

Digital infrastructure and green resilience in manufacturing: Spatial spillovers and regional convergence in China

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Article

Keywords: Digital infrastructure, manufacturing digitalization, green resilience, spatial spillovers, regional convergence, sustainable manufacturing, China

Posted Date: September 28th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10442764/v1>

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Additional Declarations: No competing interests reported.

1 **Digital infrastructure and green resilience in manufacturing: Spatial** 2 **spillovers and regional convergence in China**

3
4 **Abstract:** Digital infrastructure is reshaping manufacturing by improving data
5 connectivity, production coordination, resource allocation, and market responsiveness.
6 This study examines how digitalization supports green resilience in China's
7 manufacturing sector and how digital and green upgrading diffuse across regions. Using
8 provincial manufacturing data, we construct an evaluation system for digital
9 development and green resilience. Natural breaks classification, Moran's I, Markov
10 transition matrices, entropy weighted TOPSIS, and a coupling coordination model are
11 used to identify spatial patterns and transition dynamics. The results show significant
12 regional clustering. Provinces with stronger digital foundations tend to achieve higher
13 green resilience, while less developed regions face persistent upgrading constraints.
14 The Markov results indicate emerging regional convergence shaped by spatial
15 spillovers and local industrial conditions. This study contributes to electronic commerce
16 research by showing how digital infrastructure and data driven coordination can support
17 sustainable manufacturing transformation beyond online transactions and platform
18 markets.

19 **Keywords:** Digital infrastructure; manufacturing digitalization; green resilience;
20 spatial spillovers; regional convergence; sustainable manufacturing; China.

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1 Introduction

The global manufacturing landscape is undergoing seismic shifts fueled by resource constraints, market volatility, and escalating sustainability demands (Sachs et al., 2019; Jones et al., 2021; Kalkanci et al., 2019; Teece, 2007). These challenges are especially pronounced in rapidly industrializing economies such as China, India, and Brazil, where the imperative for structural and technological upgrades extends beyond national boundaries and shapes global manufacturing trajectories (Liu et al., 2023; Upadhayay et al., 2024). Concurrently, the rise of advanced digital technologies—including artificial intelligence, big data, blockchain, and cloud computing—has sparked a reevaluation of traditional manufacturing models (Xu et al., 2018; Guo et al., 2020). This wave of innovation, manifesting in policies like “Made in China 2025” and comparable initiatives in Germany and South Korea, seeks to enhance operational efficiency while minimizing ecological footprints (Liu et al., 2024; Ambedkar and Prakash, 2024; AL-Khatib et al., 2024; Li et al., 2024; Xie et al., 2024). Yet, despite these ambitious policy directions, uneven digital adoption and the risk of “low-end lock-in” persist, underscoring the complexity of balancing technological advancement with sustainability imperatives (Yang et al., 2024; Wei et al., 2024; Wang et al., 2024).

Although numerous studies have enriched our understanding of intelligent manufacturing (Boh et al., 2023) and environmental management (Zhang et al., 2024) in isolation, an integrated examination of how digital and green initiatives coalesce to drive sustainable manufacturing remains underexplored (DesJardine et al., 2019; Sharma et al., 2021; Ngo et al., 2024). The absence of a robust, holistic framework

obscures potential synergies between digital infrastructures and ecological imperatives, limiting both theoretical insights and actionable guidance for practitioners (Shashi et al., 2020; Cong et al., 2024). Recognizing this gap, the present study seeks to develop and validate a comprehensive evaluation indicator system that simultaneously captures the multifaceted dimensions of digitalization and green resilience. By conceptualizing digitalization as encompassing foundational infrastructure, production processes, and innovation outcomes, our approach transcends the view of technology as an isolated upgrade and situates it within the larger context of sustainable manufacturing (Zhang et al., 2023; Liu et al., 2023; Lai et al., 2023).

To operationalize this framework, we employ a multi-method empirical design that combines spatial analyses (e.g., Moran's index), Markov chain modeling, and entropy-weighted TOPSIS with coupling coordination degree assessments. These techniques illuminate the geographical patterns and temporal dynamics underlying digital-green integration, offering insights into how regional policy contexts, resource endowments, and industrial structures either facilitate or constrain sustainable outcomes. By elucidating how the interplay between digital tools and environmental strategies can yield both operational efficiencies and ecological benefits, this research advances extant theory on sustainable industrial development and provides a scalable empirical template for other global contexts. Moreover, our findings deliver actionable implications for policymakers and industry stakeholders, demonstrating how strategic investments in digital technologies—aligned with rigorous environmental standards—can catalyze balanced growth and mitigate the risk of uneven technological diffusion. In sum, this

study not only addresses a critical scholarly gap but also contributes a novel analytical lens through which modern manufacturing can be reimagined, underscoring the intertwined nature of digital transformation and ecological stewardship in shaping the future of the global industry.

The contributions of this paper are threefold. First, this study advances the literature by offering a comprehensive conceptual and empirical framework for understanding digitalization in the manufacturing industry. Rather than treating digitalization merely as a technological upgrade, we systematically examine it from three interrelated dimensions—foundational aspects of digital development, digital production processes, and the innovation outcomes that arise from digital applications. By constructing a nuanced evaluation index system, we broaden the discourse on digital transformation, highlighting how the convergence of digital and green initiatives can be more holistically assessed and integrated. This approach not only enriches existing digitalization studies but also opens new avenues for research on the intersection of digital technology and sustainability.

Second, the paper contributes theoretically by uncovering the underlying mechanisms that couple and coordinate digitalization with green resilience. Although prior work has examined these dimensions separately, limited attention has been paid to how they dynamically interact and reinforce each other. Through a structured analysis of their interplay, we illuminate the pathways by which digital tools can catalyze environmental robustness and, conversely, how green imperatives can spur further digital innovation. This investigation not only addresses a critical gap in the

literature but also lays out a robust theoretical framework for explaining how these two domains can co-evolve within the manufacturing sector.

Finally, we offer new empirical insights by examining regional variations in the coordinated development of digitalization and green resilience across diverse economic, industrial, and policy contexts. By comparing multiple regions that differ in terms of their resource endowments and industrial structures, we reveal the complex disparities that shape the trajectory of digital–green integration. Such a comparative lens not only extends theoretical discussions on the spatial dynamics of digitalization and sustainability but also provides practical guidance for policymakers and industry leaders seeking to replicate successful models in other localities or nations. Taken together, these findings deepen our understanding of how manufacturing enterprises can simultaneously harness digital transformations and environmental imperatives, thereby bolstering resilience and competitive advantage in an era of rapid global change.

2 Theory and literature review

2.1 Digitalization

Digitalization represents a strategic shift adopted by manufacturing enterprises in response to environmental changes, aiming for survival through adaptation (Del Giudice et al., 2021; Troise et al., 2022). Smart digitalization not only extends and deepens digitalization but also integrates technologies like artificial intelligence, big data, and cloud computing to transform business operations, management, and production processes intelligently (Frank et al., 2019; Liu et al., 2023). Through smart digital transformation, enterprises can not only grasp market demands more accurately

and enhance the competitiveness of their products and services but also achieve comprehensive optimization of business processes and scientific decision-making, adapting to the industrial transformations and development trends of the new era (Teece, 2018; Fischer et al., 2020). Smart digitalization encompasses a comprehensive data-integrated management model covering all elements, scenarios, and life cycles. Compared to digitalization, smart digitalization emphasizes the scale of ecosystems and depth of collaboration, integrating data throughout the manufacturing value chain from design and production to service (Kohtamäki et al., 2022; Matt et al., 2023). This integration and optimization of internal management systems establish a multi-dimensional digital ecosystem, fostering both agile applications responsive to market changes and stable applications for sustained operations (Gammelgaard and Nowicka, 2023). Smart digitalization leverages data across business segments, achieving seamless information flow and efficient resource allocation, thus maintaining a competitive edge in fierce market competition (Warner and Wäger, 2019; Meena et al., 2024). By building a system that is both adaptable and efficient, smart digitalization provides robust technical support for sustainable business development (Helfat and Raubitschek, 2018). From a practical perspective, manufacturing enterprises advancing digital transformation can adopt intelligent manufacturing, the industrial internet, and digital twins based on individual development needs (Zhou et al., 2020; Kumar and Agrawal, 2024). The transition from digitalization to smart digitalization involves continuously expanding enterprise data resources and emerging new smart digital tools (Sestino et al., 2020; Anthony, 2021). This transformation raises higher demands on

enterprises. Notably, while smart digital technologies serve as resources, they do not inherently provide a sustainable competitive advantage (Jabbour et al., 2020; Huang et al., 2015; Oduro et al., 2023). The key to sustainable competitive advantage in the context of smart digital transformation lies in integrating smart digital technologies with other resources, embedding these technologies into business processes, thus converting smart digital elements into enterprise capabilities (Baiyere et al., 2024; Meena et al., 2024). Presently, digital and intelligent technologies are highly pervasive and penetrating. In this context, enterprises across various industries in China are actively exploring and innovating in digitalization and intelligent technologies, focusing on building a new technological revolution centered around physical-virtual network systems, thereby introducing new enabling technologies (Haenlein and Kaplan, 2019; Mukul and Büyüközkan, 2023).

As emerging technologies like big data, digital technology, digital platforms, and artificial intelligence continue to evolve, the technological environment of the manufacturing sector is undergoing profound changes, along with shifts in customer demands (Javaid et al., 2022; Ciarli et al., 2021). Consequently, manufacturing enterprises need to adjust their organizational production and business models to fully leverage these advanced technologies and platforms, establishing new intelligent production and interaction models (Veile et al., 2022; Del Giudice et al., 2021). Such transformations not only enhance production efficiency but also better meet the individualized needs of customers, maintaining competitiveness (Porter and Heppelmann, 2015; Lin and Lin, 2023; Soellner et al., 2024). Smart digitalization

represents the capacity to drive business management transformation and reshaping through smart digital technologies. Its applications have transcended business levels to achieve innovation in business models (Ancillai et al., 2023; Sestino et al., 2020). Encompassing both "digitalization" and "intelligence," this study integrates these two concepts under the term "smart digitalization," reflecting the trend of their convergent development. Smart digitalization involves enhancing decision-making, optimizing business processes, and improving user experiences by integrating digital and intelligent technologies (Sestino et al., 2020; Malik et al., 2022). This process includes the collection, processing, analysis, and application of data, aiming to improve efficiency, reduce errors, and promote innovation in services and products through technological means, thus achieving more efficient operational models and gaining an advantage in fierce market competition.

In an uncertain environment, digital and intelligent transformation has become crucial for manufacturing enterprises to rejuvenate themselves (Kristoffersen et al., 2020; Chan et al., 2019). This transformation is not only a key action to enhance enterprise competitiveness but also an essential course to ensure survival and achieve long-term development (Osterrieder et al., 2020). Intelligent manufacturing is a new production method based on new information technology and management through innovation. Through intelligent manufacturing, manufacturing enterprises can realize intelligent production and management and improve production efficiency and management levels, thus enhancing product quality and reducing production costs (Culot et al., 2020; Yang et al., 2019).

The current discussion on digital intelligence mainly focuses on how enterprises can use digital technologies and intelligent tools in routine situations to optimize processes, reduce costs, improve efficiency, promote model innovation and digital transformation in the healthcare industry, the impact on regional green innovation efficiency (Elia et al., 2020; Liu et al., 2024; Yang et al., 2021). There is still insufficient exploration of how enterprises dynamically adapt and evolve during the digital intelligence transformation process, which requires further in-depth research.

2.2 Green resilience

The term “resilience” first appeared in the field of engineering and should become an important theme in the study of spatial economics (Boschma, 2017; Zhou et al., 2021; Reggiani et al., 2002). Subsequently, resilience research has mainly focused on economic geography, resonating with the evolutionary perspective in this field (Kythreotis and Bristow, 2017; Bohensky and Maru, 2011). Martin summarized existing theories on engineering and ecological resilience, proposing the concept of adaptive resilience (Martin, 2010).

Adaptive resilience refers to an economic system's sensitivity to risks, its inherent resistance, its ability to recover and grow, and its capability to reorganize swiftly after suffering external risks and shocks (Lei et al., 2014; Hu et al., 2022). As research deepens, the understanding of regional resilience has become increasingly systematic, involving multiple dimensions such as economic, social, and ecological aspects (Eraydin, 2016; Fröhlich and Hassink, 2018). The concept has been distilled into the ability to maintain stability, adapt quickly, recover, and develop in response to various

199 internal and external shocks and risks. Economic resilience describes the evolution of
200 an economic system when subjected to external shocks (Martin and Sunley, 2015). A
201 regional economic system is a complex adaptive system that continually interacts with
202 external information, evolving and developing (Martin and Sunley, 2007). This system
203 possesses the ability to resist, repair, and even surpass itself after external disturbances.

204 Green resilience in manufacturing is defined as the ability to cope with internal
205 and external shocks, such as current resource and environmental constraints, by
206 improving environmental governance, enhancing independent innovation capabilities,
207 and adopting green production methods (Borah et al., 2023; Xi et al., 2024). These
208 measures aim to restructure the internal framework to seek new development paths,
209 resist shocks, maintain system stability, adapt, and recover, thus restoring balanced
210 development and achieving the transformation and upgrading of the manufacturing
211 industry. (Liu et al., 2023; Mirzaee et al., 2024; Wu et al., 2024; Yu et al., 2021).

212 2.3 Digitalization and green resilience

213 The future trajectory of enterprises is increasingly aligning towards digitalization
214 and sustainability. Presently, there is a paucity of research on the nexus between
215 digitalization and green resilience. Existing studies predominantly focus on two areas:
216 digital transformation in relation to green development and the economic resilience
217 facilitated by digital technologies.

218 Digital transformation and green development: Research in this area is extensive
219 (Dou and Gao, 2023). For instance, Ahmed et al. (2022) discuss the impact of digital
220 transformation and green innovation on the performance of the healthcare and textile

industries, and highlights the key work of technological progress, human resource practice, and management commitment in these processes. El-Kassar and Singh (2019) examined a sample of 215 respondents from the MENA and GCC regions, discovering that enterprises focusing on digital technologies significantly drive green innovative activities, thus enhancing their competitive positioning. These technologies primarily facilitate green technological innovations through improved information transmission efficiency and augmented knowledge accumulation (Ning and Guo, 2022; Vujanović et al., 2022). In the era of Industry 4.0, the digital transformation of manufacturing enterprises represents an advanced technological modification, aiding firms in seeking novel innovation pathways and reducing the risks of innovation failures, thereby empowering green technological innovation processes (Palacios and Vrain, 2024; Ivanov et al., 2019). Technologies such as digital platforms and smart devices not only facilitate the implementation of environmental solutions but also significantly reduce energy wastage and capital costs, thereby enhancing the overall sustainability of products (Feng et al., 2022; Uddin and Rahman, 2012; Zhang et al., 2024). Additionally, Dalenogare et al. (2018) found that digital services and cloud computing technologies play a crucial role in energy saving and emission reduction during product development, while IoT technologies enhance production efficiency, optimize resource allocation, and reduce environmental pollution, thus propelling the manufacturing industry towards greener and more efficient practices (Luo et al., 2023). Li et al. (2020) explored three potential mechanisms through which digital technology applications enhance green innovation, showing significant advantages in optimizing resource utilization,

enhancing production efficiency, and reducing environmental pollution.

Digitalization and economic resilience: This segment investigates the mechanisms through which digital technologies enhance economic resilience. The development and adoption of digital technologies have been shown to significantly bolster economic resilience (Ashmore et al., 2017). Additionally, it has been argued that digital technologies can enhance economic resilience by improving the efficiency and responsiveness of government services (Hussain and Papastathopoulos, 2022; Wang and Dong, 2024). Furthermore, integrating digital technologies and resources with business systems facilitates dynamic organizational adjustments and improves adaptability to external environmental challenges (Warner and Wäger, 2019; Chan et al., 2019; Li and Chan, 2019).

Building on extant research that underscores the critical role of digitalization in bridging operational effectiveness and environmental sustainability, this study advances the concept of “smart digitalization” as a key driver of green resilience in manufacturing enterprises. While prior work often addresses digital transformation and resilience in parallel, relatively little is known about how converging digital and intelligent technologies can simultaneously enhance adaptability, foster eco-friendly innovation, and ensure sustainable development. By reframing digital transformation as a holistic process—one that integrates real-time data analytics, artificial intelligence, and IoT-enabled platforms—we shed new light on how manufacturing firms can develop dynamic capabilities that enable resource-efficient processes, robust adaptation to environmental uncertainties, and sustainable growth trajectories.

In conclusion, significant theoretical and practical progress has been made in digitalization and green resilience. However, taking China's manufacturing industry as an example, the scientific measurement of these aspects requires further exploration. Globally, research on the coupled and coordinated development effects of digitalization and green resilience in manufacturing sectors is still limited, lacking a systematic evaluation framework and indicator system. This gap highlights the need for more robust measurement and analysis of their coupling and coordination trends across various regions. Addressing these gaps will not only provide new perspectives for academic research but also offer guidance for policymakers and practitioners, collectively promoting the advancement of manufacturing industries towards higher quality and sustainability on a global scale.

3 The coupling mechanism of digitalization and green resilience in manufacturing industry

The enhancement of green resilience in the manufacturing sector relies on digital innovation, which provides the momentum for strengthening green resilience, while the continuous development of digitalization in manufacturing also requires the guidance and protection of green resilience (Luo et al., 2024; Hossain et al., 2024). Systems theory posits that systems are ubiquitous, and various subsystems within a system interact and constrain each other, collectively affecting the whole system (Chatterjee et al., 2021; Klein et al., 2022). Digitalization and green resilience are subsystems within the sustainable development system, complementing and promoting each other, forming a benign interactive and coordinated relationship that collectively advances the

sustainable development of the manufacturing sector (Leng et al., 2022; Scholz et al., 2024). The coupling and coordinated development mechanism between manufacturing digitalization and green resilience is depicted in Figure 1.

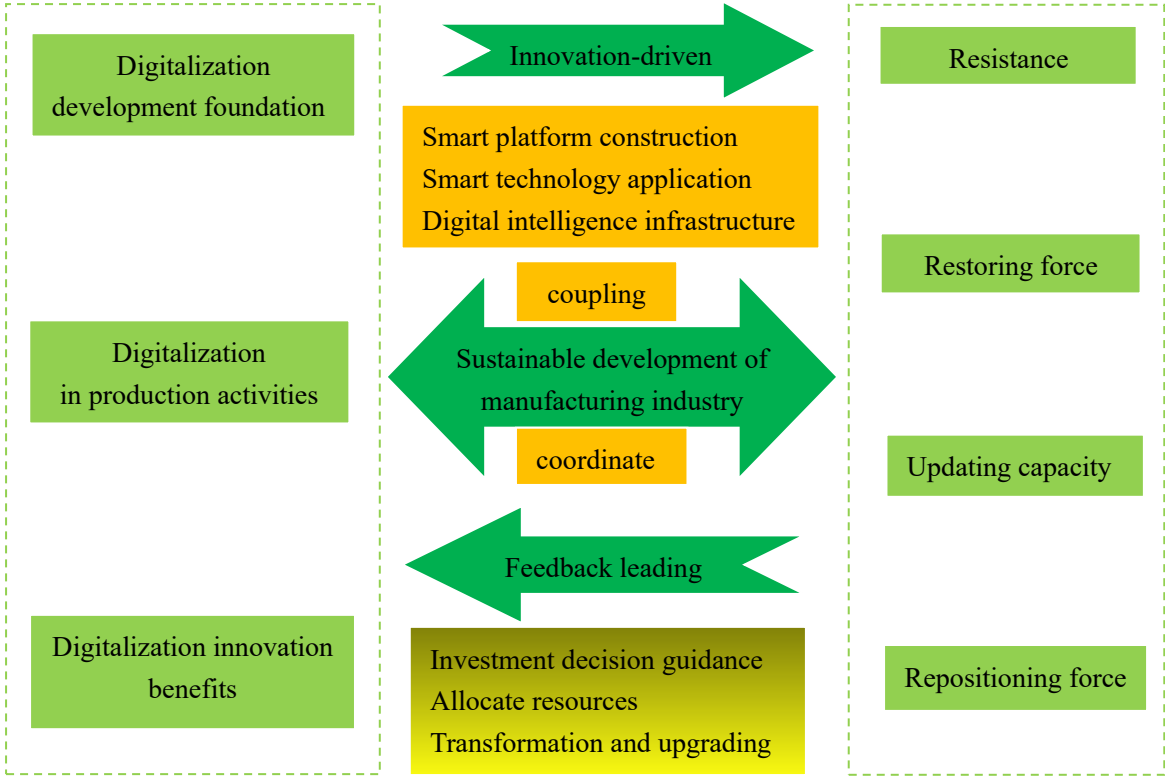


Figure 1 The coupling and coordinated development mechanism between manufacturing digitalization and green resilience

In the process of digital transformation, manufacturing is closely linked to the development of green resilience. Initially, digital infrastructure serves as a powerful technological support for green innovation factors such as capital, technology, and talent, enabling these elements to flow unimpeded across different regions and innovation entities, thus promoting the balanced enhancement of green innovation capability (Liu et al., 2024). By achieving the interconnectivity of innovative elements, these infrastructures help break down geographical and industrial barriers, optimize element matching, reduce transaction costs, and lessen the impacts of environmental

changes, thereby enhancing the industry's green resilience (Xu et al., 2024; Wu et al., 2024). Furthermore, the development of digitalization, through the integration of advanced information technology, artificial intelligence, and big data analytics, strengthens the manufacturing sector's capacity for environmental protection and sustainable development (Bag et al., 2021; Wen et al., 2022). This technological integration not only promotes the green transformation of manufacturing but also accelerates efforts to increase energy efficiency and reduce carbon emissions (Wu et al., 2024; Zhang et al., 2022). For example, intelligent manufacturing systems reduce resource waste and environmental pollution in the production process by enhancing energy and resource use efficiency. Finally, the promotion of digitalization achieves an intelligent upgrade of manufacturing, with smart platforms enabling real-time monitoring, predictive analysis, and intelligent decision-making, which enhances enterprises' ability to respond to environmental changes and market fluctuations (Han and Trimi, 2022). With digital technologies such as the Internet of Things and cloud computing, enterprises can respond swiftly to supply chain disruptions, optimize resource allocation, and scientifically formulate production strategies (Ivanov et al., 2022). This not only changes the production model of enterprises, making them more refined and efficient but also helps drive the entire manufacturing sector towards a low-carbon and environmentally friendly transformation.

In advancing the digital transformation, developing green resilience must be a core focus, ensuring that technological innovations progress in harmony with environmental protection and social responsibilities (Chin et al., 2022; Xie et al., 2022). As

environmental protection and sustainability goals continue to rise, this transformation seeks not only efficiency and profit but also attention to environmental impacts and resilience against external shocks. Firstly, green resilience indices can guide investment decisions in the manufacturing sector, aiding the industry in achieving continuous, intelligent, and efficient operations (Dohale et al., 2024). Secondly, developing green resilience promotes digital demand within enterprises, expands the digital economy, and promotes the digital, intelligent, and green upgrading of regional technology, fostering beneficial interaction and integration (Hao et al., 2024). Finally, promoting green resilience encourages traditional enterprises to adopt resource-saving and environmental protection strategies (Song et al., 2017), increase green innovation investments, and become a driving force for the development of digitalization, creating favorable conditions for the ongoing development of digitalization.

The coupling mechanism between digitalization and green resilience in manufacturing demonstrates the interdependent and promotive relationship between technological innovation and sustainable development (Ma et al., 2024; Li et al., 2024). Driven by digital innovation, green resilience in the manufacturing sector can be effectively enhanced, thus providing protection and direction for the continuous development of digitalization (Wu et al., 2024). The coupled coordination between green resilience and intelligent manufacturing is seen as a key factor for sustainable economic growth, promoting integration that drives the manufacturing sector towards more efficient, environmentally friendly, and flexible development models and achieving substantial progress in manufacturing intelligence and sustainability.

4 Methodological framework for digitalization and green resilience in manufacturing

4.1 The indicator system

This study constructs a comprehensive and scientific indicator system for evaluating the coupling between digitalization and green resilience in manufacturing, based on principles of objectivity, systematization, operability, and availability of information, combined with the actual development conditions of the manufacturing industry (As shown in Table 1).

The digitalization of manufacturing is measured from three aspects: foundational development of digitalization, digital production activities, and the benefits of digital innovation (Del et al., 2021; Parviainen et al., 2017). The foundational development encompasses data science, artificial intelligence technologies, and information technology infrastructure, including data collection, processing, analysis, and the construction of necessary hardware, software, and network facilities to support data storage and transmission. Digital production activities refer to the integration and application of data science, artificial intelligence, and information technology in the production and manufacturing processes to enhance efficiency, optimize workflows, and strengthen decision-making capabilities. By integrating advanced sensor technology, the Internet of Things, cloud computing, and big data analytics, digital production can achieve optimal resource allocation and intelligent management of processes, leading to highly automated and intelligent production activities and enhancing overall production efficiency and competitiveness (Zhou et al., 2022;

Fragapane et al., 2022). The benefits of digital innovation refer to the advantages and value growth brought about by applying data science, artificial intelligence, and information technology across various fields, which may include significant improvements in production efficiency, effective cost reductions, the creation of new products and services, and enhanced market competitiveness.

The green resilience of manufacturing is measured from four aspects: resistance, recovery, renewal, and repositioning. Resistance reflects the ability to maintain normal operations and functions in the face of external shocks, a key aspect in measuring green resilience in manufacturing (Belhadi et al., 2022). Furthermore, the economic creativity of manufacturing ensures continuous operation and economic benefits when facing challenges, providing the necessary material basis for subsequent adaptive adjustments (Michalos et al., 2010). Restoring force involves the ability to return to a stable state while maintaining internal structures and functions, reflecting the industry's ability to dynamically adjust to new conditions after encountering challenges related to resource and environmental limitations (Conz and Magnani, 2020). Updating capacity refers to the ability to use technological innovation to build new development models and paths (Dougherty, 1992); in the transition from traditional extensive production methods to more efficient and environmentally friendly methods, technological innovation plays a crucial role, enhancing energy efficiency, reducing environmental pollution, and improving economic returns. Repositioning focuses on the industry's ability to seek new development paths after a crisis, optimizing internal structures and adapting to new

developmental states in response to challenges that may no longer suit old growth models (Dittrich et al., 2007; Tzabbar, 2009; Kinkel, 2012).

Table 1 Indicator system for digitalization and green resilience in manufacturing

Main indicator	Primary indicator	Secondary indicator	Indicator measurement method	references
Manufacturing digitalization level	Digitalization development foundation	Development level of digital software (A11)	Ratio of software and information industry revenue to main manufacturing revenue	Del et al., 2021; Parviainen et al., 2017
		Industrial data processing capability (A12)	Ratio of information service industry main revenue to main manufacturing revenue	
		Digital application foundation capability (A13)	Ratio of embedded system revenue to main manufacturing revenue	
	Digitalization in production activities	Development status of smart enterprises (B21)	Main revenue of high-tech enterprises / Main manufacturing revenue	Zhou et al., 2022; Fragapane et al., 2022
		Capability for developing intelligent new products (B22)	Sales revenue of new products from high-tech enterprises / Main manufacturing revenue	

		Level of industrial intelligent equipment usage (B23)	Industrial robot penetration rate	
	Digitalization innovation benefits	Digital business efficiency in industrial sales (C31)	E-commerce transaction revenue to main manufacturing revenue	Hung and Nham, 2023 Radacic and Petković, 2023.
		Hardware basis for digitized industrial sales (C32)	Number of manufacturing enterprises with websites per hundred enterprises	
Manufacturing green resilience	Resistance	Manufacturing labor productivity per capita (D41)	Manufacturing output / Average annual number of manufacturing employees	Belhadi et al., 2022
		Manufacturing profitability (D42)	Total manufacturing profits / Main manufacturing revenue	
	Restoring force	Per capita manufacturing added value (E51)	Manufacturing added value / Average annual number of manufacturing employees	Conz and Magnani, 2020
		Comprehensive environmental	Investment in pollution control completion / Manufacturing added value	

		regulation index (E52)		
		Energy consumption per unit of manufacturing added value (E53)	Total energy consumption / Manufacturing added value	
	Updating capacity	Intensity of R&D expenditure in manufacturing (F61)	Internal expenditure on manufacturing R&D / Main manufacturing revenue	Dougherty, 1992
		Priority of green innovation in manufacturing (F62)	Number of green patent applications / Internal R&D expenditure in manufacturing	
		Intensity of green innovation in manufacturing (F63)	Number of green patent applications / Manufacturing output	
	Repositioning force	Structure of manufacturing openness to the	Foreign capital in manufacturing / Total manufacturing output	Dittrich et al., 2007; Tzabbar, 2009; Kinkel, 2012

		external world (G71)		
		Proportion of technical personnel in manufacturing (G72)	Manufacturing R&D personnel / Average annual number of manufacturing employees	

391 4.2 The measures

392 4.2.1 Entropy weighted TOPSIS method

393 TOPSIS is a comprehensive evaluation method proposed by Hwang and Yoon
394 (1981) and was improved by Chen and Hwang (1992). The entropy-weighted TOPSIS
395 method belongs to multi-objective decision analysis techniques, fundamentally
396 representing an enhanced version of the TOPSIS evaluation method. The entropy-
397 weight TOPSIS method determines the weights of each evaluation index through the
398 entropy-weight method and then uses the TOPSIS method to evaluate the relative merits
399 of the objects to be evaluated and provide a ranking reference for decision-making.
400 Combining the advantages of information entropy and TOPSIS can avoid the subjective
401 defects of the traditional TOPSIS method while improving the efficiency and quality of
402 decision-making for decision-makers. In analyzing digitalization and sustainability, it
403 is often necessary to consider indicators from multiple aspects, such as the economy,
404 society, and environment, and the objectivity of the analysis is particularly important.
405 The entropy weight TOPSIS method can reduce human bias, provide more accurate
406 decision support, and fully reflect the dynamic changes between digitalization and

sustainability, which helps to more comprehensively understand and evaluate the impacts of digitalization and sustainability. The process involves two key steps:

Weight assignment using the entropy method: Initially, weights are assigned to indicators using the entropy method, which is driven by sample data. This approach minimizes the impact of subjective weighting and human factors, enabling an objective reflection of the importance of each indicator within the system at the time of decision-making. It also effectively highlights how the weights of indicators evolve over time.

TOPSIS methodology: Also known as the technique for order preference by similarity to ideal solution, TOPSIS evaluates feasible solutions by measuring their distance from both the ideal and the negative ideal solutions. The method calculates the relative closeness of each solution to the ideal solution. The outcomes are then used to rank the solutions from best to worst based on their proximity to the ideal solution.

Detailed calculation steps in the entropy weighted TOPSIS method:

Step 1: Normalization of data - Convert the raw data into a comparable scale suitable for analysis. This can be done using various normalization techniques depending on the nature of the data and the desired impact of larger or smaller values.

Assume there are m objects to be evaluated, with n evaluation criteria. A decision matrix $A = (a_{ij})_{m \times n}$ is constructed and then normalized to obtain a standardized matrix $X = (x_{ij})_{m \times n}$.

For positive indicators (where higher values indicate better performance), the normalization is processed as follows:

428

$$x_{ij} = \frac{a_{ij} - \min_i(a_{ij})}{\max_i(a_{ij}) - \min_i(a_{ij})}, i = 1, 2, \dots, m, j = 1, 2, \dots, n \quad (1)$$

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For negative indicators (where lower values indicate better performance), the

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normalization is processed as follows:

431

$$x_{ij} = \frac{\max_i(a_{ij}) - a_{ij}}{\max_i(a_{ij}) - \min_i(a_{ij})}, i = 1, 2, \dots, m, j = 1, 2, \dots, n \quad (2)$$

432

Step 2: Calculation of entropy for each indicator - Determine the entropy for each

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indicator to measure the amount of information, variability, or disorder presented by

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the indicator values in the dataset.

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Integrating probability theory, entropy can be utilized to measure the uncertainty

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of information. Specifically, the more concentrated the data distribution, the lower the

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uncertainty, and vice versa. Herein, the decision information for each criterion can be

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represented by its entropy value, which is calculated as follows:

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$$e_j = -k \sum_{i=1}^m x_{ij} \ln x_{ij}, j = 1, 2, \dots, n \quad (3)$$

440

Where $k = 1/\ln m$, e_j ranges from 0 to 1. The degree of dispersion d_j in the

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evaluation values for the j th criterion can be represented by $d_j = 1 - e_j$, such that the

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smaller the value of e_j , the larger the value of d_j , and the more dispersed the distribution

443

of x_{ij} , the greater the importance of the j th criterion. Conversely, the same logic applies

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in the opposite scenario. Specifically, if the values of x_{ij} are all equal, it indicates that

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the criterion has no effect in the decision-making process.

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Step 3: Determination of weights - Using the entropy values, compute the weights

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for each indicator. The weight for an indicator is inversely proportional to its entropy

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value, implying that less uncertain indicators carry more weight.

Thus, the weight of the j th criterion can be represented as:

$$w_j = \frac{d_j}{\sum_j d_j}, w_j \in [0,1], \sum_j w_j = 1, j = 1, 2, \dots, n \quad (4)$$

Step 4: Construction of the weighted normalized decision matrix - Multiply the normalized values by their corresponding weights to prioritize certain aspects of the data according to their significance.

Construct the weighted decision matrix $Z = (z_{ij})_{m \times n}$, where $z_{ij} = x_{ij} w_j, i = 1, 2, \dots, m, j = 1, 2, \dots, n$.

Step 5: Identification of ideal and negative ideal solutions - Identify the best (ideal) and worst (negative ideal) possible outcomes for each criterion based on the weighted normalized matrix.

Identify the positive ideal solution Z^+ and the negative ideal solution Z^- , with the formulations as follows:

$$\begin{aligned} Z^+ &= \{\max_i z_{ij} \mid j = 1, 2, \dots, n\} = \{Z_1^+, Z_2^+, \dots, Z_n^+\} \\ Z^- &= \{\min_i z_{ij} \mid j = 1, 2, \dots, n\} = \{Z_1^-, Z_2^-, \dots, Z_n^-\} \end{aligned} \quad (5)$$

Step 6: Calculation of distance measures - Calculate the distance of each alternative to the ideal and negative ideal solutions using a suitable distance metric, typically the Euclidean distance.

Calculate the sum of the Euclidean distances D_i^+ and D_i^- from each feasible solution to the positive and negative ideal solutions, using the following formula:

$$\begin{aligned} D_i^+ &= \sqrt{\sum_{j=1}^n (Z_j^+ - z_{ij})^2}, i = 1, 2, \dots, m \\ D_i^- &= \sqrt{\sum_{j=1}^n (Z_j^- - z_{ij})^2}, i = 1, 2, \dots, m \end{aligned} \quad (6)$$

Step 7: Calculation of closeness coefficient - Determine the relative closeness of each alternative to the ideal solution. This coefficient is computed as the ratio of the distance to the negative ideal solution to the sum of the distances to both the ideal and negative ideal solutions.

Calculate the relative closeness, which is the comprehensive evaluation index, expressed as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, C_i \in [0,1], i = 1, 2, \dots, m \quad (7)$$

Wherein, the greater the value of C_i , approaching 1, the closer the corresponding solution is to the optimal, and thus, it is ranked higher in order.

Step 8: Ranking of alternatives - Finally, rank the alternatives based on the closeness coefficient. Higher values indicate solutions that are more preferable or closer to the ideal.

Utilizing the evaluation function of the entropy-weighted TOPSIS method, the level of digitalization and green resilience development in China's manufacturing industry is determined to be $S_i(C_i)$.

4.2.2 Coupling coordination degree model

This study employs the coupling coordination degree model to analyze the synergy between digitalization and green resilience in manufacturing industry. Based on the results of the entropy-weighted TOPSIS method, a model for assessing the coupling coordination degree between digitalization and green resilience in manufacturing industry is constructed, with the formula as follows:

$$O = 2 \sqrt{\frac{S_1 + S_2}{(S_1 + S_2)^2}} \quad (8)$$

$$T = \alpha S_1 + \beta S_2 \quad (9)$$

$$OT = \sqrt{O \times T} \quad (10)$$

Within the model, S_1 and S_2 represent the levels of digitalization and green resilience development in manufacturing industry, respectively. O denotes the coupling degree, with a value range of $[0,1]$. T represents the comprehensive coordination index, while α and β are coefficients to be determined. Assuming digitalization and green resilience are of equal importance in manufacturing sector, both α and β are set to 0.5. OT denotes the coupling coordination degree, which is categorized into 10 levels (Huang et al., 2020), as detailed in Table 2.

Table 2 The coupling coordination degree

Coupling coordination degree	Coordination type	Coupling coordination degree	Coordination type
$[0,0.1)$	Extreme imbalance (EI)	$[0.5,0.6)$	Barely coordination (BC)
$[0.1,0.2)$	Severe imbalance (SI)	$[0.6,0.7)$	Primary coordination (PC)
$[0.2,0.3)$	Moderate imbalance (MOI)	$[0.7,0.8)$	Intermediate coordination (IC)
$[0.3,0.4)$	Mild imbalance (MI)	$[0.8,0.9)$	Good coordination (GC)

[0.4,0.5)	Calm imbalance	[0.9,1.0)	High-quality coordination
	(CI)		(HC)

500 4.2.3 Dagum Gini coefficient

$$501 \quad G = \frac{\sum_{j=1}^k \sum_{l=1}^k \sum_{i=1}^k \sum_{r=1}^k |OT_{ji} - OT_{lr}|}{2n^2 \overline{OT}} \quad (11)$$

502 Here, G denotes the Gini coefficient, $n(n=1,2,3...30)$ represents the provinces, k
503 denotes the number of sub-regional areas, while n_j and n_l represent the number of
504 provinces in regions j and l , respectively. OT_{ji} and OT_{lr} denote the coupling
505 coordination levels of regions j and l , respectively, and $\overline{OT}$ represents the average
506 coupling coordination degree across all provinces. In line with the study of the Gini
507 coefficient, it is further decomposed into intra-regional Gini coefficient (G_w), inter-
508 regional Gini coefficient (G_{nb}), and transvariation density G_t . This decomposition
509 facilitates a more detailed analysis of intra-regional differences, inter-regional
510 disparities, and the effects of cross-regional overlaps. This method takes into account
511 the cross-overlapping issues between samples and the distribution of sub-samples,
512 effectively determining the sources of regional differences.

$$513 \quad G_{jj} = \frac{\sum_{i=1}^j \sum_{r=1}^j |OT_{ji} - OT_{jr}|}{2n_j^2 \overline{OT_j}} \quad (12)$$

$$514 \quad G_w = \sum_{j=1}^k G_{jj} p_j s_j \quad (13)$$

$$515 \quad G_{jh} = \frac{\sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |OT_{ji} - OT_{lr}|}{n_j n_h (\overline{OT_j} + \overline{OT_l})} \quad (14)$$

$$d_{jh} = \int_0^\infty dF_j(OT) \int_0^{OT} (OT - x) dF_l(x) \quad (15)$$

$$p_{jh} = \int_0^\infty dF_l(OT) \int_0^{OT} (OT - x) dF_j(x) \quad (16)$$

$$D_{jh} = \frac{d_{jl} - p_{jl}}{d_{jl} + p_{jl}} \quad (17)$$

$$G_{nb} = \sum_{j=2}^k \sum_{l=1}^{j-1} G_{jh} (p_j s_l + p_l s_j) D_{jl} \quad (18)$$

$$G_t = \sum_{j=2}^k \sum_{l=1}^{j-1} G_{jh} (p_j s_l + p_l s_j) (1 - D_{jl}) \quad (19)$$

Herein, $p_j = \frac{n_j}{n}$ represents the proportion of the number of provinces n_j within a

region j relative to the total number of provinces n , while $s_j = \frac{n_j \overline{OT_j}}{n \overline{OT}}$ denotes the

proportion of the regional j coupling coordination development level relative to the

overall coupling coordination development level of all provinces, $G = G_w + G_{nb} + G_t$.

4.2.4 Moran's Index

Moran's index is a correlation coefficient used to study spatial relationships. When the index is greater than 0, it indicates positive spatial autocorrelation; when the index is less than 0, it indicates negative spatial autocorrelation; and when the index is equal to 0, it indicates spatial randomness. The specific calculation formula is as follows:

$$Moran's I = \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (OT_i - \overline{OT})(OT_j - \overline{OT})}{S^2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}} \quad (20)$$

Where S^2 represents the sample variance, OT_i denotes the level of coupling coordination of each region i , and n ($n = 1, 2, 3, \dots, 30$) indicates the provinces. W represents the spatial geographical adjacency weights. When two provinces are

geographically adjacent, $W_{ij} = 1$, otherwise, $W_{ij} = 0$.

4.2.5 Kernel density estimation

Kernel density estimation (KDE) is a non-parametric method that allows for describing the distribution location, shape, and spread of coupling coordination degrees based solely on sample data. It offers robust characteristics. The expression for the probability density function is as follows:

$$f(OT) = \frac{1}{Nh} \sum_{i=1}^N K\left(\frac{OT_i - \overline{OT}}{h}\right) \quad (21)$$

$$K(\overline{OT}) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\overline{OT}^2}{2}\right) \quad (22)$$

Where $f(OT)$ represents the density function, N is the number of regions, h denotes the bandwidth, and $K(\bullet)$ represents the kernel function.

4.2.6 Markov Model

A Markov chain is a stochastic process in which the next state depends only on the current state. Spatial Markov chains consider the role of spatial factors in the evolution of economic phenomena, reflecting the direction and probability of transitions in coupling coordination levels. In this study, the subjects are divided into multiple levels, and changes between different levels are represented using a Markov transition probability matrix $N \times N$. The formula for calculating the maximum likelihood estimate of transition probabilities between levels is as follows:

$$P_{a \rightarrow b}^{t \rightarrow t+1} = \frac{\sum_{t=T_1}^T n_{a \rightarrow b}^{t \rightarrow t+1}}{\sum_{t=T_1}^T n_a^t} \quad (23)$$

Where a and b represent different levels, t denotes the year, n_a^t is the number of

cities at the coupling coordination level belonging to level a in year t , and $n_{a \rightarrow b}^{t \rightarrow t+1}$ is the number of cities at the coupling coordination level belonging to level b in year $t + 1$. A spatial Markov chain introduces the concept of spatial lag into the basic Markov chain framework. This modification transforms the transition probability matrix into a $N \times N \times N$ weighted transition probability matrix, allowing for the analysis of transition probabilities among study objects' levels under different neighborhood contexts.

5 Empirical analysis

5.1 Data source

This study selects provincial panel data from 2017 to 2022 for 30 provinces in China (excluding Hong Kong, Macau, Taiwan, and Tibet due to incomplete data). Data on papers and patents were manually retrieved from CNKI¹ (China National Knowledge Infrastructure), Web of Science², and the Patsnap patent database. Additional data were sourced from the 'China Statistical Yearbook'³, 'China Science and Technology Statistical Yearbook'⁴, 'China Industrial Statistics Yearbook'⁵, and various provincial statistics bureau websites. Missing data were estimated using scatter plot trend fitting methods.

5.2 Measuring the level of digitalization and green resilience in the manufacturing industry using the entropy-weighted TOPSIS method

¹ <https://www.cnki.net/>

² <https://webofscience.clarivate.cn/wos/>

³ <https://www.stats.gov.cn/english/>

⁴ <https://www.stats.gov.cn/english/>

⁵ <https://www.stats.gov.cn/english/>

Based on formulas (1) to (7), this section assesses the state of digitalization and green resilience in manufacturing (Table (3)). Table (3) displays the development levels and averages for the provinces in the eastern, central, western, and northeastern regions from 2017 to 2022. The level of digitalization in Chinese manufacturing shows a stable upward trend, indicating that digitalization is maintaining a robust developmental momentum. In contrast, the level of green resilience in Chinese manufacturing displays a fluctuating upward trend.

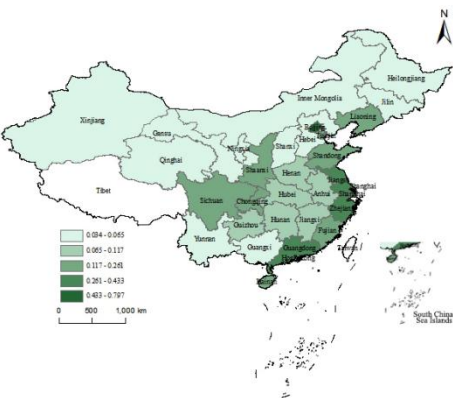
Table 3 The state of digitalization and green resilience in manufacturing

Region	Province	The development level of digitalization in manufacturing industry						The development level of green resilience in manufacturing industry					
		2017	2018	2019	2020	2021	2022	2017	2018	2019	2020	2021	2022
The eastern of China	Beijing	0.895	0.797	0.83	0.845	0.848	0.850	0.609	0.599	0.472	0.632	0.428	0.398
	Tianjin	0.197	0.261	0.226	0.192	0.178	0.157	0.26	0.34	0.312	0.39	0.442	0.354
	Hebei	0.052	0.056	0.054	0.07	0.057	0.059	0.137	0.215	0.365	0.233	0.239	0.182
	Shanghai	0.359	0.363	0.332	0.299	0.284	0.283	0.359	0.413	0.31	0.375	0.361	0.298
	Jiangsu	0.259	0.278	0.279	0.259	0.265	0.243	0.203	0.266	0.297	0.366	0.386	0.283
	Zhejiang	0.281	0.31	0.298	0.261	0.263	0.248	0.224	0.272	0.24	0.231	0.252	0.193
	Fujian	0.153	0.158	0.14	0.114	0.106	0.099	0.135	0.236	0.196	0.187	0.219	0.169
	Shandong	0.133	0.152	0.146	0.152	0.138	0.136	0.158	0.258	0.218	0.253	0.256	0.208
	Guangdong	0.398	0.433	0.414	0.367	0.355	0.326	0.173	0.264	0.225	0.228	0.3	0.231
	Hainan	0.194	0.192	0.269	0.227	0.133	0.124	0.436	0.469	0.294	0.377	0.412	0.355

	Mean value	0.292	0.300	0.299	0.279	0.263	0.253	0.269	0.333	0.293	0.327	0.330	0.267
The central of China	Shanxi	0.073	0.041	0.064	0.068	0.062	0.047	0.289	0.38	0.31	0.31	0.353	0.218
	Anhui	0.103	0.108	0.112	0.123	0.118	0.113	0.145	0.207	0.202	0.226	0.231	0.187
	Jiangxi	0.068	0.085	0.091	0.105	0.104	0.086	0.088	0.137	0.141	0.126	0.151	0.131
	Henan	0.109	0.102	0.115	0.1	0.097	0.082	0.098	0.134	0.118	0.147	0.148	0.117
	Hubei	0.100	0.117	0.117	0.119	0.111	0.103	0.14	0.214	0.177	0.172	0.227	0.195
	Hunan	0.112	0.112	0.092	0.094	0.086	0.088	0.125	0.196	0.173	0.183	0.147	0.13
	Mean value	0.094	0.094	0.099	0.102	0.096	0.087	0.148	0.211	0.187	0.194	0.210	0.163
The western of China	Inner Mongolia	0.055	0.054	0.053	0.062	0.052	0.048	0.25	0.449	0.353	0.366	0.457	0.383
	Guangxi	0.046	0.041	0.038	0.059	0.053	0.046	0.143	0.197	0.171	0.162	0.278	0.206
	Chongqing	0.182	0.247	0.202	0.182	0.17	0.138	0.137	0.24	0.201	0.204	0.184	0.168
	Sichuan	0.171	0.187	0.165	0.166	0.156	0.132	0.132	0.194	0.165	0.167	0.21	0.156
	Guizhou	0.098	0.083	0.096	0.097	0.089	0.084	0.183	0.207	0.195	0.234	0.34	0.311
	Yunnan	0.067	0.054	0.046	0.055	0.062	0.046	0.184	0.249	0.221	0.242	0.321	0.229
	Shaanxi	0.175	0.154	0.174	0.19	0.173	0.148	0.179	0.237	0.225	0.269	0.294	0.225
	Gansu	0.036	0.039	0.041	0.045	0.041	0.046	0.221	0.325	0.254	0.26	0.329	0.258
	Qinghai	0.116	0.043	0.046	0.059	0.054	0.068	0.325	0.387	0.375	0.375	0.47	0.342
	Ningxia	0.063	0.044	0.059	0.06	0.059	0.054	0.399	0.467	0.406	0.388	0.472	0.404

	Xinjiang	0.044	0.034	0.038	0.031	0.025	0.025	0.315	0.395	0.589	0.343	0.503	0.589
	Mean value	0.096	0.089	0.087	0.091	0.085	0.076	0.224	0.304	0.287	0.274	0.351	0.297
The northeast of China	Liaoning	0.185	0.171	0.1	0.089	0.078	0.068	0.253	0.283	0.245	0.297	0.305	0.244
	Jilin	0.062	0.065	0.061	0.053	0.048	0.045	0.141	0.177	0.152	0.256	0.249	0.212
	Heilongjiang	0.05	0.058	0.037	0.052	0.038	0.041	0.246	0.318	0.288	0.318	0.349	0.315
	Mean value	0.099	0.098	0.066	0.065	0.055	0.051	0.213	0.259	0.228	0.290	0.301	0.257

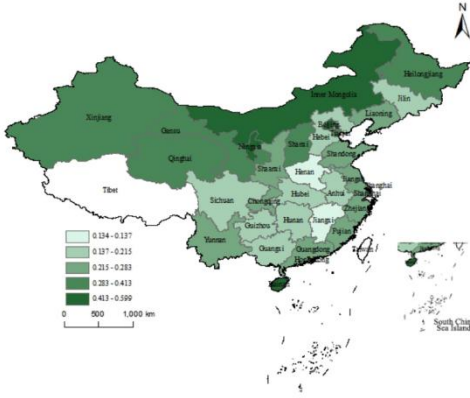
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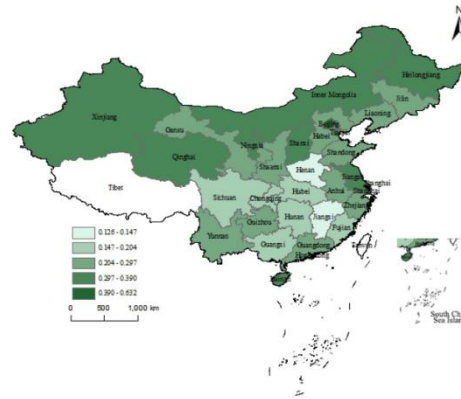
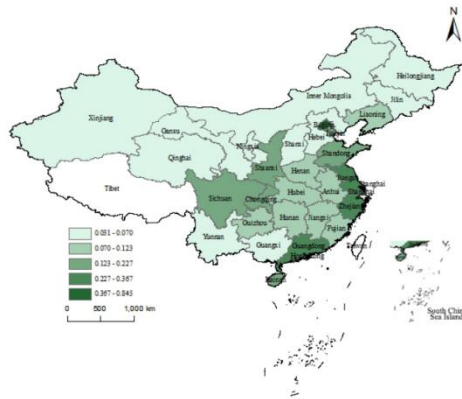
583 The development level of digitalization in
584 China's manufacturing industry in 2018

Figure 2(a)



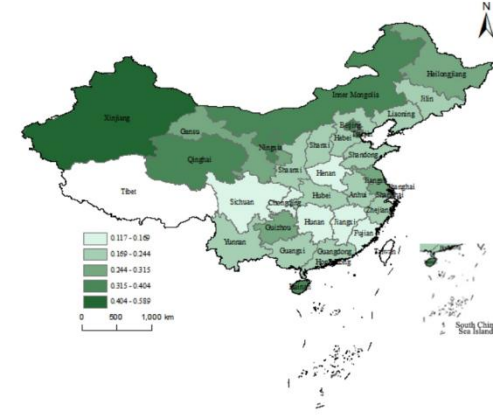
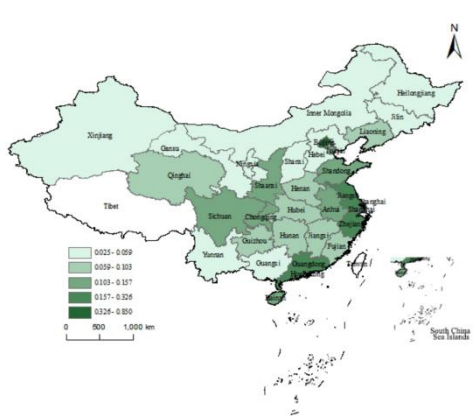
The development level of green resilience in
China's manufacturing industry in 2018

Figure 2(b)



The development level of digitalization in
China's manufacturing industry in 2020
Figure 2(c)

The development level of green resilience in
China's manufacturing industry in 2020
Figure 2(d)



The development level of digitalization in
China's manufacturing industry in 2022
Figure 2(e)

The development level of green resilience in
China's manufacturing industry in 2022
Figure 2(f)

According to the natural breaks classification method in ArcGIS, the average development levels of digitalization and green resilience in Chinese manufacturing were each divided into four tiers, revealing their spatial differentiation characteristics. As shown in Figure (2), there are significant inter-provincial differences in both the levels of digitalization and green resilience, with regional development exhibiting characteristics of being insufficient and unbalanced. The level of digitalization in

Chinese manufacturing generally shows a decreasing pattern from 'East-Central-West-Northeast', with higher levels of digitalization in regions like Beijing, Shanghai, and Guangdong, whereas regions like Heilongjiang, Xinjiang, and Ningxia are relatively lower. Additionally, areas with higher digitalization levels are mostly concentrated in the eastern regions, with a few in the central regions. The indices are generally lower in most provinces of the western and central regions, mainly because the eastern and central regions have better development of digital technologies, a more complete set of various element resources, and relatively well-developed digital infrastructure. In contrast, the western and northeastern regions lag due to the slower development of the digital economy and a relative lack of digital resources, technology, talents, and initial accumulation.

Figure (2) shows that the level of green resilience in Chinese manufacturing displays a decreasing pattern from 'East-West-Northeast-Central'. Regions like Beijing, Hainan, and Shanghai exhibit higher levels of green resilience, whereas areas like Jiangxi and Henan are relatively lower. Most parts of the western region are at a middle level of development, and the indices are generally lower in most provinces of the northeastern and central regions. This is primarily because the eastern region focuses on green development, balancing economic growth with ecological sustainability, whereas the northeastern and central regions overlook the importance of coordinated development between economy and green strategies.

Overall, the level of digitalization in Chinese manufacturing is higher than that of green resilience. The level of green resilience in Chinese manufacturing continuously

improves as the level of digitalization increases. Over time, the gap between the two is gradually narrowing, reflecting a certain degree of coordinated correlation between digitalization and green resilience development in Chinese manufacturing. From 2017 to 2022, some areas like Tianjin and Ningxia show that green resilience in Chinese manufacturing lags behind digitalization, indicating that their unbalanced development is not conducive to their coupled coordination development, suggesting significant potential for further improvement.

5.3 Measuring the coupling coordination degree between digitalization and green resilience development in manufacturing

Table 4 The coupling coordination degree between digitalization and green resilience

	Coupling degree C value	Coordination index T value	Coupling coordination degree D value	Coordination type
2017	0.836	0.208	0.389	Mild imbalance
2018	0.787	0.257	0.421	Calm imbalance
2019	0.782	0.235	0.400	Calm imbalance
2020	0.823	0.230	0.413	Calm imbalance
2021	0.730	0.306	0.443	Calm imbalance
2022	0.801	0.220	0.391	Mild imbalance

Using formulas (8) to (10), the coupling coordination degree between digitalization and green resilience development in Chinese manufacturing from 2017 to 2022 was calculated. As shown in Table (4), the coupling coordination degree

633 demonstrates fluctuating changes and is generally in a state of imbalance. This is due
634 to the high coupling degree between the two factors but a low coupling coordination
635 index, reflecting a significant positive interaction between digitalization and green
636 resilience development in Chinese manufacturing. However, this does not translate into
637 a synergistic development.

638 **Table 5** The coupling coordination degree between different region

		2017	2018	2019	2020	2021	2022	Mean	CT
The eastern of China	Beijing	0.995	0.995	0.927	0.995	0.938	0.875	0.954	HC
	Tianjin	0.504	0.605	0.563	0.571	0.63	0.538	0.569	BC
	Hebei	0.232	0.288	0.357	0.334	0.335	0.292	0.306	MI
	Shanghai	0.666	0.713	0.626	0.636	0.661	0.591	0.649	PC
	Jiangsu	0.495	0.553	0.586	0.606	0.667	0.556	0.577	BC
	Zhejiang	0.527	0.575	0.544	0.497	0.544	0.463	0.525	BC
	Fujian	0.345	0.442	0.392	0.345	0.386	0.328	0.373	MI
	Shandong	0.362	0.458	0.421	0.447	0.46	0.41	0.426	CI
	Guangdong	0.518	0.621	0.577	0.542	0.646	0.549	0.576	BC
	Hainan	0.596	0.625	0.578	0.591	0.566	0.504	0.577	BC
	Mean value	0.524	0.588	0.557	0.556	0.583	0.511	0.553	BC
The central of China	Shanxi	0.377	0.317	0.365	0.376	0.42	0.298	0.359	MI
	Anhui	0.317	0.362	0.371	0.396	0.413	0.365	0.371	MI
	Jiangxi	0.147	0.187	0.258	0.177	0.216	0.238	0.204	MOI
	Henan	0.228	0.177	0.181	0.262	0.187	0.167	0.200	MOI

	Hubei	0.308	0.38	0.347	0.327	0.401	0.364	0.355	MI
	Hunan	0.296	0.353	0.314	0.319	0.17	0.237	0.282	MOI
	Mean value	0.279	0.296	0.306	0.310	0.301	0.278	0.295	MOI
The western of China	Inner Mongolia	0.316	0.394	0.349	0.387	0.437	0.381	0.377	MI
	Guangxi	0.222	0.228	0.192	0.243	0.356	0.287	0.255	MOI
	Chongqing	0.366	0.507	0.445	0.419	0.378	0.36	0.413	CI
	Sichuan	0.351	0.41	0.367	0.352	0.418	0.334	0.372	MI
	Guizhou	0.351	0.331	0.345	0.374	0.465	0.426	0.382	MI
	Yunnan	0.305	0.308	0.262	0.309	0.403	0.303	0.315	MI
	Shaanxi	0.418	0.439	0.452	0.49	0.527	0.437	0.461	CI
	Gansu	0.226	0.287	0.257	0.292	0.349	0.321	0.289	MOI
	Qinghai	0.464	0.329	0.328	0.383	0.447	0.413	0.394	MI
	Ningxia	0.395	0.357	0.388	0.39	0.462	0.405	0.400	CI
	Xinjiang	0.302	0.274	0.325	0.256	0.315	0.315	0.298	MOI
	Mean value	0.338	0.351	0.337	0.354	0.414	0.362	0.359	MI
The northeast of China	Liaoning	0.49	0.495	0.394	0.406	0.425	0.36	0.428	CI
	Jilin	0.257	0.266	0.238	0.313	0.323	0.289	0.281	MOI
	Heilongjiang	0.299	0.357	0.246	0.341	0.347	0.332	0.320	MI
	Mean value	0.349	0.373	0.293	0.353	0.365	0.327	0.343	MI

639 According to Table (5), since 2017, the coupling coordination degree between

640 digitalization and green resilience development in Chinese manufacturing has shown a

significant upward trend in the major regions of the East, Central, and West, but the Northeast has exhibited a fluctuating state. This reflects a mutually promoting and supporting effect between the two, with the mutual promotion effect gradually increasing. In the Eastern region, most provinces are in a state of coordination, while a few areas are in imbalanced. Specifically, Beijing is in a high-quality coordination state with a coupling coordination value maintained around 0.9, while regions like Tianjin, Zhejiang, and Guangdong are barely coordinated, with values above 0.5. Hebei and Shandong are in a state of imbalance, with values around 0.4. In the Central region, most provinces, notably Jiangxi and Henan, are in a moderate imbalance, with coupling coordination values around 0.2. In the West and most of the Northeast, the coupling coordination is mildly imbalanced, with a few areas, including Chongqing and Shaanxi, on the verge of imbalance, maintaining values around 0.4, while other areas maintain values around 0.3. This could be due to the Eastern region having the most mature economic foundation for digital and green development and strong siphoning effects for technology and financial resources, while other regions have weaker manufacturing bases, lower levels of digital development, and insufficient momentum to promote green manufacturing development.

5.4 Regional differences and source decomposition in coupling coordination degree

Using formulas (11) to (19) and applying the Dagum Gini coefficient and its decomposition method, the spatial differences and their origins in the coupling coordination development between digitalization and green resilience in Chinese manufacturing from 2017 to 2022 were measured using Matlab. The results are shown

in Figure (3)-Figure (6).

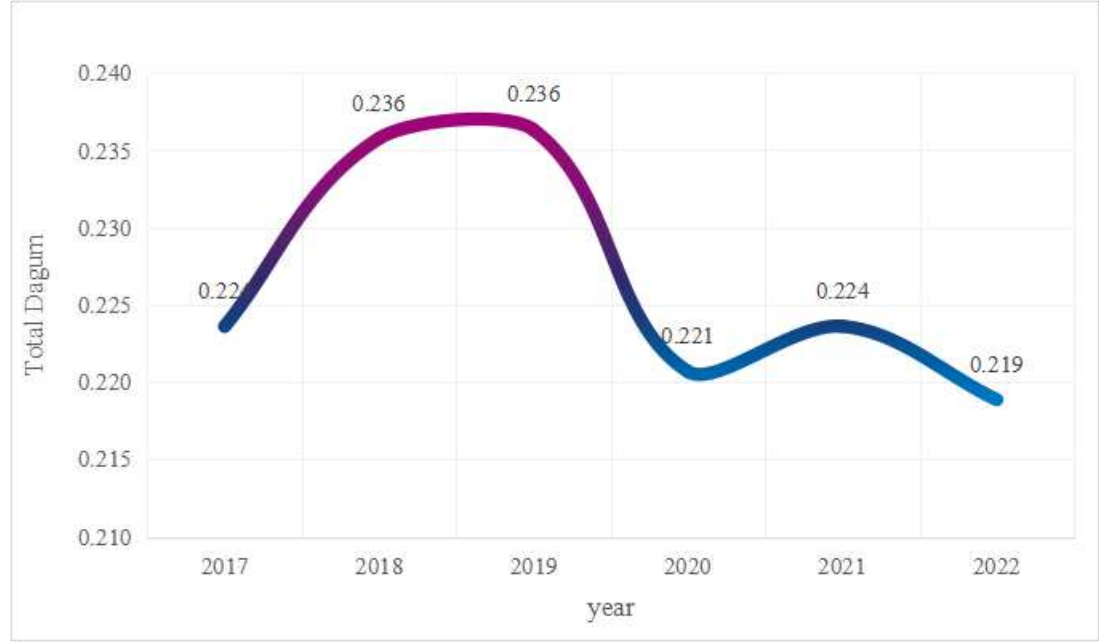


Figure 3 The evolution of total dagum in Chinese manufacturing



Figure 4 The evolution of regional dagum in Chinese manufacturing

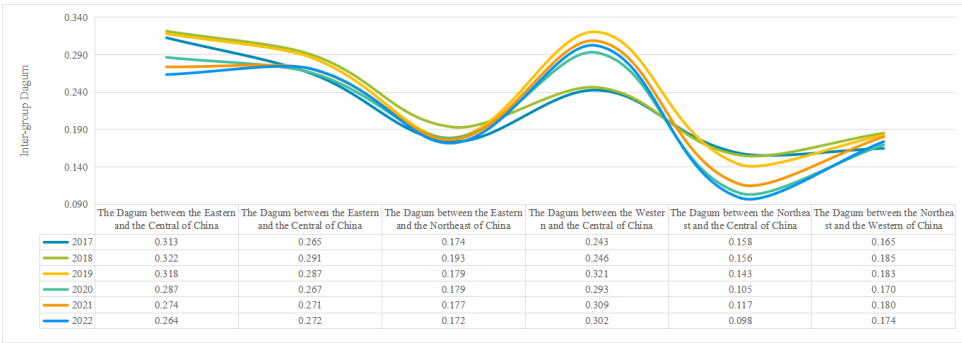


Figure 5 The evolution of inter-regional dagum in Chinese manufacturing

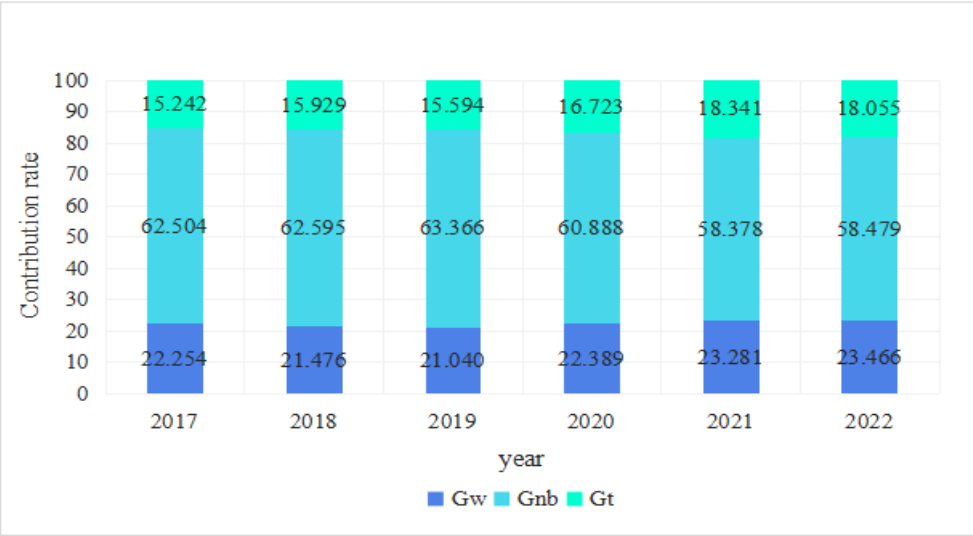


Figure 6 The evolution of contribution rate in Chinese manufacturing

5.4.1 Overall and intra-regional differences

As depicted in Figures (3) and (4), there is a discernible trend in the evolution of overall and intra-regional differences in coupling coordination degrees. The overall Gini coefficient exhibits an inverted W-shaped pattern, rising from 0.224 in 2017 to 0.236 in 2019, then dropping to 0.221 in 2020, rising again to 0.224 in 2021, and finally decreasing to 0.219 in 2022, indicating a fluctuating trend in the overall disparity of coupling coordination between digitalization and green resilience development in Chinese manufacturing. In terms of intra-regional differences from 2017 to 2022, the Western region displayed the largest internal disparities in the coupling coordination of

digitalization and green resilience development, followed by the Eastern region, with the Central region next, and the Northeast having the smallest internal differences. The substantial spatial differences within the Western region, notably in Chongqing, Shaanxi, and Ningxia maintaining coordination values around 0.4 compared to Gansu and Guangxi around 0.2, account for these variations. The Eastern and Central regions exhibit minor fluctuations in their Gini coefficients, showing relative stability due to strong digital economies in areas like Beijing, Shanghai, and Guangdong, which effectively integrate digital technology with green development and exert a radiating effect. In contrast, the Northeast has smaller Gini coefficient values, reflecting more balanced development within the region, with the Gini coefficient showing a downward trend, and provinces like Heilongjiang, Jilin, and Liaoning showing smaller differences, indicating a "club convergence" phenomenon associated with manufacturing development in the Northeast.

5.4.2 Inter-regional differences

As seen in Figure (5), from 2017 to 2022, the inter-regional Gini coefficient for the level of coupling coordination exhibited a W-shaped trend. When considering the average relative differences in coupling coordination between digitalization and green resilience development across regions, the largest disparity was between the Eastern and Central regions, reaching a difference of 0.296, while the smallest was between the Central and Northeastern regions, at just 0.129. The dynamic trend shows that changes in the level of coupling coordination between the East-West, East-Northeast, and West-Northeast were minimal, not exceeding 0.01 compared to 2017, whereas changes

between the East-Central, Central-West, and Central-Northeast were more pronounced, exceeding changes of 0.01 since 2017. The primary reasons for these regional disparities in coupling coordination levels include the superior level of digital and green development in Eastern regions such as Beijing, Shanghai, and Guangdong. Although the Central and Western regions have certain advantages in resources and factors, they are still insufficient. Additionally, the investment in digital technology and policy support related to green development varies across regions, leading to different levels of coupling coordination.

5.4.3 Sources and contributions of differences

As indicated in Figure (6), the inter-regional disparity contributes the most to the differences in coupling coordination between manufacturing digitalization and green resilience development, with an average annual contribution rate of 61.03%, showing a gradually decreasing trend from 62.50% in 2017 to 58.47% in 2022. The contribution rate of intra-regional differences is moderate, while the contribution rate of transvariation density is the lowest. Thus, inter-regional differences are the primary source of disparities in the coupling coordination development between digitalization and green resilience in manufacturing. Therefore, coordinating regional development, especially narrowing the development gap between the Eastern regions such as Beijing, Guangdong, Shanghai, and the Northeastern areas such as Heilongjiang and Jilin, holds significant importance for the sustainable development of Chinese manufacturing. Attention should also be given to cities within regions with high coupling coordination that exhibit lower levels of coordination, with this overlapping phenomenon showing

an increasing trend.

6 Discussion

6.1 Spatial correlation analysis

As indicated by Table (6), from 2017 to 2022, Moran's Index for the coupling coordination between digitalization and green resilience in Chinese manufacturing consistently passed the 10% significance level test, demonstrating a significant spatial effect. This suggests that the coupling coordination between digitalization and green resilience in Chinese manufacturing has significant spatial spillover effects, whereby neighboring regions can influence each other's coupling coordination between digitalization and green resilience. The Moran's Index showed an initial rise followed by a decline in its evolutionary trajectory. The emergence of this phenomenon can be attributed to the early stages of digital and green development, where various regions were striving to overcome their own bottlenecks in digital technology and green development. Gradually, different areas broke down traditional regional barriers, initiating cross-regional collaborative innovation. This led to increasingly tight cooperation and interaction between regions, and as a result, spatial agglomeration effects showed an upward trend. However, as digital technologies and green development matured, a complacency effect emerged among the regions, leading to a 'no progress, thus regress' situation, and the spatial agglomeration effects consequently declined.

Table 6 The Moran's index for the coupling coordination between digitalization and green resilience in Chinese manufacturing

Year	Moran value	Ei	Sdi	Z	P
2017	0.140	-0.034	0.113	1.403	0.080
2018	0.238	-0.034	0.128	2.221	0.013
2019	0.324	-0.034	0.123	2.925	0.002
2020	0.250	-0.034	0.129	2.322	0.010
2021	0.206	-0.034	0.107	1.959	0.025
2022	0.200	-0.034	0.112	1.912	0.028

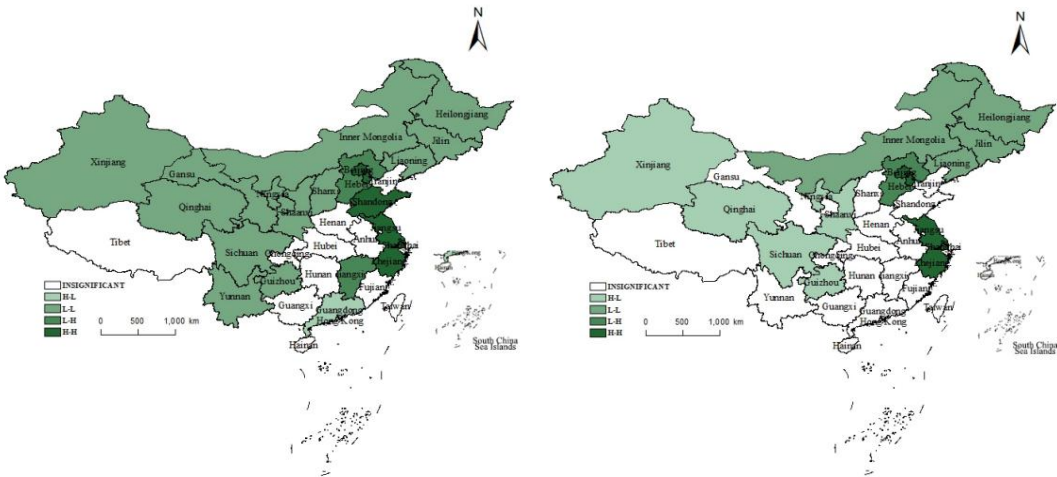


Figure 7 Local spatial auto-correlation of coupling coordination in the development of digitalization and green resilience in Chinese manufacturing

There is a significant local clustering phenomenon in the coupling coordination development level of digitalization and green resilience in Chinese manufacturing. As shown in Figure (7), major clusters include high-level aggregations in the eastern regions and low-level aggregations in the western regions. From 2017 to 2022, the coastal areas of the eastern region remained in a high-high clustering state without

significant changes, indicating that high-value provinces in the eastern region could consistently maintain a stage of benign coordinated development, gradually driving the development of surrounding provincial areas. However, changes occurred in the low-low clustering areas from 2017 to 2022, with regions such as Qinghai, Gansu, and Ningxia in the west transitioning from a low-low to a high-low clustering state, while the northeastern region remained consistently in a low-low cluster without change. This indicates a gradual reduction in low-value clusters, and with investments in digital resources and green innovation, some regions are striving to catch up. From 2017 to 2018, clustering characteristics in some regions were insignificant, suggesting that the spatial correlation types of the coupling coordination development levels in most provinces' manufacturing digitalization and green resilience did not change, and the spatial clustering characteristics exhibited strong stability.

6.2 Distribution dynamics analysis and characteristics

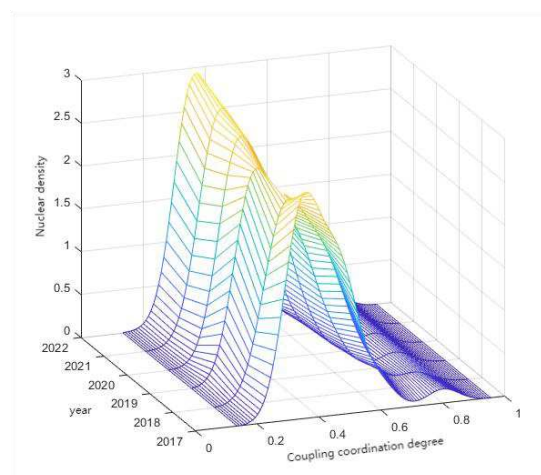


Figure 8 Kernel density of the coupling coordination degree between digitalization and green resilience from 2017 to 2022

The dynamic evolution of the coupling coordination degree between digitalization

and green resilience in Chinese manufacturing exhibits four characteristics (As shown in Figure 8):

Peak count: The kernel density curve transitions from bimodal to multimodal, with a secondary peak on each side of the main peak and the gap between the main and secondary peaks narrowing. This indicates a trend toward multi-polar differentiation in the overall level of coupling coordination, with a reduction in regional polarization and a narrowing of the overall disparity.

Distribution position: The kernel density estimation curve for coupling coordination shifts overall to the right, indicating a gradual improvement in the coupling coordination level of digitalization and green resilience across provinces and cities nationwide, reflecting an overall positive trend.

Distribution shape: The height of the main peak of the kernel density curve increases, and the width of the peaks broadens, suggesting a trend toward increasing disparities in coupling coordination levels.

Distribution extensibility: The kernel density curve exhibits a right-skewed tail, indicating that the coupling coordination level of digitalization and green resilience in some regions is far above the average. Additionally, the tail extends before contracting, indicating that after a period of increase, the level of coupling coordination experiences a decline.

In summary, while the coupling coordination level between manufacturing digitalization and green resilience in most Chinese cities has improved, the magnitude of improvement is modest, absolute differences have increased, and polarization is

evident. There remains significant potential for enhancing the coupling coordination level of digitalization and green resilience across various regions in China, and effectively leveraging the radiating influence of high-level regions is essential.

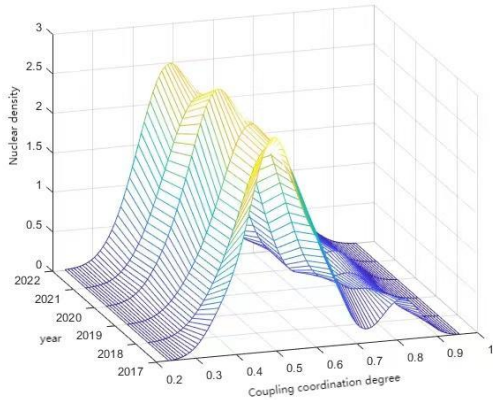


Figure 9 Nuclear density of coupling coordination degree between digitalization and green resilience in manufacturing industry of the eastern of China from 2017 to 2022

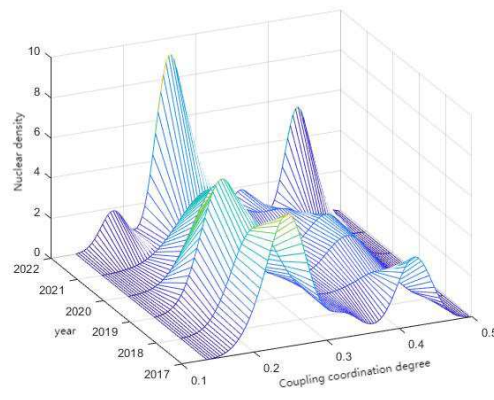


Figure 10 Nuclear density of coupling coordination degree between digitalization and green resilience in manufacturing industry of the western of China from 2017 to 2022

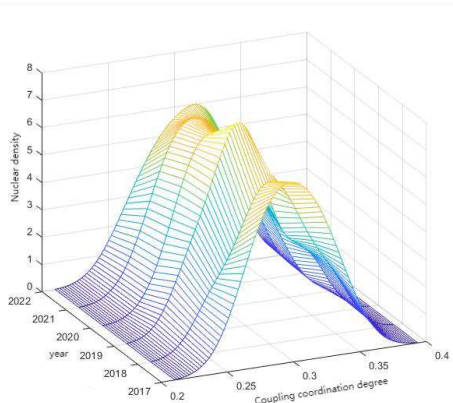


Figure 11 Nuclear density of coupling coordination degree between digitalization and green resilience in manufacturing industry of the central of China from 2017 to 2022

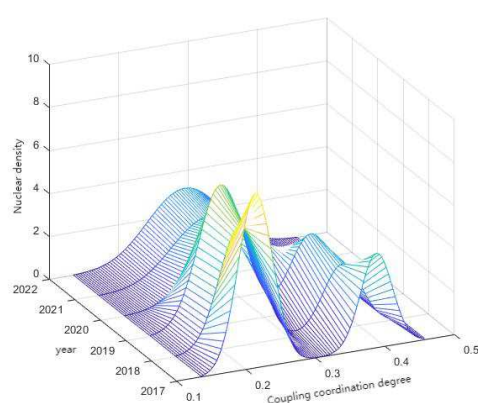


Figure 12 Nuclear density of coupling coordination degree between digitalization and green resilience in manufacturing industry of the northeastern of China from 2017 to 2022

From a distribution shape perspective, the kernel density curves of various regions demonstrate distinct trends (Figure 9-12): In the eastern region, the main peak of the

kernel density curve shows a continuous upward trend in peak height with a broadening peak width. In the western region, the main peak height of the kernel density curve initially rises, then falls, and rises again, with the peak width continuously narrowing. In the central region, the main peak height exhibits a similar trend of initially rising, then falling and rising again, with the peak width continuously broadening. In the northeastern region, the main peak height shows a continuous downward trend, with the peak width gradually narrowing.

Regarding peak count, The kernel density curve in the Eastern region consistently presents a bimodal state, with the side peak significantly lower than the main peak. The western region experiences a transition from bimodal to multimodal, with a stable height difference between the main and side peaks, indicating a shift from bipolar to multipolar differentiation. The central region evolves from an unimodal to a bimodal state, suggesting a bipolar differentiation trend within its cities. The northeastern region transitions from bimodal to unimodal and back to unimodal, indicating a brief bipolar differentiation trend followed by a return to a single-value concentration, with relatively small differences among internal cities.

Regarding distribution position, the kernel density curves of all regions gradually shift rightward over time, indicating an overall improvement in the coupling coordination between digitalization and green resilience. This trend is consistent with previous analyses, suggesting that over time, cities with lower coupling coordination degrees are decreasing, transitioning towards higher values. The Eastern region shows the most significant rightward shift, indicating a substantial improvement in the

coupling coordination levels within most cities in this region; the Central region exhibits a smaller shift, remaining stable within a certain range, indicating that the coupling coordination levels within most cities in this region are relatively stable.

From an extensibility perspective, the kernel density curve for the coupling coordination level between digitalization and green resilience in the coastal Eastern manufacturing sector exhibits a right-tailed state, with the tail converging, indicating that some cities in this region exceed the average level, but the gap with the average is narrowing. The western region experiences a transition from a right tail to a left tail as most cities in this region improve their coupling coordination levels, making low-efficiency cities the minority, resulting in a left-tailed density curve. Both the central and northeastern regions see their kernel density curves change from a left tail to a right tail, with the tail gradually converging as the efficiency levels of most cities decrease, causing the efficiency values of some high-efficiency cities to diverge further from the average, thus exhibiting a right-tailed state.

6.3 Markov chain analysis: characteristics of coupling coordination state transitions

To thoroughly analyze the spatial-temporal evolution patterns of the flow direction and position transition characteristics of the coupling coordination degree between digitalization and green resilience in Chinese manufacturing, the annual development indices were divided into four levels based on quartiles: Low (L), Medium-Low (ML), Medium-High (MH), and High (H). A Markov transition probability matrix was constructed (Table 7).

As shown in the table, when spatial interactions are not considered, the values on

the diagonal reflect the probability that the coupling coordination level between digitalization and green resilience in Chinese manufacturing remains unchanged. The respective probability values are 67.57%, 41.67%, 56.41%, and 89.47%. These values are significantly higher than the off-diagonal values, indicating that the states in the evolution process of coupling coordination between digitalization and green resilience in Chinese manufacturing are relatively stable. The values at both ends of the diagonal are larger than those in the middle, suggesting that regions with low and high levels of coupling coordination between digitalization and green resilience tend to maintain their original states, exhibiting low-level and high-level convergence phenomena.

One year later, the probability of transitioning from a low level to a medium-low level is 27.03%, while the probability of transitioning from a low level to a medium-high level is 5.41%. The probability of transitioning from a medium-low level to a medium-high level is 36.11%, and from a medium-low level to a high level is 2.78%. The probability of transitioning from a medium-high level to a high level is 5.13%. This indicates that there is potential for a leap in the coupling coordination levels between digitalization and green resilience across all levels, but the more stages the leap involves, the greater the difficulty and the lower the probability of ascension.

Table 7 The characteristics of coupling coordination state transitions

	Types of spatial lag	t/(t+1)	L	ML	MH	H	Obs
Traditional	No lag	L	0.6757	0.2703	0.0541	0.0000	37

		ML	0.1944	0.4167	0.3611	0.0278	36
		MH	0.0513	0.3333	0.5641	0.0513	39
		H	0.0000	0.0000	0.1053	0.8947	38
Spatial	L	L	0.3333	0.5000	0.1667	0.0000	6
		ML	0.5000	0.5000	0.0000	0.0000	2
		MH	0.0000	0.5000	0.2500	0.2500	4
		H	0.0000	0.0000	0.0000	0.0000	0
	ML	L	0.7333	0.2000	0.0667	0.0000	15
		ML	0.1000	0.4000	0.4500	0.0500	20
		MH	0.0455	0.2727	0.6364	0.0455	22
		H	0.0000	0.0000	0.1429	0.8571	7
	MH	L	0.8000	0.2000	0.0000	0.0000	15
		ML	0.2500	0.4167	0.3333	0.0000	12
		MH	0.0769	0.3846	0.5385	0.0000	13
		H	0.0000	0.0000	0.2500	0.7500	12
	H	L	0.0000	1.0000	0.0000	0.0000	1
		ML	0.5000	0.5000	0.0000	0.0000	2
		MH	0.0000	0.0000	0.0000	0.0000	0
		H	0.0000	0.0000	0.0000	1.0000	19

871 Based on Table (6), it is evident that the spatial correlation of the coupling
872 coordination degree between the digitization and green resilience of Chinese
873 manufacturing is significant. A spatial Markov chain is employed to explore the

changes in the transition probabilities of the coupling coordination level under spatial interaction. Firstly, the transition probabilities of the coupling coordination degree between the digitization and green resilience of Chinese manufacturing vary across different regions, indicating that the development statuses of digitization and green resilience in neighboring provinces affect the transition probabilities of the coupling coordination degree in the respective provinces. Secondly, there is a spatial spillover effect in the coupled and coordinated development of digitization and green resilience in Chinese manufacturing. The coupling coordination degree of neighboring regions influences the transition probability of the local area. From the table, it can be seen that the transition probabilities for the coupling coordination development of manufacturing digitization and green resilience vary across different regions and neighboring provinces. Lastly, provinces with a low coupling coordination level between manufacturing digitization and green resilience tend to have a suppressive effect on adjacent provinces, while provinces with a high coupling coordination level have a promoting effect on adjacent provinces.

When spatial factors are not considered, the probability of a province at the ML (Medium-Low) level transitioning to the L (Low) level is 19.44%, the probability of a province at the MH (Medium-High) level transitioning to the ML level is 33.33%, the probability of a province at the L level transitioning to the ML level is 27.03%, the probability of a province at the ML level transitioning to the MH level is 36.11%, and the probability of a province at the MH level transitioning to the H (High) level is 5.13%.

When neighboring a province at the L level, the probability of a province at the ML

level transitioning to the L level is 50%, and the probability of a province at the MH level transitioning to the ML level is 50%. When neighboring a province at the ML level, the probability of a province at the ML level transitioning to the MH level is 45%, and the probability of a province at the MH level transitioning to the H level is 4.55%. When neighboring a province at the H level, the probability of a province at the L level transitioning to the ML level is 100%, and the H level remains at 100% high level. This primarily reflects that provinces with a high level of coupling coordination between manufacturing digitization and green resilience have abundant resources, actively promote the development of the digital industry, and simultaneously increase investment in green total factor productivity. The synergistic development of digitization and greening thereby radiates and drives the development of surrounding areas. Conversely, provinces with a low level of coupling coordination between manufacturing digitization and green resilience tend to exhibit decoupling behavior in digitization and green development, which may even hinder the development of digitization and greening in neighboring areas to some extent.

7 Conclusion

Increasing global demands for reconciling digital innovation with ecological sustainability highlight an urgent need to elucidate how these two priorities evolve in tandem, particularly across diverse regional landscapes. By applying entropy-weighted TOPSIS and coupling coordination degree models to assess levels of digitization and green resilience within China's manufacturing sector—and further examining spatial and temporal dynamics through the Dagum Gini coefficient, Moran's I index, kernel

density estimation, and Markov chain analyses—this study uncovers pronounced regional disparities and evolving developmental trajectories. The results indicate a discernible gradient of “East–Central–West–Northeast” in digitization, contrasted by a “East–West–Northeast–Central” pattern in green resilience, underlining significant spatial heterogeneity. Despite a gradual convergence driven by rising digitization in most regions, the overall coupling coordination between digitization and green resilience remains suboptimal, implying substantial room for strategic improvement. Provinces in eastern and southern China (e.g., Beijing, Zhejiang, Guangdong) exhibit notably higher coordination levels than their western and northern counterparts (e.g., Chongqing, Shaanxi), with an inverted W-shaped Gini coefficient trend suggesting partial convergence and spatial agglomeration. Crucially, inter-regional differences—particularly those between eastern and central provinces—emerge as key drivers of disparity in coupled development. Moreover, low-performing regions exert negative spillover effects on neighboring areas, whereas high performers confer positive externalities, highlighting the importance of cross-provincial interdependencies. Taken together, these findings not only illuminate the uneven landscape of China’s digitization–green resilience nexus but also underscore the transformative potential of targeted policy interventions, enhanced regional collaborations, and strategic investments. From a broader perspective, recognizing and harnessing these spatial externalities can accelerate the transition toward more balanced and sustainable industrial ecosystems, thereby offering valuable insights for policymakers and industry leaders seeking to align technological innovation with environmental imperatives.

7.1 Implication for research

This research contributes significantly to the global discourse on digitization and green resilience, offering valuable insights into the divergences and commonalities between developed countries and developing countries like China:

Firstly, the study provides a nuanced definition of digitization, dissecting it into foundational development, digital production activities, and innovation benefits. This comprehensive evaluative index system is developed in response to the global theoretical frameworks, such as those suggested by Tim et al. (2021), but with a particular emphasis on the unique challenges and opportunities present in developing nations like China. these empirical results support the findings of Vial (2019) and Mubarak et al. (2021), and then enriches the theoretical and empirical studies of digital micro-effects and helps to promote the integrated development of the digital economy and the green economy. In developed countries, digitization often builds upon robust, existing infrastructures and is driven by high levels of technological adoption and consumer demand. In contrast, in developing nations, digitization can be a transformative force that leapfrogs traditional stages of industrialization but is often hampered by infrastructural deficiencies and resource constraints.

Similarly, the concept of green resilience is explored through resilience theory tailored to the specific conditions of manufacturing within China. This framework responds to and extends global research, exemplified by studies like those of Hu et al. (2022) and Wu et al. (2024), enriches the field of green development research, effectively compensates for the lack of research on green resilience development, and

provides a new perspective for green development research. The study highlights that while developed countries might focus on refining and optimizing existing green practices within well-established regulatory environments, developing countries face the dual challenge of initiating these practices amidst rapid industrial growth and often less stringent environmental regulations.

Secondly, the research addresses the integration of digitization and green resilience, with a specific focus on China's manufacturing industry, offering broader implications for both developed and developing countries. This research fills the research gap in the effective integration of digitalization and green resilience in China's manufacturing industry. By deeply exploring the coupling coordination mechanism of digitalization and green resilience development in China's manufacturing industry, it aims to reveal the complex relationship between the two and their mutual influences, expanding the research of Wu et al. (2024). It explores the coupling coordination mechanisms, revealing complex interdependencies that vary significantly by economic context. In developed countries, digitization and green resilience are often integrated into corporate strategies to comply with environmental laws and to meet consumer expectations. In contrast, in developing countries like China, these initiatives can be more closely linked to governmental policies aimed at sustainable growth and international competitiveness.

Lastly, the regional analysis within China provides a microcosm for global disparities in the adoption and effectiveness of digitization and green resilience strategies. The study uses China's regional diversity to illustrate how different levels of economic development, industrial structures, resource endowments, and policy

frameworks can influence these areas. This approach offers scalable insights for other developing regions while also providing a contrast to the more homogeneous conditions often found in developed countries. This comparative perspective is essential for developing targeted, region-specific strategies that address the unique challenges faced by industries in both developed and developing nations, promoting a more nuanced understanding of global industrial development in the context of digitization and green resilience.

7.2 Implications for policy

As global competition intensifies and environmental regulations become stricter, achieving high-quality development in manufacturing has emerged as a critical goal for various sectors. The research findings reveal the regional differences and spatial patterns of the coupled and coordinated development of digitalization and green resilience in China's manufacturing industry. For governments, it provides a scientific and rational basis for formulating regional development policies, industrial upgrading plans, and environmental policies, to achieve balanced regional development and environmental sustainability. For manufacturing enterprises, it offers a way to assess their development levels during digital transformation and green development, thereby better formulating corresponding development strategies. For researchers and scholars, it provides a fundamental research framework to deepen the understanding of the coupled and coordinated development of digitalization and green resilience in the manufacturing industry. For investors, it offers a framework to evaluate the investment potential and risks in different regions when making investment decisions. The

integrated development of digitization and green resilience, key pillars of modern manufacturing, is essential not only for enhancing corporate competitiveness but also for advancing sustainable development. Based on the findings of this research, we offer several managerial implications:

Understanding spatiotemporal differences for tailored strategy development: It is crucial for enterprises and governments to recognize and adapt to the spatiotemporal variations in the development of digitization and green resilience. Development strategies should be aligned with the unique conditions of each region. For instance, economically advanced coastal regions with robust information infrastructure might focus on integrating advanced manufacturing with smart technologies. In contrast, regions in the central and western areas could capitalize on their local resource bases and environmental capacities to emphasize green manufacturing and clean production practices. Enterprises should craft distinct pathways for digitization and green development tailored to their industrial foundations and developmental stages. Traditional manufacturing firms might pursue upgrades to achieve smart and green production, whereas new enterprises could embed digital and green technologies from inception, setting standards in intelligent and green manufacturing.

Enhancing policy support for coordinated regional development: Governments at all levels should enact targeted policies that reflect the specific needs and conditions of different regions to foster coordinated development. These policies could include financial subsidies, tax incentives, and technical support to encourage investments in digital and green technologies. Additionally, enhancing inter-regional resource and

technology coordination can facilitate complementary cooperation, boosting the synergistic development of digitization and green initiatives.

Fostering technological innovation to boost competitiveness: Technological innovation is pivotal for the coupled and coordinated development of digitization and green resilience. Enterprises should escalate their investments in developing intelligent manufacturing and green technologies to spur the industrial application of these innovations. For example, the adoption of the Internet of Things, big data, and artificial intelligence can augment the automation and intelligence of manufacturing processes. Similarly, investing in green materials and clean energy technologies can diminish resource consumption and environmental impact, culminating in greener manufacturing practices.

Leveraging data-driven approaches for precision management: Data is an invaluable asset in harmonizing the development of digitization and green resilience. Companies should establish robust systems for data collection, analysis, and application. Utilizing big data technologies to continuously monitor and analyze production data allows for precise management of manufacturing processes. Through data analytics, firms can optimize production methods and workflows, minimize energy and material use, conduct predictive maintenance, and enhance equipment efficiency and reliability. Furthermore, analyzing supply chain data can help optimize logistics and inventory management, reducing costs and mitigating risks.

7.3 Limitations and future research directions

Although this study has theoretical and practical value, this paper has several

limitations: firstly, the research scope is limited to China's manufacturing industry, but it does not involve other regions or industries. Future research should pay more attention to comparative studies across different industries to reveal the differences and regularities in the coupling and coordinated development of digitization and green resilience; secondly, this study relies on statistical data integrated multi-source data, future research should focus more on the integration of multi-source data and dynamic monitoring to improve data accuracy and real-time capability; lastly, this study is primarily based on the Chinese context and lacks cross-national comparative analysis. Future research can draw on other countries' successful experiences in digitization and green resilience to explore development paths suitable for China's national conditions.

Ethical Approval Statements

This article does not contain any studies with human participants performed by any of the authors.

Informal Consent

This article does not contain any studies with human participants performed by any of the authors.

Competing Interests

The authors declare no competing interests.

Data Availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

References

- Ahmed, R. R., Streimikiene, D., Soomro, R. H., & Streimikis, J. (2022). Digital Transformation and Industry 4.0 Initiatives for Market Competitiveness: Business Integration Management Model in the Healthcare Industry. *Journal of Competitiveness*, 14 (4), 6-24.
- AL-Khatib, A. W., Shuhaiber, A., Mashal, I., & Al-Okaily, M. (2024). Antecedents of Industry 4.0 capabilities and technological innovation: a dynamic capabilities perspective. *European Business Review*, 36(4), 566-587.
- Ambedkar, K., & Prakash, G. (2024). Evolving Dynamic Capabilities: Exploring Implications of Industry 4.0 Digital Technologies on Manufacturing. *IEEE Transactions on Engineering Management*.
- Ancillai, C., Sabatini, A., Gatti, M., & Perna, A. (2023). Digital technology and business model innovation: A systematic literature review and future research agenda. *Technological Forecasting and Social Change*, 188, 122307.
- Anthony Jnr, B. (2021). Managing digital transformation of smart cities through enterprise architecture—a review and research agenda. *Enterprise Information Systems*, 15(3), 299-331.
- Ashmore, F. H., Farrington, J. H., & Skerratt, S. (2017). Community-led broadband in rural digital infrastructure development: Implications for resilience. *Journal of Rural Studies*, 54, 408-425.
- Bag, S., Gupta, S., & Kumar, S. (2021). Industry 4.0 adoption and 10R advance manufacturing capabilities for sustainable development. *International Journal of*

1095 *Production Economics*, 231, 107844.

1096 Baiyere, A., Salmela, H., Nieminen, H., & Kankainen, T. (2024). Assessing digital
 1097 capabilities for digital transformation—The MIND framework. *Information Systems*
 1098 *Journal*.

1099 Belhadi, A., Kamble, S. S., Venkatesh, M., Jabbour, C. J. C., & Benkhalti, I. (2022).
 1100 Building supply chain resilience and efficiency through additive manufacturing: An
 1101 ambidextrous perspective on the dynamic capability view. *International Journal of*
 1102 *Production Economics*, 249, 108516.

1103 Boh, W., Constantinides, P., Padmanabhan, B., & Viswanathan, S. (2023). Building
 1104 digital resilience against major shocks. *Mis Quarterly*, 47(1), 343-360.

1105 Bohensky, E. L., & Maru, Y. (2011). Indigenous knowledge, science, and resilience:
 1106 What have we learned from a decade of international literature on “integration”?.
 1107 *Ecology and Society*, 16(4).

1108 Borah, P. S., Dogbe, C. S. K., Dzandu, M. D., & Pomegbe, W. W. K. (2023). Forging
 1109 organizational resilience through green value co-creation: The role of green technology,
 1110 green operations, and green transaction capabilities. *Business Strategy and the*
 1111 *Environment*, 32(8), 5734-5747.

1112 Boschma, R. (2017). Towards an evolutionary perspective on regional resilience. In
 1113 Evolutionary economic geography (pp. 29-47). Routledge.

1114 Chan, C. M., Teoh, S. Y., Yeow, A., & Pan, G. (2019). Agility in responding to disruptive
 1115 digital innovation: Case study of an SME. *Information Systems Journal*, 29(2), 436-
 1116 455.

1117 Chatterjee, S., Sarker, S., Lee, M. J., Xiao, X., & Elbanna, A. (2021). A possible
 1118 conceptualization of the information systems (IS) artifact: A general systems theory
 1119 perspective 1. *Information Systems Journal*, 31(4), 550-578.

1120 Chen, S. J., & Hwang, C. L. (1992). Fuzzy multiple attribute decision making methods.
 1121 *In Fuzzy multiple attribute decision making: Methods and applications* (pp. 289-486).
 1122 Berlin, Heidelberg: Springer Berlin Heidelberg.

1123 Chin, T., Shi, Y., Singh, S. K., Agbanyo, G. K., & Ferraris, A. (2022). Leveraging
 1124 blockchain technology for green innovation in ecosystem-based business models: a
 1125 dynamic capability of values appropriation. *Technological Forecasting and Social*
 1126 *Change*, 183, 121908.

1127 Ciarli, T., Kenney, M., Massini, S., & Piscitello, L. (2021). Digital technologies,
 1128 innovation, and skills: Emerging trajectories and challenges. *Research Policy*, 50(7),
 1129 104289.

1130 Cong, L. W., Yang, X., & Zhang, X. (2024). Small and medium enterprises amidst the
 1131 pandemic and reopening: Digital edge and transformation. *Management Science*.

1132 Conz, E., & Magnani, G. (2020). A dynamic perspective on the resilience of firms: A
 1133 systematic literature review and a framework for future research. *European*
 1134 *Management Journal*, 38(3), 400-412.

1135 Culot, G., Nassimbeni, G., Orzes, G., & Sartor, M. (2020). Behind the definition of
 1136 Industry 4.0: Analysis and open questions. *International Journal of Production*
 1137 *Economics*, 226, 107617.

1138 Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018). The expected

1139 contribution of Industry 4.0 technologies for industrial performance. *International*
1140 *Journal of Production Economics*, 204, 383-394.

1141 Del Giudice, M., Scuotto, V., Papa, A., Tarba, S. Y., Bresciani, S., & Warkentin, M.
1142 (2021). A self-tuning model for smart manufacturing SMEs: Effects on digital
1143 innovation. *Journal of Product Innovation Management*, 38(1), 68-89.

1144 DesJardine, M., Bansal, P., & Yang, Y. (2019). Bouncing back: Building resilience
1145 through social and environmental practices in the context of the 2008 global financial
1146 crisis. *Journal of Management*, 45(4), 1434-1460.

1147 Dittrich, K., Duysters, G., & de Man, A. P. (2007). Strategic repositioning by means of
1148 alliance networks: The case of IBM. *Research Policy*, 36(10), 1496-1511.

1149 Dohale, V., Akarte, M., Gunasekaran, A., & Verma, P. (2024). Exploring the role of
1150 artificial intelligence in building production resilience: learnings from the COVID-19
1151 pandemic. *International Journal of Production Research*, 62(15), 5472-5488.

1152 Dougherty, D. (1992). A practice-centered model of organizational renewal through
1153 product innovation. *Strategic Management Journal*, 13(S1), 77-92.

1154 Dou, Q., & Gao, X. (2023). How does the digital transformation of corporates affect
1155 green technology innovation? An empirical study from the perspective of asymmetric
1156 effects and structural breakpoints. *Journal of Cleaner Production*, 428, 139245.

1157 Elia, G., Margherita, A., & Passiante, G. (2020). Digital entrepreneurship ecosystem:
1158 How digital technologies and collective intelligence are reshaping the entrepreneurial
1159 process. *Technological Forecasting and Social Change*, 150, 119791.

1160 El-Kassar, A. N., & Singh, S. K. (2019). Green innovation and organizational

1161 performance: The influence of big data and the moderating role of management
 1162 commitment and HR practices. *Technological Forecasting and Social Change*, 144,
 1163 483-498.

1164 Eraydin, A. (2016). Attributes and characteristics of regional resilience: Defining and
 1165 measuring the resilience of Turkish regions. *Regional Studies*, 50(4), 600-614.

1166 Feng, Y., Lai, K. H., & Zhu, Q. (2022). Green supply chain innovation: Emergence,
 1167 adoption, and challenges. *International Journal of Production Economics*, 248,
 1168 108497.

1169 Fischer, M., Imgrund, F., Janiesch, C., & Winkelmann, A. (2020). Strategy archetypes
 1170 for digital transformation: Defining meta objectives using business process
 1171 management. *Information & Management*, 57(5), 103262.

1172 Fragapane, G., Ivanov, D., Peron, M., Sgarbossa, F., & Strandhagen, J. O. (2022).
 1173 Increasing flexibility and productivity in Industry 4.0 production networks with
 1174 autonomous mobile robots and smart intralogistics. *Annals of Operations Research*,
 1175 308(1), 125-143.

1176 Frank, A. G., Mendes, G. H., Ayala, N. F., & Ghezzi, A. (2019). Servitization and
 1177 Industry 4.0 convergence in the digital transformation of product firms: A business
 1178 model innovation perspective. *Technological Forecasting and Social Change*, 141,
 1179 341-351.

1180 Fröhlich, K., & Hassink, R. (2018). Regional resilience: a stretched concept?.
 1181 *European Planning Studies*, 26(9), 1763-1778.

1182 Gammelgaard, B., & Nowicka, K. (2023). Next generation supply chain management:

1183 the impact of cloud computing. *Journal of Enterprise Information Management*.

1184 Guo, Z., Richardson, J. J., Kong, B., & Liang, K. (2020). Nanobiohybrids: Materials
1185 approaches for bioaugmentation. *Science Advances*, 6(12), eaaz0330.

1186 Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past,
1187 present, and future of artificial intelligence. *California Management Review*, 61(4), 5-
1188 14.

1189 Han, H., & Trimi, S. (2022). Towards a data science platform for improving SME
1190 collaboration through Industry 4.0 technologies. *Technological Forecasting and*
1191 *Social Change*, 174, 121242.

1192 Hao, X., Miao, E., Sun, Q., Li, K., Wen, S., & Xue, Y. (2024). The impact of digital
1193 government on corporate green innovation: Evidence from China. *Technological*
1194 *Forecasting and Social Change*, 206, 123570.

1195 Helfat, C. E., & Raubitschek, R. S. (2018). Dynamic and integrative capabilities for
1196 profiting from innovation in digital platform-based ecosystems. *Research Policy*, 47(8),
1197 1391-1399.

1198 Hossain, M. R., Rao, A., Sharma, G. D., Dev, D., & Kharbanda, A. (2024). Empowering
1199 energy transition: Green innovation, digital finance, and the path to sustainable
1200 prosperity through green finance initiatives. *Energy Economics*, 107736.

1201 Hu, X., Li, L., & Dong, K. (2022). What matters for regional economic resilience amid
1202 COVID-19? Evidence from cities in Northeast China. *Cities*, 120, 103440.

1203 Hung, B. Q., & Nham, N. T. H. (2023). The importance of digitalization in powering
1204 environmental innovation performance of European countries. *Journal of Innovation*

1205 **& Knowledge**, 8(1), 100284.

1206 Huang, J., Na, Y., & Guo, Y. (2020). Spatiotemporal characteristics and driving
1207 mechanism of the coupling coordination degree of urbanization and ecological
1208 environment in Kazakhstan. *Journal of Geographical Sciences*, 30, 1802-1824.

1209 Huang, K. F., Dyerson, R., Wu, L. Y., & Harindranath, G. (2015). From temporary
1210 competitive advantage to sustainable competitive advantage. *British Journal of*
1211 *Management*, 26(4), 617-636.

1212 Hussain, M., & Papastathopoulos, A. (2022). Organizational readiness for digital
1213 financial innovation and financial resilience. *International Journal of Production*
1214 *Economics*, 243, 108326.

1215 Hwang, C. L., Yoon, K., Hwang, C. L., & Yoon, K. (1981). Methods for multiple
1216 attribute decision making. *Multiple attribute decision making: methods and*
1217 *applications a state-of-the-art survey*, 58-191.

1218 Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and
1219 Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal*
1220 *of Production Research*, 57(3), 829-846.

1221 Ivanov, D., Dolgui, A., & Sokolov, B. (2022). Cloud supply chain: Integrating Industry
1222 4.0 and digital platforms in the “Supply Chain-as-a-Service”. *Transportation Research*
1223 *Part E: Logistics and Transportation Review*, 160, 102676.

1224 Jabbour, C. J. C., Fiorini, P. D. C., Ndubisi, N. O., Queiroz, M. M., & Piato, É. L. (2020).
1225 Digitally-enabled sustainable supply chains in the 21st century: A review and a research
1226 agenda. *Science of the Total Environment*, 725, 138177.

1227 Javaid, M., Haleem, A., Singh, R. P., Suman, R., & Gonzalez, E. S. (2022).
 1228 Understanding the adoption of Industry 4.0 technologies in improving environmental
 1229 sustainability. *Sustainable Operations and Computers*, 3, 203-217.

1230 Jones, M. D., Hutcheson, S., & Camba, J. D. (2021). Past, present, and future barriers
 1231 to digital transformation in manufacturing: A review. *Journal of Manufacturing*
 1232 *Systems*, 60, 936-948.

1233 Kalkanci, B., Rahmani, M., & Toktay, L. B. (2019). The role of inclusive innovation in
 1234 promoting social sustainability. *Production and Operations Management*, 28(12),
 1235 2960-2982.

1236 Kinkel, S. (2012). Trends in production relocation and backshoring activities: changing
 1237 patterns in the course of the global economic crisis. *International Journal of*
 1238 *Operations & Production Management*, 32(6), 696-720.

1239 Klein, H. J., Solinger, O. N., & Duflo, V. (2022). Commitment system theory: The
 1240 evolving structure of commitments to multiple targets. *Academy of Management*
 1241 *Review*, 47(1), 116-138.

1242 Kohtamäki, M., Rabetino, R., Parida, V., Sjödin, D., & Henneberg, S. (2022). Managing
 1243 digital servitization toward smart solutions: Framing the connections between
 1244 technologies, business models, and ecosystems. *Industrial Marketing Management*,
 1245 105, 253-267.

1246 Kristoffersen, E., Blomsma, F., Mikalef, P., & Li, J. (2020). The smart circular economy:
 1247 A digital-enabled circular strategies framework for manufacturing companies. *Journal*
 1248 *of Business Research*, 120, 241-261.

1249 Kumar, R., & Agrawal, N. (2024). Shaping the future of industry: Understanding the
 1250 dynamics of industrial digital twins. *Computers & Industrial Engineering*, 191,
 1251 110172.

1252 Kythreotis, A. P., & Bristow, G. I. (2017). The ‘resilience trap’: exploring the practical
 1253 utility of resilience for climate change adaptation in UK city-regions. *Regional Studies*,
 1254 51(10), 1530-1541.

1255 Lai, K. H., Feng, Y., & Zhu, Q. (2023). Digital transformation for green supply chain
 1256 innovation in manufacturing operations. *Transportation Research Part E: Logistics
 1257 and Transportation Review*, 175, 103145.

1258 Lei, Y., Wang, J. A., Yue, Y., Zhou, H., & Yin, W. (2014). Rethinking the relationships
 1259 of vulnerability, resilience, and adaptation from a disaster risk perspective. *Natural
 1260 Hazards*, 70, 609-627.

1261 Leng, J., Sha, W., Wang, B., Zheng, P., Zhuang, C., Liu, Q., ... & Wang, L. (2022).
 1262 Industry 5.0: Prospect and retrospect. *Journal of Manufacturing Systems*, 65, 279-295.

1263 Li, T. C., & Chan, Y. E. (2019). Dynamic information technology capability: Concept
 1264 definition and framework development. *The Journal of Strategic Information Systems*,
 1265 28(4), 101575.

1266 Li, X., Zhang, Y., Zhou, S., Zhao, Z., & Zhao, Y. (2024). Exploration and future trends
 1267 on spatial correlation of green innovation efficiency in strategic emerging industries
 1268 under the digital economy: A social network analysis. *Journal of Environmental
 1269 Management*, 359, 121005.

1270 Li, Y., Dai, J., & Cui, L. (2020). The impact of digital technologies on economic and

environmental performance in the context of industry 4.0: A moderated mediation model. *International Journal of Production Economics*, 229, 107777.

Li, Z., Liu, C., Li, W., Chen, J., & Kang, Y. (2024). The Impact of Digital Economy Industry Development on Manufacturing Innovation Path Driven by Big Data. *IEEE Transactions on Engineering Management*.

Lin, S., & Lin, J. (2023). How organizations leverage digital technology to develop customization and enhance customer relationship performance: An empirical investigation. *Technological Forecasting and Social Change*, 188, 122254.

Liu, B., Wang, Y., Jiang, N., & Zhang, X. (2024). The impact of digital industrialization and industrial digitalization on regional green innovation efficiency in China-From the perspective of the innovation value chain. *Journal of Cleaner Production*, 478, 144015.

Liu, J., Zhao, X., Chen, J., & Wang, J. (2023). Conditions towards manufacturing upgrading in the era of Industry 4.0. *International Journal of Production Research*, 1-20.

Liu, L., Song, W., & Liu, Y. (2023). Leveraging digital capabilities toward a circular economy: Reinforcing sustainable supply chain management with Industry 4.0 technologies. *Computers & Industrial Engineering*, 178, 109113.

Liu, Q., Chen, R., & Yu, Q. (2024). Improving sustainable performance of China's new energy industry through collaborative innovation network resilience. *Renewable and Sustainable Energy Reviews*, 201, 114625.

Liu, X., Liu, F., & Ren, X. (2023). Firms' digitalization in manufacturing and the structure and direction of green innovation. *Journal of Environmental Management*,

1293 335, 117525.

1294 Liu, Y., Zhang, J. Z., Jasimuddin, S., & Babai, M. Z. (2024). Exploring servitization
 1295 and digital transformation of manufacturing enterprises: Evidence from an industrial
 1296 internet platform in China. *International Journal of Production Research*, 62(8),
 1297 2812-2831.

1298 Liu, Y., Zhang, X., & Shen, Y. (2024). Technology-driven carbon reduction: Analyzing
 1299 the impact of digital technology on China's carbon emission and its mechanism.
 1300 *Technological Forecasting and Social Change*, 200, 123124.

1301 Luo, S., Xiong, Z., & Liu, J. (2024). How does supply chain digitization affect green
 1302 innovation? Evidence from a quasi-natural experiment in China. *Energy Economics*,
 1303 107745.

1304 Luo, S., Yimamu, N., Li, Y., Wu, H., Irfan, M., & Hao, Y. (2023). Digitalization and
 1305 sustainable development: How could digital economy development improve green
 1306 innovation in China?. *Business Strategy and the Environment*, 32(4), 1847-1871.

1307 Ma, J., Yang, L., Wang, D., Li, Y., Xie, Z., Lv, H., & Woo, D. (2024). Digitalization in
 1308 response to carbon neutrality: Mechanisms, effects and prospects. *Renewable and
 1309 Sustainable Energy Reviews*, 191, 114138.

1310 Malik, P. K., Singh, R., Gehlot, A., Akram, S. V., & Das, P. K. (2022). Village 4.0:
 1311 Digitalization of village with smart internet of things technologies. *Computers &
 1312 Industrial Engineering*, 165, 107938.

1313 Martin, R. (2010). Roepke lecture in economic geography—rethinking regional path
 1314 dependence: beyond lock-in to evolution. *Economic Geography*, 86(1), 1-27.

1315 Martin, R., & Sunley, P. (2007). Complexity thinking and evolutionary economic
1316 geography. *Journal of Economic Geography*, 7(5), 573-601.

1317 Martin, R., & Sunley, P. (2015). On the notion of regional economic resilience:
1318 conceptualization and explanation. *Journal of Economic Geography*, 15(1), 1-42.

1319 Matt, D. T., Pedrini, G., Bonfanti, A., & Orzes, G. (2023). Industrial digitalization. A
1320 systematic literature review and research agenda. *European Management Journal*,
1321 41(1), 47-78.

1322 Meena, A., Dhir, S., & Sushil, S. (2024). Coopetition, strategy, and business
1323 performance in the era of digital transformation using a multi-method approach: Some
1324 research implications for strategy and operations management. *International Journal*
1325 *of Production Economics*, 270, 109068.

1326 Michalos, G., Makris, S., Papakostas, N., Mourtzis, D., & Chryssolouris, G. (2010).
1327 Automotive assembly technologies review: challenges and outlook for a flexible and
1328 adaptive approach. *CIRP Journal of Manufacturing Science and Technology*, 2(2),
1329 81-91.

1330 Mirzaee, H., Samarghandi, H., & Willoughby, K. (2024). Comparing resilience
1331 strategies for a multistage green supply chain to mitigate disruptions: A two-stage
1332 stochastic optimization model. *Journal of Cleaner Production*, 471, 143165.

1333 Mubarak, M. F., Tiwari, S., Petraite, M., Mubarik, M., & Raja Mohd Rasi, R. Z. (2021).
1334 How Industry 4.0 technologies and open innovation can improve green innovation
1335 performance? *Management of Environmental Quality: An International Journal*,
1336 32(5), 1007-1022.

1337 Mukul, E., & Büyüközkan, G. (2023). Digital transformation in education: A systematic
1338 review of education 4.0. *Technological Forecasting and Social Change*, 194, 122664.

1339 Ngo, V. M., Quang, H. T., Hoang, T. G., & Binh, A. D. T. (2024). Sustainability-related
1340 supply chain risks and supply chain performances: The moderating effects of dynamic
1341 supply chain management practices. *Business Strategy and the Environment*, 33(2),
1342 839-857.

1343 Ning, L., & Guo, R. (2022). Technological diversification to green domains:
1344 Technological relatedness, invention impact and knowledge integration capabilities.
1345 *Research Policy*, 51(1), 104406.

1346 Oduro, S., De Nisco, A., & Mainolfi, G. (2023). Do digital technologies pay off? A
1347 meta-analytic review of the digital technologies/firm performance nexus. *Technovation*,
1348 128, 102836.

1349 Osterrieder, P., Budde, L., & Friedli, T. (2020). The smart factory as a key construct of
1350 industry 4.0: A systematic literature review. *International Journal of Production*
1351 *Economics*, 221, 107476.

1352 Parviainen, P., Tihinen, M., Kääriäinen, J., & Teppola, S. (2017). Tackling the
1353 digitalization challenge: how to benefit from digitalization in practice. *International*
1354 *Journal of Information Systems and Project Management*, 5(1), 63-77.

1355 Palacios-Fenech, J., & Vrain, E. (2024). Measuring the adoption and discontinuance of
1356 low carbon digitally-enabled innovations: Exploring repeat survey quality. *Journal of*
1357 *Cleaner Production*, 434, 140311.

1358 Porter, M. E., & Heppelmann, J. E. (2015). How smart, connected products are

transforming companies. *Harvard Business Review*, 93(10), 96-114.

Radicić, D., & Petković, S. (2023). Impact of digitalization on technological innovations in small and medium-sized enterprises (SMEs). *Technological Forecasting and Social Change*, 191, 122474.

Reggiani, A., De Graaff, T., & Nijkamp, P. (2002). Resilience: an evolutionary approach to spatial economic systems. *Networks and Spatial Economics*, 2, 211-229.

Sachs, J. D., Schmidt-Traub, G., Mazzucato, M., Messner, D., Nakicenovic, N., & Rockström, J. (2019). Six transformations to achieve the sustainable development goals. *Nature Sustainability*, 2(9), 805-814.

Scholz, R. W., Köckler, H., Zscheischler, J., Czichos, R., Hofmann, K. M., & Sindermann, C. (2024). Transdisciplinary knowledge integration PART II: Experiences of five transdisciplinary processes on digital data use in Germany. *Technological Forecasting and Social Change*, 199, 122981.

Sestino, A., Prete, M. I., Piper, L., & Guido, G. (2020). Internet of Things and Big Data as enablers for business digitalization strategies. *Technovation*, 98, 102173.

Sharma, V., Raut, R. D., Mangla, S. K., Narkhede, B. E., Luthra, S., & Gokhale, R. (2021). A systematic literature review to integrate lean, agile, resilient, green and sustainable paradigms in the supply chain management. *Business Strategy and the Environment*, 30(2), 1191-1212.

Shashi, Centobelli, P., Cerchione, R., & Ertz, M. (2020). Managing supply chain resilience to pursue business and environmental strategies. *Business Strategy and the Environment*, 29(3), 1215-1246.

1381 Soellner, S., Helm, R., Klee, P., & Endres, H. (2024). Industrial service innovation:
 1382 Exploring the transformation process to digital servitization in industrial goods
 1383 companies. *Industrial Marketing Management*, 117, 288-303.

1384 Song, M., Cen, L., Zheng, Z., Fisher, R., Liang, X., Wang, Y., & Huisingh, D. (2017).
 1385 How would big data support societal development and environmental sustainability?
 1386 Insights and practices. *Journal of Cleaner Production*, 142, 489-500.

1387 Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations
 1388 of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319-
 1389 1350.

1390 Teece, D. J. (2018). Profiting from innovation in the digital economy: Enabling
 1391 technologies, standards, and licensing models in the wireless world. *Research Policy*,
 1392 47(8), 1367-1387.

1393 Tim, Y., Cui, L., & Sheng, Z. (2021). Digital resilience: How rural communities
 1394 leapfrogged into sustainable development. *Information Systems Journal*, 31(2), 323-
 1395 345.

1396 Troise, C., Corvello, V., Ghobadian, A., & O'Regan, N. (2022). How can SMEs
 1397 successfully navigate VUCA environment: The role of agility in the digital
 1398 transformation era. *Technological Forecasting and Social Change*, 174, 121227.

1399 Tzabbar, D. (2009). When does scientist recruitment affect technological repositioning?.
 1400 *Academy of Management Journal*, 52(5), 873-896.

1401 Upadhayay, N. B., Rocchetta, S., Gupta, S., Kamble, S., & Stekelorum, R. (2024).
 1402 Blazing the trail: The role of digital and green servitization on technological innovation.

1403 *Technovation*, 130, 102922.

1404 Veile, J. W., Schmidt, M. C., & Voigt, K. I. (2022). Toward a new era of cooperation:
 1405 How industrial digital platforms transform business models in Industry 4.0. *Journal of*
 1406 *Business Research*, 143, 387-405.

1407 Vial, G. (2019). Reflections on quality requirements for digital trace data in IS research.
 1408 *Decision Support Systems*, 126, 113133.

1409 Vujanović, N., Radošević, S., Stojčić, N., Hisarciklilar, M., & Hashi, I. (2022). FDI
 1410 spillover effects on innovation activities of knowledge using and knowledge creating
 1411 firms: Evidence from an emerging economy. *Technovation*, 118, 102512.

1412 Wang, W., & Dong, Y. (2024). Spatial-temporal coupling and interactive effects of
 1413 digital finance and green technology innovation: Empirical evidence from China.
 1414 *Journal of Cleaner Production*, 470, 143354.

1415 Wang, Z., Chu, E., & Hao, Y. (2024). Towards sustainable development: How does ESG
 1416 performance promotes corporate green transformation. *International Review of*
 1417 *Financial Analysis*, 91, 102982.

1418 Warner, K. S., & Wäger, M. (2019). Building dynamic capabilities for digital
 1419 transformation: An ongoing process of strategic renewal. *Long Range Planning*, 52(3),
 1420 326-349.

1421 Wei, L., Li, W., & Jin, Z. (2024). Global value chains participation and trade-induced
 1422 carbon inequality: A comparative analysis of developed and developing economies.
 1423 *Ecological Economics*, 220, 108186.

1424 Wen, H., Zhong, Q., & Lee, C. C. (2022). Digitalization, competition strategy and

1425 corporate innovation: Evidence from Chinese manufacturing listed companies.
1426 *International Review of Financial Analysis*, 82, 102166.

1427 Wu, L., Zhu, C., & Wang, G. (2024). The impact of green innovation resilience on
1428 energy efficiency: A perspective based on the development of the digital economy.
1429 *Journal of Environmental Management*, 355, 120424.

1430 Xi, M., Liu, Y., Fang, W., & Feng, T. (2024). Intelligent manufacturing for
1431 strengthening operational resilience during the COVID-19 pandemic: a dynamic
1432 capability theory perspective. *International Journal of Production Economics*, 267,
1433 109078.

1434 Xie, W., Zheng, D., Li, Z., Wang, Y., & Wang, L. (2024). Digital technology and
1435 manufacturing industrial change: Evidence from the Chinese manufacturing industry.
1436 *Computers & Industrial Engineering*, 187, 109825.

1437 Xie, X., Wu, Y., & Tejerob, C. B. G. (2022). How responsible innovation builds
1438 business network resilience to achieve sustainable performance during global outbreaks:
1439 An extended resource-based view. *IEEE Transactions on Engineering Management*.

1440 Xu, L. D., Xu, E. L., & Li, L. (2018). Industry 4.0: state of the art and future trends.
1441 *International Journal of Production Research*, 56(8), 2941-2962.

1442 Xu, S., Zhong, M., & Wang, Y. (2024). Can innovative industrial clusters enhance urban
1443 economic resilience? A quasi-natural experiment based on an innovative pilot policy.
1444 *Energy Economics*, 134, 107544.

1445 Yang, H., Kumara, S., Bukkapatnam, S. T., & Tsung, F. (2019). The internet of things
1446 for smart manufacturing: A review. *IISE Transactions*, 51(11), 1190-1216.

1447 Yang, J., Jiang, C., Gao, L., & Yu, S. (2024). Green transformation and manufacturing
1448 value chain climbing: the moderating role of environmental regulations. *Applied*
1449 *Economics*, 1-16.

1450 Yang, M., Fu, M., & Zhang, Z. (2021). The adoption of digital technologies in supply
1451 chains: Drivers, process and impact. *Technological Forecasting and Social Change*,
1452 169, 120795.

1453 Yu, Y., Zhang, J. Z., Cao, Y., & Kazancoglu, Y. (2021). Intelligent transformation of the
1454 manufacturing industry for Industry 4.0: Seizing financial benefits from supply chain
1455 relationship capital through enterprise green management. *Technological Forecasting*
1456 *and Social Change*, 172, 120999.

1457 Zhang, G., Yang, Y., & Yang, G. (2023). Smart supply chain management in Industry
1458 4.0: the review, research agenda and strategies in North America. *Annals of Operations*
1459 *Research*, 322(2), 1075-1117.

1460 Zhang, H., Wang, X., & Akhtar, M. W. (2024). Digital transformation, supplier
1461 concentration, and CEO financial experience: Unveiling the dynamics of innovation
1462 performance in Chinese firms. *Journal of Cleaner Production*, 442, 140825.

1463 Zhang, H., Wu, J., Mei, Y., & Hong, X. (2024). Exploring the relationship between
1464 digital transformation and green innovation: The mediating role of financing modes.
1465 *Journal of Environmental Management*, 356, 120558.

1466 Zhang, L., Mu, R., Zhan, Y., Yu, J., Liu, L., Yu, Y., & Zhang, J. (2022). Digital economy,
1467 energy efficiency, and carbon emissions: Evidence from provincial panel data in China.
1468 *Science of the Total Environment*, 852, 158403.

1469 Zhou, G., Zhang, C., Li, Z., Ding, K., & Wang, C. (2020). Knowledge-driven digital
1470 twin manufacturing cell towards intelligent manufacturing. *International Journal of*
1471 *Production Research*, 58(4), 1034-1051.

1472 Zhou, L., Jiang, Z., Geng, N., Niu, Y., Cui, F., Liu, K., & Qi, N. (2022). Production and
1473 operations management for intelligent manufacturing: A systematic literature review.
1474 *International Journal of Production Research*, 60(2), 808-846.

1475 Zhou, Q., Zhu, M., Qiao, Y., Zhang, X., & Chen, J. (2021). Achieving resilience through
1476 smart cities? Evidence from China. *Habitat International*, 111, 102348.

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