMEs. While regulation is often perceived as a constraint on innovation, emerging evidence suggests that clear and well-designed regulatory frameworks may strengthen the association between AI Capital and business innovation by providing firms with guidance, legitimacy, and greater clarity regarding risk. In this context, the knowledge dimension of AI Capital, particularly an understanding of AI risks, ethical considerations, and regulatory requirements, becomes a critical enabler of effective GenAI adoption rather than a barrier. Recent research indicates that AI regulation can act as a positive moderator, enhancing the association between AI and innovation outcomes (Wang and Zhang, 2025b).

Applied to the English context, regulatory frameworks such as the UK's pro-innovation approach to AI governance may support SMEs by clarifying acceptable uses of GenAI, promoting trust among customers and partners, and reducing legal and reputational risks associated with AI deployment. When firms align their AI Capital with responsible governance principles, regulation may facilitate rather than hinder innovation by enabling more confident investment, broader organisational adoption, and stronger collaboration with external stakeholders. In this sense, regulatory knowledge and compliance capabilities form an integral component of AI Capital, reinforcing the effectiveness of GenAI applications in driving innovation while supporting ethical, transparent, and sustainable business practices.

8.4 Limitations and future research

While this study provides insights into the role of AI Capital in fostering business innovation among SMEs, certain limitations should be acknowledged. Addressing these limitations in future research will enhance the understanding of AI-driven innovation and contribute to more effective policy and business strategies. A key limitation of this study is its reliance on self-reported measures of AI Capital and business innovation. Although the AI Capital for Business scale was rigorously developed and validated, self-reported data may be prone to response biases, such as social desirability bias or the overestimation of AI competencies. Businesses may perceive themselves as more AI-proficient or innovative than they actually are, leading to potential distortions in the findings. In addition, variation in respondents' subjective interpretations of AI-related concepts may introduce inconsistencies in the reported data. While diagnostic tests suggest that this bias is unlikely to materially distort the estimated relationships, the presence of common method variance at the measurement level cannot be fully ruled out. Future research could complement self-reported measures with objective indicators of AI adoption and innovation outcomes, such as AI investment levels, AI-driven productivity improvements, machine-learning deployment in decision-making processes, R&D expenditure, patenting activity, or realised revenues from new products. Incorporating third-party data sources, including industry reports or government statistics, could further enhance the robustness of assessments of AI's impact on business innovation (Segarra-Blasco et al., 2025; Grashof and Kopka, 2023). In addition, the use of multi-source data or greater temporal separation between the measurement of explanatory and outcome variables would further strengthen empirical robustness.

Another limitation concerns the study's geographical scope. The focus on SMEs in England limits the generalisability of findings to other regions and business contexts. While the UK presents a strong case for examining AI adoption in SMEs, differences in business environments, regulatory frameworks, and digital infrastructures across countries could affect AI-driven innovation (Arroyabe et al., 2024; Segarra-Blasco et al., 2025). Cultural attitudes towards AI, levels of digital literacy, and government-led AI strategies may vary significantly between developed and emerging economies, influencing the extent to which businesses integrate AI into their operations. Future research should extend this analysis to other national and regional contexts, particularly in developing economies where AI adoption patterns may be shaped by financial constraints, regulatory challenges, and disparities in digital infrastructure development (Mendy, 2021; Al Dhaheri et al., 2024). A cross-country comparative approach would provide deeper insights into the contextual factors that enable or hinder AI-driven business transformation.

Additionally, the study primarily examines the short-term relationship between AI Capital and business innovation using a two-wave panel dataset covering 2024 and 2025. While the longitudinal approach provides stronger causal insights than cross-sectional studies, AI adoption is a dynamic process that unfolds over longer periods (Mariani et al., 2023). Businesses may experience delays in realising the benefits of AI adoption due to learning curves, integration challenges, and the need for complementary organisational changes. Future studies should adopt extended longitudinal designs to capture the long-term effects of AI Capital on innovation, business sustainability, and competitive positioning. Examining how AI adoption evolves across different business life cycles, such as early-stage start-ups and established SMEs, would provide more nuanced insights into how AI Capital develops and is associated with innovation over time (Drydakis, 2022).

The study also does not fully account for sectoral variations in AI adoption and innovation. While the sample includes SMEs from diverse industries, the effects of AI Capital may differ significantly between sectors. Certain industries, such as financial services, may be more advanced in AI-driven automation and analytics, whereas traditional sectors may lag in adoption due to cost barriers, regulatory constraints, or workforce resistance to AI integration. As a result, the average effects reported in this study may mask meaningful sector-specific dynamics in how AI-related knowledge, skills, and capabilities translate into innovation outcomes. Future research should conduct sector-specific analyses to determine whether AI Capital has differential effects on innovation depending on industry characteristics, regulatory environments, and market competition levels. Additionally, industry-specific case studies could help uncover best practices for AI implementation across different business domains.

Another limitation is the lack of qualitative insights into how SMEs implement AI strategies in practice. While the study quantifies the association between AI Capital and business innovation, it does not explore how businesses develop AI-driven solutions, overcome implementation barriers, or integrate AI into decision-making processes and operational workflows (Canhoto and Clear, 2020). The human and organisational dimensions of AI adoption are central to understanding how businesses navigate AI-related transformations. Future research could incorporate qualitative methods to generate richer insights into the organisational dynamics, strategic challenges, and contextual factors associated with AI adoption.

Furthermore, this study does not explicitly account for ethical and social concerns related to AI adoption in SMEs. While AI Capital includes elements of compliance and cybersecurity, broader ethical issues such as algorithmic bias, workforce displacement, and consumer trust in AI-driven decision-making are increasingly important (Drydakis, 2022). SMEs, unlike large corporations, may lack the resources to implement robust ethical AI frameworks or comply with evolving AI regulations, potentially exposing them to reputational and legal risks. Future research should examine how SMEs navigate the ethical challenges of AI deployment and whether responsible AI practices contribute to business innovation and long-term sustainability (Grashof and Kopka, 2023). Investigating the role of ethical AI certifications, industry guidelines, and government regulations in shaping AI adoption among SMEs would offer valuable policy insights.

Finally, while the study provides strong empirical evidence of the positive relationship between AI Capital and business innovation, it does not fully explore potential moderating or mediating factors that might influence this relationship. Organisational culture, leadership attitudes towards AI, and external market dynamics may play critical roles in shaping how AI Capital translates into innovation outcomes (Teece et al., 2016). For example, businesses with a strong culture of digital transformation may derive greater benefits from AI adoption compared to those with more traditional organisational structures. Future studies could incorporate moderation and mediation analyses to better understand the mechanisms through which AI capital is associated with business innovation and whether specific business characteristics amplify or constrain these associations. Additionally, exploring the role of collaborative networks could provide further insights into how SMEs build and leverage AI competencies.

9. Conclusion

This study examined whether AI Capital, defined as firms' AI-related knowledge, skills, and capabilities, was associated with business innovation among SMEs in England. Focusing on AI Capital as an internal organisational resource rather than on AI technologies alone, the analysis used longitudinal panel data and a newly developed AI Capital for Business scale. The findings indicate a positive and statistically significant association between AI Capital and multiple dimensions of innovation, including product and service innovation, process innovation, technology adoption, market and customer engagement, and organisational culture and strategy. These associations were robust across alternative specifications and consistent across firms of different sizes, financial performance levels, and stages of maturity. Policy implications suggest that technology diffusion alone may be insufficient. Training, advisory support, innovation grants, and regulatory clarity could strengthen the association between AI Capital and business innovation.

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Table 1. Descriptive statistics. Means (Std. Dev.)

	Panel I: Total sample	**Panel II: Paired observations sample**	**Panel III: Difference test**
Businesses experiencing a revenue growth rate greater than 5% (%)	38.96 (0.48)	39.28 (0.48)	z=0.10; p>0.10
Businesses with more than 50 employees (%)	45.26 (0.49)	45.43 (0.49)	z=0.05; p>0.10
Businesses operating for more than 10 years (%)	51.76 (0.50)	52.18 (0.50)	z=0.13; p>0.10
AI Capital of Business scale (c.)	149.09 (49.01)	149.55 (48.83)	t=0.15; p>0.10
AI Capital of Business scale: Knowledge theme (c.)	49.83 (16.50)	49.99 (16.41)	t=0.15; p>0.10
AI Capital of Business scale: Skills theme (c.)	49.77 (16.62)	49.92 (16.58)	t=0.14; p>0.10
AI Capital of Business scale: Capabilities theme (c.)	49.48 (16.15)	49.62 (16.10)	t=0.14; p>0.10
Business Innovation scale (c.)	90.35 (19.15)	90.30 (19.01)	t=0.04; p>0.10
Business Innovation scale: Product and Service Innovation theme (c.)	17.99 (4.14)	17.97 (4.12)	t=0.07; p>0.10
Business Innovation scale: Process Innovation theme (c.)	18.11 (4.16)	18.12 (4.13)	t=0.03; p>0.10
Business Innovation scale: Technology Adoption theme (c.)	18.03 (3.90)	18.02 (3.86)	t=0.04; p>0.10
Business Innovation scale: Market and Customer Engagement theme (c.)	18.09 (4.01)	18.07 (3.97)	t=0.08; p>0.10
Business Innovation scale: Organisational Culture and Strategy theme (c.)	18.12 (3.86)	18.09 (3.86)	t=0.12; p>0.10
Sector: Manufacturing (%)	7.42 (0.26)	7.53 (0.26)	z=0.06; p>0.10
Sector: Construction (%)	5.38 (0.22)	5.55 (0.22)	z=0.12; p>0.10
Sector: Wholesale and retail trade (%)	8.71 (0.28)	8.73 (0.28)	z=0.01; p>0.10
Sector: Financial and insurance services (%)	8.53 (0.27)	8.33 (0.27)	z=0.11; p>0.10
Sector: Information and communication (%)	8.53 (0.27)	8.33 (0.27)	z=0.11; p>0.10
Sector: Transportation and storage (%)	7.79 (0.26)	7.53 (0.26)	z=0.15; p>0.10
Sector: Real estate (%)	8.34 (0.27)	7.93 (0.27)	z=0.24; p>0.10
Sector: Professional, scientific and technical services (%)	9.09 (0.28)	9.12 (0.28)	z=0.01; p>0.10
Sector: Administrative and support services (%)	8.34 (0.27)	8.33 (0.27)	z=0.01; p>0.10
Sector: Education (%)	8.90 (0.28)	9.12 (0.28)	z=0.12; p>0.10
Sector: Health and social work services (%)	9.83 (0.29)	9.92 (0.29)	z=0.04; p>0.10
Sector: Leisure, hospitality and tourism (%)	9.09 (0.28)	9.52 (0.29)	z=0.23; p>0.10
Observations	539	504	

Notes: The data set covers the years 2024 and 2025. (c.) Continuous variable.

Table 2. Tabulation analysis. Means (Std. Dev.)		
	Panel I. AI Capital of Business scale (c.)	**Panel II. Business Innovation scale (c.)**
Businesses experiencing a revenue growth rate greater than 5% (n=198)	192.83 (16.56)	107.72 (9.20)
Businesses experiencing a revenue growth rate less than 5% (n=306)	121.54 (41.85)	79.02 (14.73)
Difference test	t=22.83, p<0.01	t=24.47, p<0.01
Businesses with more than 50 employees (n=229)	183.96 (22.69)	104.79 (11.33)
Businesses with fewer than 50 employees (n=275)	120.89 (44.38)	78.24 (15.34)
Difference test	t=18.85, p<0.01	t=21.70, p<0.01
Businesses operating for more than 10 years (n=263)	179.03 (31.57)	101.78 (13.73)
Businesses operating for fewer than 10 years (n=241)	117.37 (43.78)	77.77 (15.81)
Difference test	t=18.24, p<0.01	t=18.24, p<0.01
Wave one: 2024 (n=252)	147.57 (49.91)	89.00 (19.02)
Wave two: 2025 (n=252)	151.52 (47.74)	91.59 (18.96)
Difference test	t=0.90, p>0.10	t=1.53, p>0.10

Notes: The data set covers the years 2024 and 2025. Paired observations are used. (c.) Continuous variable.

Table 3. Correlation matrix

	AI Capital of Business scale	**AI Capital of Business scale: Knowledge theme**	**AI Capital of Business scale: Skills theme**	**AI Capital of Business scale: Capabilities theme**	**Business Innovation scale**	**Business Innovation scale: Product and Service Innovation theme**	**Business Innovation scale: Process Innovation theme**	**Business Innovation scale: Technology Adoption theme**	**Business Innovation scale: Market and Customer Engagement theme**	**Business Innovation scale: Organisational Culture and Strategy theme**	**Businesses experiencing a revenue growth rate greater than 5%**	**Businesses with more than 50 employees**	**Businesses operating for more than 10 years**
AI Capital of Business scale	1												
AI Capital of Business scale: Knowledge theme	0.994 (0.000)***	1											
AI Capital of Business scale: Skills theme	0.995 (0.000)***	0.985 (0.000)***	1										
AI Capital of Business scale: Capabilities theme	0.993 (0.000)***	0.981 (0.000)***	0.982 (0.000)***	1									
Business Innovation scale	0.948 (0.000)***	0.945 (0.000)***	0.942 (0.000)***	0.943 (0.000)***	1								
Business Innovation scale: Product and Service Innovation theme	0.913 (0.000)***	0.909 (0.000)***	0.907 (0.000)***	0.907 (0.000)***	0.953 (0.000)***	1							
Business Innovation scale: Process Innovation theme	0.899 (0.000)***	0.897 (0.000)***	0.893 (0.000)***	0.893 (0.000)***	0.957 (0.000)***	0.887 (0.000)***	1						
Business Innovation scale: Technology Adoption theme	0.899 (0.000)***	0.896 (0.000)***	0.892 (0.000)***	0.893 (0.000)***	0.952 (0.000)***	0.890 (0.000)***	0.893 (0.000)***	1					
Business Innovation scale: Market and Customer Engagement theme	0.903 (0.000)***	0.901 (0.000)***	0.899 (0.000)***	0.896 (0.000)***	0.955 (0.000)***	0.884 (0.000)***	0.901 (0.000)***	0.889 (0.000)***	1				
Business Innovation scale: Organisational Culture and Strategy theme	0.900 (0.000)***	0.895 (0.000)***	0.892 (0.000)***	0.897 (0.000)***	0.939 (0.000)***	0.872 (0.000)***	0.868 (0.000)***	0.863 (0.000)***	0.873 (0.000)***	1			
Businesses experiencing a revenue growth rate greater than 5%	0.713 (0.000)***	0.708 (0.000)***	0.706 (0.000)***	0.714 (0.000)***	0.737 (0.000)***	0.723 (0.000)***	0.704 (0.000)***	0.711 (0.000)***	0.693 (0.000)***	0.676 (0.000)***	1		
Businesses with more than 50 employees	0.643 (0.000)***	0.636 (0.000)***	0.639 (0.000)***	0.644 (0.000)***	0.695 (0.000)***	0.665 (0.000)***	0.696 (0.000)***	0.607 (0.000)***	0.667 (0.000)***	0.610 (0.000)***	0.612 (0.000)***	1	
Businesses operating for more than 10 years	0.631 (0.000)***	0.628 (0.000)***	0.625 (0.000)***	0.629 (0.000)***	0.631 (0.000)***	0.603 (0.000)***	0.633 (0.000)***	0.593 (0.000)***	0.578 (0.000)***	0.595 (0.000)***	0.566 (0.000)***	0.586 (0.000)***	1

Notes: The data set covers the years 2024 and 2025. Paired observations are used (n=504). (***) Statistically significant at the 1% level.

Table 4. Regression outcomes

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII
	Pooled OLS. Business Innovation scale	**Random Effects. Business Innovation scale**	**Fixed Effects. Business Innovation scale**	**Random Effects. Business Innovation scale: Product and Service Innovation theme**	**Random Effects. Business Innovation scale: Process Innovation theme**	**Random Effects. Business Innovation scale: Technology Adoption theme**	**Random Effects. Business Innovation scale: Market and Customer Engagement theme**	**Random Effects. Business Innovation scale: Organisational Culture and Strategy theme**
AI Capital of Business scale	0.315 (0.008)***	0.316 (0.010)***	0.322 (0.032)***	0.066 (0.002)***	0.059 (0.003)***	0.061 (0.003)***	0.064 (0.003)***	0.063 (0.003)***
Businesses experiencing a revenue growth rate greater than 5%	2.687 (0.740)***	2.780 (0.925)***	3.227 (2.718)	0.716 (0.272)***	0.595 (0.286)**	0.721 (0.277)***	0.494 (0.280)*	0.313 (0.282)
Businesses with more than 50 employees	4.802 (0.698)***	4.400 (0.861)***	2.077 (2.226)	0.876 (0.254)***	1.279 (0.267)***	0.906 (0.259)***	0.975 (0.261)***	0.430 (0.264)
Businesses operating for more than 10 years	0.196 (0.658)	0.380 (0.820)	1.133 (2.248)	-0.026 (0.241)	0.508 (0.254)**	-0.187 (0.245)	-0.221 (0.248)	0.276 (0.250)
F	398.67	-	28.39	-	-	-	-	-
Prob>F	0.000	-	0.000	-	-	-	-	-
R-squared	0.924	-	0.913	-	-	-	-	-
Wald chi2	-	3452.37	-	1830.71	1559.81	1494.65	1527.23	1403.36
Prob>chi2	-	0.000	-	0.000	0.000	0.000	0.000	0.000
R-squared	-	0.924	-	0.855	0.847	0.834	0.841	0.828
Breusch and Pagan Lagrangian multiplier test	chibar2=135.09 p<0.01			chibar2=90.69 p<0.01	chibar2=129.99 p<0.01	chibar2=97.92 p<0.01	chibar2=111.43 p<0.01	chibar2=110.14 p<0.01
Hausman test	chi2=1.53 p>0.10			chi2=5.77 p>0.10	chi2=7.43 p>0.10	chi2=5.65 p>0.10	chi2=3.81 p>0.10	chi2=2.54 p>0.10
Observations	504	504	504	504	504	504	504	504

Notes: The data set covers the years 2024 and 2025. Paired observations are used. Pooled OLS and Random Effects models control for sectoral fixed effects. Coefficients and standard errors are reported with three decimal places; test statistics are reported with two decimal places, following Stata 19 output conventions. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level. (*) Statistically significant at the 10% level.

Table 5. Regression outcomes

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX
	Fixed Effects. Business Innovation scale	**Fixed Effects. Business Innovation scale**	**Fixed Effects. Business Innovation scale**	**Random Effects. Business Innovation scale. Businesses experiencing a revenue growth rate less than 5%**	**Random Effects. Business Innovation scale. Businesses experiencing a revenue growth rate greater than 5%**	**Random Effects. Business Innovation scale. Businesses with fewer than 50 employees**	**Random Effects. Business Innovation scale. Businesses with more than 50 employees**	**Random Effects. Business Innovation scale. Businesses operating for fewer than 10 years**	**Random Effects. Business Innovation scale. Businesses operating for more than 10 years**
AI Capital of Business scale: Knowledge theme	0.700 (0.076)***	-	-	-	-	-	-	-	-
AI Capital of Business scale: Skills theme	-	0.613 (0.088)***	-	-	-	-	-	-	-
AI Capital of Business scale: Capabilities theme	-	-	0.622 (0.086)***	-	-	-	-	-	-
AI Capital of Business scale	-	-	-	0.306 (0.011)***	0.408 (0.027)***	0.311 (0.011)***	0.340 (0.023)***	0.312 (0.013)***	0.332 (0.018)***
Businesses experiencing a revenue growth rate greater than 5%	3.948 (2.789)	3.466 (2.954)	4.066 (2.932)	-	-	2.089 (1.408)	2.550 (1.437)*	2.394 (1.591)	2.666 (1.233)**
Businesses with more than 50 employees	2.230 (2.287)	3.310 (2.409)	2.881 (2.400)	4.027 (1.153)***	4.092 (1.274)***	-	-	3.978 (1.411)***	4.370 (1.083)***
Businesses operating for more than 10 years	0.795 (2.321)	2.954 (2.423)	3.340 (2.403)	0.496 (1.013)	0.545 (1.404)	0.500 (1.047)	0.129 (1.370)	-	-
F	23.67	14.67	15.52	-	-	-	-	-	-
Prob>F	0.000	0.000	0.000	-	-	-	-	-	-
R-squared	0.910	0.901	0.897	-	-	-	-	-	-
Wald chi2	-	-	-	1139.82	392.71	1119.54	597.54	987.38	1097.27
Prob>chi2	-	-	-	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	-	-	-	0.872	0.765	0.872	0.816	0.880	0.880
Breusch and Pagan Lagrangian multiplier test	chibar2=129.77 p<0.01	chibar2=124.99 p<0.01	chibar2=126.28 p<0.01	chibar2=89.71 p<0.01	chibar2=32.35 p<0.01	chibar2=76.30 p<0.01	chibar2=51.81 p<0.01	chibar2=66.15 p<0.01	chibar2=64.24 p<0.01
Hausman test	chi2=9.88 p<0.05	chi2=10.99 p<0.05	chi2=14.08 p<0.01	chi2=0.88 p>0.10	chi2=0.85 p>0.10	chi2=0.43 p>0.10	chi2=0.01 p>0.10	chi2=0.96 p>0.10	chi2=0.38 p>0.10
Observations	504	504	504	306	198	275	229	241	263

Notes: The data set covers the years 2024 and 2025. Paired observations are used. Random Effects models control for sectoral fixed effects. Coefficients and standard errors are reported with three decimal places; test statistics are reported with two decimal places, following Stata 19 output conventions. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level. (*) Statistically significant at the 10% level.

Table 6. Regression outcomes

	Model I	Model II	Model III
	Pooled OLS. Business Innovation scale	**Random Effects. Business Innovation scale**	**Fixed Effects. Business Innovation scale**
AI Capital of Business scale	0.318 (0.007)***	0.320 (0.010)***	0.322 (0.032)***
Businesses experiencing a revenue growth rate greater than 5%	2.799 (0.742)***	2.955 (0.929)***	3.227 (2.718)
Businesses with more than 50 employees	4.976 (0.701)***	4.602 (0.867)***	2.077 (2.226)
Businesses operating for more than 10 years	-0.366 (0.654)	-0.421 (0.815)	1.133 (2.248)
F	404.83	-	28.39
Prob>F	0.000	-	0.000
R-squared	0.920	-	0.909
Wald chi2	-	3522.28	-
Prob>chi2	-	0.000	-
R-squared	-	0.920	-
Breusch and Pagan Lagrangian multiplier test	chibar2=120.48 p<0.01		
Hausman test	chi2=2.21 p>0.10		
Observations	539	539	539

Notes: The data set covers the years 2024 and 2025. Total sample. Pooled OLS and Random Effects models control for sectoral fixed effects. Coefficients and standard errors are reported with three decimal places; test statistics are reported with two decimal places, following Stata 19 output conventions. (***) Statistically significant at the 1% level.

Appendix

Table AI. AI Capital of Business scale. Descriptive statistics. Means (Std. Dev.)

	Panel I Wave one: 2024	Panel II Wave two: 2025	Panel III Difference test
Theme A: Knowledge			
Understanding AI Fundamentals			
1. We understand how AI enhances business operations.	3.13 (1.17)	3.44 (1.24)	t=2.88, p<0.01
2. We understand the ethical considerations involved in implementing AI in our business.	3.18 (1.16)	3.49 (1.27)	t=2.86 , p<0.01
3. We understand how AI automates tasks to improve efficiency.	3.26 (1.26)	3.37 (1.28)	t=0.97, p>0.10
AI in Decision-Making			
4. We understand how AI improves decision-making through data analysis.	3.26 (1.32)	3.42 (1.27)	t=1.38, p>0.10
5. We understand how to integrate AI applications into our business processes.	3.32 (1.15)	3.36 (1.09)	t=0.40, p>0.10
AI for Customer Management			
6. We understand how AI enhances customer relationships.	3.32 (1.13)	3.42 (1.11)	t=1.00, p>0.10
7. We understand how AI provides immediate answers to customer queries.	3.21 (1.33)	3.26 (1.28)	t=0.42, p>0.10
8. We understand how AI collects information on customers' purchase history, transactions, and digital footprints.	3.40 (1.12)	3.48 (1.16)	t=0.78, p>0.10
AI in Business Operations			
9. We understand the use of AI-powered applications for project management.	3.14 (1.31)	3.23 (1.35)	t=0.75, p>0.10
10. We understand how AI supports real-time data analysis for better decision-making.	3.23 (1.40)	3.38 (1.30)	t=1.24, p>0.10
AI for Financial Management			
11. We understand how AI is applied to payments, accounting, and cash flow forecasting.	3.23 (1.34)	3.35 (1.27)	t=1.03, p>0.10
AI in Marketing			
12. We understand how AI targets audiences and offers personalized shopping suggestions.	3.32 (1.15)	3.36 (1.15)	t=0.39, p>0.10
Data Privacy and Cybersecurity			
13. We understand how AI enhances cybersecurity.	3.14 (1.39)	3.25 (1.26)	t=0.93, p>0.10
14. We understand the regulations governing the use of AI in business.	3.39 (1.11)	3.51 (1.16)	t=1.18, p>0.10
AI Risks and Trends			
15. We understand the risks and limitations of using AI in our operations.	3.38 (1.14)	3.42 (1.22)	t=0.38, p>0.10
Theme B: Skills			
Implementing AI Applications			
16. We have used AI applications to support our business operations.	3.29 (1.33)	3.43 (1.26)	t=1.21, p>0.10
AI in Communication			
17. We have used AI applications for communication operations within our business.	3.33 (1.12)	3.48 (1.22)	t=1.43, p>0.10
AI in Customer Management			
18. We have used AI applications to manage customer information and interactions.	3.22 (1.36)	3.32 (1.28)	t=0.84, p>0.10
19. We have used AI applications to offer immediate customer support through chatbots.	3.30 (1.13)	3.37 (1.12)	t=0.69, p>0.10
AI in Marketing			
20. We have used AI applications to create marketing strategies, including targeting specific audiences.	3.33 (1.21)	3.40 (1.20)	t=0.65, p>0.10
21. We have used AI applications to manage personalised shopping suggestions and recommendations.	3.17 (1.37)	3.34 (1.32)	t=1.41, p>0.10
AI in Sales and Competitor Analysis			
22. We have used AI applications to track inventory and sales.	3.40 (1.16)	3.37 (1.25)	t=0.27, p>0.10
23. We have used AI applications to collect information on competitors' product assortments, pricing, and promotional activities.	3.26 (1.15)	3.36 (1.25)	t=0.93, p>0.10
AI in Financial and Legal Operations			
24. We have used AI applications to prepare financial reports and conduct cash flow forecasting.	3.19 (1.34)	3.28 (1.27)	t=0.77, p>0.10
25. We have used AI applications in legal services to manage contracts and ensure compliance.	3.32 (1.13)	3.38 (1.18)	t=0.58, p>0.10
Optimizing Workflows with AI			
26. We have used AI applications to manage business workflows.	3.30 (1.20)	3.40 (1.20)	t=0.93, p>0.10
27. We have used AI applications to identify and address inefficiencies and streamline operations.	3.20 (1.34)	3.30 (1.25)	t=0.86, p>0.10
AI in Recruitment and HR			
28. We have used AI applications for recruitment and HR management.	3.30 (1.27)	3.39 (1.24)	t=0.80, p>0.10
Data Analysis and Cybersecurity			
29. We have used AI applications to analyse customer behaviour and predict trends.	3.24 (1.39)	3.32 (1.28)	t=0.67, p>0.10
30. We have used AI applications for data security and privacy protection.	3.38 (1.11)	3.34 (1.11)	t=0.40, p>0.10
Theme C: Capabilities			
Adapting to AI Technologies			
31. We can adopt new AI applications to improve our business operations.	3.26 (1.29)	3.29 (1.23)	t=0.26, p>0.10
Driving Long-term Planning with AI			
32. We can plan long-term business processes using AI.	3.15 (1.35)	3.23 (1.30)	t=0.67, p>0.10
33. We can ensure AI applications are customised to meet long-term business needs.	3.41 (1.10)	3.38 (1.07)	t=0.31, p>0.10
Scaling and Strategic Operations with AI			
34. We can expand our operations by leveraging AI-driven efficiency.	3.39 (1.12)	3.42 (1.16)	t=0.29, p>0.10
35. We can make strategic decisions based on AI-driven financial forecasting.	3.12 (1.35)	3.27 (1.27)	t=1.28, p>0.10
Enhancing Customer and Employee Engagement			
36. We can enhance customer engagement through AI applications.	3.38 (1.09)	3.50 (1.15)	t=1.20, p>0.10

37. We can ensure that employees feel confident using AI applications to improve customer and business interactions.	3.30 (1.18)	3.38 (1.21)	t=0.75, p>0.10
Improving Service and Marketing with AI			
38. We can improve service quality through AI-powered real-time customer support.	3.32 (1.14)	3.42 (1.22)	t=0.95, p>0.10
39. We can gain a competitive advantage through AI-driven targeting and personalisation.	3.28 (1.22)	3.34 (1.22)	t=0.55, p>0.10
AI in Compliance and Ethics			
40. We can ensure that AI applications comply with legal regulations and ethical standards.	3.22 (1.30)	3.22 (1.19)	t=0.07, p>0.10
Exploring AI's Potential in Marketing and Ensuring the Credibility of Digital Content			
41. We can identify new ways to implement AI in marketing.	3.32 (1.14)	3.38 (1.17)	t=0.58, p>0.10
42. We can enhance our business's digital credibility using AI applications to address fake product reviews.	3.32 (1.19)	3.42 (1.21)	t=0.93, p>0.10
Collaborative and HR Processes with AI			
43. We can enhance team collaboration using AI applications.	3.17 (1.30)	3.30 (1.21)	t=1.16, p>0.10
44. We can ensure efficient hiring processes using AI applications.	3.21 (1.24)	3.24 (1.18)	t=0.27, p>0.10
AI for Cybersecurity and Legal Services			
45. We can protect customer data and improve cybersecurity using AI applications.	3.18 (1.30)	3.30 (1.19)	t=1.08, p>0.10
Observations	252	252	

Notes: The dataset covers the years 2024 and 2025. Paired observations are used. Each item is assessed on a five-point Likert scale (Strongly Disagree – Strongly Agree). All items refer to respondents' assessment of current or past organisational realities. Theme A captures current perceived knowledge of AI, Theme B reflects past and current use of AI applications, and Theme C assesses current perceived capabilities.

Appendix

Table AII. Business Innovation scale. Descriptive statistics. Means (Std. Dev.)

	Panel I Wave one: 2024	**Panel II Wave two: 2025**	**Panel III Difference test**
Theme A: Product and Service Innovation			
1. Our business frequently develops new or improved products or services to meet customer needs.	3.45 (0.93)	3.64 (1.02)	t=2.18, p<0.05
2. Creating new products or services is crucial for our business success.	3.57 (0.99)	3.75 (0.98)	t=2.05, p<0.05
3. Compared to similar small businesses, we excel at offering innovative products or services.	3.54 (1.00)	3.61 (1.00)	t=0.78, p>0.10
4. In the past three years, we have introduced new or significantly improved products or services.	3.56 (0.97)	3.66 (0.93)	t=1.18, p>0.10
5. We actively encourage and implement product or service ideas from our team members.	3.48 (1.00)	3.65 (1.01)	t=1.89, p<0.10
Theme B: Process Innovation			
6. We regularly seek ways to enhance our production or service delivery processes.	3.53 (1.01)	3.67 (1.03)	t=1.54, p>0.10
7. Improving our operational processes is vital for maintaining competitiveness.	3.61 (0.98)	3.69 (1.00)	t=0.90, p>0.10
8. We assess our process improvements against industry standards to ensure efficiency.	3.58 (0.94)	3.67 (0.98)	t=1.05, p>0.10
9. Over the past three years, we have adapted our processes to better meet market demands.	3.56 (0.98)	3.59 (0.96)	t=0.34, p>0.10
10. Our business values and implements process improvement suggestions from employees.	3.59 (0.96)	3.73 (0.99)	t=1.61, p>0.10
Theme C: Technology Adoption			
11. We are open to adopting new technologies that enhance our business operations.	3.57 (0.97)	3.60 (0.94)	t=0.35, p>0.10
12. Our business effectively uses digital tools to improve efficiency and customer engagement.	3.53 (0.97)	3.61 (0.97)	t=0.92, p>0.10
13. We integrate appropriate technologies to streamline our processes and services.	3.56 (0.96)	3.75 (0.91)	t=2.28, p<0.05
14. Maintaining current and efficient technological systems is essential for our success.	3.61 (0.96)	3.69 (0.94)	t=0.94, p>0.10
15. We consider and adopt technological solutions that have proven successful in other businesses.	3.51 (0.91)	3.57 (0.92)	t=0.73, p>0.10
Theme D: Market and Customer Engagement			
16. We actively seek and utilize customer feedback to drive innovation.	3.52 (1.01)	3.58 (1.02)	t=0.66, p>0.10
17. Our business conducts regular market research to identify emerging trends and opportunities.	3.53 (0.91)	3.71 (0.90)	t=2.23, p<0.05
18. We design our products or services based on a deep understanding of customer needs.	3.61 (0.99)	3.63 (0.91)	t=0.23, p>0.10
19. We quickly adapt our offerings in response to market changes or customer feedback.	3.61 (0.93)	3.76 (0.97)	t=1.77, p<0.10
20. Our business seeks opportunities to enter new markets with innovative products or services.	3.57 (0.94)	3.59 (1.00)	t=0.23, p>0.10
Theme E: Organizational Culture and Strategy			
21. We foster a culture that encourages creativity and innovation among our employees.	3.59 (0.95)	3.62 (1.05)	t=0.33, p>0.10
22. Our business includes innovation as a key component in strategic planning.	3.59 (0.94)	3.68 (0.96)	t=1.06, p>0.10
23. We allocate sufficient resources (time, budget, personnel) to support innovative initiatives.	3.58 (0.95)	3.67 (0.93)	t=1.07, p>0.10
24. We assess and manage risks associated with implementing new ideas or technologies.	3.54 (0.94)	3.69 (0.98)	t=1.75, p<0.10
25. Our team engages in continuous learning to keep up with industry innovations and best practices.	3.50 (0.95)	3.69 (1.05)	t=2.13, p<0.05
Observations	252	252	

Notes: The data set covers the years 2024 and 2025. Paired observations are used. Each item is assessed through a five-point Likert scale (Strongly Disagree- Strongly Agree).

Appendix

Table A.III. Scale Validation. AI Capital of Business scale

	Panel I. AI Capital of Business scale (All items)	**Panel II. AI Capital of Business scale (Theme oriented)**
Cronbach's Alpha (α) (All items: 45 items)	0.98	-
Cronbach's Alpha (α) (Theme A. Knowledge: 15 items)	-	0.98
Cronbach's Alpha (α) (Theme B . Skills: 15 items)	-	0.98
Cronbach's Alpha (α) (Theme C. Capabilities: 15 items)	-	0.98
H-test (H index) (All items: 45 items)	0.80	-
H-test (H index) (Theme. Knowledge: 15 items)	-	0.80
H-test (H index) (Theme. Skills: 15 items)	-	0.81
H-test (H index) (Theme. Capabilities: 15 items)	-	0.79
Chi-squared to degrees of freedom ratio (chi2/df)	2.0	2.0
Root Mean Square Error of Approximation (RMSEA)	0.045	0.045
Standardised Root Mean Square Residual (SRMR)	0.013	0.013
Normed Fit Index (NFI)	0.942	0.943
Relative Noncentrality Index (RNI)	0.970	0.971
Comparative Fit Index (CFI)	0.970	0.971
Incremental Fit Index (IFI)	0.970	0.971

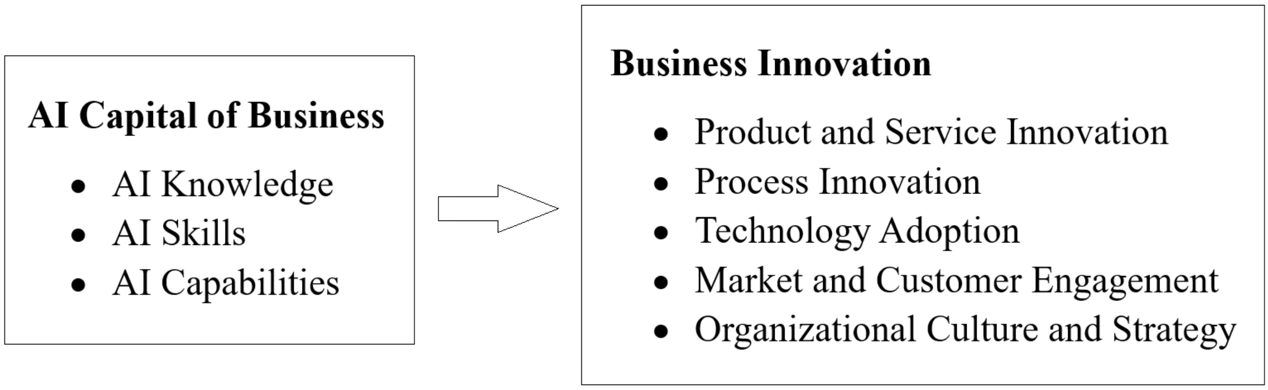
Notes: The data set covers the years 2024 and 2025 (n=504). Paired observations are used.

Appendix
Table A.IV. Scale Validation. Business Innovation scale

	Panel I. Business Innovation scale (All items)	**Panel II. Business Innovation scale (Theme oriented)**
Cronbach's Alpha (α) (All items: 25 items)	0.97	-
Cronbach's Alpha (α) (Theme A. Product and Service Innovation: 5 items)	-	0.89
Cronbach's Alpha (α) (Theme B. Process Innovation: 5 items)	-	0.89
Cronbach's Alpha (α) (Theme C. Technology Adoption: 5 items)	-	0.87
Cronbach's Alpha (α) (Theme D. Market and Customer Engagement: 5 items)	-	0.88
Cronbach's Alpha (α) (Theme E. Organizational Culture and Strategy: 5 items)	-	0.85
H-test (H index) (All items: 25 items)	0.86	-
H-test (H index) (Theme A. Product and Service Innovation: 5 items)	-	0.64
H-test (H index) (Theme B. Process Innovation: 5 items)	-	0.64
H-test (H index) (Theme C. Technology Adoption: 5 items)	-	0.60
H-test (H index) (Theme D. Market and Customer Engagement: 5 items)	-	0.63
H-test (H index) (Theme E. Organizational Culture and Strategy: 5 items)	-	0.63
Chi-squared to degrees of freedom ratio (chi2/df)	2.1	2.2
Root Mean Square Error of Approximation (RMSEA)	0.048	0.048
Standardised Root Mean Square Residual (SRMR)	0.024	0.023
Normed Fit Index (NFI)	0.942	0.943
Relative Noncentrality Index (RNI)	0.968	0.969
Comparative Fit Index (CFI)	0.968	0.969
Incremental Fit Index (IFI)	0.968	0.969

Notes: The data set covers the years 2024 and 2025 (n=504). Paired observations are used.

Figure 1. The relationship between AI Capital of Business and Business Innovation



Notes: The figure presents the AI Capital and Business Innovation model, which suggests that businesses with greater AI Capital are better positioned to drive business innovation.