Technological Forecasting & Social Change 213 (2025) 124013

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Artificial intelligence augmenting human intelligence for manufacturing firms to create green value: Towards a technology adoption perspective

Lei Huang [a], Tachia Chin [a,*], Armando Papa [b,c,d], Paola Pisano [e]

[a] School of management, Zhejiang University of Technology, Hangzhou, China
[b] Department of Economics and Statistics, University of Salerno, Salerno, Italy
[c] School of Business, University of Nicosia, Nicosia, Cyprus
[d] HSE University, Moscow, Russia
[e] Economic and Statistic department, University of Torino, Torino, Italy

ARTICLE INFO

Keywords:
Artificial intelligence
Human intelligence
Intellectual capital
Green value creation
Technology adoption

ABSTRACT

Artificial intelligence (AI) profoundly influences value creation by boosting efficiency, fostering innovation and driving new business models and technological advancements, all while nurturing human intelligence (HI). However, the collaboration between AI and HI, crucial for augmenting the creation of green value and achieving sustainable development in manufacturing firms, remains ambiguous. We employed panel data from 935 A-share listed manufacturing firms in China (2010–2022) to reveal the potential influence mechanism of AI and HI collaboration on green value creation. Our findings revealed that AI technology adoption facilitated manufacturing firms in harnessing their HI for green value creation. Under the influence of AI technology adoption, HI, as with manufacturing firms' human and structural capital, contributed positively to green value creation. It is noteworthy that while higher-quality relational capital served as a potential driving force for manufacturing firms in creating green value, heightened AI technology adoption significantly impeded enthusiasm for this mechanism. The conclusions elucidate the intricate relationship between AI and HI collaboration and green value creation, expanding the application of technology adoption within the green innovation ecosystem. Furthermore, they offer practical insights for manufacturing firms in their pursuit of green value creation.

1. Introduction

With the rising popularity of the ecosystem view, human focus has shifted from competition to synergy, as well as from understanding individual development to comprehending symbiotic development with the outside world (Moore, 1993; Nambisan, 2018). Cooperation and symbiosis between organisations increasingly emphasise their value advantages. Ecosystem participants co-evolve while simultaneously competing with each other (Adner, 2006). Promoting the deep integration of innovation agents and the technological environment within an ecosystem (Adner and Kapoor, 2016; Lee et al., 2023) and building a green innovation ecosystem are strategic choices to seize new opportunities for manufacturing transformation (Bag and Pretorius, 2022; Jia et al., 2023). Currently, artificial intelligence (AI) technology is fully being integrated into various fields, impacting the human economy, politics, culture, society and ecological civilisation construction with new concepts, forms and models (Callen et al., 2023). This integration has extensive and profound effects on human production and life (Stefano et al., 2022). Particularly for firms, both big and small, efforts have been initiated to incorporate AI as a cornerstone of their value-creation strategies.

The creation of value originates from the identification, acquisition and restructuring of different resources within the innovation ecosystem to form new combinations (Adner and Kapoor, 2010; Amit and Han, 2017; Al-Omoush et al., 2023). Scarce, valuable and irreplaceable heterogeneous resources are crucial to value creation, with AI considered not only a technology but also a resource (Ahn and Chen, 2022). AI provides green-related knowledge, information and technological resources for manufacturing firms to enhance their ability to create green value (Lugosi, 2021). Technology can change the mode of value delivery and creation in the innovation ecosystem (Chatterjee et al., 2020), assisting innovation agents in analysing, integrating and allocating both

* Corresponding author.
E-mail addresses: leihuang0813@zjut.edu.cn (L. Huang), tachiachin@zjut.edu.cn (T. Chin), apapa@unisa.it (A. Papa), paola.pisano@unito.it (P. Pisano).

https://doi.org/10.1016/j.techfore.2025.124013
Received 2 September 2024; Received in revised form 17 January 2025; Accepted 25 January 2025

internal and external resources. The application of AI technology empowers both the innovation chain and the value chain, making all aspects of innovative production data driven and intelligent (El-Kassar and Singh, 2019; Valle-Cruz and García-Contreras, 2023). It helps manufacturing firms promptly identify value demands and effectively address them, thereby promoting green value creation and sustainable development.

Human intelligence (HI) encompasses cognitive abilities, such as thinking, self-awareness and intention (Fan et al., 2021). HI enables specific abilities, such as remembering, learning, understanding, planning, logical reasoning, problem-solving and communication. Within the green innovation ecosystem, the key to creating green value for manufacturing firms lies in HI resources (Wright et al., 2001; Li et al., 2021). The boundary between AI and HI lies in the level of cognition and creativity, and currently, AI is still in a 'semi-cognitive' stage (Guikema, 2022). The most appropriate approach should be to delegate tasks based on the strengths of machines and humans. However, the current value creation of firms is limited to the utilisation of existing resources (including tangible and intangible resources). The utilisation of new-generation AI technology resources is very limited, and integrating external AI and internal HI for value creation in firms is a dual deficiency of cognition and ability. Therefore, collaborating with AI and HI to promote green value creation and achieve sustainable green development in manufacturing firms is a hot topic worthy of attention in both academic and business circles.

Creating green value involves enhancing the utilisation of core resources in the production of products or services to meet customer needs, consequently reducing resource or energy consumption and waste (Priem et al., 2018; Schilling and Seuring, 2023). Despite the richness of achievements in value creation research, the literature has paid limited attention to green value creation. Previous studies have explored value creation from various perspectives. The first perspective includes production factors, exploring the contributions of different production factors to value creation. These include the value forms and quantities provided by different production factors (Itami and Nishino, 2010; Niu et al., 2021), transition in key production factors (Tantalo and Priem, 2016; Bag and Pretorius, 2022), data production factors (Pinochet et al., 2021) and intellectual capital (Li et al., 2021; Lugosi, 2021; Santarsiero et al., 2023). The second includes input-output processes, providing a deeper analysis of the impact of different factors on the efficiency of value creation. Production factor resources have a fundamental role in firm value creation, but the arrangement and combination of different factor resources, such as resource allocation and utilisation (Baert et al., 2016), digital resource configuration (Amit and Han, 2017; Sultana et al., 2022) and resource collaboration (Al-Omoush et al., 2023), can affect the efficiency of value creation. The third includes customer views, exploring the reverse driving effect of market demand on value creation. This encompasses value co-creation between firms and customers (Xie et al., 2016; Jost and Susser, 2020) and demand-side strategy (Priem et al., 2018; Guo et al., 2022). The fourth includes financial aspects, exploring the driving role of social responsibility (Broadstock et al., 2020; Reimsbach and Braam, 2023) and business models (IHeanachor et al., 2021; Schilling and Seuring, 2023) in value creation. The final perspective includes the value chain. The acquisition, organisation, circulation and utilisation of resources in the digital era, such as the digital global value chain (Oliveira et al., 2021; Lee et al., 2023) and value co-creation in the closed-loop supply chain (Zhang et al., 2022; Liu et al., 2021), will have a significant impact on their value creation. These studies have explored the issue of value co-creation at different stages of the value chain. However, analysing the green value creation of manufacturing firms within the innovation ecosystem from an environmental perspective is still in its developmental stage.

As a driving force for the ongoing scientific and technological revolution, AI has garnered unprecedented attention. Existing research has extensively examined AI's impact at the macro and micro levels, addressing aspects such as employment (Felten et al., 2021; Yang, 2022), economic growth (Makridis and Mishra, 2022; Yang et al., 2023), income inequality (Acemoglu and Restrepo, 2020), employee innovation (Ahn and Chen, 2022; Yin et al., 2024), education (Smirnov et al., 2023), emergency management (Fan et al., 2021; Dubey et al., 2022; Guikema, 2022), diagnosis (Lei et al., 2020; Sahu et al., 2023; Yao et al., 2023), innovation and entrepreneurship management (Pietronudo et al., 2022; Shepherd and Majchrzak, 2022; Giudice et al., 2022), the supply chain (Sinha and Anand, 2017; Khan and Sinha, 2022; Ivanov, 2023; Valle-Cruz and García-Contreras, 2023) and decision-making and predictions (Azadeh et al., 2012; Balasubramanian et al., 2022). The above-mentioned studies have explored the impact of AI on various aspects of human production and life from different perspectives, but unfortunately, the current research lacks a comprehensive investigation into how AI technology affects the green value creation of manufacturing firms.

To address these gaps, our objective is to explore the relationship between HI and the green value creation of manufacturing firms as well as the impact of AI technology on it. Our empirical study focuses specifically on listed Chinese manufacturing firms. The potential contributions include expanding the understanding of the relationship between HI and green value creation. Additionally, we aim to unveil how AI technology adoption influences green value creation and interacts with HI, providing new insights into the green transformation of the manufacturing industry. Finally, we comprehensively evaluate green value creation using both forward and reverse indicators, contributing valuable insights to the organisational-level measurement of green value creation.

The following section elucidates the theoretical foundation for AI and HI collaboration to augment manufacturing firms' green value creation and formulates the hypotheses. Section 3 outlines the methods employed in this study, and Section 4 elucidates the findings. The concluding section encompasses research summaries, theoretical contributions, managerial implications, limitations and future research directions.

2. Theoretical background and hypothesis development

2.1. Value creation within the innovation ecosystem

An innovation ecosystem is a network composed of multiple actors (Adner, 2006), including participants and a series of environmental elements (Adner and Kapoor, 2016). As a source of value creation, members within the innovation ecosystem can drive the bidirectional flow of internal and external resources through open strategies (Nambisan, 2018), thereby enhancing value-creation capabilities. Simultaneously, the innovation ecosystem can break through traditional barriers and leverage network-embedding effects to promote value co-creation among different participants (Beltagui et al., 2020).

Actor network theory (ANT) suggests that scientific knowledge is a dynamic network process formed by the interaction and construction of multiple heterogeneous actors (Callon and Latour, 1981). An actor network is not textual or physical but a constantly evolving and flowing actor trace (Latour, 1986). Actors include both traditional sociological human actors (e.g., people, social groups or organisations) and all non-human actors (e.g., technology, artefacts, cultural concepts or institutions) (Sayes, 2014). Drawing upon ANT, manufacturing firms and AI technology are the two main actors within the innovation ecosystem. The core actors in creating value for manufacturing firms are humans. Human knowledge, experience and judgment play a crucial role in the success of innovation (Lugosi, 2021). Human behaviour can promote innovation and value creation through innovative activities, collaborative relationships and knowledge sharing (Santarsiero et al., 2023). As a tool and resource, technology can change human production modes, organisational forms and market structures, thereby promoting innovation and value creation (Adner and Kapoor, 2010). Interaction and cooperation between humans and technology are key to achieving value creation.

The advent of the new generation of AI technology has laid the groundwork for the expansion of HI, and its impact on the innovation ecosystem is noteworthy. The AI era has brought unprecedented uncertainty to traditional manufacturing. Therefore, it is crucial to understand how human beings, as carriers of knowledge resources and capabilities, and technological factors affect the value creation of manufacturing firms and the evolution of innovation ecosystems.

2.2. The core knowledge resource of HI: Intellectual capital

The development of HI has undergone a long historical evolution, progressing from the basic ability of simple counting to the advanced capability of conceptual abstraction. HI manifests at different levels of development (Fan et al., 2021). Compared to AI, HI exhibits several significant features. First, HI represents the ability of human beings to engage in autonomous reasoning activities. Second, it enables human beings to express and create knowledge, particularly through the utilisation of tacit knowledge. Third, it can formulate plans and arrangements for future actions as well as actively learn for specific purposes. Fourth, it possesses the most crucial human abilities—thinking ability and conscious activity (Brooks, 1991; Bennett, 2022).

In simple terms, HI refers to the ability of humans to learn from experience, adapt to new situations, understand and process abstract concepts and use knowledge to manipulate the environment (Searle, 1980). Drawing on value creation theory, firm value creation is the process of utilising various internal and external resources and capabilities to achieve a competitive advantage (Tantalo and Priem, 2016; Valle-Cruz and García-Contreras, 2023). The focus of this process is on the human beings within an organisation. Therefore, the green value creation of manufacturing firms involves using their HI in the process of creating products or services that meet customer needs. This, in turn, can improve the utilisation rate of core resources (Xie et al., 2016), thereby reducing the consumption and waste of resources or energy. Additionally, manufacturing firms leverage HI to minimise their impact on the environment, such as by reducing carbon emissions in the process of value creation, thereby effectively improving environmental efficiency (Reimsbach and Braam, 2023).

In the knowledge economy era, market competition has evolved into a contest for knowledge and talent (Farzaneh et al., 2022). This shift has led to an extension of the concept of capital to encompass knowledge and the intelligence that possesses and generates knowledge—referred to as intellectual capital (IC) (Edvinsson and Malone, 2005; Hanifah et al., 2022). IC, as a concretised resource of HI, plays a pivotal role in the pursuit of organisational value appreciation (Kang and Snell, 2009; Xu and Li, 2022). It encompasses all knowledge-based strategic resources within an organisation, such as experience, creativity, technology, processes and relationships, collectively known as the core capital of IC (Oliveira et al., 2010). Additionally, IC has been demonstrated to be fundamental for implementing innovation in manufacturing firms (Dost et al., 2016; Beltramino et al., 2021).

As a strategic resource, IC furnishes firms with ample knowledge resources and dynamic capabilities to engage with the market, facilitating the creation of green value (Bassi and Van Buren, 2007; Tseng and Goo, 2013). According to Bayraktaroglu et al. (2019), the effective utilisation of knowledge resources and capabilities is integral to firm growth. Consequently, we assert that IC is the paramount HI for organisations. IC serves as a continuous input, propelling organisational value creation by not only relying on internal human capital but also harnessing structural and relational capital from inter-organisational relationships (Li et al., 2021). Therefore, we posit that all dimensions of IC constitute the core driving force for manufacturing firms to implement green value creation. Human capital ensures the talent necessary for green value creation, while structural capital provides internal institutional support and relational capital ensures organisational collaboration.

2.3. AI technology adoption within the innovation ecosystem

Human beings continually develop intelligent tools as an extension of their capabilities to enhance HI (Fan et al., 2021; Giudice et al., 2022). The innovation ecosystem encompasses both innovation agents and an innovation environment (Chin et al., 2022). Serving as core players in this ecosystem, manufacturing firms establish close interactions with other stakeholders through supply chains, industry–university research alliances and innovation networks (Huang et al., 2022). While AI represents just one aspect of the technological environment, this environment plays a crucial role in ensuring the vitality of the innovation ecosystem (Chatterjee et al., 2020). In addition, the relationship between resources and environmental context is reciprocal, guided by the constructivism resource view (Shepherd and Majchrzak, 2022). The innovation ecosystem is essentially 'jointly constructed' through the coupling and interaction of the innovation agents and environment. Within an open green innovation ecosystem, the creation of green value for manufacturing firms becomes a strategic choice that integrates the internal HI with the external technological environment of the firm (El-Kassar and Singh, 2019; Chin et al., 2024).

AI plays a crucial role in providing technical conditions for resource coordination among participants in the innovation ecosystem. It significantly enhances the efficiency of resource matching and facilitates the realisation of new value-creation paths (Yoo et al., 2012; Tang et al., 2022). Notably, AI technology enables closer integration of various entities and innovative resources across different fields within the system (Beltagui et al., 2020). In the era of industrial big data, AI technology plays a pivotal role in driving intelligent production in manufacturing firms, ultimately facilitating the creation of green value (Yam et al., 2023). On the one hand, AI promotes technological innovation across various entities within the green innovation system by optimising the technological environment, strengthening technology spillovers and accumulating innovative elements (Felten et al., 2021; Yang, 2022). Technological innovation, as a key force, contributes significantly to green development. Concurrently, AI technology facilitates green improvements in manufacturing production processes through real-time monitoring of pollution emissions, precise governance and optimising and upgrading clean production models (Makridis and Mishra, 2022). Analysing this dynamic relationship from a technology adoption perspective can enhance our understanding of the intricate interplay between the process and the results of green value creation in manufacturing firms. Therefore, we propose the following hypothesis:

H1: Manufacturing firms' AI technology adoption has a significant positive impact on their green value creation within the green innovation ecosystem.

2.4. AI and HI collaboration to augment manufacturing firms for green value creation

As value creation models transform, the entire social system is transitioning into an era of collaboration between HI and AI (Callen et al., 2023). The remarkable advancements in AI are facilitating and driving the integration of AI and HI to achieve technological forecasting and assessment across various industries and domains. The combination of AI algorithms with human decision-makers enhances organisational agility and adaptability to changing conditions (Dubey et al., 2022; Chin et al., 2022). However, in the nascent application of AI and HI in the green value-creation field of manufacturing firms, several debates persist.

Simultaneously, we recognise the significance of HI in the value-creation process and the variations in resources across different value logics. IC does not singularly influence firm value creation; rather, its impact is realised through the coupling of human capital, structural capital and relational capital (Tseng and Goo, 2013; Hanifah et al., 2022). Therefore, it is essential to conduct specific analyses of the different dimensions of IC.

2.4.1. Human capital and AI technology adoption

In manufacturing firms, human capital stands out as the most critical component of HI and serves as the ultimate driver of value creation, fuelled by creativity and initiative (Xu and Li, 2022). The human capital within a manufacturing firm encompasses the collective knowledge, skills, experience and other personal abilities of all personnel, including employees and managers (Bayraktaroglu et al., 2019). These capabilities can be cultivated, maintained and strengthened through various means, including formal education, training programmes and self-perception, thereby enhancing the overall stock of organisational human capital (Hanifah et al., 2022).

Notably, human capital imbued with green consciousness plays a pivotal role in stimulating the green innovation process within firms. It contributes to enhancing production and manufacturing efficiency by reducing resource and energy consumption while improving utilisation rates (Tseng and Goo, 2013). Additionally, human capital with a green mindset is instrumental in planning and resolving green issues within organisations (Edvinsson and Malone, 2005; Guenster et al., 2011). The impact of human capital on green value creation stems primarily from the abilities, attitudes and experiences of employees and encompasses their capacity to optimise practices, reflect on challenges and devise solutions (Tang et al., 2022). In the realm of green innovation, high-quality human capital can swiftly identify core issues, make informed decisions and enable firms to respond adeptly to changes in the external environment (Wright et al., 2001; Yousaf, 2021). Furthermore, in the era of the green economy, high-quality human capital positively influences both customers and the environment. For instance, enhancing product or service reliability contributes to increased customer satisfaction and social recognition (Liebowitz and Suen, 2013), ultimately creating higher green value for customers, the environment and society.

AI technology adoption plays a pivotal role in enhancing the efficiency of green value creation by elevating the level of human capital within manufacturing firms. First, in the context of high AI technology adoption, manufacturing employees can rapidly acquire new green knowledge. This accelerated learning not only bolsters individual development (Verma and Singh, 2022) but also facilitates the transformation and upgrading of firm human capital, thereby augmenting the capacity to generate green value.

Moreover, AI technology adoption enables the infusion of digital technology into firms, thereby upgrading traditional technologies and opening avenues for R&D personnel to pursue iterative green technology innovations (Jia et al., 2023). Within the realm of AI technology adoption, R&D personnel leverage next-generation digital technologies to complement and enhance traditional approaches, thereby enabling a precise analysis of green production (Yam et al., 2023).

Lastly, AI technology adoption contributes to enhanced awareness among managers regarding environmental issues related to existing products and technologies. This heightened awareness aims to propel manufacturing firms towards improving products and technologies guided by green demand (Bassi and Van Buren, 2007; Li et al., 2021), ultimately intensifying the creation of green value. Therefore, based on these observations, we propose the following hypothesis:

H2a: Human capital significantly promotes manufacturing firms to create green value, and AI technology adoption significantly positively moderates this relationship.

2.4.2. Structural capital and AI technology adoption

Structural capital serves as the manifestation of HI within manufacturing firms, encompassing organisational structure, culture, internal control systems and workflow (Oliveira et al., 2010; Farzaneh et al., 2022). It takes various forms, including hardware, software, technology, institutions, databases, organisational structure and information systems, which can be copied, shared and disseminated within an organisation (Liebowitz and Suen, 2013; Yousaf, 2021).

The impact of structural capital on green value creation in manufacturing firms manifests in several aspects. First, high-quality structural capital facilitates convenient channels for the transformation of green knowledge, especially in improving organisational resource utilisation. Well-structured organisations support cross-departmental communication and information sharing among internal members (Dost et al., 2016), leading to enhanced operational efficiency, reduced resource redundancy and subtle improvements in the efficiency of resource value creation (Li et al., 2021). Second, the organisational collaboration and integration mechanisms embedded in structural capital contribute to the enhancement of corporate culture and organisational structure, providing conditions conducive to the promotion of green value-creation activities (Beltramino et al., 2021). Third, high-quality structural capital encourages flexibility in expressing ideas and learning norms (Farzaneh et al., 2022). This fosters emotional dependence and organisational commitment among employees, thereby promoting positive green innovation behaviours (Tseng and Goo, 2013; Farzaneh et al., 2022) aimed at creating green value.

AI technology adoption plays a crucial role in enhancing the flexibility of organisational structures and management systems, effectively elevating the level of structural capital and fostering green value creation. First, the widespread adoption of AI technology is driving a transformation in the internal management approaches of firms (Raisch and Krakowski, 2021). In the context of the digital and green economy, changes in organisational structure and culture necessitate employees to assume roles beyond their traditional functions (Bertani et al., 2021). Manufacturing firms must initiate top-level design, cultivate new skills among employees and promote green value creation to adapt to shifts in the external environment.

Second, AI technology adoption brings about changes in traditional business and value-creation models (Raisch and Krakowski, 2021). Historically dominated by individual firms and exhibiting closed-source characteristics, these models have evolved in the AI era to integrate a broader range of external resources across organisational boundaries. This integration allows users or external R&D personnel to actively participate in the entire process of green value creation, fostering open networked innovation and providing significant momentum for manufacturing firms to continuously generate green value.

Third, AI technology adoption enhances the organisational and management efficiency of value-creation activities. The impact of AI technology adoption is evident in the revolution of internal organisational structures towards networking and flattening (Yam et al., 2023), breaking down barriers between different links, modules and departments within firms. These revolutions have made organisational structures more flexible and resilient, facilitating communication and the sharing of green knowledge elements among different systems (Liebowitz and Suen, 2013; Verma and Singh, 2022). Therefore, based on these observations, we propose the following hypothesis:

H2b: Structural capital significantly promotes manufacturing firms to create green value, and AI technology adoption significantly positively moderates this relationship.

2.4.3. Relational capital and AI technology adoption

Relational capital is an intangible asset of HI within manufacturing firms, offering a potential driving force for green value creation (Tseng and Goo, 2013). In the process of green value creation, the contribution of relational capital lies in establishing a 'bridge' between firms and their stakeholders (Kale et al., 2000; Li et al., 2021). Firms achieve benefit sharing with stakeholders through positive interactions with customers, suppliers and communities. This shared technology exchange community facilitates communication and coordination among different entities (Oliveira et al., 2010), thereby building a technological bridge for product and technology restructuring, 'co-green innovation' and expanding the scope of green value creation (Yousaf, 2021).

High-quality relational capital can maintain a high level of trust with stakeholders, thereby improving the potential for green technology to be applied to diverse customers and markets (Li et al., 2021). It also permeates green innovation concepts throughout the supply chain network, incorporating environmental and social responsibility principles. Manufacturing firms leverage relational capital to guide other entities in green innovation, effectively reducing resource and energy consumption in the innovation process (Xu and Li, 2022), lowering costs, enhancing green value creation and achieving a balance between profitability and environmental protection (Kammerer, 2009; Yousaf, 2021).

As an increasing number of manufacturing firms leverage AI technology adoption to reduce energy consumption and enhance resource efficiency, the quest for improved green value creation is intensifying (Callen et al., 2023). However, it is essential to acknowledge that the expansion of business boundaries driven by AI technology has elevated organisational relationship capital while simultaneously introducing heightened uncertainty and complexity (Raisch and Krakowski, 2021). First, manufacturing firms with elevated relational capital often find themselves deeply embedded in relational networks, resulting in more homogeneous knowledge and skills (Beltramino et al., 2021). Constrained by group consciousness, these firms may resist acquiring new knowledge and opportunities from external sources, thus weakening the positive impact of AI technology adoption on green value creation.

Second, when manufacturing firms possessing rich relationship capital confront AI technology adoption, the substantial impact of AI may lead them to resist absorbing new ideas and to seek to maintain the stability of existing relationship networks. This resistance may result in 'shortsighted behaviour' (Jia et al., 2023) and a more conservative approach to green value creation (Tang et al., 2022).

Third, AI technology adoption may encourage manufacturing firms with higher levels of relational capital to develop a 'free-riding' mentality, potentially diminishing their motivation for independent green innovation (Raisch and Krakowski, 2021). This, in turn, weakens the overall influence of relational capital in promoting green value creation.

Lastly, the introduction of AI technology in the workplace, coupled with environmental changes and technological progress, has generated heightened job insecurity among employees (Yam et al., 2023). In response, employees may unintentionally engage in high-risk green innovation behaviours to avoid mistakes, inadvertently inhibiting their green value-creation activities. Therefore, based on these observations, we propose the following hypothesis:

H2c: Relational capital significantly promotes manufacturing firms to create green value, but this mechanism is weakened in the presence of higher AI technology adoption.

Based on the above discussion, we constructed an analytical framework for AI–HI collaboration and green value creation to explore the impact mechanism of AI technology adoption in the green value-creation process of manufacturing firms. The specific conceptual model is shown in Fig. 1.

3. Methods

3.1. Sample and data

We utilised Chinese A-share listed firms as the initial sample. Drawing on prior studies (Duan et al., 2021; Huang et al., 2022), the authors applied the following criteria to select the final sample. First, manufacturing firms were selected based on their classifications and codes within China's national industrial economy (GB/4754–2011). Second, firms with no green invention patent applications during the research period (2010–2022) were excluded. Third, firms marked with 'ST' and '*ST' were eliminated. Fourth, firms whose core variables could not be matched with data from other variables were excluded. Finally, firms with significant missing variable data were also eliminated. We chose manufacturing firms as the sample because, first and foremost, manufacturing is an important component of China's industrial system and is the leading industry in the national economy. According to data from the Chinese Ministry of Industry and Information Technology, the total number of manufacturing firms in China reached 6.03 million in 2023, with manufacturing added value accounting for 26.2 % of GDP and about 30 % of the global total, firmly ranking it first in the world. Second, while the proportion of manufacturing as a secondary industry has decreased, there have been continuous problems, such as environmental pollution and overcapacity, that have had a huge impact on the environment. Third, under the requirements of carbon neutrality goals, exploring the green development of the manufacturing industry is not only a result of policy regulation but also a requirement of market competition. Therefore, choosing manufacturing firms for the sample has important theoretical value and practical implications.

This study drew on two distinct data sources. The first encompassed fundamental data, such as financial metrics, patent records and research and development (R&D) information, at the manufacturing firm level. These details were derived from the CSMAR database and the annual reports of the respective firms. The second source consisted of environmental protection and corporate social responsibility (CSR)–related data for manufacturing firms obtained from Rankins CSR Ratings reports (www.rksratings.cn) and Hexun CSR reports (www.hexun.com).

Given that data related to R&D innovation and environmental governance in the annual reports and third-party databases were notably absent before 2010 for the sample firms, this study opted for data consistency and result stability by restricting the sample period to 2010–2022. Recognising that the green value-creation process of manufacturing firms exhibits a lag in output effects, the main effect test employed dependent variable data from 2011 to 2022 to mitigate endogeneity issues. Other variables were considered within the range of 2010–2021. Ultimately, this study compiled panel data samples from 939 A-share listed manufacturing firms over 12 years.

Additionally, for robustness testing, the dependent variable measurement data utilised was the annual pollutant discharge equivalent.

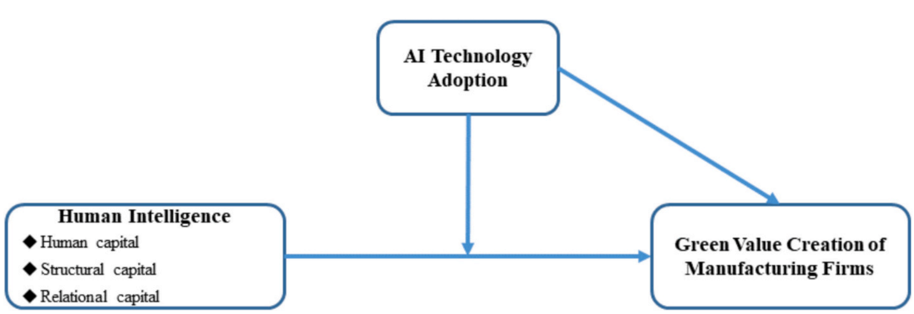

Fig. 1. Conceptual model.

This served as a reverse indicator, eliminating the need for lag consideration. Consequently, the data sample interval for robustness testing extended from 2010 to 2022.

3.2. Measures

3.2.1. Dependent variable: Green value creation in manufacturing firms

As mentioned earlier, green value creation involves enhancing resource utilisation, minimising resource or energy consumption and reducing waste in the process of developing products or services (Priem et al., 2018; Schilling and Seuring, 2023). For manufacturing firms, creating green value necessitates not only the achievement of economic benefits but also the attainment of environmental benefits (Guenster et al., 2011; Yousaf, 2021). In the realm of economic value, manufacturing firms secure economic rent through green innovation and realise environmental value by mitigating their impact on the environment through the application of green technology. To measure the green value creation of the sample firms, this study employed two key indicators: green innovation efficiency and emission pollutant equivalents.

Green innovation efficiency serves as a positive indicator that directly mirrors the level of green value creation, encompassing both the research and development (R&D) efficiency and the application efficiency of green technology (Yousaf, 2021). The data for this metric were primarily computed using the two-stage data envelope analyse-slack based model (DEA-SBM) model. On the other hand, the equivalent value of pollutants emitted by manufacturing firms functions as a reverse indicator. A higher value indicates a lower level of green value creation (Kock et al., 2012; Reimsbach and Braam, 2023). According to the 'Management Measures for the Collection of Pollutant Discharge Fees in China', the pollutant emissions of firms primarily include chemical oxygen demand and ammonia nitrogen emissions in industrial wastewater, as well as sulphur dioxide and nitrogen oxide emissions in industrial exhaust gas. To quantify these emissions, we standardised the emissions of the aforementioned four pollutants, converting them into a unified pollution-equivalent number. We then summed the pollution equivalent numbers (adding 1 before taking the logarithm) to derive the pollution equivalent value. This value reflects the pollution emission levels of manufacturing firms.

3.2.2. Independent variables

The degree of adoption and application of AI in the actual production process of manufacturing firms significantly influences such firms' value creation (Lee et al., 2022; Verma and Singh, 2022; Zhang et al., 2024). While previous studies have often measured AI using indicators such as total factor productivity, the technological progress index, number of patent authorisations and per capita equipment value (Pillai and Sivathanu, 2020; Shepherd and Majchrzak, 2022; Cirillo et al., 2023), these metrics may not accurately capture AI technology adoption. Drawing from existing studies, we adopted the per-capita value of AI-related machinery and equipment within manufacturing firms as an indicator to measure AI adoption in the green innovation ecosystem.

IC, the embodiment of HI resources in manufacturing firms, has evolved into a distinctive strategic resource and a fundamental driver of value creation (Beltramino et al., 2021; Lugosi, 2021). Following the prevailing accounting methodology, investments in human capital are predominantly represented by salaries paid. Structural capital investments, encompassing management systems and corporate culture development, are typically accounted for within management expenses. Similarly, relational capital, involving activities such as sales channel development and customer relationship management, is reflected in sales expenses. Building on existing research (Bayraktaroglu et al., 2019), this study employed specific financial metrics to measure each dimension of IC. Human capital (HC) is gauged using compensation and cash accounts paid to employees, structural capital (SC) is measured through administrative expenses in the income statement and relational capital (RC) is assessed via selling expenses. Subsequently, the value-added (VA) coefficient method was applied to derive specific values for each dimension. The VA of a firm is composed of net profit, depreciation expenses, financial expenses, income tax, payable wages and welfare expenses.

3.2.3. Control variables

Manufacturing firms at different life stages can significantly influence innovation (Kock et al., 2012). Firms experiencing better growth, in contrast to those facing greater downward development pressure, are more inclined to embrace green innovation and value creation (Wolf, 2014; Huang et al., 2022) to align with the demands of the times. Thus, firm growth is considered the first control variable measured by the growth rate of operating income.

Green value creation, viewed at the social level as a contribution to the ecological environment, is directly influenced by the level of social responsibility and impacts the motivation of manufacturing firms (Broadstock et al., 2020; Huang et al., 2022). As such, the social responsibility scores disclosed in the corporate social responsibility reports were employed as a control variable.

Firm size, the third control variable, is crucial, as larger firms possess advantages in manpower, capital and risk resistance (Santoro et al., 2018). Previous studies have indicated that firm size directly influences willingness and performance in creating green value (Forés and Camisón, 2016). Manufacturing firm size was quantified using the logarithm of total assets.

R&D investment has been identified as the foundation for manufacturing firms to undertake green technology innovation and directly impacts such firms' ability and performance in creating green value (Huang et al., 2022). Hence, the intensity of R&D expenditure was the fourth control variable, measured by the proportion of R&D expenditure to the main business income.

Financial leverage, reflecting a firm's operating and financial situation, plays a crucial role. Firms with relatively abundant financial resources and sound operating conditions possess a stronger ability to engage in green innovation and value creation (Flammer, 2021). Financial leverage, the fifth control variable, was measured through the asset–liability ratio.

In addition, environmental management authentication signifies that manufacturing firms garner more recognition in environmental governance and pollutant emissions control (Kock et al., 2012; Yousaf, 2021; Huang et al., 2022), reflecting their level of green value creation. This article incorporated the number of manufacturing firms that had obtained environmental management authentication as a control variable.

Furthermore, the supervision of manufacturing firms by environmental authorities is a pivotal factor influencing green innovation and value creation. Conversely, firms subjected to penalties by environmental authorities place greater emphasis on green value creation (Huang et al., 2022; Reimsbach and Braam, 2023). Environmental supervision was measured using dummy variables and served as the seventh control variable. Detailed names and measures of all variables are presented in Table 1.

Table 1
Variables and measures.

Variables	Variable name	Variable measures	Source reference
Dependent variables	Green value creation (GVC)	Green innovation efficiency (GIE).	Priem et al., 2018; Schilling and Seuring, 2023
		The natural logarithm of the number of pollutant emission equivalent plus 1.	Yousaf, 2021; Reimsbach and Braam, 2023
Independent variables	AI technology adoption (AIA)	The per capita value of AI-related machinery and equipment.	Pillai and Sivathanu, 2020; Zhang et al., 2024; Cirillo et al., 2023
	HI-human capital (HHC)	VA/HC	Bayraktaroglu et al., 2019
	HI-structural capital (HSC)	VA/SC	Bayraktaroglu et al., 2019
	HI-relation capital (HRC)	VA/RC	Bayraktaroglu et al., 2019
Control variables	Firm growth (FG)	The growth rate of a firm's operating income.	Wolf, 2014; Huang et al., 2022
	Corporate Social Responsibility (CSR)	The score of social responsibility in the CSR annual report.	Broadstock et al., 2020; Huang et al., 2022
	Firm size (FS)	Logarithm of total assets.	Forés and Camisón, 2016
	Intensity of R&D expenditure investment (RDE)	R&D expenditure / main business income.	Huang et al., 2022
	Financial leverage (FL)	Asset-liability ratio	Huang et al., 2022
	ISO authentication (IA)	1 means passed ISO authentication and 0 means others.	Yousaf, 2021; Huang et al., 2022
	Environmental supervision (ES)	1 means key pollution monitoring firms and 0 means others	Huang et al., 2022; Reimsbach and Braam, 2023

3.3. Model

This article employed a panel data model to analyse the relationship mechanism between HI and the green value creation of manufacturing firms. Simultaneously, we explored the potential interaction mechanism of AI technology adoption from the technology adoption perspective to comprehensively measure the possible influence mechanism of the collaboration between AI and HI on the green value creation of manufacturing firms. The following regression model was constructed:

$$\mathrm{GVC}_{i,t} = \alpha_0 + \alpha_1 \mathrm{AIA}_{i,t} + \alpha_2 \mathrm{HHC}_{i,t} + \alpha_3 \mathrm{HSC}_{i,t} + \alpha_4 \mathrm{HSC}_{i,t} + \Sigma_i^j \delta \bullet \mathrm{Controls}_{i,t} + \mu_{1,i,t} + \varepsilon_{1,i,t} \quad (1)$$

$$\begin{aligned} \mathrm{GVC}_{i,t} = {} & \alpha_0 + \alpha_1 \mathrm{AIA}_{i,t} + \alpha_2 \mathrm{HHC}_{i,t} + \alpha_3 \mathrm{HSC}_{i,t} + \alpha_4 \mathrm{HSC}_{i,t} \\ & + \beta_1 \mathrm{AIA}_{i,t} \times \mathrm{HHC}_{i,t} + \beta_2 \mathrm{AIA}_{i,t} \times \mathrm{HSC}_{i,t} \\ & + \beta_3 \mathrm{AIA}_{i,t} \times \mathrm{HRC}_{i,t} + \Sigma_i^j \delta \bullet \mathrm{Controls}_{i,t} + \mu_{1,i,t} + \varepsilon_{1,i,t} \end{aligned} \quad (2)$$

For formulas (1) and (2), the abbreviations for all variables can be found in Table 1. Additionally, a, β and δ in the models represent the regression coefficients of the model intercept term, independent variables and control variables, respectively. Here, i represents different manufacturing firms and t represents the year. $\sum \delta \bullet Controls$ refers to the set of other control variables not shown in the model. μ represents the random disturbance item and ε is the residual item.

Table 2
Descriptive statistics of variables.

Variables	Mean	S.D.	Min	P50	Max	N
GVC1	1.052	0.371	0.272	1.027	1.992	11,935
GVC2	0.143	0.005	0.131	0.144	0.153	11,935
AIA	−0.021	0.046	−0.054	−0.027	1.582	11,935
HHC	102.0	35.37	−15.95	80.83	269.4	11,935
HSC	1.921	4.093	−124.2	1.776	194.4	11,935
HRC	−0.041	4.132	−13.06	0.302	19.27	11,935
CSR	21.24	15.72	−17.19	17.99	90.87	11,935
RDE	0.079	0.322	−0.087	0.036	12.59	11,935
ES	0.236	0.421	0.000	0.000	1.000	11,935
IA	0.255	0.433	0.000	0.000	1.000	11,935
FS	22.28	1.168	19.59	22.19	26.45	11,935
FG	0.165	0.388	−0.658	0.121	4.024	11,935
FL	0.428	0.188	0.027	0.428	0.908	11,935

4. Results

4.1. Descriptive statistics and correlation analysis

Table 2 presents the mean, median, standard deviation, minimum, maximum and sample size of all the variables in this study. The mean of green innovation efficiency (GVC1) was 1.052, ranging from a minimum of 0.272 to a maximum of 1.992, which indicated significant variation in the current green innovation efficiency among manufacturing firms. The pollution emission equivalent data of manufacturing firms (GVC2) suggested a relatively small difference in pollution emissions. The mean of AI technology adoption was −0.021, with a range from −0.054 to 1.582. The overall distribution exhibited an obvious triangular structure, indicating that the utilisation of AI technology adoption by most manufacturing firms in China was at a relatively low level.

The results of the IC data revealed significant differences among manufacturing firms in terms of human capital, structural capital and relational capital. Concerning the control variables, there were notable variations in the social responsibility, R&D investment and growth of manufacturing firms, while differences in other variables were relatively small.

Table 3 displays the correlation coefficient matrices among the variables. The results indicated a significant positive correlation between AI adoption, structural capital and green value creation. Additionally, relational capital exhibited a positive correlation with green value creation, while human capital was negatively correlated. These findings provide preliminary support for the theories presented in this article. However, determining the intrinsic causal relationship between variables necessitates controlling for other influencing factors and excluding alternative theoretical explanations. The observed correlations formed the foundation of the subsequent regression analysis.

4.2. Hypotheses test results

Before the regression analysis, we conducted Hausman and Breusch-Pagan tests (Huang et al., 2022; Wang and Shibayama, 2022). The results indicated a rejection of the original hypotheses ($p = 0.000$, $p = 0.000$). As a result, the fixed-effect model was deemed appropriate for this article.

Table 4 presents the regression results of the main hypotheses. In Model (1), the benchmark model, most control variables demonstrated a significant correlation with the green value creation of manufacturing firms, underscoring the necessity of controlling these variables. The intensity of R&D investment was significantly positive, suggesting that sustained and long-term R&D investment is essential for green value creation in manufacturing firms. Environmental supervision and authentication both play pivotal roles in reflecting the green value creation of manufacturing firms. Environmental supervision signifies a practice of green innovation driven by external institutional pressure, while environmental authentication directly mirrors the level of green

Table 3
Correlation coefficient matrix of variables.

Variables	GVC	AIA	HHC	HSC	HRC	CSR	RDE	ES	IA	FS	FG	FL
GVC	1											
AIA	0.098***	1										
HHC	−0.006	−0.004	1									
HSC	0.025***	0.106***	0.011	1								
HRC	0.010	0.002	0.000	0.003	1							
CSR	−0.239***	−0.068***	0.017*	0.163***	−0.001	1						
RDE	0.055***	0.004	0.005	−0.002	0.001	−0.075***	1					
ES	0.388***	0.115***	0.012	0.082***	0.004	−0.112***	−0.026***	1				
IA	0.075***	−0.027***	0.011	0.021**	−0.017*	0.127***	−0.030***	0.081***	1			
FS	0.269***	0.144***	0.010	0.141***	0.012	0.142***	−0.167***	0.299***	0.075***	1		
FG	−0.115***	−0.013	0.002	0.104***	−0.001	0.087***	−0.049***	−0.033***	−0.031***	0.047***	1	
FL	0.059***	0.069***	−0.049***	−0.060***	0.011	−0.107***	−0.024***	0.063***	−0.005	0.426***	0.020**	1

*, **, and *** indicate that they pass the test at the levels of 10 %, 5 %, and 1 %, respectively.

Table 4
Regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AIA		0.293***					0.103**	0.051*	0.024***	0.014*
		(0.075)					(0.008)	(0.001)	(0.001)	(0.000)
HHC			0.119***			0.074***	0.095*			0.002**
			(0.014)			(0.007)	(0.054)			(0.001)
HSC				0.057***		0.003***		0.036*		0.001*
				(0.007)		(0.001)		(0.021)		(0.001)
HRC					0.001*	0.001**			0.010*	0.010***
					(0.001)	(0.001)			(0.001)	(0.003)
HHC × AIA							0.015**			0.003*
							(0.007)			(0.001)
HSC × AIA								0.086*		0.026**
								(0.052)		(0.007)
HRC × AIA									−0.033***	0.237***
									(0.004)	(0.070)
CSR	−0.004***	−0.004***	−0.003***	−0.004***	−0.004***	−0.002***	−0.005***	−0.006***	−0.005***	−0.016***
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
RDE	0.145***	0.144***	0.152***	0.151***	0.144***	0.079***	0.312***	0.308***	0.108***	0.509***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.005)	(0.082)	(0.082)	(0.017)	(0.043)
ES	0.254***	0.252***	0.247***	0.244***	0.254***	0.118***	0.168***	0.163***	0.265***	1.037***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.005)	(0.031)	(0.031)	(0.019)	(0.035)
IA	0.046***	0.046***	0.042***	0.049***	0.046***	0.024***	0.009	0.014	0.033	0.109***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)	(0.005)	(0.040)	(0.040)	(0.022)	(0.036)
FS	0.243***	0.241***	0.255***	0.244***	0.243***	0.131***	0.273***	0.233***	0.197***	0.829***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.003)	(0.031)	(0.034)	(0.011)	(0.022)
FG	−0.102***	−0.101***	−0.096***	−0.109***	−0.102***	−0.052***	−0.093***	−0.104***	−0.069***	−0.316***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.004)	(0.027)	(0.026)	(0.016)	(0.032)
FL	−0.058**	−0.054**	−0.099***	−0.056*	−0.058**	−0.050***	−0.492***	−0.366**	−0.093*	−0.199*
	(0.027)	(0.027)	(0.030)	(0.030)	(0.027)	(0.016)	(0.166)	(0.168)	(0.054)	(0.115)
Constant	−4.324***	−4.273***	−4.640***	−4.430***	−4.325***	−1.921***	−4.914***	−4.061***	−3.451***	−16.69***
	(0.109)	(0.110)	(0.119)	(0.117)	(0.110)	(0.061)	(0.681)	(0.738)	(0.240)	(0.472)
Observations	11,935	11,935	11,935	11,935	11,935	11,935	11,935	11,935	11,935	11,935
R-squared	0.396	0.397	0.404	0.415	0.397	0.408	0.269	0.275	0.348	0.322
P	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses, *, **, and *** indicate that they pass the test at the levels of 10 %, 5 %, and 1 %, respectively.

value creation. Large-scale manufacturing firms may exhibit higher risk resistance, potentially contributing to better green performance in creating green value. Notably, social responsibility, firm growth and financial leverage exhibited significant negative effects, contrary to intuitive expectations. This discrepancy may stem from the close association between green value creation and strategic orientation, leading to differences in strategies and response times among manufacturing firms. Additionally, the process-oriented and lagged nature of green value creation may contribute to a lack of immediate results in the short term.

In Model (2), we tested the impact of AI technology adoption, revealing an estimated coefficient of 0.293 that was significant at the 1 % level. Additionally, in the tests of Models (7)–(10), this effect remained significantly positive. These findings strongly suggest that AI technology adoption exerts a substantial positive influence on the green value creation of manufacturing firms, confirming H1.

Examining the results of Models (3) and (7), we analysed the effect of human capital from both HI and AI technology adoption on the green value creation of manufacturing firms. In Model (3), the coefficient of HHC was 0.119, significant at the 1 % level. In Model (7), the coefficient of HHC × AIA was 0.015, significant at the 5 % level. These results indicate that a higher level of human capital contributes to enhanced creativity and initiative in the value-creation process. This encourages manufacturing firms to leverage their HI resources for green value creation, with this mechanism being particularly crucial in the context of higher AI technology adoption. Collectively, these outcomes validate H2a.

Models (4) and (8) investigated how the structural capital of HI in manufacturing firms influenced green value creation under the influence of AI technology adoption. In Model (4), the coefficient of HSC was 0.057, significant at the 1 % level. In Model (8), the coefficient of HSC × AIA was 0.086, significant at the 10 % level. These findings suggest that the structural capital of manufacturing firms utilising their HI resources can indeed promote green value creation. Importantly, this mechanism became more pronounced in the context of higher AI technology adoption, validating H2b.

Models (5) and (9) explored changes in the mechanism by which manufacturing firms utilised their HI resources to create green value through relational capital when exposed to higher AI technology adoption. In Model (5), the coefficient of HRC was 0.001, significant at the 10 % level. In Model (9), the coefficient of HRC × AIA was −0.033, significant at the 1 % level. These results suggest that manufacturing firms can promote green value creation by leveraging their relational capital. However, this impact mechanism was significantly weakened in the presence of higher external AI technology adoption. These findings support H2c.

4.3. Robustness test

4.3.1. Replacing the dependent variable measurement

In the test to replace the dependent variable measure, we utilised the pollutant emission equivalent of manufacturing firms as a proxy variable for green value creation to examine the hypothesis. To account for the inverse relationship between the emission pollutant equivalent and green value creation, we processed the data accordingly. Table 5 presents the robustness test results for replacing the dependent variable measurement.

Similarly, Model (1) served as the benchmark, the chosen control variables exhibited a significant impact on green value creation, measured by the reverse variable of the pollutant discharge equivalent. Model (2) tested the impact of AI technology adoption, yielding an estimated coefficient of 0.381, significant at the 1 % level. The effects remained significantly positive in Models (7)–(10), further supporting H1. Models (3)–(5) and (7)–(9) investigated the effects of different dimensions of HI and AI technology adoption on green value creation in manufacturing firms. In Models (3) and (7), the coefficient of HHC was 0.013, significant at the 10 % level, while the coefficient of HHC × AIA was 0.030, significant at the 1 % level. In Models (4) and (8), the coefficient of HSC was 0.343, and the coefficient of HSC × AIA was 0.729, both significant at the 1 % level. In Models (5) and (9), the coefficient of HRC was 0.771, significant at the 1 % level, and the coefficient of HRC × AIA was −0.001, significant at the 5 % level. These results further verify and support hypotheses H2a, H2b and H2c.

Furthermore, in Tables 4 and 5, Models (6) and (10) include both the main effect and all interaction effects, respectively. While the direction of each estimated effect remained consistent, there were slight changes in the coefficients and significance levels. This can be attributed to the inclusion of all regression terms, particularly the interaction terms of AI technology adoption, which may have introduced collinearity. Nonetheless, despite these adjustments, the empirical results continued to support the research hypothesis, indicating a certain degree of robustness.

4.3.2. Excluding industries with high digitalization

A discernible disparity exists between the demand for and the extent of integration with AI technology across industries exhibiting varying degrees of digitization. Industries that are highly digitalized offer a more robust data foundation, superior technical conditions, and ample talent support, facilitating the adoption of AI technology by manufacturing firms. Furthermore, within these highly digitalized industries, the traits of knowledge and capital intensity are increasingly prominent, accompanied by a higher quality and abundance of intellectual capital. Consequently, to mitigate the influence of industry digitalization on the green value creation efforts of manufacturing firms, we conducted robustness testing on industry samples with differing levels of digitization. Table 6 displays the robustness test results specifically for the

Table 5
Robustness test results for replacing the dependent variable measurement.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AIA		0.381***					0.021*	0.040*	0.011**	0.072**
		(0.061)					(0.006)	(0.012)	(0.000)	(0.002)
HHC			0.013*			0.007**	0.019***			0.091*
			(0.007)			(0.107)	(0.007)			(0.127)
HSC				0.343***		0.208*		0.037*		0.198**
				(0.130)		(0.133)		(0.019)		(0.149)
HRC					0.771***	3.205***			0.768***	2.603***
					(0.259)	(1.003)			(0.259)	(0.920)
HHC × AIA							0.030***			4.834
							(0.002)			(1.261)
HSC × AIA								0.729***		7.966***
								(0.053)		(2.616)
HRC × AIA									−0.001**	4.724***
									(0.000)	(1.337)
CSR	−0.364***	−0.362***	−0.363***	−0.373***	−0.364***	−0.407***	−0.354***	−0.352***	−0.364***	−0.361***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)
RDE	1.543***	1.536***	1.544***	1.638***	1.540***	1.727***	1.509***	1.511***	1.539***	1.533***
	(0.064)	(0.064)	(0.064)	(0.067)	(0.064)	(0.070)	(0.064)	(0.064)	(0.064)	(0.064)
ER	0.179***	0.177***	0.179***	0.202***	0.179***	0.212***	0.171***	0.172***	0.179***	0.177***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
EC	0.040***	0.040***	0.039***	0.032***	0.039***	0.038***	0.038***	0.039***	0.039***	0.040***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
SIZE	1.304***	1.292***	1.304***	1.160***	1.303***	1.342***	1.277***	1.271***	1.303***	1.293***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.017)	(0.019)	(0.017)	(0.017)	(0.017)	(0.017)
CG	−0.221***	−0.218***	−0.220***	−0.193***	−0.220***	−0.218***	−0.204***	−0.206***	−0.220***	−0.217***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.017)	(0.019)	(0.017)	(0.017)	(0.017)	(0.017)
LR	−0.074***	−0.071***	−0.074***	−0.055***	−0.073***	−0.069***	−0.074***	−0.070***	−0.074***	−0.071***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)
Constant	0.176***	0.170***	0.047	−0.223***	−0.989**	−3.743***	0.192***	0.029	−0.982**	−2.905***
	(0.010)	(0.010)	(0.071)	(0.051)	(0.391)	(1.151)	(0.071)	(0.052)	(0.391)	(1.058)
Observations	11,935	11,935	11,935	11,935	11,935	11,935	11,935	11,935	11,935	11,935
R-squared	0.589	0.590	0.589	0.551	0.589	0.587	0.595	0.596	0.589	0.591
P	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses, *, **, and *** indicate that they pass the test at the levels of 10 %, 5 %, and 1 %, respectively.

Table 6
Robustness test results for excluding industries with high digitalization.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AIA		1.609***				1.499***	1.265***	1.714***
		(0.227)				(0.244)	(0.285)	(0.232)
HHC			0.002***			0.001**		
			(0.000)			(0.000)		
HSC				0.007***			0.006***	
				(0.002)			(0.002)	
HRC					0.014***			0.003
					(0.004)			(0.007)
HHC × AIA						0.004		
						(0.004)		
HSC × AIA							0.074*	
							(0.043)	
HRC × AIA								−0.371*
								(0.197)
CSR	−0.004***	−0.004***	−0.005***	−0.005***	−0.004***	−0.004***	−0.004***	−0.004***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
RDE	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ES	0.203***	0.194***	0.204***	0.201***	0.203***	0.195***	0.193***	0.194***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
IA	0.062***	0.060***	0.062***	0.063***	0.062***	0.061***	0.062***	0.061***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
FS	0.151***	0.140***	0.151***	0.146***	0.151***	0.140***	0.137***	0.140***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
FG	−0.127***	−0.126***	−0.129***	−0.135***	−0.128***	−0.128***	−0.132***	−0.128***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)
FL	0.541***	0.541***	0.551***	0.569***	0.548***	0.551***	0.565***	0.550***
	(0.035)	(0.034)	(0.035)	(0.036)	(0.035)	(0.035)	(0.035)	(0.034)
Constant	−2.549***	−2.266***	−2.568***	−2.472***	−2.553***	−2.276***	−2.215***	−2.270***
	(0.161)	(0.166)	(0.162)	(0.165)	(0.161)	(0.166)	(0.167)	(0.165)
Observations	5361	5361	5361	5361	5361	5361	5361	5361
R-squared	0.440	0.445	0.440	0.441	0.442	0.446	0.447	0.448
P	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses, *, **, and *** indicate that they pass the test at the levels of 10 %, 5 %, and 1 %, respectively.

exclusion of highly digitalized industries.

Model (1) still demonstrates the effectiveness of control variables selection. Model (2) tested the impact of AI technology adoption, with an estimated coefficient of 1.609, significant at the 1 % level. After excluding the influence of high digitalization industries, H1 still maintains robustness.

Models (3) and (6) demonstrated the impact of HHC and AI technology adoption in manufacturing firms on green value creation. In model (3), the coefficient of HHC was 0.002, significant at the 1 % level; The coefficient of HHC × AI in model (6) was 0.004, which had no significant promoting effect on green value creation. The reason for this result may be that in manufacturing firms with low levels of digitization, employees generally lack digital skills related to AI technology. In this case, they often rely more on their initiative and creativity to engage in green value creation activities.

Models (4) and (7) showed the impact of HSC and AI technology adoption on green value creation in manufacturing firms. The coefficient of HSC in the model (4) was 0.007, significant at the 1 % level; The coefficient of HSC × AI in the model (7) was 0.074, significant at the 10 % level. Hypothesis H2b was further validated. Models (5) and (8) reflected the impact of HRC and AI technology adoption on green value creation in manufacturing firms. The coefficient of HRC in model (5) was 0.014, significant at the 1 % level; The coefficient of HRC × AI in the model (8) was −0.371, significant at the 10 % level, indicating the robustness of H2c.

5. Discussion and conclusion

AI opens up new possibilities for human value creation, rejuvenating production factors, content and various fields. Addressing the imperative of green and sustainable development, the exploration of how manufacturing firms can leverage their HI in collaboration with AI to create environmentally friendly value has become a focal point in both theoretical and practical domains (Guikema, 2022).

Despite extensive research on systematic value creation (Niu et al., 2021; Oliveira et al., 2021; Al-Omoush et al., 2023; Reimsbach and Braam, 2023; Santarsiero et al., 2023), there remains significant room for investigating the green value creation of manufacturing firms. Moreover, while the existing literature extensively examines the impact of AI from macro and micro perspectives (Felten et al., 2021; Balasubramanian et al., 2022; Pietronudo et al., 2022; Ivanov, 2023; Yin et al., 2024), there is a dearth of studies exploring the boundary conditions of AI technology adoption's impact on green value creation in manufacturing firms. In contrast to previous studies, this article delved into the potential interaction mechanisms of AI technology adoption by comprehensively measuring the impact of collaboration between AI and HI on the green value creation of manufacturing firms within the green innovation ecosystem.

The empirical analysis of data from 935 A-share listed manufacturing firms in China yielded the following conclusions. First, AI technology adoption has significantly and positively impacted the green value creation of manufacturing firms. In other words, AI technology adoption facilitates the use of HI by manufacturing firms within the green innovation ecosystem.

Second, the human capital and structural capital of HI within manufacturing firms have a significant positive impact on such firms' green value creation, and AI technology adoption significantly moderates this relationship. That is, high-quality human capital enhances creativity and initiative in the process of creating green value, thereby contributing to green innovation and a higher value for customers, the environment and society. Simultaneously, high-quality structural capital acts as a lubricant for manufacturing firms to create green value. Human and structural capital, the most critical HI resources and capabilities within an organisation, are indispensable elements in the process of creating green value for manufacturing firms. Especially in complex entities and contexts with distinct characteristics within the green innovation ecosystem, such mechanisms have become even more important due to the impact of AI technology adoption.

Third, the relational capital of HI can significantly promote manufacturing firms to create green value, but AI technology adoption negatively moderates this relationship. That is to say, high-quality relational capital can serve as a potential driving force for manufacturing firms to create green value. However, heightened AI technology adoption significantly impedes enthusiasm for this mechanism.

5.1. Theoretical contributions

This study contributes to theory and the literature in several ways. First, it adopts a green development perspective to explore the relationship mechanism and internal logic of how manufacturing firms utilise HI for green value creation, which has important theoretical value. Specifically, we examined whether and how IC, as the core resource and capability of HI, can drive the green value creation of manufacturing firms for sustainable development, both theoretically and empirically. Previous studies have focused predominantly on the antecedents and mechanisms of value creation and IC (Amit and Han, 2017; Li et al., 2021; Lugosi, 2021; Pinochet et al., 2021; Santarsiero et al., 2023; Schilling and Seuring, 2023). However, there is a notable gap in the literature regarding the role of IC as an HI resource and its impact on the green value creation of manufacturing firms. Therefore, our findings expand the scope of research on the relationship between HI and green value creation within organisations, shedding light on the driving factors of green value creation in manufacturing firms.

Second, we revealed the mechanism through which AI technology influences the green value creation of manufacturing firms from a technology adoption perspective. This introduces a novel research idea and direction for studying the development of green transformation in the manufacturing industry. While previous studies have extensively explored the direct impact of AI technology at the macro and micro levels (Acemoglu and Restrepo, 2020; Balasubramanian et al., 2022; Verma and Singh, 2022; Yang et al., 2023; Yin et al., 2024), the influence mechanism of AI technology as a technological environment in the green value creation of innovation entities in the green innovation ecosystem remains insufficiently explained. Thus, our conclusions contribute by applying actor network theory to green value creation and offering new insights for manufacturing firms as innovation subjects engaged in green value creation within the green innovation ecosystem. Importantly, this study introduces a fresh perspective for exploring issues related to green development.

Third, this article explored the research topic of green value creation for manufacturing firms in a green innovation ecosystem from the perspective of AI and HI collaboration. Additionally, we employed two indicators, green innovation efficiency and pollution emission equivalent, to comprehensively evaluate and measure the green value creation of manufacturing firms. Although the measurement of green innovation (El-Kassar and Singh, 2019; Chin et al., 2022) and value creation (Tantalo and Priem, 2016; Li et al., 2021; Schilling and Seuring, 2023) are extensively studied in the literature, these measurements primarily rely on green patents or financial indicators. While these positive indicators reflect essential issues to a certain extent, they also have certain limitations. In light of these shortcomings, we chose to test the relationship mechanism using positive indicators (green technology research and development and application efficiency) and negative indicators (pollution emissions equivalent). The efficiency of green technology R&D and application reflects the economic and environmental benefits of green value creation, with larger values indicating higher levels of green value creation for manufacturing firms. Conversely, the pollutant emissions equivalent value serves as a reverse indicator of green value creation, where larger values signify lower levels of green value creation in manufacturing firms. Therefore, our conclusions offer a valuable supplement to the measurement of green value creation at the organisational level.

5.2. Practical implications

The findings of this study offer valuable operational and practical implications for government and manufacturing firms making strategic decisions on green development.

First, the green value creation of manufacturing firms depends heavily on green innovation, a complex process that necessitates collaboration and integration within the green innovation ecosystem (Wolf, 2014; Huang et al., 2022). To achieve green value creation, manufacturing firms should continually expand their green knowledge base, enhance the interaction and integration of green knowledge across different fields and avoid knowledge isolation. This involves encouraging employees to share green knowledge, reconfiguring existing technical knowledge (Forés and Camisón, 2016) and embracing new concepts, such as co-creation networks and leverage, to disrupt traditional value-creation methods (Oliveira et al., 2021; Hanifah et al., 2022). In the green innovation ecosystem, manufacturers should steer clear of value chains and information silos. By embracing a new value system, manufacturing firms can enhance their green value creation through innovative business models, resetting product architectures, data value mining, external resource integration, optimised business processes and other avenues, thereby achieving sustainable market competition.

Second, HI, represented by IC, stands as the most critical resource and capability for manufacturing firms in the process of green value creation. Despite advancements in AI technology facilitating resource interaction, the relationship between HI and AI remains essentially a relationship between humans and tools (Callen et al., 2023). It is undeniable that AI has surpassed humans in scientific computing and deductive performance, but it is still a derivative and a functional imitation of HI. Human capital, particularly green talent, plays a pivotal role as the driving force behind other forms of capital (Dost et al., 2016). Manufacturing firms can improve their green knowledge, ability and technology through employee education and training (Wright et al., 2001; Tseng and Goo, 2013). Human capital, structural capital, and relational capital work together to increase the stock of green knowledge (Liebowitz and Suen, 2013), contributing to green value creation. Manufacturers need to systematically transform the knowledge, experience and skills hidden within green human capital into overall organisational knowledge and integrate it into areas such as organisational structure and culture to leverage the role of green value creation (Jost and Susser, 2020). Simultaneously, maintaining friendly relationships with stakeholders enhances the capital stock of green relations and sustains the potential driving force of green value creation in manufacturing firms (Li et al., 2021).

Third, manufacturing firms should leverage external AI technology adoption to drive green value creation in green innovation ecosystems. Strengthening AI technology adoption can promote the efficiency of human green value creation during the digitalisation and intelligence promotion processes. This involves integrating internal and external green resources and deepening the integration of AI technology and green innovation processes to enhance the ability to create green value (Felten et al., 2021). Building a green talent team, cultivating employees' green insights, thinking patterns, and knowledge and using AI technology adoption to drive employees to participate in green innovation are crucial for upgrading green value creation (Verma and Singh, 2022; Yang, 2022). Leveraging digital technology to optimise organisational structures and management mechanisms promotes collaborative green innovation among departments (Raisch and Krakowski, 2021), thereby improving the efficiency of green value creation. Manufacturers should strive to reduce their embedding in relationship networks, maintain reasonable relationship strength and avoid path dependence to prevent their reluctance to think and short-sighted behaviours from hindering AI technology adoption and driving green value creation in manufacturing firms (Beltramino et al., 2021; Jia et al., 2023). Our primary focus should be on enhancing the AI capabilities of organisations and employees, utilising AI to bolster human creativity rather than impede it.

Fourth, our findings hold profound implications for both government decision-making and the advancement of pertinent industrial sectors. The government should formulate comprehensive policies to encourage manufacturing firms to adopt AI technology, incorporating incentives such as tax relief and R&D subsidies (Reimsbach and Braam, 2023). Additionally, it could establish a dedicated fund to support manufacturers in their AI research and application endeavors, ultimately driving the green transformation of the manufacturing sector. The government should intensify its efforts to cultivate and attract talent in the artificial intelligence area (Dubey et al., 2022; Schilling and Seuring, 2023), thereby providing intellectual support to manufacturing firms and expediting the widespread adoption and application of AI technology within manufacturing. Concurrently, the government must establish an exhaustive regulatory framework to ensure the legality, safety, and ethical standards of artificial intelligence technology applications. Additionally, industry associations ought to formulate stringent industry benchmarks for the deployment of AI technology (Hanifah et al., 2022; Cirillo et al., 2023), thereby nurturing the evolution of manufacturing towards environmentally friendly and intelligent paradigms.

5.3. Limitations and directions for the future

While this study empirically tested the collaboration of AI and HI on the green value creation of manufacturing firms from an environmental perspective, certain limitations warrant consideration. In future research, it is essential to expand and deepen the exploration of green development and transformation within manufacturing firms. First, although we uncovered the direct mechanism by which HI contributes to the creation of green value in manufacturing firms, we did not consider the mediating mechanism between HI and green value creation. Future research should delve into the process of creating green value and explore its most comprehensive impact mechanisms. Second, this article employed IC as a proxy variable for HI in manufacturing firms. However, there is significant heterogeneity in the level of IC among manufacturing firms in different industries. Therefore, future research could consider a more precise classification of manufacturing firms in various industries. Third, we focused solely on examining the direct impact mechanism of the single dimension of AI technology adoption on green value creation and its interaction with IC in manufacturing firms. In future studies, we aim to further explore the diverse impact mechanisms of AI technology adoption in different dimensions of green value creation.

These future research directions will address the current limitations and contribute to a more nuanced understanding of the collaboration between AI and HI in the context of green value creation for manufacturing firms.

CRediT authorship contribution statement

Lei Huang: Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Funding acquisition, Data curation, Conceptualization. **Tachia Chin:** Supervision, Project administration, Conceptualization. **Armando Papa:** Supervision, Software, Methodology, Formal analysis. **Paola Pisano:** Resources, Methodology, Formal analysis, Data curation.

Acknowledgment

The authors are very grateful for the editor's helpful comments, suggestions and the two anonymous reviewers. This paper was supported by the National Social Science Fund of China (Grant No.22CGL013). It is based on research funded by the Basic Research Program of the HSE University. The authors thank them heartedly for funding this study.

Data availability

Data will be made available on request.

References

Acemoglu, D., Restrepo, P., 2020. Robots and jobs: evidence from US labor markets. J. Polit. Econ. 128 (6), 2188–2244.

Adner, R., 2006. Match your innovation strategy to your innovation ecosystem. Harv. Bus. Rev. 84 (4), 98–107.

Adner, R., Kapoor, R., 2010. Value creation in innovation ecosystems: how the structure of technological interdependence affects firm performance in new technology generations. Strateg. Manag. J. 31 (3), 306–333.

Adner, R., Kapoor, R., 2016. Innovation ecosystems and the pace of substitution: re-examining technology S-curves. Strateg. Manag. J. 37 (4), 625–648.

Ahn, M.J., Chen, Y.C., 2022. Digital transformation toward AI-augmented public administration: the perception of government employees and the willingness to use AI in government. Gov. Inf. Q. 39 (2), 101664. https://doi.org/10.1016/j.giq.2021.101664.

Al-Omoush, K.S., de Lucas, A., del Val, M.T., 2023. The role of e-supply chain collaboration in collaborative innovation and value-co creation. J. Bus. Res. 158. https://doi.org/10.1016/j.jbusres.2023.113647.

Amit, R., Han, X., 2017. Value creation through novel resource configurations in a digitally enabled world. Strateg. Entrep. J. 11 (3), 228–242.

Azadeh, A., Ziaei, B., Moghaddam, M., 2012. A hybrid fuzzy regression-fuzzy cognitive map algorithm for forecasting and optimization of housing market fluctuations. Expert. Syst. 39 (1), 298–315.

Baert, C., Meuleman, M., Debruyne, M., Wright, M., 2016. Portfolio entrepreneurship and resource orchestration. Strateg. Entrep. J. 10 (4), 346–370.

Bag, S., Pretorius, J.H.C., 2022. Relationships between industry 4.0, sustainable manufacturing and circular economy: proposal of a research framework. Int. J. Organ. Anal. 30 (4), 864–898.

Balasubramanian, N., Ye, Y., Xu, M., 2022. Substituting human decision-making with machine learning: implications for organizational learning. Acad. Manag. Rev. 47 (3), 448–465.

Bassi, L.J., Van Buren, M.E., 2007. Valuing investment in green intellectual capital. Int. J. Technol. Manag. 18 (2), 414–432.

Bayraktaroglu, A.E., Calisir, F., Baskak, M., 2019. Intellectual capital and firm performance: an extended VAIC model. J. Intellect. Cap. 20 (3), 406–425.

Beltagui, A., Rosli, A., Candi, M., 2020. Exaptation in a digital innovation ecosystem: the disruptive impacts of 3D printing. Res. Policy 49 (1), 103833. https://doi.org/10.1016/j.respol.2019.103833.

Beltramino, N.S., Garcia-Perez-de-Lema, D., Valdez-Juarez, L.E., 2021. The role of intellectual capital on process and products innovation. Empirical study in SMEs in an emerging country. J. Intellect. Cap. 23 (4), 741–764.

Bennett, M.T., 2022. Computable Artificial General Intelligence. ArXiv. https://doi.org/10.48550/arXiv.2205.10513. 2023-05-09.

Bertani, F., Ponta, L., Raberto, M., Teglio, A., Cincotti, S., 2021. The complexity of the intangible digital economy: an agent-based model. J. Bus. Res. 129, 527–540.

Broadstock, D.C., Matousek., Meyer, M., ATzeremes, N.G., 2020. Does corporate social responsibility impact firms' innovation capacity? The indirect link between environmental & social governance implementation and innovation performance. J. Bus. Res. 119, 99–110. https://doi.org/10.1016/j.jbusres.2019.07.014.

Brooks, R.A., 1991. Intelligence without representation. Artif. Intell. 47, 139–159.

Callen, A., Beth, A.B., Anne-Laure, F., 2023. "Collaborating" with AI: taking a system view to explore the future of work. Organ. Sci. 34 (5), 1672–1694.

Callon, M., Latour, B., 1981. Unscrewing the big leviathan: How actors macro-structure reality and how sociologists help them to do so. In: Knorr-Cetina, K., Cicourel, A.V. (Eds.), Advances in Social Theory and Methodology: Towards an Integration of Micro-and Macro-Sociologies. Routledge, Boston, MA, pp. 277–303.

Chatterjee, S., Moody, G., Lowry, P.B., Chakraborty, S., Hardin, A., 2020. Information technology and organizational innovation: harmonious information technology affordance and courage-based actualization. J. Strateg. Inf. Syst. 29 (1), 101596. https://doi.org/10.1016/j.jsis.2020.101596.

Chin, T., Ghouri, M.W.A., Jin, J., Deveci, M., 2024. AI technologies affording the orchestration of ecosystem-based business models: the moderating role of AI knowledge spillover. Humanities and Social Sciences Communications 11 (1), 1–13.

Chin, T., Shi, Y., Singh, S.K., Agbanyo, G.K., Ferraris, A., 2022. Leveraging blockchain technology for green innovation in ecosystem-based business models: a dynamic capability of values appropriation. Technol. Forecast. Soc. Chang. 183, 121908. https://doi.org/10.1016/j.techfore.2022.121908.

Cirillo, V., Fanti, L., Mina, A., Ricci, A., 2023. The adoption of digital technologies: investment, skills, work organization. Struct. Chang. Econ. Dyn. 66, 89–105.

Dost, M., Badir, Y.F., Ali, Z., Tariq, A., 2016. The impact of intellectual capital on innovation generation and adoption. J. Intellect. Cap. 17 (4), 675–695.

Duan, Y., Huang, L., Luo, X., Cheng, T.C.E., Liu, H., 2021. The moderating effect of absorptive capacity on the technology search and innovation quality relationship in high-tech manufacturing firms. J. Eng. Technol. Manag. 62, 101656.

Dubey, R., Bryde, D.J., Dwivedi, Y.K., Graham, G., Foropon, C., 2022. Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: a practice-based view. Int. J. Prod. Econ. 250, 108618. https://doi.org/10.1016/j.ijpe.2022.108618.
Edvinsson, L., Malone, M.S., 2005. Intellectual Capital-Realizing your Firm 'S True Value by Finding its Hidden Roots. Harper Business, New York.
El-Kassar, A.N., Singh, S.K., 2019. Green innovation and organizational performance: the influence of big data and the moderating role of management commitment and HR practices. Technol. Forecast. Soc. Chang. 144, 483–498.
Fan, C., Zhang, C., Yahja, A., Mostafavi, A., 2021. Disaster City digital twin: a vision for integrating artificial and human intelligence for disaster management. Int. J. Inf. Manag. 56, 102049. https://doi.org/10.1016/j.ijinfomgt.2019.102049.
Farzaneh, M., Wilden, R., Afshari, L., Mehralian, G., 2022. Dynamic capabilities and innovation ambidexterity: the roles of intellectual capital and innovation orientation. J. Bus. Res. 148, 47–59.
Felten, E., Raj, M., Seamans, R., 2021. Occupational, industry, and geographic exposure to artificial intelligence: a novel dataset and its potential uses. Strateg. Manag. J. 42, 2195–2217.
Flammer, C., 2021. Corporate green bonds. J. Financ. Econ. 142 (2), 499–516.
Forés, B., Camisón, C., 2016. Does incremental and radical innovation performance depend on different types of knowledge accumulation capabilities and organizational size? J. Bus. Res. 69 (2), 831–848.
Giudice, M.D., Scuotto, V., Ballestra, L.V., Pironti, M., 2022. Humanoid robot adoption and labour productivity: a perspective on ambidextrous product innovation routines. Int. J. Hum. Resour. Manag. 33 (6), 1098–1124.
Guenster, N., Bauer, R., Derwall, J., Koedijk, K., 2011. The economic value of corporate eco-efficiency. Eur. Financ. Manag. 17 (4), 679–704.
Guikema, S., 2022. Artificial intelligence for natural hazards risk analysis: potential, challenges, and research needs. Risk Anal. 40 (6), 1117–1123.
Guo, H., Guo, A.Q., Ma, H.J., 2022. Inside the black box: how business model innovation contributes to digital start-up performance. J. Innov. Knowl. 7 (2). https://doi.org/10.1016/j.jik.2022.100188.
Hanifah, H., Abd Halim, N., Vafaei-Zadeh, A., Nawaser, K., 2022. Effect of intellectual capital and entrepreneurial orientation on innovation performance of manufacturing SMEs: mediating role of knowledge sharing. J. Intellect. Cap. 23 (6), 1175–1198.
Huang, L., Wang, C., Chin, T., Huang, J., Cheng, X., 2022. Technological knowledge coupling and green innovation in manufacturing firms: moderating roles of mimetic pressure and environmental identity. Int. J. Prod. Econ. 248, 108482. https://doi.org/10.1016/j.ijpe.2022.108482.
Iheanachor, N., David-West, Y., Umukoro, I.O., 2021. Business model innovation at the bottom of the pyramid – a case of mobile money agents. J. Bus. Res. 127, 96–107.
Itami, H., Nishino, K., 2010. Killing two birds with one stone—profit for now and learning for the future. Long Range Plan. 43 (2–3), 364–369.
Ivanov, D., 2023. Intelligent digital twin (iDT) for supply chain stress-testing, resilience, and viability. Int. J. Prod. Econ. 263, 108938. https://doi.org/10.1016/j.ijpe.2023.108938.
Jia, N., Luo, X., Fang, Z., Liao, C., 2023. When and how artificial intelligence augments employee creativity. Acad. Manag. J. https://doi.org/10.5465/amj.2022.0426.
Jost, P.J., Susser, T., 2020. Firm -customer interaction in mass customization. Int. J. Prod. Econ. 220, 107454.
Kale, P., Singh, H., Perlmutter, H., 2000. Learning and protection of proprietary assets in strategic alliances: building relational capital. Strateg. Manag. J. 21 (3), 217–237.
Kammerer, D., 2009. The effects of customer benefit and regulation on environmental product innovation. Empirical evidence from appliance manufacturers in Germany. Ecol. Econ. 68 (8–9), 2285–2295.
Kang, S.C., Snell, S.A., 2009. Intellectual capital architectures and ambidextrous learning: a framework for human resource management. J. Manag. Stud. 46 (1), 65–92.
Khan, M.N., Sinha, A.K., 2022. Development of a sustainable supply chain network for the cement manufacturing industry using real-coded genetic algorithm. Soft. Comput. 26 (22), 12235–12255.
Kock, C.J., Santaló, J., Diestre, L., 2012. Corporate governance and the environment: what type of governance creates greener companies? J. Manag. Stud. 49, 492–514.
Latour, B., 1986. Laboratory Life: The Construction of Scientific Facts. Princeton university press.
Lee, J.Y., Kim, D., Choi, B., Jiménez, A., 2023. Early evidence on how industry 4.0 reshapes MNEs' global value chains: the role of value creation versus value capturing by headquarters and foreign subsidiaries. J. Int. Bus. Stud. 54, 599–630.
Lee, Y.S., Kim, T., Choi, S., Kim, W., 2022. When does AI pay off? AI-adoption intensity, complementary investments, and R&D strategy. Technovation 118, 102590.
Lei, Y., Yang, B., Jiang, X., Jia, F., Nandi, A.K., 2020. Applications of machine learning to machine fault diagnosis: a review and roadmap. Mech. Syst. Signal Process. 138, 106587. https://doi.org/10.1016/j.ymssp.2019.106587.
Li, X., Nosheen, S., Ul Haq, N., Gao, X., 2021. Value creation during fourth industrial revolution: use of intellectual capital by most innovative companies of the world. Technol. Forecast. Soc. Chang. 163, 120479. https://doi.org/10.1016/j.techfore.2020.120479.
Liebowitz, J., Suen, C.Y., 2013. Developing knowledge management metrics for measuring green intellectual capital. J. Intellect. Cap. 1 (1), 54–67.
Liu, Z., Li, K.W., Tang, J., Gong, B., Huang, J., 2021. Optimal operations of a closed-loop supply chain under a dual regulation. Int. J. Prod. Econ. 233, 107991. https://doi.org/10.1016/j.ijpe.2020.107991.
Lugosi, P., 2021. The value creation cycle of peer review. Ann. Tour. Res. 86, 103092. https://doi.org/10.1016/j.annals.2020.103092.
Makridis, C.A., Mishra, S., 2022. Artificial intelligence as a service, economic growth, and well-being. J. Serv. Res. 25 (4), 505–520.
Moore, J.F., 1993. Predators and prey: a new ecology of competition. Harv. Bus. Rev. 71 (3), 75–86.
Nambisan, S., 2018. Architecture vs. ecosystem perspectives: reflections on digital innovation. Inf. Organ. 28 (2), 104–106.
Niu, Y.M., Jiang, Z.B., Geng, N., Jiang, S., 2021. Disclosing the formation and value creation of servitization through influential factors: a systematic review and future research agenda. Int. J. Prod. Res. 59 (23), 7057–7089.
Oliveira, L., Fleury, A., Fleury, M.T., 2021. Digital power: value chain upgrading in an age of digitization. Int. Bus. Rev. 30 (6). https://doi.org/10.1016/j.ibusrev.2021.101850.
Oliveira, L., Rodrigues, L.L., Craig, R., 2010. Intellectual capital reporting in sustainability reports. J. Intellect. Cap. 11 (4), 575–594.
Pietronudo, M.C., Croidieu, G., Schiavone, F., 2022. A solution looking for problems? A systematic literature review of the rationalizing influence of artificial intelligence on decision-making in innovation management. Technol. Forecast. Soc. Chang. 182, 121828. https://doi.org/10.1016/j.techfore.2022.121828.
Pillai, R., Sivathanu, B., 2020. Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. BIJ 27, 9, 2599–2629.
Pinochet, L.H.C., Amorim, G.D.B., Lucas, D., de Souza, C.A., 2021. Consequential factors of big data's analytics capability: how firms use data in the competitive scenario. J. Enterp. Inf. Manag. 34 (5), 1406–1428.
Priem, R.L., Wenzel, M., Koch, J., 2018. Demand-side strategy and business models: putting value creation for consumers center stage. Long Range Plan. 51 (1), 22–31.
Raisch, S., Krakowski, S., 2021. Artificial intelligence and management: the automation–augmentation paradox. Acad. Manag. Rev. 46 (1), 192–210.
Reimsbach, D., Braam, G., 2023. Creating social and environmental value through integrated thinking: international evidence. Bus. Strateg. Environ. 32 (1), 304–320. https://doi.org/10.1002/bse.3131.
Sahu, A.R., Palei, S.K., Mishra, A., 2023. Data-driven fault diagnosis approaches for industrial equipment: a review. Expert. Syst. 41, e13360. https://doi.org/10.1111/exsy.13360.
Santarsiero, F., Carlucci, D., Jarrar, Y., 2023. Creating value from big data: a knowledge assets-based view. Knowl. Manag. Res. Pract. 21 (4), 714–724.
Santoro, G., Bresciani, S., Papa, A., 2018. Collaborative modes with cultural and creative industries and innovation performance: the moderating role of heterogeneous sources of knowledge and absorptive capacity. Technovation 92-93, 102040. https://doi.org/10.1016/j.technovation.2018.06.003.
Sayes, E., 2014. Actor–Network Theory and methodology: Just what does it mean to say that nonhumans have agency? Soc. Stud. Sci. 44 (1), 134–149.
Schilling, L., Seuring, S., 2023. Mobile financial service-enabled micro-businesses driving sustainable value creation in emerging markets. Technol. Forecast. Soc. Chang. 192. https://doi.org/10.1016/j.techfore.2023.122596.
Searle, J.R., 1980. Minds, brains, and programs. Behav. Brain Sci. 3 (3), 417–457.
Shepherd, D.A., Majchrzak, A., 2022. Machines augmenting entrepreneurs: opportunities (and threats) at the Nexus of artificial intelligence and entrepreneurship. J. Bus. Ventur. 37 (4), 106227. https://doi.org/10.1016/j.jbusvent.2022.106227.
Sinha, A.K., Anand, A., 2017. Towards fuzzy preference relationship based on decision making approach to access the performance of suppliers in environmental conscious manufacturing domain. Comput. Ind. Eng. 105, 39–54.
Smirnov, E., Dvoryatkina, S., Martyushev, N., Shcherbatykh, S., 2023. Software package to support Students' research activities in the hybrid intellectual environment of mathematics teaching. Mathematics 11 (4). https://doi.org/10.3390/math11040952.
Stefano, B., Alberto, F., Gabriele, S., Masaaki, K., 2022. Opening up the black box on digitalization and agility: key drivers and main outcomes. Technol. Forecast. Soc. Chang. 178, 121567. https://doi.org/10.1016/j.techfore.2022.121567.
Sultana, S., Akter, S., Kyriazis, E., 2022. How data-driven innovation capability is shaping the future of market agility and competitive performance? Technol. Forecast. Soc. Chang. 174, 121260.
Tang, P.M., Koopman, J., Mcclean, S.T., Zhang, J.H., Li, C.H., De Cremer, D., Lu, Y., Ng, C.T.S., 2022. When conscientious employees meet intelligent machines: an integrative approach inspired by complementarity theory and role theory. Acad. Manag. J. 65 (3), 1019–1054.
Tantalo, C., Priem, R.L., 2016. Value creation through stakeholder synergy. Strateg. Manag. J. 37 (2), 314–329.
Tseng, C.Y., Goo, Y.J., 2013. Green intellectual capital and corporate value in an emerging economy: empirical study of Taiwanese manufacturers. R&D Manag. 35 (2), 187–201.
Valle-Cruz, D., & García-Contreras, R. (2023). Towards AI-driven transformation and smart data management: emerging technological change in the public sector value chain. Public Policy and Administration, 0(0). doi:https://doi.org/10.1177/09520767231188401.
Verma, S., Singh, V., 2022. Impact of artificial intelligence-enabled job characteristics and perceived substitution crisis on innovative work behavior of employees from high-tech firms. Comput. Hum. Behav. 131, 107215. https://doi.org/10.1016/j.chb.2022.107215.
Wang, J., Shibayama, S., 2022. Mentorship and creativity: effects of mentor creativity and mentoring style. Res. Policy 51 (3), 104451.
Wolf, J., 2014. The relationship between sustainable supply chain management, stakeholder pressure and corporate sustainability performance. J. Bus. Ethics 119 (3), 317–328.
Wright, P.M., Dunford, B.B., Snell, S.A., 2001. Green human resource and the resource based view of the firm. J. Manag. 27 (6), 701–721.
Xie, K., Wu, Y., Xiao, J.H., Hu, Q., 2016. Value co-creation between firms and customers: the role of big data-based cooperative assets. Inf. Manag. 53 (8), 1034–1048.

Xu, J., Li, J., 2022. The interrelationship between intellectual capital and firm performance: evidence from China's manufacturing sector. J. Intellect. Cap. 23 (2), 313–341.
Yam, K.C., Tang, P.M., Jackson, J.C., Su, R., Gray, K., 2023. The rise of robots increases job insecurity and maladaptive workplace behaviors: multimethod evidence. J. Appl. Psychol. 108 (5), 850–870.
Yang, C.H., 2022. How artificial intelligence technology affects productivity and employment: firm-level evidence from Taiwan. Res. Policy 51 (6), 104536. https://doi.org/10.1016/j.respol.2022.104536.
Yang, S.F., Ma, D., Shen, Z.Y., Wen, L., Dong, L., 2023. The impact of artificial intelligence industry agglomeration on economic complexity. Economic Research-Ekonomska Istraživanja 36 (1), 1420–1448.
Yao, S., Shen, P., Dai, T., Dai, F., Wang, Y., Zhang, W., Lu, H., 2023. Human understandable thyroid ultrasound imaging AI report system - a bridge between AI and clinicians. IScience 26 (4), 106530. https://doi.org/10.1016/j.isci.2023.106530.
Yin, M., Jiang, S.Y., Niu, X.Y., 2024. Can AI really help? The double-edged sword effect of AI assistant on employees' innovation behavior. Comput. Hum. Behav. 150, 107987. https://doi.org/10.1016/j.chb.2023.107987.
Yoo, Y., Boland, R.J., Lyytinen, K., Majchrzak, A., 2012. Organizing for innovation in the digitized world. Organ. Sci. 23 (5), 1398–1408.
Yousaf, Z., 2021. Go for green: green innovation through green dynamic capabilities: accessing the mediating role of green practices and green value co-creation. Environ. Sci. Pollut. Res. 28 (39), 54863–54875.
Zhang, S., Meng, Q.C., Xie, J.C., 2022. Closed-loop supply chain value co-creation considering equity crowdfunding. Expert Syst. Appl. 199. https://doi.org/10.1016/j.eswa.2022.117003.
Zhang, Y., Hu, S., Chen, L., 2024. Internet technology adoption and firm energy efficiency: evidence from China. Technol. Forecast. Soc. Chang. 201, 123214.

Lei Huang, PhD, is an assistant professor at the School of Management, Zhejiang University of Technology (ZJUT), Hangzhou, China. His research focuses are knowledge management & organizational innovation, green development of manufacturing firms, green innovation, and cross-cultural management. He has published more than ten articles in top English and Chinese journals, such as Journal of Business Research, International Journal of Production Economics, Journal of Knowledge Management, Asia Pacific Journal of Management, Journal of Engineering and Technology Management. And he also is a guest editor and anonymous reviewer for many Journals, among which International Journal of Production Economics (IJPE) awarded him the "Outstanding Reviewer" Academic Award in 2020.

Tachia Chin, PhD, is a Professor at School of Management, Zhejiang University of Technology, Hangzhou, China. She earned her Ph.D. at Jinan University and completed her post-doc study at Sun Yat-sen University. She has more than 10 years of working experience as a senior HR/CSR executive for foreign-invested manufacturing firms in China. She has published more than 100 articles in top English and Chinese journals such as Technological Forecast and Social Change, International Journal of Production Economics, Journal of International management, International Journal of Human Resource Management, Career Development International and Journal of Knowledge Management, and has served as a leading guest editor for Asia Pacific Business Review, Journal of Knowledge Management and Career Development International. Her research focuses are cross-cultural management, Knowledge Management, leadership and strategic HRM.

Armando Papa, Ph.D., is currently Full Professor of management, innovation and marketing at the department of Economics and Statistics at the University of Salerno. *He is Fellow (F-EMAB) of the EuroMed Research Business Institute (EMRBI) and he is research member of the GNOSIS - Mediterranean Institute for Management Science, School of Business at the University of Nicosia, Cyprus. Priorly he has been associate professor of marketing at the University of Teramo. He earned the Italian National qualification as Full Professor in 2020. Earlier, he joined the University of Rome Universitas Mercatorum. He was formerly research fellow at ICxT Innovation Center, University of Turin. He holds a Ph.D. in Management from the University of Naples Federico II and a Postgraduate Master in Finance (2011). He is also Member of the EuroMed Research Business Institute. He won the Best Paper Award at the 9th EuroMed Conference in Warsaw (Poland) in 2016. He is skilled in Knowledge Management, Open Innovation and Technology Entrepreneurship, Corporate Governance and Family Business. He is Associate Editor of Journal of Knowledge Economy (Springer) and Managing Editor of Journal of Knowledge Management (Emerald) and International Studies in Management and Organization (Taylor & Francis). He is listed as Innovation Manager at the Italian Ministry of Economic Development. Engaged in various peer-review processes for several ranked and outstanding international management. He is engaged as editorial board member for the Journal of Intellectual Capital, British Food Journal, Management Research Review, and other international journals. He is member of the I.P.E. Business School of Naples*.

Paola Pisano, Associate Professor of Economics and Business Management at the Department of Economics and Statistics of the University of Turin, Paola Pisano holds a respected academic background and extensive professional experience in the field of innovation and technology. A prolific author and researcher, Paola Pisano has contributed over 90 publications to esteemed national and international academic journals, and authored two books on innovation and emerging technologies. Her research and teaching activities are distinguished by its focus on the profound impact of emerging technologies, new business models and policy on organizations, industries, and countries. Currently, Paola Pisano is a member of the Bureau of UNESCO's Women4Ethical AI platform, promoting ethical and responsible AI practices. She serves as the Director of the 'Laboratorio Smart City' at the University of Turin, leading research and initiatives on smart city solutions.