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Innovative horizons: the impact of AI on entrepreneurial performance

Hanan Alsharah 

Business Management, University of Essex, Colchester, UK

ABSTRACT

This paper investigates the impact of artificial intelligence (AI) on entrepreneurial performance, focusing on firm performance and creativity. While extensive research highlights AI's operational advantages, its impact on fostering entrepreneurial creativity remains insufficiently explored. Drawing on social exchange theory, the study examines how five AI constructs influence firm performance and creativity, which comprise the firm's entrepreneurial performance. Additionally, the paper emphasizes the role of these exchanges in enhancing AI's impact on business outcomes and strengthening entrepreneurial performance. Through a cross-sectional survey and quantitative analysis, the research finds that AI significantly enhances both firm performance and firm creativity, with the latter being a crucial element of entrepreneurial performance, and environmental dynamics playing a critical moderating role. This study contributes to businesses and policymakers aiming to leverage AI for both operational efficiency and creative innovation, providing a framework that connects AI implementation to successful entrepreneurial performance.

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Introduction

Artificial intelligence (AI) has rapidly evolved from a futuristic concept to an indispensable technology shaping modern businesses. Its capacity to process vast amounts of data, automate complex processes, and generate actionable insights has revolutionized industries, providing firms with new tools to drive competitive advantage (Feijóo et al., 2020). Across manufacturing, finance, and retail sectors, AI technologies—ranging from machine learning algorithms to predictive analytics—have streamlined operations, enhanced customer engagement, and enabled faster adaptation to market fluctuations (Chauhan et al., 2021). Governments worldwide also recognize AI's transformative potential, investing heavily in AI infrastructure to accelerate societal progress. The paper highlights AI's transformative potential, where equal emphasis is placed on its implications for entrepreneurial processes such as decision-making, risk-taking, and innovation. This balance underscores how AI enhances entrepreneurial creativity and operational performance, ensuring that the discussion remains centered on the interplay between technology and entrepreneurship. By linking AI constructs directly to entrepreneurial performance, the study provides actionable insights for businesses seeking to integrate AI while maintaining their entrepreneurial agility.

Entrepreneurial performance is referred as the evaluation and measurement of the productivity and effectiveness of entrepreneurs in achieving their organizational goals. Entrepreneurial performance measures the results and outcomes of efforts that a dynamic, skilled, and alert entrepreneur makes in their decision-making and other key operations and processes. Existing research on artificial intelligence extensively addresses its operational benefits in enhancing firm performance, particularly productivity and efficiency. However, a significant gap exists in understanding how AI contributes to firm creativity, which is essential for an entrepreneurial routine. This study bridges the gap by focusing on the dual impact of AI on firm performance and creative innovation, emphasizing the interplay of specific AI

CONTACT Hanan Alsharah  h.alsharah@essex.ac.uk  Business Management, University of Essex, Colchester, UK

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constructs and dynamic environmental factors. Overall, this process plays a key role in boosting a company's performance and effectiveness. It allows professionals to determine what else needs to be done and which gaps can be addressed to enhance decision-making. By exploring specific AI constructs such as decision-making, management, and productivity, the research highlights how AI simultaneously drives efficiency and fosters creativity, thereby enabling firms to achieve a competitive edge through balanced performance enhancements. To explore this relationship, Social Exchange Theory (SET) is adopted as the guiding framework, and it generally posits that reciprocal benefits shape social interactions. Initially proposed by Homans (1958, 1961), SET referred to the principle that people always strive to minimize costs and maximize benefits when acting in a certain way (Abrutyn & McCaffree, 2021). Furthermore, researchers have begun to explore the component of unequal resource distribution and its determinants, thereby adding to the SET theory (Abrutyn & McCaffree, 2021). Molm and other researchers have distinguished between reciprocal and negotiated exchange, examining the concepts of reward power, coercion power, and punishment power (Abrutyn & McCaffree, 2021). Interestingly, SET was used by researchers for different purposes and in various spheres. For instance, in their essay, Nord (1969) applied the theory to better understand the concept of social conformity, indicating that it worked somewhat similarly to people weighing costs and benefits before making decisions.

Historically, SET has been applied to technological solutions by examining how organizations exchange resources, such as data or automation, for operational efficiencies and competitive advantages. For example, in the context of information systems, SET has been used to explain how businesses leverage technology to improve productivity in exchange for investments in IT infrastructure (Li et al., 2024). In this study, AI adoption is viewed as an exchange between businesses, customers, and employees, where the inputs—such as data, automation, and decision-support systems—yield reciprocal benefits in the form of enhanced performance, creativity, and customer loyalty. SET provides a strict and robust framework for understanding the dual impact of AI on entrepreneurial performance.

This paper examines five specific AI constructs: AI Skills (AIS), AI Management (AIM), AI-Driven Decision-Making (AIDDM), AI Basic (AIB), and AI Productivity (AIP) and their influence on firms' operational and creative capacities. For example, AI-driven decision-making enables data-driven insights that enhance strategic decision-making, while AI management focuses on integrating AI systems to improve overall productivity.

Furthermore, the moderating effects of environmental dynamics (ED) and innovation culture (IC) on the relationship between AI and business outcomes must be explored. ED refers to the external factors, such as market volatility and technological change, that influence how businesses implement AI. On the other hand, IC represents the internal environment, where a firm's commitment to fostering innovation and adaptability plays a pivotal role in how AI adoption translates into performance and creativity.

By employing a cross-sectional research design and quantitative analysis of survey data, this study aims to answer two key questions: How do the identified AI constructs influence FP and FC? What role do ED and IC play in moderating these effects? The research thus contributes to theoretical discourse and practical insights, offering valuable guidance for businesses looking to optimize AI-driven outcomes for firm performance and creativity.

The paper is organized as follows: The next section reviews relevant literature on AI's role in business performance and creativity, particularly emphasizing SET as the guiding framework. An outline of the research model and hypotheses follows this. The methodology section details the research design and data analysis techniques, and the results section presents key findings. The paper's conclusion consists of a discussion of implications for both research and practice, along with suggestions for future research directions.

Research background and theoretical foundations

AI technologies

The profound influence that AI can spur wherever it is integrated lies in specific technological solutions it brings. For businesses, ML, automation, and predictive analytics tend to be the most impactful (Chauhan et al., 2021). The first is a branch of AI that utilizes algorithms and statistical frameworks to allow computers to enhance their efficiency on designated tasks over time without direct programming (Sarker,

2021). Specifically, ML enables systems to glean insights from data, recognize trends, and make choices or forecasts based on that information, rendering it a potent instrument for automation and advanced problem-solving across various fields (Sarker, 2021).

In turn, automation denotes implementing technology, including software, machinery, or robotics, to execute tasks or operations with minimal human involvement (Syed et al., 2020). In business environments, automation is utilized across diverse sectors, such as production (e.g. employing robots for assembly lines), clerical duties (e.g. automating data input or payroll processing), and client support (e.g. chatbots managing routine queries) (Hsu & Lin, 2023; Syed et al., 2020). With advancements in AI and ML, automation is evolving, enabling systems to tackle increasingly complex tasks.

Lastly, predictive analytics comprises the utilization of statistical procedures, data mining, and ML algorithms to analyze previous data and project future occurrences (Chauhan et al., 2021). Its chief aim is to generate actionable insights that empower organizations to predict trends and make evidence-based, data-informed choices to optimize both performance and strategy.

AI integration levels

The surge of AI across multiple industries has radically changed how organizations operate, invent, and expand. In the modern business landscape, AI is not only reforming the private sector but also impacting public entities and educational spheres (Feijóo et al., 2020). The private sector has adopted AI as a tool to enhance productivity and expand its market reach. ML, predictive analytics, and automation enable companies to enhance production systems, lower costs, and improve customer relations through individualized services (Coombs et al., 2020). These advancements would allow businesses to make informed decisions, enhance their response to market trends, and discover new revenue streams (Pearson et al., 2020).

In the public sphere, governments and other institutions acknowledge AI's potential to enhance service delivery and policymaking. AI-powered solutions help streamline public services across various sectors, including healthcare, education, transportation, and law enforcement (Kawtar & Khadija, 2024). Governments are increasingly utilizing AI to improve operational efficiency, reduce bureaucratic delays, and provide more personalized services to citizens (Bhattacharya et al., 2024). AI's role in public institutions also extends to national security, where it is being employed in areas such as cybersecurity and intelligence analysis (Bhattacharya et al., 2024). These advancements illustrate how AI is becoming integral to managing public infrastructure and improving governance (Bhattacharya et al., 2024). The application of AI across these domains demonstrates the widespread potential for this technology to enhance public services and drive innovation in governance.

The academic domain holds an essential place in the enhancement and integration of AI technologies. Universities and research centers stand at the forefront of AI research, offering the theoretical frameworks and practical implementations that drive forward AI advancements (Gašević et al., 2023). Collaborative actions between academia, the private sector, and the government have forged a symbiotic loop that accelerates the rate of AI growth and dissemination (Bhattacharya et al., 2024). Research, overall, has been fundamental in extending the frontiers of AI, empowering companies and public entities to tap into its full scope.

The expanding framework facilitating AI incorporation across private, public, and academic domains guarantees that AI will persist in amplifying its influence on society. Cloud-based data hubs, which aid in the storage and examination of extensive data sets, are essential to AI's advancement (Pothukuchi, 2022). By connecting these systems, companies and institutions can preserve valuable expertise while transitioning toward more automated, AI-centric operational models (Dwivedi et al., 2021).

AI and digital infrastructure

A robust digital infrastructure is essential for integrating sophisticated AI systems into both commercial and digital realms. Establishing a coherent system for AI incorporation at the organizational level is crucial, as it allows businesses to capitalize on the prospects that arise from the adoption of AI (Krafft et al., 2020). However, the efficacy of this integration is determined by specific contextual influences, such as

industry attributes, which can shape how AI is embraced and utilized (Kaiser & Kuhn, 2020; Lakshmi & Bahli, 2020).

AI lowers barriers to entry, enabling entrepreneurs with limited resources or technical skills to participate in creative industries. This democratization is evident in the proliferation of AI-assisted self-publishing, music production, and digital art, allowing more creators to bring their ideas to market quickly and at lower cost (Liguori et al., 2024). However, this also leads to market saturation, making it harder for new entrants to achieve visibility and commercial success. Entrepreneurs are leveraging AI to develop novel business models, such as personalized content recommendations, AI-powered design services, and automated marketing solutions. AI enables rapid prototyping, audience targeting, and product iteration, allowing startups to scale more efficiently and respond to market trends in real time. In music and publishing industries, for example, platforms utilise AI to match content with consumer preferences, thereby streamlining the supply and demand process. Recent advancements in AI have had a profound impact on entrepreneurship in the creative industries. AI tools enable faster, cheaper, and more accessible content creation, fostering innovation and new business models. However, these benefits are accompanied by challenges related to copyright, market saturation, and creator inequality (Ciabuschi et al., 2020; Saarikko et al., 2020). The future of entrepreneurship in creative industries will depend on how stakeholders balance technological innovation with ethical, legal, and economic considerations, ensuring that AI enhances, rather than undermines, human creativity and sustainable business growth. Furthermore, regulatory environments and cultural expectations can significantly impact the ease with which AI can be incorporated into an organization's operational framework (Hernández-Betancur et al., 2020). As suggested by Seeber et al. (2020) and Kumar (2020), any successful AI integration at the firm level should be comprehensive, addressing change at multiple organizational levels (Ciabuschi et al., 2020; Saarikko et al., 2020). Moreover, it is crucial to establish standardized training courses to equip employees with the necessary knowledge to work effectively with AI systems. Data analytics should also be utilized to identify specific opportunities for regional economic growth.

AI has already proved its capacity to refine essential functions in various domains, such as logistics, marketing, and financial forecasting, leading to notable enhancements in operational efficiency and competitive edge (Mikalef et al., 2020). These advancements should be perceived as opportunities rather than dangers, as they equip organizations with innovative tools and tactics to prosper in a swiftly changing environment.

AI and sustainability

AI's relationship with sustainability is characterized by both significant opportunities and notable challenges across environmental, economic, and social dimensions. On the positive side, AI technologies are increasingly leveraged to advance the United Nations' Sustainable Development Goals (SDGs), particularly in areas such as climate action, resource management, and environmental monitoring (Wang et al., 2025). For example, AI-driven systems are used for weather prediction, water management, emissions tracking, and waste monitoring, enabling more efficient and targeted interventions in environmental conservation and disaster response. These applications can contribute to reducing global greenhouse gas emissions, with estimates suggesting AI could help cut emissions by 1.5–4% by 2030 through optimization and smarter resource allocation.

However, the rapid expansion and commercialization of AI also introduce substantial environmental costs. The training and deployment of Large Language Models (LLMs) and generative AI systems require vast computational resources, leading to high electricity consumption, significant water usage for cooling data centres, and increased greenhouse gas emissions (Mikalef et al., 2020). For instance, data centers supporting AI models often house tens of thousands of servers and are major consumers of both energy and water, while also generating electronic waste and relying on critical minerals that may be unsustainably sourced. The environmental impact of AI is further compounded by the ongoing operational demands of these systems, with image generation and general-purpose models being especially energy-intensive.

Efforts to mitigate AI's environmental footprint include optimizing the energy efficiency of AI systems, deploying models on edge devices (which use less energy than cloud-based systems), and powering data centers with renewable energy sources. Legislative frameworks such as the European Union's (EU)

AI Act and guidelines from the National Institute of Standards and Technology (NIST) are beginning to address sustainability in AI's design, training, and deployment, though standardized measurement and accountability remain ongoing challenges (Rudko et al., 2021). The development of open-source tools for estimating the carbon emissions of AI models is a step toward greater transparency and responsible innovation.

While AI offers transformative potential for advancing sustainability goals, its environmental costs must be carefully managed through technological, regulatory, and operational strategies.

Privacy and security considerations

While digital tools have become increasingly pivotal in the business realm, their adoption has been hindered by ongoing concerns about confidentiality and security. The regulatory framework also affects the magnitude of these apprehensions, as it can mould public perception and trust in digital tools (Hu et al., 2023). Legal adherence is crucial for companies, which must conform to data protection statutes and ensure the accuracy and integrity of employee and consumer information to enhance corporate security (Chen et al., 2020). Emphasizing adherence to these regulations is vital to alleviate risks and safeguard both the organization and its users. Furthermore, AI can assist in talent acquisition and retention, enhancing productivity by mechanizing processes and refining decision-making at the organizational level (Lee et al., 2019).

In the realm of global commerce, businesses entering international markets must develop products with broad appeal, considering diverse cultural preferences and complying with international laws (El-Mahdy et al., 2024). Successful international ventures often hinge on an understanding of localized needs and the lived experiences of target consumers (Engström & Strimling, 2020; Wang et al., 2022). In today's rapidly evolving technological environment, it is crucial for companies utilising AI to remain vigilant and continually assess their competitive position. It can be achieved through strategies such as niche marketing and the agile adoption of new technologies (Chen et al., 2024). Additionally, corporate entities must recognize the importance of addressing the societal and environmental impacts of their operations.

Artificial intelligence (AI) and social exchange theory

SET serves as an invaluable lens through which to examine business and AI integration. SET posits that interactions between parties are guided by the principle of reciprocity, where benefits exchanged between entities create a sense of mutual obligation (Homans, 1961). In business, this concept of exchange becomes essential when considering the interactions between businesses and consumers, as well as employees and organizations (Saarikko et al., 2020).

SET, traditionally rooted in management literature, offers a useful framework for understanding the value exchange that occurs when firms adopt AI technology. It is built on the premise that interactions between individuals or entities are governed by the exchange of resources based on a cost-benefit analysis. The theory emphasizes reciprocity, trust, and long-term relationships, where each party in the exchange seeks to maximize rewards while minimizing costs. Relationships grow stronger when the benefits provided by one party are deemed valuable by the other, fostering mutual dependence and commitment over time. These exchanges can involve both tangible (monetary, goods) and intangible (information, trust) resources. The resulting success of the relationship depends on the perceived balance between what each party gives and receives (Homans, 1961).

In the domain of AI-driven business, SET enables the exploration of the dynamics of value exchange not merely in the conventional context of financial dealings but also in the exchange of data and knowledge. AI technology modifies the character of benefits exchanged between organizations and consumers, presenting a more intricate and detailed form of interaction where data becomes the new commodity (Orozco et al., 2024). As AI systems compile extensive arrays of consumer data, businesses harness this information to elevate customer experiences, personalize offerings, and enhance operational productivity (Orozco et al., 2024). These results correspond with SET's theory, where businesses exchange insights derived from AI in return for consumer dedication and engagement.

Moreover, the adoption of AI technology alters the way organizations interact with their employees. Within the workplace, SET can be used to understand how AI-driven processes create a new form of exchange where non-monetary benefits, such as flexibility, efficiency, and enhanced job satisfaction, are provided to employees (Rudko et al., 2021). AI likewise allows employees to concentrate on more meaningful tasks, delegating repetitive and low-value work to machines. In return, employees provide the business with higher levels of creativity, problem-solving capabilities, and innovation (Rudko et al., 2021). This reciprocal relationship strengthens organizational performance and aligns with the SET's focus on non-monetary exchanges, which contributes to enhanced employee satisfaction and productivity.

In this context, SET demonstrates why incorporating AI can be highly beneficial for firms. Specifically, by presenting valuable, data-informed recommendations to consumers, companies can build trust and loyalty, which are vital for supporting long-term relationships (Rudko et al., 2021).

AI has the capability to transform traditional transactions by providing a more agile and versatile method for business operations. For instance, AI-enhanced platforms allow firms to more accurately customize their offerings in line with current consumer inclinations, stimulating innovation and adaptability (Chen et al., 2024). The SET model can be employed in this situation by viewing AI as an intermediary mechanism that fosters more effective exchanges between enterprises and consumers (Orozco et al., 2024). In this scenario, AI enables business leaders to present tailored solutions to their customers, enhancing the perceived value of their products and services, which in turn fosters loyalty and lasting customer relationships. Therefore, SET provides a conceptual framework for understanding how companies can utilize AI to advance customer interaction and organizational success.

Furthermore, recent studies highlight AI's role in operational efficiency, particularly in automation and predictive analytics, but its contribution to entrepreneurial creativity remains underexplored (Chen et al., 2024; Mikalef et al., 2020).

Hypothesis development

Building on the established advantages of AI in enhancing business flexibility, communication, and customer engagement, we introduce specific hypotheses derived from these insights. By equipping entrepreneurs with these skills, organizations can identify patterns, forecast trends, and devise creative solutions to complex challenges, ensuring both firm performance and enhanced creativity. These skills allow businesses to integrate AI into their operations, optimizing processes and addressing customer needs with greater precision. AIM encompasses the strategic oversight and governance of AI systems within a firm. Effective AIM involves not only the selection and implementation of AI technologies but also the continuous monitoring of their performance to ensure alignment with business objectives. This factor is crucial in balancing the potential risks and rewards associated with AI, enabling firms to effectively leverage AI in ways that enhance operational efficiency and market competitiveness.

The third factor, AIDDM, highlights the role of AI in enhancing the quality and speed of business decisions. By automating complex decision-making processes and analyzing large datasets in real time, AI helps businesses make more informed, timely, and accurate decisions. AIB refers to the foundational technologies that support AI integration within a firm's operations, including ML algorithms, predictive analytics, and automation tools (Ivcevic & Grandinetti, 2024). Finally, AIP focuses on the impact of AI on a firm's output and overall efficiency. In other words, it refers to the tangible improvements in business processes, such as reduced costs, faster production times, and enhanced customer service, that result from the adoption of AI (González-Sendino et al., 2024). The hypotheses developed in the following section will test the extent to which these AI factors contribute to organizational success and sustained competitive advantage.

AI and business performance

The cultivation of AIS within organizations fosters enhanced operational capabilities, which in turn bolsters business outcomes (Mikalef et al., 2020). As companies advance their adeptness in utilizing AI technologies, they can seamlessly embed these tools into their current processes, leading to more accurate decision-making and efficient operations. Such expertise also empowers organizations to adapt more

swiftly to market changes and consumer preferences, ensuring that their products or services stay relevant and competitive (Dwivedi et al., 2021). By cultivating strong AI systems, companies position themselves to unlock the full benefits of AI, thereby enhancing their performance and increasing their chances of success.

Moreover, the ability to manage AI effectively assumes a pivotal role in aligning AI technologies with a company's broader business objectives. Effective AIM enables firms to not only select and implement the right AI tools but also continuously assess their performance to mitigate risks and optimize benefits. This strategic oversight allows businesses to extract maximum value from AI systems, improving their operational efficiency and competitiveness (Adamides & Karacapilidis, 2020). Firms with robust AIM capabilities are thus better equipped to scale their operations, adapt to market demands, and sustain long-term growth, positively impacting their overall performance.

Similarly, AIDDM enhances a firm's ability to make more accurate and timely business decisions, which is crucial for maintaining a competitive advantage. By automating the decision-making workflow, AI reduces human error and accelerates the analysis of complex information sets, leading to swifter and more informed strategic decisions. This capability enables companies to respond to real-time information, adapt to industry fluctuations, and capitalise on opportunities with greater speed than their adversaries. Consequently, firms utilizing AIDDM are poised to achieve increased performance through better resource management, risk oversight, and market adaptability.

In this context, having a strong foundational AI infrastructure enables firms to integrate AI technologies more seamlessly into their operations. By building a robust AIB, businesses can support more advanced AI applications that drive efficiency and innovation (Ivcevic & Grandinetti, 2024). This foundational layer enables the easier scalability and adaptability of AI solutions, contributing to market share growth (Adamides & Karacapilidis, 2020). Therefore, a well-established AIB ensures that businesses can improve their processes without significant interruptions and stay ahead of technological advancements, directly benefiting their performance in the long run.

Lastly, AIP improvements have a direct and measurable impact on a firm's output, resulting in enhanced business performance. By leveraging AI to automate routine tasks, reduce errors, and expedite production times, businesses can enhance their operational efficiency while lowering costs (González-Sendino et al., 2024). Additionally, AIP gains allow firms to deliver higher-quality products and services, which can bolster customer satisfaction and loyalty (González-Sendino et al., 2024). The continuous improvements in efficiency and service delivery enabled by AI translate into better financial outcomes, positioning firms for sustained growth and success.

These notions serve as a basis for the first set of the study's hypotheses (Figure 2):

- H1: AIS positively influences FP.
- H2: AIM positively influences FP.
- H3: AIDDM positively influences FP.
- H4: AIB positively influences FP.
- H5: AIP positively influences FP.

AI and business creativity

AI enhances creativity by enabling businesses to explore uncharted territories and create new strategies that go beyond incremental improvements, addressing fundamental market challenges and consumer needs (Chen et al., 2024). Creativity involves generating original and valuable ideas that meet specific business objectives, making it a broader and more inclusive concept than innovation (Gajdzik & Wolniak, 2022).

AIS assumes a central position in fostering business creativity by equipping firms with the technical expertise needed to explore new ideas and concepts. The ability to utilize AI effectively allows firms to process and analyze vast amounts of data, revealing patterns and insights that inspire creative solutions to complex problems (Alaassar et al., 2020; Moşteanu, 2019). With well-developed AIS, businesses can craft original strategies and adapt to emerging trends more proactively (Chen et al., 2024). Firms that invest in AIS thus have a greater capacity to generate creative, customer-centered solutions that set them apart from competitors.

In turn, AIM is directly responsible for overseeing the creative use of AI within a firm. Effective management of AI systems enables businesses to govern how AI is applied across different contexts, fostering an environment conducive to creativity (Weller, 2019). For example, long-term-oriented strategic oversight facilitates the application of AI to uncover new business opportunities, experiment with creative business models, and develop novel approaches to meet customer needs. Consequently, well-managed AI fosters a cycle of continuous creativity within organizations. Therefore, Table 1 presents the theoretical explanation of each construct, including its influences on firm performance and creativity, with relevant examples.

From a short-term perspective, AIDDM enhances creativity by enabling businesses to rapidly evaluate data and adjust strategies based on real-time market insights (Moşteanu, 2019). AI's capacity to assess large datasets almost instantaneously allows firms to make informed, creative decisions that align with changing market conditions (Chen et al., 2024). This capacity for rapid adjustment encourages businesses to be more flexible and innovative, leading to the generation of new ideas and approaches that would not have been possible without AI's analytical power. This way, the application of AI in decision-making processes enables firms to identify creative business opportunities.

A firm's AIB lays the groundwork for creative activities by providing the necessary infrastructure to explore and implement AI-driven solutions. As mentioned earlier, a solid AI foundation enables businesses to integrate AI technologies seamlessly into their operations, providing the means to explore innovative possibilities (Ivcevic & Grandinetti, 2024). That is, the scalability of AI systems enables firms to test new ideas in a controlled, efficient manner, allowing them to iterate and refine concepts more rapidly (Tatineni & Boppana, 2021). The ability to experiment and adapt continuously gives firms a competitive edge, ensuring they stay ahead in a dynamic market.

Finally, AIP supports FC by enabling businesses to devote more time to creative and strategic initiatives. By automating routine tasks and procedures, such as data entry, report generation, and predictive analysis, and improving operational efficiency, AI frees up human resources that can be redirected toward innovation and creativity (Eziefule et al., 2022; González-Sendino et al., 2024). The increased productivity creates more space for experimentation and the exploration of new business models, products, and services. In the meantime, the resulting agility and responsiveness to market changes foster a culture of creativity that thrives on flexibility and continuous improvement.

The outlined connection between FC and AI factors leads to the formulation of the second set of hypotheses (Figure 2):

- H6: AIS positively influence FC.
- H7: AIM positively influences FC.
- H8: AIDDM positively influences FC.
- H9: AIB positively influences FC.
- H10: AIP positively influences FC.

Moderating effects of IC and ED

IC and ED are pivotal in moderating the relationship between AI implementation and business outcomes. IC, which embodies a company's openness to new ideas, creativity, and experimentation, significantly impacts FC by encouraging innovative thinking and risk-taking among employees (Alenizi et al., 2024). In this context, fostering a strong internal culture (IC) within a firm enables AI-driven initiatives to thrive, as employees are more likely to embrace new technologies, propose creative solutions, and experiment with AI applications. As Papadouli and Papakonstantinou (2023) suggest, AI adoption in firms helps organizations identify weak points in their marketing strategies, leading to recalibration and enhanced creativity. Therefore, a culture that promotes innovation enables firms to maximize the creative potential that AI brings, driving new product development, process improvements, and overall business growth.

Research highlights that aligning AI adoption with a firm's strategic goals and accounting for ED can significantly enhance productivity and creativity (Kristoffersen et al., 2020). For example, by integrating AI with traditional industries and fostering public-private partnerships, firms can capitalize on AI's

Table 1. AI constructs and influences.

AI constructs	Theoretical explanation	Citations	Firm performance & creativity examples
AI skills (AIS)	<p>AI skills are not only vital for technical innovation but are also foundational to organizational agility, personal career growth, and the broader adaptation of society to technological change. Theoretical frameworks and empirical evidence converge on the view that a balanced, inclusive approach to AI skill development—encompassing both technical and human-centric competencies—is essential for sustainable success in the age of AI.</p> <p>Share Export Rewrite Related</p> <p>How does AI's role in skill augmentation balance human expertise and machine support? Why is developing AI skills essential for future workforce competitiveness How can AI help bridge the gap between current human skills and industry demands? What are the potential risks of over-reliance on AI for skill development How does understanding the paradox of augmentation inform effective AI skill training</p>	(Dwivedi et al., 2021)	Firms with strong AI skills can automate routine tasks, optimize operations, and make data-driven decisions, leading to measurable improvements in productivity and efficiency. For example, McKinsey estimates that AI could add \$4.4 trillion in productivity growth globally, with firms that successfully embed AI skills capturing a significant share of this value.
AI management (AIM)	AI Management (AIM) is theoretically justified as an essential organizational capability that bridges the technical, ethical, and strategic dimensions of AI deployment. By grounding AIM in socio-technical theory, control-accountability alignment, and dynamic governance, organizations can harness AI's benefits while safeguarding against its risks. The adoption of robust frameworks and principles for AIM is critical to ensuring that AI serves as a force for organizational and societal good.		AI automates repetitive and time-consuming tasks, such as inventory management, customer service, and logistics, leading to significant increases in operational efficiency and reductions in human error and operating costs. For example, manufacturing firms use AI to predict and prevent machine faults, minimizing downtime and maintenance expenses.
AI-driven decision-making (AIDDM)	<p>AI-driven decision-making represents a paradigm shift in how organizations and individuals process information, leveraging computational power to overcome inherent human limitations. The foundation rests on three pillars:</p> <p>Augmentation of bounded rationality, Optimization of uncertainty management, Synergistic human-AI collaboration</p>	(Olan et al., 2022)	AI-driven decision-making significantly enhances firm performance by improving decision accuracy, speed, and resource allocation, while also enabling more effective strategic planning and risk management. At the same time, AIDDM boosts organizational creativity by freeing up human capacity for innovative work and facilitating the exploration of novel solutions, especially in firms with strong innovation cultures. Case studies across sectors—from e-commerce to technology—demonstrate that firms leveraging AIDDM achieve higher productivity, greater adaptability, and sustained competitive advantage.
AI basic (AIB)	AI Basic (AIB) is theoretically justified as both a model for exploring the building blocks of intelligence and as a practical approach to automating complex, human-like tasks within specific domains. Its development draws on interdisciplinary insights from computer science, cognitive psychology, neuroscience, and related fields, and represents the essential first tier in the broader hierarchy of AI research and application.	(Adamides & Karacapilidis, 2020)	AI Basic (AIB) technologies significantly enhance firm performance by automating processes, improving decision-making, and enabling scalable operations. They also support creativity by augmenting human capabilities, freeing time for innovation, and providing tools for ideation and content creation. Real-world examples across industries—from manufacturing to retail and healthcare—demonstrate that firms adopting AIB not only achieve operational gains but also foster a culture of continuous innovation and creative problem-solving.
AI productivity (AIP)	The theoretical argument for AI Productivity is that AI fundamentally reshapes the production function by automating routine work, amplifying human cognition, enabling superior data-driven decisions, and fostering organizational innovation. These mechanisms collectively drive substantial and measurable productivity gains at the individual, organizational, and macroeconomic levels.	(Tatineni & Boppana, 2021)	AI Productivity (AIP) significantly boosts firm performance by automating routine work, enhancing operational efficiency, and enabling faster, more accurate decision-making. It also fosters creativity by empowering both highly skilled and less-experienced workers to contribute more innovative ideas and solutions. Case studies from leading firms like Meta and JPMorgan, as well as empirical research across sectors, demonstrate that AI not only increases output and profitability but also elevates the creative capacity of organizations.

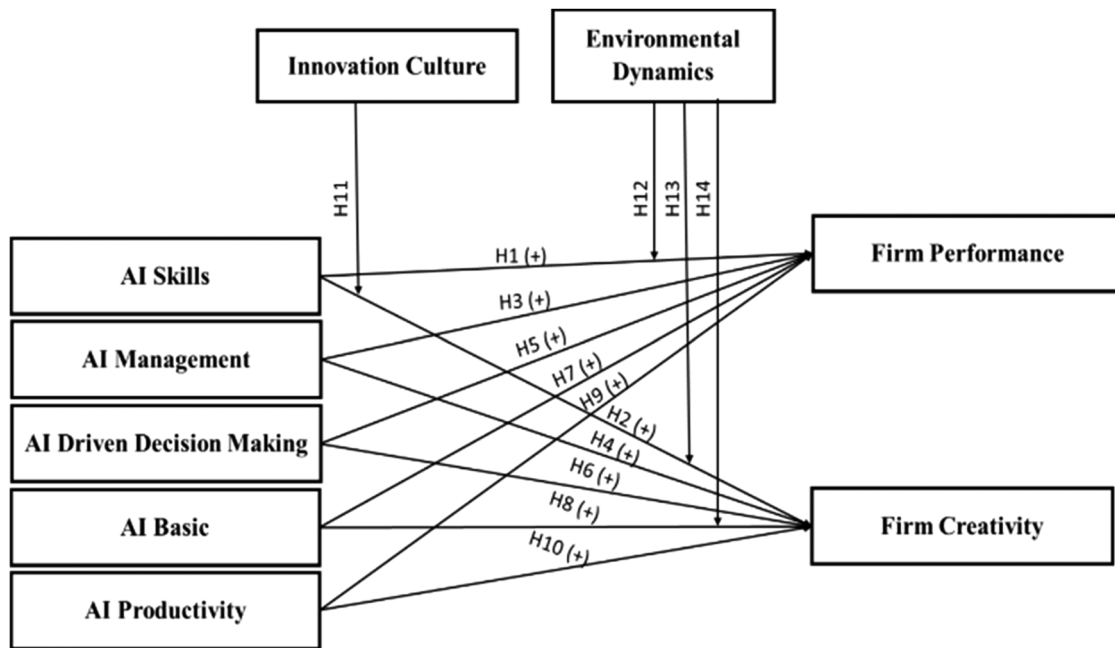


Figure 1. Relationship diagram of the framework of the study.

capabilities to drive economic growth and innovation (Alaassar et al., 2020). In this regard, AI becomes a catalyst for broader economic development and societal progress. Firms that successfully align their IC with external environmental factors can leverage AI to stay competitive in dynamic markets, enhance their creative output, and achieve sustained growth (Chen et al., 2024; Weller, 2019).

Moreover, IC and ED ensure that AI adoption is not merely a technological upgrade but a strategic initiative aligned with the firm's long-term objectives. Figure 1 shows the relationship between AI and its effect on the firm with IC and ED. Also, in this figure, you may see the relationship between IC and ED and the impact of FP and FC as well. By fostering an innovation-driven culture and being responsive to external environmental changes, firms can address market challenges more effectively, ensuring that AI implementation contributes meaningfully to business performance and creativity (Moşteanu, 2019). This strategic alignment allows firms to navigate uncertainties while reaping the benefits of AI technologies. Thus, IC and ED are deemed important for ensuring that AI adoption drives meaningful business outcomes, including enhanced FP and FC.

In this context, the last set of hypotheses (Figure 2) for this study is formulated as follows:

- H11: IC moderates the relationship between AIS and FC.
- H12: ED moderates the relationship between AIS and FP.
- H13: ED moderate the relationship between AIS and FC.
- H14: ED moderate the relationship between AIB and FC.

Research method

Research design

The current investigation assumes a descriptive research design. This design framework is suitable for the investigation because no preconceived views or opinions were formed prior to embarking on the research project. This type of research design thus has a low risk of bias (Wilde, 2020). This property of the research process equally makes it possible to expand the findings of the investigation beyond the primary scope of the research (Kwak & Yoon, 2020). This paper systematically explores AI's impact on business, employing quantitative synthesis to derive findings on the effect on performance and creativity. It unveils both positive outcomes and challenges organizations encounter in AI integration, offering valuable insights into operational dynamics (Hu & Bentler, 1999; Shen et al., 2020). The materials included in

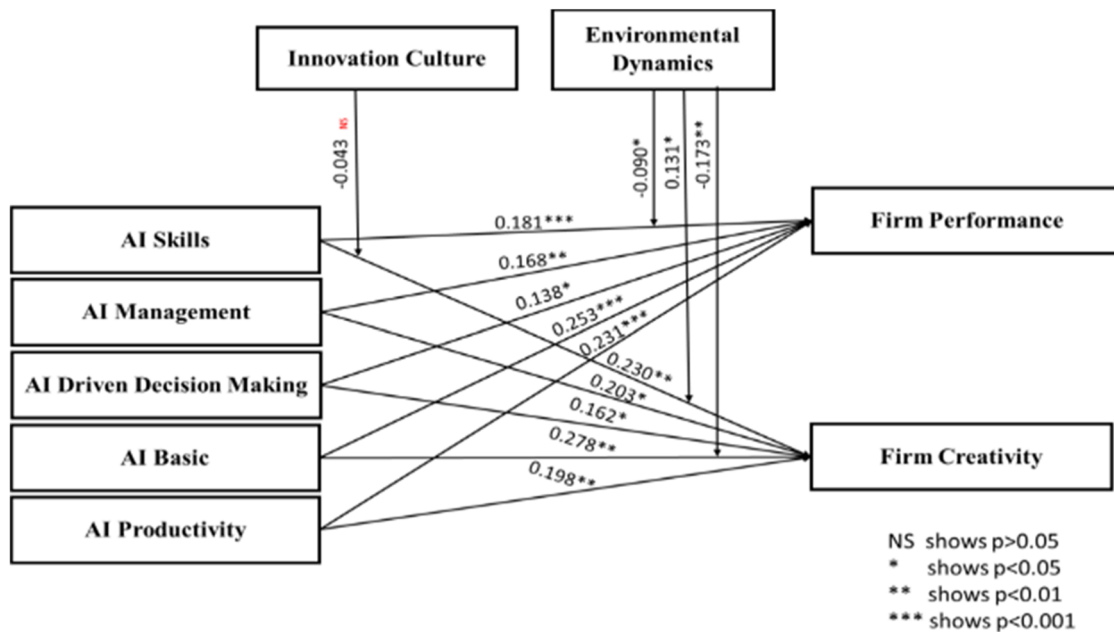


Figure 2. Hypothesis coefficients.

this study include a thorough review of academic articles and research papers related to the application of AI in business, productivity, creativity, and risk assessment (Chesbrough, 2020). Sources of information include scientific journals, industry reports, and expert opinions.

The research method employed a comprehensive analysis and synthesis of information from various sources to assess the impact of contextual factors on the relationship between AI adoption and business success (Dwyer, 2020; Thomas et al., 2020).

Questionnaire design and measures

The questionnaire was segmented into two parts. The first part gathered demographic information about the respondents, such as their gender, age, educational qualifications, and residence, while the second was focused on the study's problem. These variables were pivotal for the assessment as they aided in scrutinizing the traits of the respondents and their influence on their opinions (Hildebrand et al., 2020). Consequently, it became feasible to discern the effects of cultural or societal conditioning on the perspectives presented by the participants in the study (Kristoffersen et al., 2020). Consent was obtained from the participants via the same document, as the first page required them to affix their signatures to a declaration acknowledging that they comprehended all the details of the study, including their voluntary involvement. In the questionnaire, we did obtain formal consent from all participants before collecting the data for this study. The constructs employed in the examination are cataloged in Table 2 below. Also, Table 3 will show the constructs employed in this study, and their reliability metrics are summarized. This table provides details such as composite reliability (CR) and average variance extracted (AVE) values for each construct, ensuring the validity and reliability of the measures used in the study.

Data analysis and results

Preliminary analysis

In the study, AMOS was employed to examine the effects captured by our assessment model and the subsequent structural regression model, as outlined by Anderson and Gerbing. This statistical software facilitated a detailed evaluation of the relationships between variables through covariance structure analysis (Jain & Ranjan, 2020). Additionally, for both the Measurement and Structural Model Analysis, the

Table 2. Reliability analysis of constructs.

Construct	Composite reliability (CR)	Average variance extracted (AVE)
AIS	0.856	0.543
AIM	0.779	0.543
AIDDM	0.822	0.536
AIB	0.830	0.550
AIP	0.816	0.526
FP	0.843	0.573
FC	0.810	0.591
IC	0.768	0.525
ED	0.816	0.526

Notes: AIS: AI skills; AIM: AI management; AIDDM: AI-driven decision-making; AIB: AI basic; AIP: AI productivity; FP: firm performance; FC: firm creativity; IC: innovation culture; ED: environmental dynamics.

Table 3. Standardized regression weights for constructs.

Construct	Item	Factor loading
AIS	AIS5	0.773
	AIS4	0.703
	AIS3	0.726
	AIS2	0.736
	AIS1	0.743
AIM	AIM1	0.742
	AIM2	0.635
	AIM3	0.821
AIDDM	AIDDM1	0.685
	AIDDM2	0.723
	AIDDM3	0.758
	AIDDM4	0.760
AIB	AIB1	0.736
	AIB2	0.724
	AIB3	0.780
	AIB4	0.726
AIP	AIP1	0.756
	AIP2	0.713
	AIP3	0.719
	AIP4	0.712
FP	FP1	0.719
	FP2	0.743
	FP3	0.721
	FP4	0.840
FC	FC1	0.896
	FC2	0.657
	FC3	0.732
IC	IC1	0.759
	IC2	0.705
	IC3	0.709
ED	ED1	0.717
	ED2	0.708
	ED3	0.715
	ED4	0.761

study utilized the James Gaskin AMOS plugin. This plugin provided enhanced functionality for executing complex SEM techniques, enabling one to accurately measure constructs and assess the validity and reliability of the model configurations. This combination of advanced tools ensured a rigorous analysis, adhering to contemporary standards in structural equation modeling.

The demographic statistics from the study reveal the varied backgrounds of the 309 contributors involved. The gender distribution among the contributors is relatively even, with males making up 54.4% (168 individuals) and females constituting 45.3% (140 individuals). An extra participant categorized as 'Other' comprises 0.3% of the sample. The majority of contributors fall within the age bracket of 25 to 30 years, accounting for 59.2% (183 individuals), followed by 27.2% (84 individuals) in the 31 to 35-year range, 11.3% (35 individuals) aged 36 to 40, and 2.3% (7 individuals) over 40 years.

Educational backgrounds were predominantly at the bachelor's degree level, with 83.8% (259 individuals), while 8.1% (25 individuals) held a master's degree, and another 8.1% were senior high school graduates. Geographically, the participants were widely dispersed, with the United States of America (31.1%, 96 individuals) and the United Kingdom (24.9%, 77 individuals) hosting the largest groups,

Table 4. Demographic distribution of participants.

Demographic variable	Category	Frequency	Percent
Gender	Female	140	45.3
	Male	168	54.4
	Other	1	0.3
Age	25–30	183	59.2
	31–35	84	27.2
	36–40	35	11.3
	Above 40	7	2.3
Educational Background	Bachelor's Degree	259	83.8
	Master's Degree	25	8.1
	Senior High School Graduate	25	8.1
Location	Canada	64	20.7
	China	2	0.6
	Kuwait	29	9.4
	Others	4	1.3
	Singapore	37	12.0
	United Kingdom	77	24.9
	United States of America	96	31.1

followed by Canada (20.7%, 64 individuals), Singapore (12%, 37 individuals), Kuwait (9.4%, 29 individuals), and smaller representations from China (0.6%, 2 individuals) and other locations (1.3%, 4 individuals). The diverse demographic composition underscores the broad geographic and socio-cultural representation in the study.

In Table 4, shows the demographic distribution of participants, including gender, age, educational background, and geographic location. This shows the important of the diversity of the sample and supports the generalizability of the findings.

Measurement model

Using James Gaskin plugins, this study utilized a range of validity indices to ensure the robustness and reliability of the constructs within the measurement model. Composite Reliability (CR) scores, ranging from 0.768 to 0.856, indicated satisfactory internal consistency among the constructs, confirming the reliability of the measures (Wang et al., 2020). Average Variance Extracted (AVE) values between 0.525 and 0.591 indicated strong convergent validity, suggesting that a significant portion of the variance in observed variables was attributable to the latent constructs. Discriminant validity was also affirmed as MSV values were consistently lower than the AVE values for all constructs, further establishing the uniqueness of each construct.

Significant correlations were observed between constructs such as AIM and AIDDM at 0.363 ($p < 0.001$), reflecting strong and meaningful inter-construct relationships (Libai et al., 2020). These relationships align with theoretical expectations and provide empirical support for the hypothesized links within the model. Additionally, the Heterotrait-Monotrait ratios were significantly below the conservative threshold of 0.85, as suggested by Henseler et al. (2015), confirming clear discriminative validity among constructs and ensuring accurate interpretations of the causal relationships specified in the model.

After evaluating consistency and precision, the model's general fit was assessed using several fit indices. The Chi-Square/DF (CMIN/DF) ratio was 1.127, situated within the outstanding range and reflecting a very favorable congruence between the hypothesized model and the actual data (Pekkarinen et al., 2020). The Comparative Fit Index (CFI) was 0.988, comfortably surpassing the usual threshold of 0.95, suggesting a superb fit. Similarly, the Standardized Root Mean Square Residual (SRMR) was 0.045, and the Root Mean Square Error of Approximation (RMSEA) was 0.020, both well within the acceptable limits and demonstrating a superior fit of the model to the data. These metrics collectively illustrate that the model is aptly suited to clarify the observed variances and covariances, corroborating the methodological rigor of the performed analysis and the efficacy of the selected SEM approach.

Factor loadings for the variables in this study were also thoroughly analyzed and found to meet the established threshold of 0.50, indicating adequate item reliability and construct validity. For instance, loadings within the AIS construct ranged from 0.703 to 0.773, and AIM showed a robust range from 0.635 to 0.821. Similarly, other constructs such as AIDDM, AIB, AIP, FP, FC, IC, and ED all demonstrated

strong loadings, with the highest observed at 0.896 for FC1. These values not only affirm the constructs' individual integrity but also substantiate the overall structural integrity of the chosen model.

Model testing

In this research study, the impact of various technologically backed constructs on FP and FC was examined. The analysis revealed significant relationships between the two variables. Notably, it was discovered that both AIS and AIM have robust impacts on organizational success. For instance, AIS positively influenced organizational success based on the equation FP ($\beta = 0.181$, $p=0.001$). It was equally demonstrated that it had a significant impact on performance FC ($\beta = 0.230$, $p=0.002$). At the same time, the findings of the study revealed that AI had a positive effect on FP ($\beta = 0.168$, $p=0.008$) and FC ($\beta = 0.203$, $p=0.015$). The findings of this study equally addressed the role of AI in decision-making. Relative to this area of the analysis, AIDDM accounted for positive business outcomes FP ($\beta = 0.138$, $p=0.022$) with an effect size of FC ($\beta = 0.162$, $p=0.044$). Additionally, constructs like AIB and AIP similarly had strong positive influences on FP, with the latter notably affecting FC. In Table 5, shows the direct effects of the AI constructs on firm outcomes, including firm performance (FP) and firm creativity (FC). This table presents the regression coefficients, p-values, and fit indices, demonstrating the statistical significance and robustness of the relationships.

Moderating effects

The analysis of moderating effects in the structural model further expands one's understanding of how different contexts and interactions between variables can influence the relationships between AI constructs and firm outcomes. The study evaluated several moderating variables to see how they alter the effects of AI-related factors on FP and FC. Significant results were observed in the moderating effect analysis. For instance, AIS modified by ED negatively impacted FP ($\beta = -0.090$, $p=0.018$), suggesting that in certain dynamic environments, the direct positive impact of AIS on performance may be dampened.

Conversely, the interaction of AIM with ED positively influenced FC ($\beta = 0.131$, $p=0.021$), indicating that more dynamic environments could enhance the positive effects of AIM on FC. Furthermore, AIB moderated by ED also showed a significant negative influence on FC ($\beta = -0.173$, $p=0.005$), suggesting that the benefits perceived from AI might decrease creativity in highly dynamic settings. Interestingly, the interaction between AIS and IC did not significantly affect FC ($\beta = -0.043$, $p=0.423$), implying that the cultural context related to innovation does not significantly alter the relationship between AIS and FC.

The model fit for the moderation analysis remained excellent, demonstrating the robustness of the moderating effects within the structural model. The CMIN/DF ratio was 1.085, the CFI was 0.988, the SRMR was 0.042, and the Root RMSEA was 0.017. These fit measures indicate that the model with the moderators included provides an accurate representation of the data and supports the validity of the obtained results. In Table 6, it shows the moderating effects of predictors, and the outcomes moderator estimate the P-value. The results provide insights into how external and internal factors influence the impact of AI on firm performance and creativity.

Table 5. Direct effects of AI constructs on firm outcomes.

Predictor → outcome	Estimate	p-value
AIS → FP	0.181	0.001
AIM → FP	0.168	0.008
AIDDM → FP	0.138	0.022
AIB → FP	0.253	<0.001
AIP → FP	0.231	<0.001
AIS → FC	0.230	0.002
AIM → FC	0.203	0.015
AIDDM → FC	0.162	0.044
AIB → FC	0.278	0.002
AIP → FC	0.198	0.008

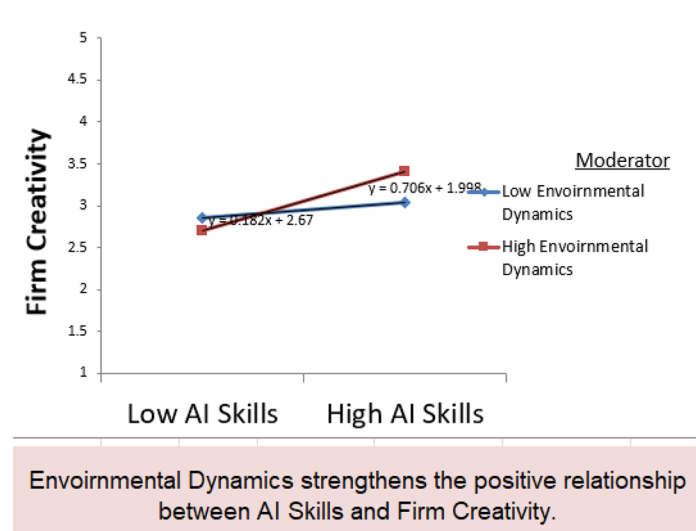
CMIN/DF = 1.127, CFI = 0.988, SRMR = 0.045, RMSEA = 0.020, PClose = 1.000.

Notes: CMIN/DF: Chi-Square/DF; CFI: comparative fit index; SRMR: standardized root mean square residual; RMSEA: root mean square error of approximation.

Table 6. Moderating effects.

Predictor → outcome	Moderator	Estimate	p-value
FP ← AIS_x_ED	ED	−0.090	0.018
FC ← AIM_x_ED	ED	0.131	0.021
FC ← AIB_x_ED	ED	−0.173	0.005
FC ← AIS_x_IC	IC	−0.043	0.423

CMIN/DF = 1.085, CFI = 0.988, SRMR = 0.042, RMSEA = 0.017, PClose = 1.000.

**Figure 3.** Relationship between AI skills and firm performance.

As shown in Figure 2 above, ED have a more significant role to play in influencing FP and FC compared to IC. This statement is supported by the fact that IC did not meet the significance threshold of $p > 0.05$. This figure represents the cut-off point for evaluating whether actions from one variable affected another (Hu & Bentler, 1999). The rest of the variables met the significance threshold of $p > 0.05$, indicating the absence of a cause-and-effect relationship between AI and FP (Henseler et al., 2015). The findings support the narrative that ED play a significant role in influencing the relationship between AI, FP, and FC.

Post-hoc analysis

Figure 3 depicts that ED substantially diminishes the positive correlation between AIS and FP. With minimal ED, the correlation is more accentuated ($y = 0.544x + 2.212$), while it weakens under high ED conditions ($y = 0.184x + 2.696$). Similarly, ED exhibits a comparable moderating influence on the connection between AIB and FC: elevated ED results in a more gradual slope ($y = 0.03x + 3.012$), signifying a diminished connection, unlike the more robust relationship seen in low dynamic settings ($y = 0.722x + 1.86$). Regarding FC, Figure 4 indicates that ED amplifies the positive association with AIS. The slope is notably steeper in high dynamic contexts ($y = 0.706x + 1.998$) in contrast to lower ones ($y = 0.102x + 2.67$). These results underscore the intricate interactions between AI constructs and the business context, implying that the efficacy of AI in enhancing FP and FC can greatly rely on external circumstances.

Discussion

AI constructs effect on FP

The results demonstrate a clear and significant influence of AI constructs on FP, confirming the existing literature that suggests AI plays a critical role in driving business success. Each AI construct makes a positive contribution to FP, although the magnitude and mechanisms of these effects vary across the constructs. Firstly, AIS emerged as a strong determinant of FP, **confirming the H1**. Firms with high levels

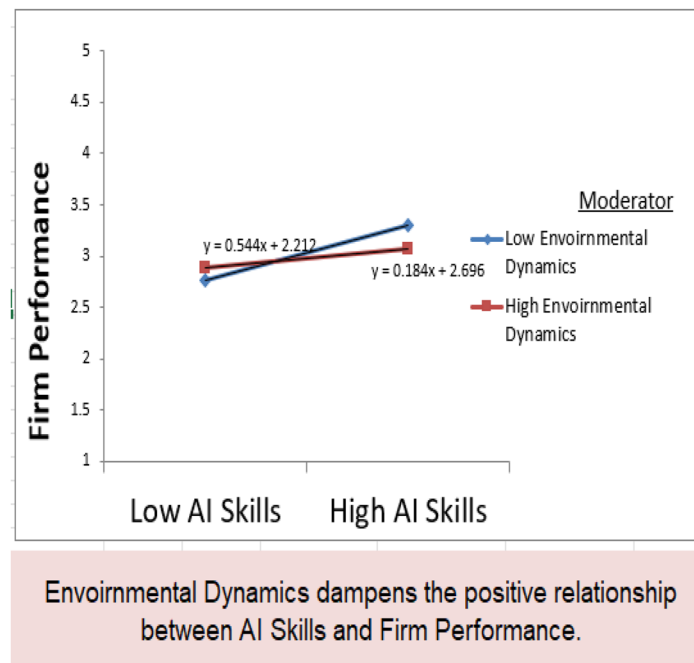


Figure 4. Relationship between AI skills and firm creativity.

of AIS benefit from enhanced technical and analytical abilities, allowing them to integrate AI technologies more effectively into their operations. Secondly, the confirmed positive relationship between AIM and FP **proves H2** and highlights the importance of strategic oversight and governance in the deployment of AI technologies (Moşteanu, 2019). Effective AIM thus goes beyond the technical implementation of AI systems; it encompasses strategic decision-making regarding which AI applications to prioritize, ensuring that AI-driven initiatives align with broader business goals.

Thirdly, the **confirmation of H3** regarding the impact of AIDDM on FP reflects the growing reliance of firms on AI for data-driven insights. The ability to make informed and timely decisions is crucial for maintaining a competitive edge in today's fast-paced markets, and AIDDM provides firms with the agility needed to stay ahead of their competitors. Fourthly, AIB was confirmed to exert a strong positive influence on FP, **proving the H4**. Thus, the foundation provided by AI enables firms to build more complex AI-driven systems over time, further solidifying their performance improvements (Ivcevic & Grandinetti, 2024). Lastly, the **confirmation of H5** shows that AIP has a significant positive impact on FP, indicating that AI adoption leads to measurable gains in performance (González-Sendino et al., 2024).

AI constructs effect on FC

The results of this study reveal that each AI construct contributes to a culture of innovation, transforming traditional creativity processes within firms into more dynamic, efficient, and scalable operations. **H6 was confirmed**, indicating that the integration of AIS in a firm expands the boundaries of what is creatively possible by enhancing employees' ability to experiment with AI technologies. The **confirmation of H7** highlights the role of AIM in steering the creative energies of a firm toward strategic goals (Chen et al., 2024). In this sense, AIM acts as a creative catalyst, ensuring that innovation is not just a byproduct of AI use but a deliberate outcome of strategic planning.

H8 also proved to be correct, validating the AIDDM's contribution to FC through new and actionable insights that stimulate creative thinking. The data-driven approach to creativity allows firms to ground their innovations in solid evidence, reducing the risk associated with creative endeavors (Chen et al., 2024). AI significantly shapes entrepreneurial risk-taking by both reducing and transforming the nature of risks faced by entrepreneurs. AI's ability to automate repetitive tasks, analyze vast datasets, and generate predictive insights enables entrepreneurs to make more informed decisions, identify new business

opportunities, and optimize strategies—thereby lowering the perceived barriers to risk-taking. For example, AI-powered analytics can assess market trends, forecast demand, and support financial planning, which helps entrepreneurs anticipate and mitigate risks before they escalate.

Empirical research shows that firms with a higher propensity for risk-taking are more likely to adopt AI, leveraging it as a strategic resource to experiment with innovative products and business models despite uncertainties. AI adoption thus enhances internal capabilities and competitive advantage. Furthermore, AI-driven risk assessment tools can identify potential threats, prevent fraud, and streamline compliance, making risk management more proactive and precise.

In the meantime, **confirmation of H9** illustrates the role of AIB as the bedrock upon which creative processes can flourish. In essence, AIB provides the operational scaffolding that supports and accelerates creative output, making it possible for firms to innovate at a faster pace (Alaassar et al., 2020). Finally, the **truthfulness of H10** was established, proving that AIP enhances FC by optimizing the efficiency of creative processes (Alaassar et al., 2020). Namely, AIP not only boosts the quantity of creative output but also improves its quality by enabling firms to refine their ideas more quickly and effectively.

IC and ED moderation

The analysis of the moderating effects of IC and ED on AI constructs and firm outcomes presents nuanced insights into how these external factors influence the relationships between AI, FP, and FC. First and foremost, the results of the study **disproved H11**, which hypothesized that IC would moderate the relationship between AIS and FC. The interaction between AIS and IC did not meet the significance threshold, suggesting that IC does not significantly alter the relationship between AIS and FC.

This unexpected outcome may be attributed to the complexity of translating an innovative culture into tangible creative outcomes when AI technologies are involved (Mikalef & Gupta, 2021). Although a strong IC theoretically promotes creativity, the results indicate that possessing AIS may be sufficient for driving creativity regardless of the cultural context. In this scenario, the technical capabilities and problem-solving potential offered by AIS may already provide firms with the tools they need to foster creativity, limiting the influence of IC. Additionally, organizational structures and management practices may play a larger role in shaping creativity than the broader cultural emphasis on innovation. Overall, further, more nuanced research into the IC's moderation of AIS and FC is necessary.

In the meantime, **H12 was supported**, confirming that ED moderates the relationship between AIS and FP. The study found a significant moderating effect of ED on this relationship with a negative influence. The findings suggest that in more dynamic environments, the positive effects of AIS on FP are dampened. Such an outcome aligns with expectations, as dynamic environments often introduce uncertainty and instability that can hinder the full realization of AIS' potential (Chehabeddine & Tvaronavičienė, 2020). Firms in stable environments have more consistent conditions to apply AI-driven insights and technical skills, allowing them to optimize processes and improve performance. However, in highly dynamic environments, rapid changes and market fluctuations may disrupt the implementation of AI strategies, reducing their impact on performance (Chehabeddine & Tvaronavičienė, 2020). The support of H12 highlights the importance of stability for AI-driven performance improvements, as firms may struggle to adapt their AI strategies in highly volatile settings.

The results also **supported H13**, demonstrating that ED positively moderate the relationship between AIS and FC. The study revealed that dynamic environments enhance the positive relationship between AIS and FC, with a stronger impact observed in more dynamic settings. This outcome suggests that firms in dynamic environments may benefit from the increased need for adaptability and innovation, which AIS help to address (Chen et al., 2024). In such settings, AI technologies provide the necessary flexibility to experiment with creative solutions and respond quickly to changing conditions (Alenizi et al., 2024). The heightened demand for innovation in dynamic environments likely stimulates creativity, and firms that possess strong AIS are better equipped to capitalize on these opportunities. Thus, dynamic environments act as a catalyst for creative output, allowing AIS to have a greater impact on innovation and creativity within the firm.

Last but not least, **H14 was supported as well**, with the study showing that ED significantly moderate the connection between AIB and FC. However, the moderating effect was negative, indicating that

in highly dynamic environments, the benefits of AIB technologies on creativity may diminish. It suggests that while AIB technologies, such as automation and foundational ML tools, can support creativity in stable environments, they may struggle to adapt to rapidly changing conditions in more dynamic settings. Basic AI tools may lack the flexibility and sophistication needed to foster creativity when external conditions are constantly evolving (Mikalef & Gupta, 2021). As a result, firms relying heavily on foundational AI technologies may find it more difficult to innovate in dynamic environments, as these tools may not be agile enough to support the fast-paced creative processes required. Future research that would delve deeper into the inverse moderating effect of ED on the relationship between AIB and FC might uncover the actual reasons for such behavior.

Conclusion and recommendations

This study imparts invaluable insights for practitioners seeking to incorporate AI into their commercial strategies to augment both efficiency and ingenuity. Through the analysis of the particular AI elements, the study accomplished its primary goals by providing actionable recommendations on how these elements affect organizational results. One of the primary objectives of this investigation was to examine how AI-enhanced decision-making, oversight, and productivity impact FP. The study verifies that AI can significantly enhance FP when effectively integrated into business operations. For practitioners, this signifies that cultivating and advancing AIS within their teams is essential to unleashing the capabilities of AI technologies. By committing to AI education and fostering an environment that encourages ongoing skill development, companies can ensure that AI adoption leads to tangible performance improvements. Furthermore, robust AIM practices that synchronize AI projects with strategic business objectives are crucial for optimizing the benefits of AI investments. These conclusions highlight the necessity of not only acquiring AI technologies but also cultivating the requisite expertise and management frameworks to facilitate their efficient deployment.

The study also endeavored to explore the impact of AI on FC, with a focus on how AI fosters innovation and adaptability in dynamic business environments. The results demonstrate that AI-driven creativity can be a powerful source of competitive advantage, especially for firms operating in rapidly changing markets. Practitioners should view AI as a tool not just for efficiency but for fostering creativity and innovation within their organizations. AIS and AIP were demonstrated to significantly enhance FC, enabling businesses to generate new ideas, innovate products, and streamline creative processes. To capitalize on this potential, firms should actively integrate AI into their innovation workflows, ensuring that AI technologies are leveraged to support creative problem-solving, ideation, and rapid iteration. This approach will enable firms to remain competitive by continually adapting to market shifts and introducing novel solutions to meet customer demands.

Another principal aim was to assess the moderating influences of environmental conditions, such as market fluctuations and regulatory frameworks, on the efficacy of AI adoption. The research indicates that environmental determinants play a crucial role in moderating the potency of AI mechanisms on organizational outcomes. In consistent environments, AI-driven enhancements in organizational performance are more prominent, whereas in fluctuating environments, the inventive advantages of AI are augmented. For professionals, this implies that AI approaches must be customized to the unique circumstances of their operational contexts. In stable markets, companies should concentrate on utilizing AI for operational efficiency and performance improvements, while in more unpredictable markets, AI should serve as a tool for fostering innovation and inventive adaptation. Comprehending the external context is essential for maximizing AI investments and ensuring that AI efforts align with overarching business objectives.

The results further highlight the difficulties that businesses may encounter when embedding AI, particularly in shifting or unpredictable contexts. While AI presents various benefits, companies must be equipped to navigate the complexities of AI incorporation, including the need for continuous upskilling, aligning AI with strategic objectives, and responding to environmental changes. For firms operating in highly volatile markets, the research suggests that AIB technologies might be less effective in promoting creativity. Instead, organizations may need to invest in more advanced AI systems that are better suited to adapt to changing conditions. This outcome highlights the importance of adaptability and resilience

in AI integration, enabling businesses to effectively manage external challenges while leveraging AI's potential to enhance both performance and innovation.

Finally, while IC was hypothesized to moderate the relationship between AIS and FC, the study found that it did not significantly alter this relationship. The absence of a statistically meaningful connection suggests that the presence of AIS alone may be sufficient to drive creativity within firms, regardless of the broader IC. For practitioners, this means that fostering technical AI competencies may be more critical than cultivating an innovation-centric culture when it comes to achieving creative outcomes. However, it is important to note that while IC did not meet the significance threshold in this study, further research may be needed to fully understand its role in different organizational contexts.

Limitations

Although this investigation delivers significant insights into the role of AI in FP and FC, several limitations must be acknowledged. For example, the sample, despite its heterogeneity, was predominantly drawn from the United States, United Kingdom, and Canada, potentially limiting the transferability of the findings to other areas, particularly those with less developed AI infrastructure. Future inquiries should strive for a more globally diverse sample. The research also addressed the moderating roles of IC and ED, with limited evidence concerning the impact of IC. This outcome highlights the necessity for further research into additional situational factors, such as organizational framework or leadership, which could provide a more thorough view of the conditions where AI integration is most beneficial.

The industry emphasis of the study was expansive, yet it did not probe profoundly into how AI influences sector-specific impediments, indicating a necessity for industry-centric evaluations in subsequent research. Furthermore, the study did not extensively cover technological and regulatory limitations, such as data confidentiality and cybersecurity, which might impact AI adoption. Finally, the cultural elements affecting AI adoption were not meticulously scrutinized. Considering that cultural perspectives on innovation and technology differ across regions, future inquiries should explore how cultural variances influence the connection between AI and organizational outcomes. Addressing these shortcomings will improve the comprehension of AI's role in business achievement across diverse settings and sectors.

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Hanan Alsharah: Conceptualization, Methodology, Data Curation, Formal Analysis, Resources, Writing – Original Draft Preparation, Writing – Review and Editing, and Project Administration.

Ethical approval

This study received ethical approval from the Social Sciences Ethics Sub-Committee at the University of Essex (reference ETH2324-0512). All research involving human participants was conducted in accordance with the University of Essex guidelines.

Authors' contributions

CRedit: **Hanan Alsharah:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

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About the author

Dr. Hanan Alsharah is a PhD researcher in Business and Artificial Intelligence at the University of Essex, United Kingdom. She holds a Master's degree in Business Innovation and a Bachelor's in Business Administration. Her research focuses on the intersection of artificial intelligence, entrepreneurship, and digital transformation, with a particular emphasis on empowering startups and women-led ventures in emerging markets. Dr. Alsharah is also an academic lecturer, innovation consultant, and founder of INNOTECH, a consultancy firm dedicated to enabling AI-driven business solutions. Her scholarly work contributes to the advancement of inclusive innovation ecosystems and sustainable digital entrepreneurship.

ORCID

Hanan Alsharah  <http://orcid.org/0000-0002-4862-2381>

Data availability statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. For inquiries, please contact Hanan Alsharah at: h.alsharah@essex.ac.uk.

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