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# The potential of smart factories in reducing environmental emissions: the evidence from Chinese listed manufacturing firms

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The nature of smart factories to help manufacturing firms reducing environmental emissions has attracted the widespread attention of governments and industries. However, some research also worried that if smart factories were not effectively constructed, they may increase firms' environmental emissions. To address this concern, we use PSM-progressive DID model to analyze the relationships between the construction of smart factories and environmental emissions, based on 144 Chinese listed manufacturing firms. The main findings are as follow. First, the construction of smart factories can lead to the short-term increase of 7.55% GHG emissions (1.001 tCO2e) and 4.12% air pollutants cost (1.011 $) per $M operation cost for firms. Second, the negative impact of smart factory construction on GHG emissions can be partially explained by physical technologies. Third, mimetic institution (industrial maturity of environment management system) can reduce the negative impact of smart factory construction, but coercive institution (government regulation) and normative institution (social media attention) have no significant moderating effect. With these findings, this study provides a clear understanding of how the construction of smart factories influences firms' environmental sustainability and accordingly offers insights for business considering environmental objectives in smart factory development.

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## Introduction

Because global manufacturing firms consume 54% of the world's energy and contribute to one-fifth of global GHG emissions (World Economic Forum (WEF) 2022), developing economically and environmentally sustainable production methods in the manufacturing sector is considered a crucial solution to reduce firms' environmental emissions for global environmental challenges (US Environmental Protection Agency 2017). As an emerging production paradigm, smart factories harness the technological potential, provided by automated data sensing and analysis and advanced manufacturing technologies, to enable companies tracking their environmental footprint and optimize production processes (Meng et al. 2018). For instance, the U.S. Clean Energy Smart Manufacturing Innovation Institute has investigated how smart factories, through enhancing process control, reducing waste, minimizing downtime, and improving performance and productivity, can save energy and consequently lower environmental emissions (Kok and Malkani 2020). Nevertheless, the adoption of additional technologies by smart factories also raises concerns about increased energy consumption and environmental emissions due to the demand for high-energy consuming and computationally powerful processors (Terry et al. 2020). Unfortunately, empirical evidence regarding how smart factories impact firms' environmental emissions remains lacking.

The potential for smart factories to reduce environmental emissions primarily stems from their significant differences compared to traditional automated factories. Drawing on the synthesis of enterprise practices and academic research (Osterrieder et al. 2020), smart factories can be regarded as production systems integrating multiple digital and physical technologies, capable of autonomously collecting and analyzing factory data. It is important to note that traditional automated factories have long employed robotics and automation. However, due to the lack of connectivity among personnel, assets, and data management systems in traditional factories, firms must continuously coordinate and integrate these resources in manual manner. Compared to traditional automated factories, smart factories introduce features such as data sensing, device interconnectivity, and intelligent analytics (Strozzi et al. 2017; Osterrieder et al. 2020). "Data sensing" aids manufacturing firms in capturing data on energy consumption, emissions, equipment wear, etc. (Nitlarp and Kiattisin 2022). "Device interconnectivity" and "intelligent analytics" optimize production processes and control machine auto-sleep modes (Majeed et al. 2021). All these are expected to enhance manufacturing firms' efficiency of energy and resource utilization, thereby offering the potential to reduce corporate environmental emissions (Abubakr et al. 2020).

However, some qualitative studies indicate that if not effectively implemented, smart factories may increase firms' environmental emissions (Ma et al. 2023). First, the development of smart factory technology by manufacturing firms is often driven by economic goals (Olsen and Tomlin 2020), while environmental goals often require additional efforts. When manufacturing companies consider both economic and environmental objectives, they may face huger challenges because many firms have no sufficient capability to achieve both objectives through implementing smart factories (Oláh et al. 2020). Second, smart factories consume significant energy by using advanced technologies, including facilities such as data center to support real-time data collection and storage, and equipment such as 3D printing. This can lead to increased resource consumption and, consequently, higher emissions of pollutants and greenhouse gases (Meng et al. 2018).

Thus, there is a need to investigate the relationship between the construction of smart factories and its impact on environmental emissions. However, existing studies that have paid notably attention on smart factories still suffer from three inherent limitations. First, while some studies have investigated operational and financial performance affected by smart factories (Kamble et al. 2020; Bai et al. 2022), the impact of smart factories on environmental emissions was only discussed conceptually and qualitatively. Due to the inconsistent argument on the impact of smart factories on environmental emissions, an empirical study based on firm-level data can provide insights for firms to invest in environment-friendly smart factories. Second, some studies concentrated on the impact of digital technologies on environmental emissions (Ye et al. 2023) and other environmental performance (Li et al. 2020; Chiarini 2021; Du et al. 2023; Yang et al. 2023). However, in addition to digital technologies as intangible resources, smart factories also apply physical technologies as tangible resources to represent the advanced manufacturing capabilities (Osterrieder et al. 2020; Bai et al. 2022). There is no evidence about whether and how smart factories affect firms' environmental emissions by using digital technologies or physical technologies. Third, firms construct smart factories for the primary objectives to enhance economic goals (Olsen and Tomlin 2020). However, in addition to meeting their own development goals, they must also meet the expected goals of the institutional environment where they operate (Tina Dacin et al. 2002). Consequently, when firms face more green pressure from the institutional environment, they might consider environmental goals more (Guo et al. 2023). Thus, institutional factors are expected to enhance firms' motivation to explore the potential of smart factories to improve environment due to the legality (Hanna et al. 2023). However, existing studies fail to examine the impact of institutional factors on the construction of smart factories for improving environmental emissions. Corresponding to these gaps, three questions are researched in our study.

RQ1: Whether does the construction of smart factories affect firms' environmental emissions?

RQ2: Through which technologies (digital or physical) does the construction of smart factories affect firms' environmental emissions?

RQ3: What institutional factors moderate the relationship between the construction of smart factories and firms' environmental emissions?

We choose China as the context for this research. For 12 consecutive years, China has held the position as the world's largest manufacturing country, with its manufacturing value-added accounting for nearly 30% of the global total (Yang et al. 2021; China SCIO 2024; Xu 2023). Given that the manufacturing industry is a primary contributor to global energy consumption and environmental emissions, studying the impact of China's manufacturing sector is crucial in addressing global environmental challenges. Meanwhile, China has prioritized smart factories in key industrial policies, such as "Made in China 2025" and the "14th Five-Year Intelligent Manufacturing Development Plan". Consequently, after 2012, Chinese firms have been driven by the dual goals of smart factory implementation and environmental protection, aligning with our research questions. Thus, we utilize data from 144 Chinese listed manufacturing companies from 2012 to 2021 and apply PSM-progressive DID model (Hu et al. 2024) to analyze the environmental emissions of firms constructing smart factories.

The main conclusions of the study are as follows. First, the construction of smart factories increases corporate GHG emissions and air pollutants cost in short term. Second, differences in the degree of using digital and physical technologies do not explain the effect of smart factory construction on pollutants emissions, but higher degree of using physical technologies increases GHG emission when firms construct smart factory.

Third, we investigate the moderating role of three institutional factors. The coercive institution and mimetic institution have no moderating role, but firms with stronger normative institution (higher maturity of environmental management systems (EMS)) have lower GHG emission when they construct smart factory.

Accordingly, this study makes several significant contributions. First, whereas existing studies have analyzed the operational and financial impacts of smart factory construction (e.g., Bai et al. 2022), this study identifies that smart factory construction can increase environmental emissions in short term and hence enriches the research of the impact of smart factory construction on firm performance. Second, we identify the significant mediating effect of physical technologies for smart factory construction to increase GHG emissions, which provide the understanding on the potential mechanism of smart factory construction to affect environmental emissions. Third, we examine the moderating effects of three institutional factors including coercive, normative, and mimetic institution, which provides references for policymakers and firms' stakeholders and facilitate them to consider environmental goals in smart factory construction.

The structure of this paper is as follows. The first section presents an introduction to the topic. The second section provides a review of relevant literature. The third section introduces the theoretical hypotheses of this study. The fourth section describes the data collection process and the methodology used in the study. In the fifth section, the results of the study are elaborated. The sixth section discusses the results and provides relevant explanations. The seventh section offers the conclusions of the paper and managerial insights derived from the study.

## Literature review

**Smart factory definition**. In 2012, Germany introduced the "Industry 4.0" industrial policy, centered around the concept of the "smart factory". Subsequently, the concept of the smart factory has been widely adopted in both corporate practices and academic research. We analyze the definition of smart factories from two perspectives: corporate practices reflecting the current state of smart factory construction and academic research envisioning the future form of smart factories. Regarding corporate practices, we find the definitions and practices of smart factories from global leading consulting firms (e.g., Accenture[1], Deloitte[2], and Gartner[3]), service companies (e.g., Training Within Industry[4], IOT Analytics[5], and Advanced Technology Services[6]), and industrial enterprises (e.g., Oracle[7], and SAP[8]). In these companies constructing or participating in the construction of smart factories, a close association with "data" and "connected" is evident. In other words, smart factories require autonomous data collection and analysis, as well as the interconnection of equipment, personnel, and systems. Meanwhile, academic research, driven by the purpose of smart factories, defines them as a fully connected manufacturing system, mainly operating without human intervention by generating, transferring, receiving, and processing necessary data to perform all tasks required for producing various goods (Strozzi et al. 2017; Osterrieder et al. 2020, p. 1; Choi et al. 2022). It is evident that academic research still emphasizes the key terms "data" and "connected".

Based on the discussion on "data" and "connected", the whole process of smart factory construction is achieved by integrating digital technologies and physical technologies (Bai et al. 2020). Specifically, digital technologies refer to information and communication technologies to support data analysis and intelligent control, including big data, cloud computing, blockchain, AI (Osterrieder et al. 2020). Physical technologies refer to facilities and equipment to support data processing and advanced manufacturing technologies, including facilities such as data center and platform servers, and equipment such machines with sensors, robotics, 3D printing, etc. (Bai et al. 2022).

**Corporate environmental performance**. The corporate environmental performance underscores that manufacturing companies should not only produce products in an economically viable manner but should also minimize their negative impact on the environment while conserving energy and natural resources (US Environmental Protection Agency 2017). Existing research has analyzed environmental performance indicators, including emissions, resource consumption, and habitat preservation (Jaehn 2016; Mulusew and Hong 2024). Specifically, the environmental emissions dimension includes GHG emissions and pollutants emissions (Duanmu et al. 2018), while the resource consumption dimension includes the use of green materials, electricity consumption, water consumption, energy consumption intensity, and energy efficiency (Akbar and Irohara 2018). This study selects environmental emissions as the measure of environmental performance, due to the following key considerations. First, environmental emissions represent the most direct means through which companies impact the environment. Additionally, environmental emissions indirectly reflect the energy consumption patterns of firms. Second, within the framework of Sustainable Development Goals, a primary objective of environmental sustainability for manufacturing companies is to enhance efficiency while concurrently reducing pollution levels and minimizing greenhouse gas emissions (Shahbaz et al. 2022). Third, from the perspective of the production processes of greenhouse gases and significant pollutants, the "GHG" contributing to global warming and the "GHG" causing environmental pollution share a common origin, primarily stemming from the combustion and consumption of fossil fuels. The inclusion of both pollutant emissions and GHG emissions comprehensively reflects the types of environmental emissions produced by firms.

**The impact of smart factory technologies on environmental performance**. Existing literature predominantly analyzed the impact of specific digital technologies or digital transformations on corporate environmental performance. However, in addition to digital technologies as intangible resources, smart factories also apply physical technologies as tangible resources to represent the advanced manufacturing capabilities (Liu et al. 2023). Additional physical technologies may lead to more environmental emissions due to huge energy consumption from data operations facilities and advanced manufacturing. However, there exist only a few analyses and discussions on the relationship between the construction of smart factories and environmental performance, adopting quantitative and qualitative approaches and analyzing digital and physical technologies.

For quantitative studies, most of researchers posited that digital technologies or digital transformations compel enterprises to comprehensively collect environmental data (Li et al. 2020), optimize logistics and supply chain processes (Ye et al. 2023), and enhance green innovation (Yang et al. 2023; Du et al. 2023), thereby improving environmental performance. Specifically, some scholars have conducted analyses based on questionnaire surveys to examine the impact of digital technologies on overall environmental performance of firms, but they have not identified specific dimensions of environmental performance (Schniederjans and Hales 2016; Li et al. 2020; Chiarini 2021). Other researchers, using operational data from enterprises, have analyzed the influence of digital technologies on the number of green innovation patents (Du et al. 2023; Yang et al. 2023) and emissions (Ye et al. 2023), but they only quantitatively analyzed the environmental impact of digital technologies. Since smart factories are not limited to digital technologies (Strozzi et al. 2017; Osterrieder et al. 2020), existing quantitative studies still lack the understanding about whether and how smart factories affect firms' environmental emissions by simultaneously using both digital and physical technologies.

For qualitative research, scholars have presented a dual perspective on the impact of smart factory implementation on the environmental performance of enterprises. On the one hand, the literature suggested that smart factories, leveraging various digital and physical technologies, can achieve automatic data sensing and analysis (Osterrieder et al. 2020). This capability aids manufacturing enterprises in capturing data related to energy consumption, emissions, equipment wear, among others (Nitlarp and Kiattisin 2022), optimizing production processes, and controlling automatic machine shutdowns (Majeed et al. 2021; Wei et al. 2024). On the other hand, some scholars argued that if companies do not implement or construct smart factories correctly, an increase of energy consumption can be expected (Oláh et al. 2020; Masanet et al. 2020). For instance, Meng et al. (2018) discussed that the adoption of Industry 4.0 technologies may increase the use of data centers and cloud computing, which, in turn, could lead to increased energy consumption, subsequently increasing pollutant and greenhouse gas emissions. Masanet et al. (2020) discussed the potential environmental impacts of smart manufacturing, including increased energy consumption if energy-efficient technologies are not used. Although these qualitative studies delved into the dialectical impact of smart factories (Oláh et al. 2020; Masanet et al. 2020), the environmental impacts of smart factories still need empirical support from firm-level data.

**Institutional environment**. The institutional environment indicates that "firms engage in non-profitable activities (such as environmental measures) to enhance their legitimacy" (Hanna et al. 2023). In other words, in addition to meeting their own needs, firms must meet the needs of their institutional environment (DiMaggio and Powell 1983; Wu et al. 2023). Specifically, institutional environment refers to three forms, i.e., coercive, normative, and mimetic institution (Scott 2010). The coercive institutional environment refers to laws, regulations, and policies by government or agencies, to restrict firms' behavior and provide guidance (Clemens and Douglas 2006). The normative institutional environment refers to standard or ordinance by professional organizations such as industry associations or social media (Fehr and Schurtenberger 2018). The mimetic institutional environment refers to industrial learning and imitation (Barreto and Baden-Fuller 2006).

Prior studies have emphasized the correlation of institutional environments with digital innovation or environmental practices. For example, Hinings et al. (2018) emphasized that digital transformation is institutional change due to complexity. Wang et al. (2018a) pointed out that regulatory pressures and normative pressures can facilitate firms to implement environment management. Additionally, other studies also emphasized the moderating role of institutional environments for the impact of digital technologies. For example, Guo et al. (2023) pointed out that cultural institutional environments can positively influence the application of digital technologies to enhance environmental innovation. However, the construction of smart factories is more complex, as it combines both digital and physical technologies. Consequently, the institutional environment may be more important for smart factory construction to enhance environmental performance. Nevertheless, existing studies have not analyzed the moderating impact of institutional environment on the relationship between smart factory construction and its environmental impact. Besides, existing studies have also tended to consider institutional environment as a whole, rather than distinguishing coercive, normative, and mimetic institutional factors. Accordingly, relevant discussions on how these three institutional factors affect the relationship between smart factory construction and environmental performance have been largely ignored.

## Theoretical hypotheses

**Smart factory and environmental emissions**. Compared to traditional automated factories, smart factories introduce three key features: data perception, equipment interconnection, and intelligent analytics (Choi et al. 2022). Based on the fundamental principles that environmental emissions primarily stem from the combustion of fossil fuels and industrial production processes, smart factories leverage these features to assist enterprises in reducing environmental emissions through both prevention and control measures. Specifically, from a preventative perspective on environmental emissions, smart factories facilitate a shift from individual machine optimization to system-wide optimization through "equipment interconnection" (Wang et al. 2018b). Additionally, the "intelligent analysis" capabilities of smart factories aid enterprises in optimizing production processes and controlling machine dormancy automatically (Ma et al. 2023). Both approaches contribute to enhancing the efficiency of fossil fuel consumption, subsequently lowering pollutants emissions (Lin and Zhao, 2016). On the other hand, from a control perspective on environmental emissions, the "data perception" capability of smart factories (Abell et al. 2017) enables comprehensive awareness of equipment usage. It automates the collection of data on pollutant emissions (Gunasekaran et al. 2017), thereby assisting enterprises in monitoring pollutants emission data and implementing targeted emission control measures.

However, while smart factories bring benefits such as optimized production processes and environmental data monitoring, increased equipment and data center operation may induce increased environmental emissions. On the one hand, the "data perception" and "equipment interconnection" of smart factories are achieved by deploying a large number of sensors and low latency communication modules. The operations of the necessary technical facilities and equipment may consume a substantial amount of energy, potentially offsetting the advantages brought by smart factory construction (Oláh et al. 2020). On the other hand, massive amounts of data are collected and stored, which requires more local computing servers as data center and results in significant energy consumption (Meng et al. 2018). Although many firms use cloud computing technologies and outsource data centers to third-party firms, existing evidence supports that adopting local computing servers is the mainstream practice when firms building smart factories. According to McKinsey's cloud computing research in 2021 for Chinese firms, the average level of cloud computing usage for manufacturing activities is about 10%, among which 20% is used by cloud leaders and nearly 5% by cloud laggards[9]. Most of these firms use a combination of private clouds and local servers. Furthermore, even if manufacturing firms use cloud computing, the servers supporting cloud computing are still mainly deployed within the enterprise. This is especially the case for smart factories, as production data are normally viewed as one of the most important data for manufacturing firms and it is difficult for firms to entrust production data to third-party data centers. For example, the Great Wall Motor Co., Ltd. has built its own cloud platforms to provide cloud services for its sub-factories, but local servers were deployed[10]. Thus, the smart factory construction can induce more local servers needs and higher energy consumption. Consequently, this may lead to an increase in GHG emissions for firms. Based on the above discussion, we propose two dialectical hypotheses.

*H1a: Smart factory construction will reduce corporate pollutants emissions.*

*H1b: Smart factory construction will increase corporate GHG emissions.*

**Mediating mechanism of smart factories construction affecting environmental emissions**. Referring to the definition of smart factories, a key distinction between smart factories and traditional automated factories lies in the automatic collection, utilization, and analysis of data. Consequently, the construction of smart factories involves an increased investment in digital and physical technologies. Due to the differences between digital and physical technologies, they may have divergent impacts on corporate environmental emissions.

Digital technologies are regarded as intangible asset of smart factories (Bai et al. 2022). First, smart factories employ cloud computing technologies, including the Internet of Things (IoT), to establish "data perception" capabilities (Abell et al. 2017). This facilitates comprehensive awareness within enterprises of equipment usage, energy, and resource consumption, as well as data on pollutants and GHG emissions (Gunasekaran et al. 2017). This capability is advantageous for monitoring environmental emission indicators. Second, smart factories, utilizing cloud computing technologies such as the IoT, build "device interconnection" capabilities (Wang et al. 2018b). This transformation enables a shift from individual machine optimization to system-wide optimization, ultimately reducing environmental emissions through the optimization of production processes (Majeed et al. 2021). Third, smart factories leverage big data and AI technologies to establish "intelligent analysis" capabilities. By employing big data technologies to analyze factory data and utilizing AI technologies to optimize production processes and control machine sleep cycles (Ma et al. 2023), these factories contribute to enhanced production efficiency, subsequently lowering overall environmental emissions for enterprises. Based on these considerations, we propose the following hypothesis.

*H2a: The construction of smart factories through applying digital technologies can low environmental emissions.*

Physical technology is defined as the tangible assets of smart factories. In comparison to digital technology, the use of physical technology may contribute to increased environmental emissions for enterprises. First, smart factories employ data facilities and equipment such as robots, sensors, 3D printing to support data processing and advanced manufacturing (Bai et al. 2022). In contrast to traditional automated factories, these devices often require higher levels of computation or precision processing, necessitating more complex maintenance and monitoring systems. Consequently, these devices are typically energy-intensive, leading to higher energy consumption and increased carbon emissions (Chiarini 2021). Second, smart factories rely heavily on electronic devices. Insufficient environmental management of smart factories may result in an increase in electronic waste. Electronic waste contains toxic substances that, if not properly handled, can contribute to environmental pollution (Chiarini 2021). Third, smart factories utilize a substantial number of distributed data processing modules and large centralized data centers to store and process the vast amount of data generated during the production process. These data modules and centers require significant electrical power to operate and produce corresponding heat, necessitating cooling systems for temperature control. This leads to additional energy consumption and increased carbon emissions (Waibel et al. 2017). Therefore, we argue that the heightened use of physical technology in smart factories contributes to increased environmental emissions.

*H2b: The construction of smart factories through applying physical technologies can increase environmental emissions.*

**Moderating mechanisms of smart factories construction affecting environmental emissions**. Manufacturing firms construct smart factories primarily for enhancing cost, efficiency, flexibility, responsiveness, and quality (Olsen and Tomlin 2020). Considering environmental goals in smart factories often require additional efforts from manufacturing firms. Therefore, the motivation for firms to construct smart factories for reducing environmental emissions is limited. However, institutional factors can enhance this motivation. Accordingly, we contend that three institutional environmental factors will moderate the relationship between smart factories and environmental emissions. First, regarding coercive institutional factor, government regulations typically serve as an effective legal means to enforce environmental measures by businesses. They entail the government's oversight and enforcement of laws and regulations on businesses, e.g., with a crucial approach being the establishment of a priority pollution monitoring list. This list, enforced through penalties and temporary shutdowns, encourages businesses to incorporate environmental goals into the process of constructing smart factories (Shen and Wang 2018).

Second, for normative institutional factor, the social attention represents stakeholders, such as media and non-governmental organizations, using public opinion pressure to encourage businesses to pay more attention to environmental goals (Lyu et al. 2022). Given the critical importance of corporate reputation in market competition and brand value, exposure of environmental pollution or irresponsible behavior can lead to consumer and investor resistance and condemnation. Hence, the social attention prompts firms to consider environmental objectives during the construction of smart factories.

Third, for mimetic institutional factors, the maturity of EMS within the industry where a company operates can guide its mimicking behavior. Firms in the same industry usually provide more valuable references for successful operations (Yang and Kang 2020). Thus, if the industry has a high maturity of EMS, it has accumulated environmental management knowledge and skills (Jeong and Lee 2022). This provides more knowledge or skills to firms for intra-industry imitation. Consequently, these companies find it easier and more cost-effective to consider environmental goals during smart factory construction. Leveraging the technologies within smart factories, they can promote more effective environmental management, thereby enhancing the potential of smart factories to reduce environmental emissions.

Based on the above discussion, we propose the following hypotheses.

*H3a: Government regulation positively moderates the potential of smart factory construction to reduce environmental emissions.*

*H3b: Social attention positively moderates the potential of smart factory construction to reduce environmental emissions.*

*H3c: The EMS maturity of the industry in which the firm operates positively moderates the potential of smart factory construction to reduce environmental emissions.*

## Data and methodology

**Smart factory identification and data collection**. We selected the time frame from 2012 to 2021 as the sample period to shortlist Chinese manufacturing enterprises because the latest

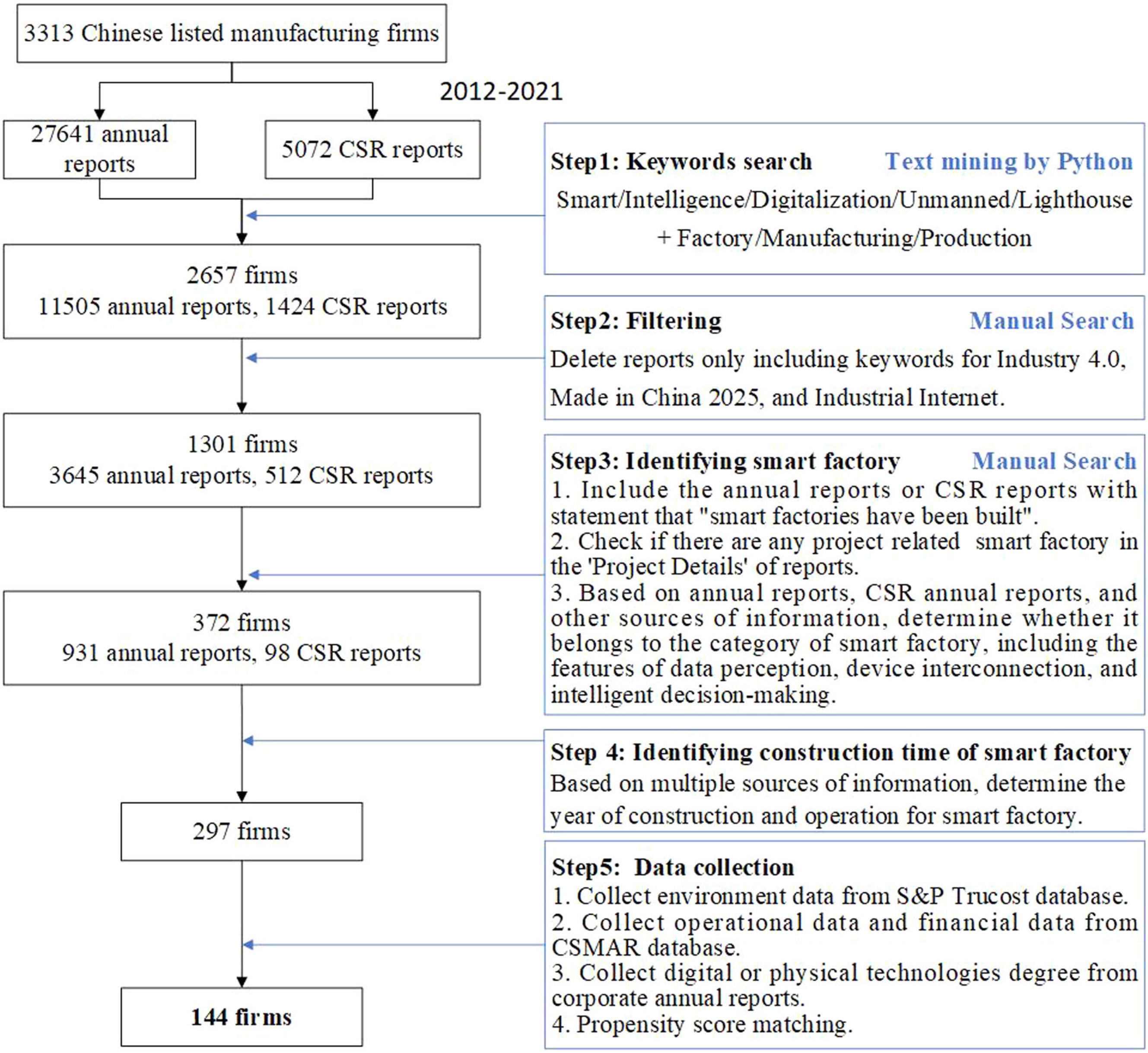


**Fig. 1** The process of data collection.

environment data provided by the Trucost database were up to 2021. The rationale behind this choice is as follows: in 2012, the "Industry 4.0" strategy was first proposed, subsequently leading to the release of national strategic plans and industrial policies by developed and developing countries. Influenced by global and Chinese industrial policies, Chinese firms commenced the construction of smart factories in 2012. We established the following procedure (Fig. 1) to identify whether Chinese manufacturing firms initiated the construction of smart factories.

As of 2022, there are 3313 listed manufacturing companies in China. We judged whether firms have constructed smart factories according to Steps 1–4 in Fig. 1. Data perception, equipment connectivity, and intelligent analysis are the three key elements of smart factories (Osterrieder et al. 2020; Olsen and Tomlin 2020; Choi et al. 2022). Therefore, in this paper, we evaluated whether a company's factory fell within the category of a smart factory based on data sensing (use of sensors, 5G, etc., to construct industrial IoT), equipment connectivity (possessing interconnected machines capable of autonomously executing system instructions), and intelligent decision-making (utilizing technologies like artificial intelligence for intelligent analysis systems). Through the data collection process depicted in Fig. 1, we initially identified 297 firms out of these 3313 A-share listed manufacturing firms in China that have constructed smart factories.

Then, we collected environmental emission data from S&P Trucost database (Cui et al. 2023), which provides GHG emissions data and other environmental emission data, on an annual basis since 2005. The database has typically covered an average of 5046 firms/year, which represent ~99% of global market capitalization (Cenci et al. 2023). Trucost database reports all three scopes of GHG emissions in units of tons of $CO_2$ emitted in a year, and we used the data of Scope 1 and Scope 2 which reflected the GHG emissions within firms. Scope 1 emissions are direct emissions from owned or controlled sources, and Scope 2 emissions are indirect emissions from the generation of purchased energy. Scope 1 and Scope 2 emissions are defined as a firm's emissions (Ardia et al. 2023). The database also reports air pollutant cost and waste cost to measure other environmental emissions. Moreover, Trucost's GHG emissions data are a combination of self-reported and estimated data. For the self-reported data, the GHG emissions are measured according to the Greenhouse Gas Protocol. For the estimated data, Trucost utilizes a common industry methodology, which consists of three steps (Marquis et al. 2016). First, Trucost assigns a firm's annual revenues to a subset of 464 standardized industries based on data from the FactSet database, company annual reports, company regulatory filings, and company feedback. Second, Trucost's model estimates a firm's total annual GHG emissions and resources consumed (e.g., metals, water, oil, gas, and mined materials) based on the firm's revenues in each industry. These calculations are based on environmental factors derived from a number of pollution release and transfer registries and economic input–output models. Third, Trucost sends the calculations to business managers for confirmation and validation.

We further collected operational and financial data from the China Stock Market & Accounting Research (CSMAR) database for the 297 identified companies. The CSMAR database is a professional financial database developed with reference to well-known international databases such as the University of Chicago's CRSP, Standard & Poor's Compustat, New York Stock Exchange TAQ, I/B/E/S, Thomson. It combines with the economic and financial conditions of China and includes financial, stock, industry, and other data of listed Chinese companies. The database has been widely used in existing literature (Lee et al. 2023; Chen et al. 2022). After excluding companies with missing data and following matching progress, we ended up with 144 firms with 3960 observations.

### Variables

*Dependent variables*. Environmental emissions are normally quantified in terms of GHG emissions per unit and pollutant-specific emissions (including air pollutants and waste pollutants) per unit. Accordingly, three variables were established in this paper for the measurement of environmental emissions, with the following rationale. First, due to the high correlation between environmental emissions and corporate output or production, we utilized emissions per unit of turnover rather than total emissions. Second, given the significant heterogeneity in environmental emissions per unit among enterprises with different production processes, assessing the precise impact of smart factory construction on environmental emissions is challenging. We followed the approach of Jeong and Lee (2022) by applying a logarithmic transformation to the environmental emissions per unit. Based on the above, we set Log GHG to measure GHG emissions per operation cost, and Log Air and Log Waste to measure pollutant emissions.

- *Log* GHG intensity is the logarithmic amount of tCO2e/ $M, which reflects GHG emissions tons per one million operation cost.
- *Log Air* pollutants intensity is the logarithmic amount of air pollutants cost per one million operation cost. Air pollutants cost data means the cost of damage when firms emit air pollutants.
- *Log Waste* intensity is the logarithmic amount of waste cost per one million operation cost. Waste cost data means the cost of damage when firms emit waste.

*Mediating and moderating variables*. For the meditating effects, we estimated the impact of digital technologies and physical technologies. We introduced the variables "Digital" and "Physical". First, "Digital" was measured by the logarithm of the frequency of keywords related to a specific digital technology appearing in the annual reports of enterprises, indicating the level of attention or usage of a particular digital technology. This measurement method has been employed in various studies as a proxy variable for the extent of an enterprise's engagement with relevant digital technologies (Li et al. 2020; Nasiri et al. 2022; Yang et al. 2023). We focused on key digital technologies, including big data, AI, cloud computing, and blockchain, with reference to the keywords associated with each digital technology, as illustrated in Zhu et al. (2023). Second, "Physical" was measured by the logarithm of the frequency of keywords related to a specific physical technology appearing in the annual reports of enterprises. Relevant keywords included platform, center, sensor, facilities, equipment, factory, and terminal related to smart factory.

For moderating effects, first, "Government regulation" was measured by a dummy variable whether a firm was included in the national priority pollution monitoring list provided by the Ministry of Ecology and Environment's data center (Fang et al. 2020). The variable was set as 1 if a firm was included in the list, otherwise it was 0. Firms on the national key monitoring list are often associated with significant environmental hazards, and the likelihood of penalties for environmental violations is substantially higher. This may incentivize companies to consider more environmental objectives when constructing smart factories (Cai et al. 2020). Second, the measure of "Social media attention" used media attention as agent variable, which is represented by the natural logarithm of the total number of news reports related to the company in a given year (Chen and Mai 2024). Third, "Industrial EMS maturity" in which the firm operates was measured by the average of the EMS maturity of firms in the same industry, whereas the maturity of EMS is defined as the number of years since the enterprise obtained ISO 14001 certification. It serves as a proxy for the skills and knowledge accumulated by the enterprise after obtaining the ISO 14001 certification (Jeong and Lee 2022).

*Control variables*. We considered three dimensions of company characteristics, board characteristics, and corporate environmental measures, and set eight control variables as follows.

- Leverage (LEV): the leverage is the ratio of total liabilities to total assets at the end of the period (Clarkson et al. 2008). Companies with lower leverage have more resources and capabilities to invest in energy saving and emission reduction.
- Return on assets (ROA): ROA controls for the company's profitability, calculated as net profit divided by total assets. Previous research has empirically supported a positive correlation between energy-saving performance and ROA (Yadav et al. 2017).
- Tobin's Q: Tobin's Q is the ratio of a company's market value to the replacement cost of its assets, reflecting the external market's evaluation and investment in the company's prospects or long-term growth when considering all available information (Yiu et al. 2020). Tobin's Q influences a company's environmental impact when constructing smart factories, which aligns with the long-term strategic planning of the enterprise.
- Board size (Board_size) and board independence (INDR): for board characteristics, Ferrell et al. (2016) suggested that companies with good governance incur lower agency costs, leading to more CSR engagement and more environmental management responsibilities. We used board size (Board_size) and INDR to reflect the company's governance structure. Board size is the natural logarithm of the number of board members, while board independence is the proportion of independent directors in the board.

**Table 1 Descriptive statistics results.**

| Variables | *N* | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| Log GHG intensity | 1545 | 5.673 | 1.131 | 0.614 | 9.492 |
| Log Air pollutants intensity | 1545 | 9.111 | 0.845 | 3.977 | 12.68 |
| Log Waste intensity | 1545 | 7.363 | 0.658 | 2.740 | 11.29 |
| Digital | 1543 | 1.812 | 1.287 | 0 | 5.768 |
| Physical | 1379 | 2.124 | 1.223 | 0 | 6.219 |
| Government regulation | 1545 | 0.469 | 0.499 | 0 | 1 |
| Social media attention | 915 | 3.497 | 0.927 | 1 | 7 |
| Industrial EMS maturity | 1545 | 1.670 | 1.028 | 0.0403 | 7.121 |
| Size | 1545 | 23.45 | 1.054 | 20.40 | 26.65 |
| LEV | 1545 | 2.642 | 1.859 | 0.762 | 23.00 |
| ROA | 1545 | 0.0600 | 0.0719 | −0.635 | 0.655 |
| Tobin's Q | 1545 | 2.025 | 1.487 | 0.743 | 22.15 |
| Board_size | 1545 | 2.140 | 0.203 | 1.609 | 2.890 |
| INDR | 1545 | 38.26 | 6.587 | 25 | 80 |
| ISO 14001 certification | 1545 | 0.619 | 0.486 | 0 | 1 |
| Green patents | 1545 | 0.730 | 1.009 | 0 | 4.844 |

- ISO 14001 certification and green patents: for corporate environmental management, we introduced a dummy variable indicating whether the company has obtained ISO 14001 certification (Jeong and Lee 2022). In contrast to the independent variable measuring the maturity of the environmental management system, this variable is set to 1 only in the year when the company obtains ISO 14001 certification. It serves to control for the unique impact generated in the year of ISO 14001 certification. Additionally, we used the natural logarithm of the number of green patents as a proxy for the company's level of green technological innovation.

*Descriptive statistics*. Descriptive statistics results are shown in Table 1. Log GHG, Log Air, and Log Waste have a mean value of 5.673, 9.111, and 7.363, respectively; a minimum value is 0.614, 3.977, and 2.740, respectively; a maximum value is 9.492, 12.68, and 11.29, respectively. This shows significant variability for environmental emissions across firms. The results of Pearson correlations among variables are shown in Table 2.

**Empirical methods**. According to Hu et al.'s (2024) studies, we applied PSM-progressive DID model to estimate the impact of smart factory construction on corporate environmental emissions. Compared with DID model, PSM-progressive DID model can avoid sample selection bias to compromise the reliability of results. First, the propensity score matching (PSM) was used to identify the untreated group of firms (i.e., the firms that have not constructed smart factories) and then match them with the treated group of firms (i.e., the firms that have constructed smart factories). In our study, we matched treated firms with untreated firms based on control variables year by year as the 1:1 matching standard. We only kept matched treated firms and excluded unmatched firms (Wang et al. 2024). Second, parallel trend assumption was tested to keep similarity for treated group and untreated group. Third, according to Formula (1), we performed progressive DID model to estimate treated effect. Additionally, if only analyzing the environmental emission changes before and after the establishment of smart factories, the results could be influenced by time effects and heterogeneity among enterprises (Jeong and Lee 2022), leading to incorrect estimates of causal relationships. Following the study by Jeong and Lee (2022), we considered time and individual enterprise fixed effects (Harwell et al. 1992). Subsequent Hausman test results ($p < 0.01$) also

**Table 2 Pearson correlations matrix.**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Log GHG intensity | 1 | | | | | | | | | | | | | | |
| Log Air pollutants intensity | 0.822*** | 1 | | | | | | | | | | | | | |
| Log Waste intensity | 0.660*** | 0.716*** | 1 | | | | | | | | | | | | |
| Digital | −0.288*** | −0.274*** | −0.225*** | 1 | | | | | | | | | | | |
| Government regulation | 0.205*** | 0.196*** | 0.171*** | −0.171*** | 1 | | | | | | | | | | |
| Social media attention | 0.064* | 0.126*** | 0.158*** | 0.05 | 0.019 | 1 | | | | | | | | | |
| Industrial EMS maturity | 0.367*** | 0.279*** | 0.304*** | 0.027 | 0.266*** | −0.007 | 1 | | | | | | | | |
| Size | 0.215*** | 0.086*** | 0.076*** | −0.023 | 0.185*** | 0.239*** | 0.203*** | 1 | | | | | | | |
| LEV | −0.046* | −0.009 | 0.090*** | −0.029 | −0.071*** | 0.015 | −0.110*** | −0.393*** | 1 | | | | | | |
| ROA | 0.138*** | 0.196*** | 0.224*** | 0.019 | −0.037 | 0.194*** | −0.038 | −0.141*** | 0.290*** | 1 | | | | | |
| Tobin's Q | −0.031 | 0.055** | 0.108*** | 0.064** | −0.112*** | 0.273*** | −0.077*** | −0.308*** | 0.362*** | 0.429*** | 1 | | | | |
| Board_size | 0.043* | 0.02 | −0.016 | −0.101*** | 0.102*** | 0.021 | 0.022 | 0.271*** | −0.142*** | −0.031 | −0.080*** | 1 | | | |
| INDR | 0.053** | 0.058** | 0.032 | 0.052** | −0.008 | 0.070** | 0.019 | 0.045* | −0.015 | −0.007 | 0.014 | −0.447*** | 1 | | |
| ISO 14001 certification | 0.052** | 0.001 | −0.003 | 0.042* | 0.120*** | −0.041 | 0.204*** | 0.050** | −0.044* | −0.01 | −0.037 | 0.056** | −0.088*** | 1 | |
| Green patents | −0.036 | −0.095*** | −0.092*** | 0.088*** | −0.080*** | −0.022 | 0.098*** | 0.226*** | −0.186*** | −0.109*** | −0.083*** | 0.106*** | −0.017 | 0.052** | 1 |

***, **, and * denote regression results passing significance tests at 1%, 5%, and 10% confidence levels, respectively.

**Table 3 Smart factory construction and corporate environmental emissions.**

| | Log GHG intensity | Log Air pollutants intensity | Log Waste intensity |
|---|---|---|---|
| | **Model 1.1** | **Model 1.2** | **Model 1.3** |
| treat*period | 0.0818*** | 0.0425** | 0.0718** |
| | (0.0269) | (0.0192) | (0.0324) |
| Controls | Yes | Yes | Yes |
| Firm fixed | Yes | Yes | Yes |
| Year fixed | Yes | Yes | Yes |
| *N* | 1545 | 1545 | 1545 |
| $R^2$ | 0.0899 | 0.1360 | 0.0993 |

Robust standard errors are reported in brackets in the table.
*** and ** denote regression results passing significance tests at 1% and 5% confidence levels, respectively.

supported our use of a fixed effects model rather than a random effects model.

$$\mathrm{EP}_{it} = \alpha_i + \beta_{DID} treat_i \times period_{it} + A_C C_{it} + u_{it} + v_{it} + \varepsilon_{it} \quad (1)$$

$\mathrm{EP}_{it}$ represents the environmental emissions of firm $i$ in year $t$, including pollutants emissions per unit of revenue and GHG emissions per unit of revenue. $treat_i$ represents whether firm $i$ is as the treated firm. $period_{it}$ represents whether firm $i$ constructs smart factory in year $t$. $C_{it}$ represents the control variables matrix of firm $i$ in year $t$. $\beta_{DID}$ represents the treatment effect of smart factory construction. $u_{it}$ represents the individual fixed effect, and $v_{it}$ represents the time fixed effect.

Furthermore, although fixed effects models address the impacts of time effects and enterprise heterogeneity, they remain susceptible to issues related to serial correlation and observation period selection (Jeong and Lee 2022). Hence, we assessed the treatment effects for each individual year $\beta_{year}$, thereby mitigating estimation biases induced by linear trends. The model is structured as follows:

$$\mathrm{EP}_{it} = \alpha_0 + \beta_{year} treat_i \times year_{it} + A_C C_{it} + u_{it} + v_{it} + \varepsilon_{it} \quad (2)$$

To test the hypothesis regarding the mediating effects in H2, i.e., whether the construction of smart factories leads to an increase in a company's attention and usage of digital or physical technologies, subsequently influencing environmental emissions, a three-step approach was employed. First, based on Formula (1), we obtained the treatment effect of smart factory construction on corporate environmental emissions $\beta_{DID}$. Second, using Formula (3), we obtained the treatment effect of smart factory construction on the extent of a company's application of digital or physical technologies $\gamma_{DID}$. Third, relying on Formula (4), the coefficients of the simultaneous impact of smart factory construction and digital or physical technologies on a company's environmental performance, denoted as $\varphi_{DID}$ and $\beta_{technologies}$, were acquired. If $\beta_{DID} \neq \varphi_{DID}$, and $\gamma_{DID}$, $\beta_{technologies}$ are all significant, the relationship between the extent of digital or physical technologies application and the reduction of corporate environmental emissions due to smart factory construction is considered mediated. The mediating effect is calculated as $\gamma_{DID} \cdot \beta_{digital}$.

$$digital_{it} = \alpha_0 + \gamma_{DID} treat_i \times period_{it} + B_C C_{it} + u_{it} + v_{it} + \varepsilon_{it} \quad (3)$$

$$\mathrm{EP}_0 = \alpha_0 + \varphi_{DID} treat_i \times period_{it} + \beta_{digital} digital_{it} + A_C C_{it} + u_{it} + v_{it} + \varepsilon_{it} \quad (4)$$

To examine the moderation effects posited in H3, namely, whether a company's institutional environment factors moderate the relationship between smart factory construction and corporate environmental emissions, the moderation effects model is presented below:

$$\begin{aligned}\mathrm{EP}_{it} = {} & \alpha_0 + \beta_{DID\times E\_Management} treat_i \times period_{it} \times E\_Management_{it} \\ & + \beta_{DID} \times treat_i \times period_{it} + \beta_{E\_Management} E\_Management_{it} \\ & + A_C C_{it} + u_{it} + v_{it} + \varepsilon_{it}\end{aligned} \quad (5)$$

## Results and discussions

### Results for H1

*Baseline model*. Based on Formula (1), Table 3 presents the results of the relationship between smart factory construction and corporate pollutants emissions. The results of Model 1.1 indicate that smart factory construction significantly increased 8.18% GHG emissions per operation cost ($\beta = 0.0818^{***}$) in short term, averaging 1.085 tCO2e/$M. The results of Model 1.2 indicate that smart factory construction increased 4.25% air pollutants cost per operation cost ($\beta = 0.0425^{***}$), averaging 1.043 $/$M. The results of Model 1.3 indicate that smart factory construction increased 7.18% waste cost per operation cost ($\beta = 0.0718^{***}$), averaging 1.074 $/$M. From the above, it is possible to conclude that smart factory construction increases corporate environmental emissions. H1a is not supported, but H1b is supported.

In short, our study indicates a significant increase in environmental emission per operation cost due to smart factory construction. This provides a new finding that smart factory construction can cause worse environmental performance, including GHG emissions and air pollutants. The negative impact may be induced by more technical facilities and equipment (Ma et al. 2023), or higher energy consumption needs for data center operations and intelligent algorithm training (Meng et al. 2018).

*Parallel trend test*. Furthermore, to mitigate the effects of serial correlation and observational period selection, based on Formula (2), we computed the treatment effects for each year before and after the implementation of smart factory construction. The results are presented in Fig. 2. On the one hand, Fig. 2a–c presents that treated group and untreated group had no significant difference for environmental emissions in the three periods prior to the event, which supports the parallel trend assumption. On the other hand, Fig. 2a indicates that GHG emissions per operation cost significantly increased within 2 years after the smart factory construction. Figure 2b indicates that air pollutants cost per operation cost significantly increased within 1 year after the smart factory construction. Figure 2c indicates that waste cost per operation cost significantly increased within one year after the smart factory construction. These results emphasize the negative impact of smart factory construction is short term. However, it does not mean that we can ignore the environmental damage of smart factory construction, as we have not found any evidence of positive impacts.

*Placebo test*. To avoid the effects of unobservable factors, according to the study of Li et al. (2024), we performed a placebo test with 500 random sampling for $treat_i \times period_{it}$ in Formula (1). The kernel density of the coefficients of $treat_i \times period_{it}$ in each sampling is shown in Fig. 3. The estimated coefficients are centered around 0 based on normal distribution, which meets the expectation of the placebo test.

*Other robustness test*. First, we deleted the sample for firms in the medical manufacturing industry because these firms were greatly affected during the COVID-19 epidemic. The results are shown in

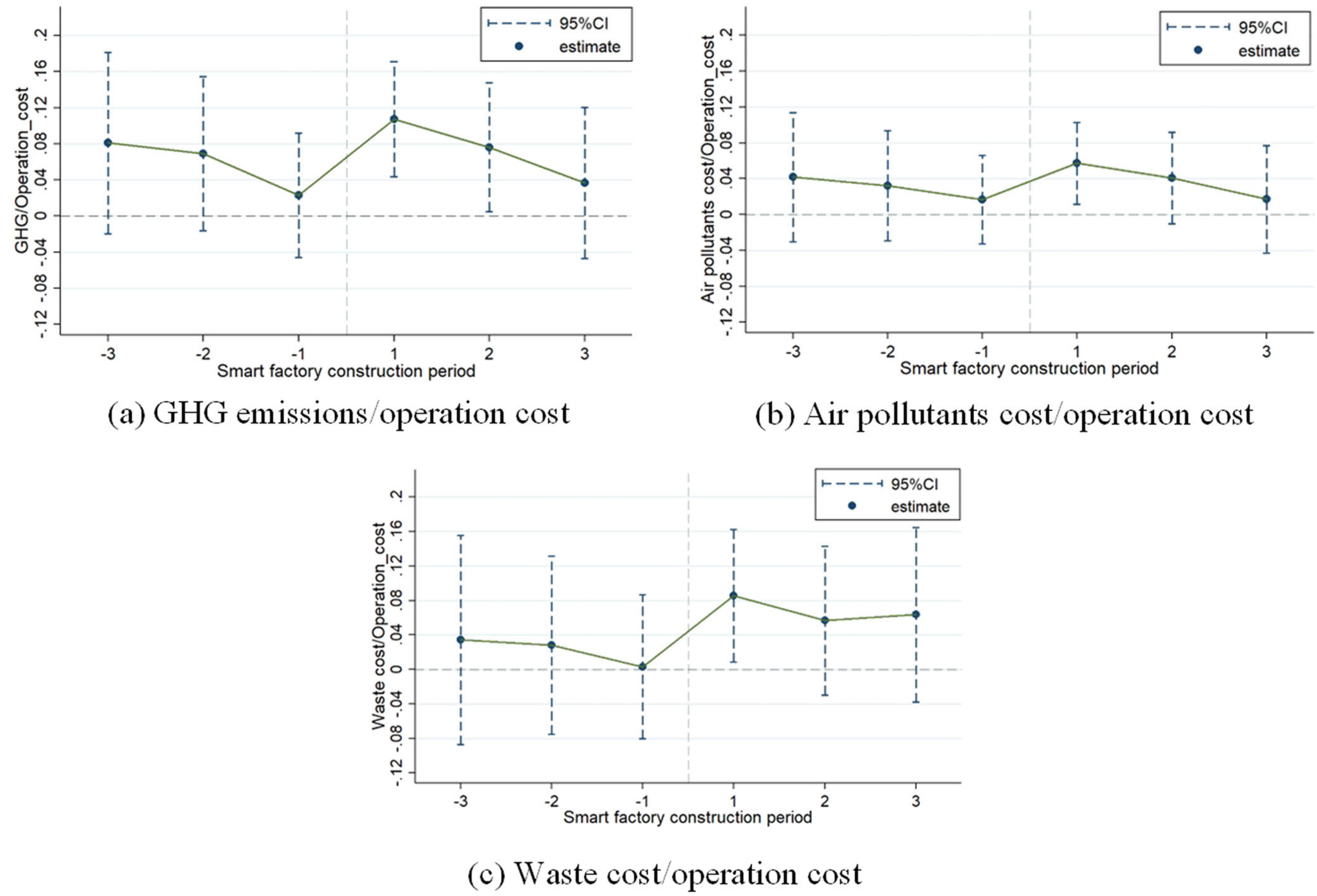


**Fig. 2 The parallel trends of the impact of smart factory construction period on environmental emissions. a**The environmental emission for GHG emissions. **b** The environmental emission for air pollutants cost. **c** The environmental emission for waste cost.

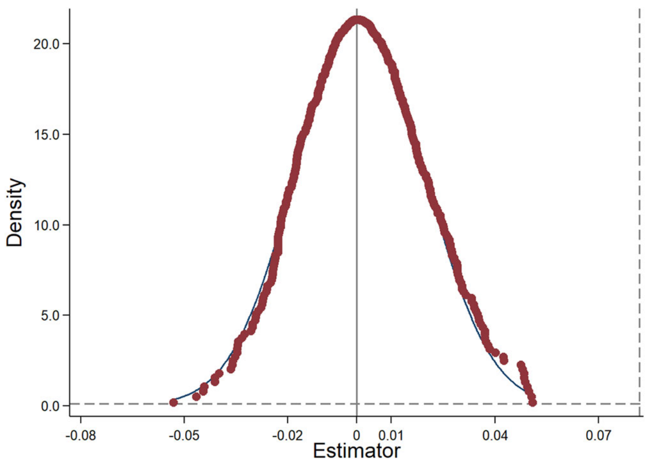


**Fig. 3** The placebo test.

Models 2.1–2.3 in Table 4. The results of H1 for GHG emissions and air pollutants cost are robust.

Second, we also performed a 5% tail trimming on the sample for avoiding the effects of outliers. The results are shown in Models 2.4–2.6 in Table 3. The results are still robust.

Third, in addition to increased emissions from data and equipment use, smart factories may reduce environmental emissions due to the reduction of employee numbers. GHG emissions related to employment are mainly induced by electricity consumption of staff office and fossil fuel combustion in staff canteen, which are included in Scope 1 and Scope 2 of GHG emissions. Since the dependent variable-GHG intensity is measured by Scope 1 and Scope 2, the change of the dependent variable measured by GHG emissions in our study is the result mixing the change of energy usage as well as the change of emissions related to personnel after constructing a smart factory. Thus, in order to control the impact of employment, we added "number of employees" as a control variable. The results are shown in Models 2.7–2.9 of Table 4. Findings show that the impact of smart factory construction on environmental emissions remains significantly positive, demonstrating robustness. Notably, after controlling for employee numbers, the negative impact is similar with results in Table 3, indicating that the reduction of employee numbers may not be an important factor.

Fourth, firms can rely on renewable energy credits to offset environmental emissions, which may bias the environmental impact of smart factories. Based on the analysis of firms' annual reports and CSR reports, we used a dummy variable to represent whether firms use renewable energy or not. Searching keywords included "renewable energy", "clean energy", "green energy", "solar energy", "energy storage", "green electricity", "water power", "wind power", "solar power", "methane", and "photovoltaic". If the annual report or CSR report of a firm involves one of these keywords, we considered this firm use renewable energy as credits. The results are presented in Models 2.10–2.12 in Table 4. The coefficient of treatment variable is significant, and our models keep robustness. Notably, the coefficient of treatment variable in Model 2.10 increases compared with that in Model 1.1. This result indicates that after controlling renewable

**Table 4 The results for robustness test for environmental emissions (Part 1).**

| | Log GHG intensity | Log Air pollutants intensity | Log Waste intensity |
|---|---|---|---|
| | Sample without medical firms | | |
| | Model 2.1 | Model 2.2 | Model 2.3 |
| treat*period | 0.0675** | 0.0420** | 0.0502 |
| | (0.0286) | (0.0206) | (0.0336) |
| *N* | 1386 | 1386 | 1386 |
| $R^2$ | 0.0796 | 0.1260 | 0.1070 |
| | Sample with a 5% tail trimming | | |
| | Model 2.4 | Model 2.5 | Model 2.6 |
| treat*period | 0.0873*** | 0.0419** | 0.0760*** |
| | (0.0238) | (0.0178) | (0.0222) |
| *N* | 1545 | 1545 | 1545 |
| $R^2$ | 0.1080 | 0.1370 | 0.1230 |
| | Controls including employee | | |
| | Model 2.7 | Model 2.8 | Model 2.9 |
| treat*period | 0.0812*** | 0.0414** | 0.0727*** |
| | (0.0270) | (0.0192) | (0.0325) |
| Employee | 0.0242 | 0.0477 | −0.0415 |
| | (0.0477) | (0.0340) | (0.0575) |
| *N* | 1545 | 1545 | 1545 |
| $R^2$ | 0.0901 | 0.1380 | 0.0999 |
| | Controls including renewable energy credits | | |
| | Model 2.10 | Model 2.11 | Model 2.12 |
| treat*period | 0.0824*** | 0.0422** | 0.0705** |
| | (0.0270) | (0.0193) | (0.0325) |
| Renewable energy credits | −0.0109 | 0.0053 | 0.0212 |
| | (0.0251) | (0.0180) | (0.0303) |
| *N* | 1545 | 1545 | 1545 |
| $R^2$ | 0.0901 | 0.1360 | 0.0998 |
| | Controls including other emission reduction practices | | |
| | Model 2.13 | Model 2.14 | Model 2.15 |
| treat*period | 0.0821*** | 0.0426** | 0.0715** |
| | (0.0269) | (0.0192) | (0.0324) |
| Emission reduction credits | −0.0157 | −0.0033 | 0.0126 |
| | (0.0166) | (0.0119) | (0.0200) |
| *N* | 1545 | 1545 | 1545 |
| $R^2$ | 0.0909 | 0.1360 | 0.0997 |
| Controls | Yes | Yes | Yes |
| Firm fixed | Yes | Yes | Yes |
| Year fixed | Yes | Yes | Yes |

Robust standard errors are reported in brackets in the table.
*** and ** denote regression results passing significance tests at 1% and 5% confidence levels, respectively.

energy credits, the negative impact of smart factory construction on GHG emissions is stronger. However, the coefficient of "renewable energy use" in Models 2.10–2.12 is not significant and does not have a significant impact on environmental emissions. This may also indicate that the use degree of renewable energy by firms is still low as a substitute for conventional energy.

Fifth, similarly, firms can use emission reduction credits to offset environmental emissions, which can bias the environmental impact of smart factories. We have already controlled for the variables "whether the firm is ISO 14001 certified" and "the number of green patents" to eliminate the potential impact of the firm's EMS and environmental innovations on emissions. However, these two variables may not be able to cover the impact of other emission reduction measures, so we added a new control variable—"emission reduction credits". Specifically, "emission reduction credits" is a numerical variable that calculates the logarithm of the number of adopted emission reduction practices, and it can be gained from CSMAR database. Specifical practices include environmental education and training, special environmental actions, environmental emergency response mechanisms, environmental honors or awards, air pollution control, wastewater pollution control, dust control, solid waste utilization and disposal, noise and light pollution control, and clean production implementation. Results are shown in Table 4 for Models 2.13–2.15, showing that the models remain robust after being controlled. Also, the coefficient of treatment variable in Model 2.13 increases compared with that in Model 1.1. This indicates that after controlling other emission reduction practices, the negative impact of smart factory construction on GHG emissions is stronger.

Last, there are differences in the mix of power generation types and the process of decarbonization of power generation in different provinces of China, which might result in different carbon emission factors for the electricity consumption of firms in different provinces. It is difficult to eliminate this bias directly through the "electricity consumption * emission factor" approach. On the one hand, there is a lack of data on emission factors for each province. The China Development and Reform Commission and the Ministry of Ecology and Environment (MOE) only released the carbon emission factors for the power grids of each province in 2010, 2012, 2018, and 2021, respectively. On the other hand, there is insufficient disclosure of electricity consumption data by Chinese firms, and existing databases do not have estimation of electricity consumption data by Chinese firms. In this case, we addressed this bias by controlling for province fixed effects. Specifically, we considered the interaction term of year and province fixed effects, which controls for the effect of provinces with different emission factors across years. The results are presented in Models 3.1–3.3 of Table 5. The results remain robust after controlling for year*province fixed effects. Furthermore, Models 3.4–3.6 in Table 5 consider all potential bias induced by emissions related to personnel, renewable energy credits, emissions reduction credits, and the difference in emissions factor for various provinces. The results are still robust. Besides, they indicate that the construction of smart factories can lead to the short-term increase of 7.55% GHG emissions (1.001 tCO2e) and 4.12% air pollutants cost (1.011 $) per $M operation cost for firms.

**Mediating effect of digital technologies for H2**. Based on Eq. (3), we examined the mediating effects of digital or physical technology on the relationship between smart factory construction and environmental emissions. First, Model 4.1 of Table 6 and Model 5.1 of Table 7 indicate that smart factory construction significantly increased the use or focus degree of physical and digital technologies. This supports that smart factory was constructed based on the application of physical and digital technologies. Second, Model 4.1 and Model 4.2 of Table 6 indicate that physical technologies played a partial mediating role in the relationship between smart factory construction and GHG emissions per operation cost (mediating effect = 0.1665*0.0384). However, Model 4.3 and Model 4.4 indicate that physical technologies had no mediating role for air pollutants cost and waste cost. Third, the results of Table 7 indicate that the use of digital technologies did not increase corporate environmental emissions. Thus, H2a is not supported, and H2b is supported only for GHG emissions.

We also considered the interactive effects of physical and digital technologies. The results are presented in Table 8. Specifically, we compared the mediating effect of the extent of physical technology use in the higher and lower digital technology

**Table 5 The results for robustness test for environmental emissions (Part 2).**

| | Log GHG intensity Model 3.1 | Log Air pollutants intensity Model 3.2 | Log Waste intensity Model 3.3 | Log GHG intensity Model 3.4 | Log Air pollutants intensity Model 3.5 | Log Waste intensity Model 3.6 |
|---|---|---|---|---|---|---|
| treat*period | 0.0745** | 0.0411** | 0.0831** | 0.0755** | 0.0412** | 0.0816** |
| | (0.0302) | (0.0202) | (0.0343) | (0.0304) | (0.0203) | (0.0344) |
| Employee | | | | 0.0316 | 0.0078 | −0.0270 |
| | | | | (0.0552) | (0.0369) | (0.0626) |
| Renewable energy use | | | | −0.0265 | −0.0023 | 0.0349 |
| | | | | (0.0292) | (0.0195) | (0.0330) |
| Emission reduction | | | | −0.0001 | −0.0090 | −0.0085 |
| | | | | (0.0199) | (0.0133) | (0.0226) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed | Yes | Yes | Yes | Yes | Yes | Yes |
| Year*province fixed | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 1545 | 1545 | 1545 | 1545 | 1545 | 1545 |
| $R^2$ | 0.2840 | 0.4070 | 0.3730 | 0.286 | 0.408 | 0.374 |

Robust standard errors are reported in brackets in the table.
** denote regression results passing significance tests at 5% confidence levels.

**Table 6 The mediating effect of physical technologies for smart factory construction and GHG emissions.**

| | Model 4.1 Physical technologies | Model 4.2 Log GHG intensity | Model 4.3 Log Air pollutants intensity | Model 4.4 Log Waste intensity |
|---|---|---|---|---|
| treat*period | 0.1665*** | 0.0758*** | 0.0399** | 0.0691** |
| | (0.0523) | (0.0271) | (0.0203) | (0.0327) |
| Physical | | 0.0384** | 0.0209 | 0.0159 |
| | | (0.0176) | (0.0126) | (0.0213) |
| Controls | Yes | Yes | Yes | Yes |
| Firm fixed | Yes | Yes | Yes | Yes |
| Year fixed | Yes | Yes | Yes | Yes |
| *N* | 1543 | 1543 | 1543 | 1543 |
| $R^2$ | −0.4160 | −0.0947 | −0.1380 | −0.0993 |

Robust standard errors are reported in brackets in the table.
*** and ** denote regression results passing significance tests at 1% and 5% confidence levels, respectively.

**Table 7 The mediating effect of digital technologies for smart factory construction and GHG emissions.**

| | Model 5.1 Digital technologies | Model 5.2 Log GHG intensity | Model 5.3 Log Air pollutants intensity | Model 5.4 Log Waste intensity |
|---|---|---|---|---|
| treat*period | 0.180*** | 0.0841*** | 0.0444** | 0.0698** |
| | (0.0611) | (0.0271) | (0.0194) | (0.0327) |
| Digital | | −0.0104 | −0.00535 | 0.0113 |
| | | (0.0151) | (0.0108) | (0.0182) |
| Controls | Yes | Yes | Yes | Yes |
| Firm fixed | Yes | Yes | Yes | Yes |
| Year fixed | Yes | Yes | Yes | Yes |
| *N* | 1543 | 1543 | 1543 | 1543 |
| $R^2$ | −0.2830 | −0.0901 | −0.1350 | −0.0991 |

Robust standard errors are reported in brackets in the table.
*** and ** denote regression results passing significance tests at 1% and 5% confidence levels, respectively.

**Table 8 The inter-effect of physical technologies and digital technologies.**

| | High degree of digital technology use | | Low degree of digital technology use | |
|---|---|---|---|---|
| | Model 6.1 Physical technologies | Model 6.2 GHG/ Operation cost | Model 6.3 Physical technologies | Model 6.4 GHG/ Operation cost |
| treat*period | 0.221*** | 0.0612** | 0.245*** | 0.0644** |
| | (0.0660) | (0.0292) | (0.0660) | (0.0292) |
| Physical | | 0.0301** | | 0.0342** |
| | | (0.0160) | | (0.0160) |
| Controls | Yes | Yes | Yes | Yes |
| Firm fixed | Yes | Yes | Yes | Yes |
| Year fixed | Yes | Yes | Yes | Yes |
| *N* | 781 | 781 | 887 | 887 |
| $R^2$ | 0.2370 | 0.0811 | 0.2370 | 0.0811 |

Robust standard errors are reported in brackets in the table.
*** and ** denote regression results passing significance tests at 1% and 5% confidence levels, respectively.

use groups. The results show that the mediating effect of the degree of physical technology use is greater in the lower digital technology use group. This suggests that higher levels of digital technology use can attenuate the increase in environmental emissions in association with physical technology use.

In sum, the negative impact of smart factory construction on GHG emissions can be partially explained by physical technologies. This indicates that more physical technologies induce higher GHG emissions per operation cost. Related reasons can be that smart factory construction applies more data facilities and electronic devices to support operations of digital technologies (Waibel et al. 2017; Chiarini 2021), and energy insensitive equipment to support advanced manufacturing. Additionally, compared with existing studies arguing that digital technologies can improve environmental performance (Yang et al. 2023; Du et al. 2023), we have not found any evidence to support the positive effect of digital technologies of smart factories. The reason may be that digital technologies cannot directly reduce

**Table 9 The moderating effect of institutional environment on the potential of smart factory construction to affect GHG emissions.**

| | Model 7.1 Log GHG intensity | Model 7.2 Log GHG intensity | Model 7.3 Log GHG intensity |
|---|---|---|---|
| treat*period | 0.0711** | 0.137 | 0.174*** |
| | (0.0328) | (0.1657) | (0.0511) |
| treat*period *KeyPollMonUnit | 0.0226 | | |
| | (0.0396) | | |
| KeyPollMonUnit | −0.0198 | | |
| | (0.0273) | | |
| treat*period *Media_attention | | −0.0307 | |
| | | (0.0446) | |
| Media_attention | | 0.0209 | |
| | | (0.0252) | |
| treat*period *Industry_EMS_maturity | | | −0.0482** |
| | | | (0.0229) |
| Industry_EMS_maturity | | | 0.0483 |
| | | | (0.0410) |
| Controls | Yes | Yes | Yes |
| Firm fixed effect | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes |
| $N$ | 1545 | 915 | 1545 |
| $R^2$ | −0.0905 | −0.0906 | −0.0947 |

Robust standard errors are reported in brackets in the table.
*** and ** denote regression results passing significance tests at 1% and 5% confidence levels, respectively.

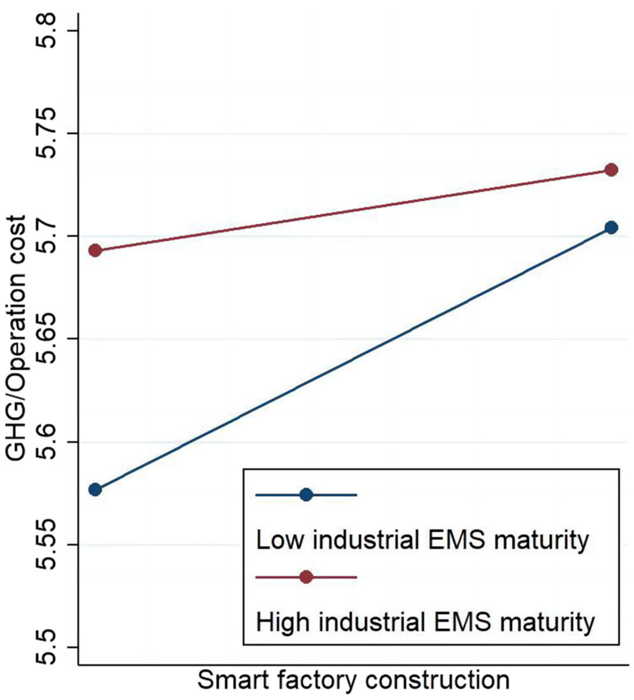


**Fig. 4** The moderating effect of industrial EMS maturity for smart factory construction and GHG emissions.

environmental emission; and the smart factory construction increases GHG emission by applying more physical facilities and equipment.

**Moderating effect of corporate institutional environment**. According to Eq. (5), we further examined the moderating effect of institutional factors on the relationship between smart factory construction and environmental emissions. First, Models 7.1 and 7.2 of Table 9 indicate that government regulation and social media attention had no significant moderating effect. Second, Model 7.3 of Table 9 indicates that industrial EMS maturity generated a negative moderating effect on the relationship between smart factory construction and GHG emissions ($\beta = -0.0482^{***}$). This result reflects that firms in the industry with higher EMS maturity can reduce the negative effect of GHG emission by smart factory construction. Figure 4 also shows higher industrial EMS maturity can make the line smoother. Thus, H3a and H3b are not supported, and H3c is supported but only for GHG emissions.

From the above, the moderating roles of three institutional factors are mixed. On the one hand, governmental regulation and social media attention did not play significant moderating role for smart factory construction and environmental emissions. The reason may be that government and social media have not paid enough attention to the environmental impact of smart factories. On the other hand, industrial EMS maturity negatively moderated the relationship. This means that firms in the industry with high maturity of EMS can reduce the negative impact of smart factory construction by accumulating environmental management knowledge and skills (Jeong and Lee 2022) or stronger environmental awareness.

**Post-hoc analysis**. On the one hand, some firms outsource their servers to third-party data centers, which results in energy consumption not being counted in the emissions data of the sample firms. Thus, we also analyzed the difference in environmental emissions between firms for "using third-party data centers" and "using local servers". Specifically, we searched for the keywords of "firm name + cloud manufacturing/server/data center" based on multiple information sources such as annual reports and news reports. If the search results mentioned that the firm cooperated with third-party firms and used cloud computing services of third-party firms, the firm was classified as firms for "using third-party data centers". If the search results indicated that the firm used cloud computing technology but did not cooperate with third-party firms or mentioned that the firm built its own data center, the firm was classified as "using local servers". Then, we analyzed these two groups of sample firms and presented the results in Table 10. Models 8.1, 8.3, and 8.5 show the environmental emission results for the sample firms "using local servers" and Models 8.2, 8.4, and 8.6 show the environmental emission results for the sample firms "using third-party data centers". The results suggest that GHG emission intensity and waste intensity of the sample firms "using local servers" are significant and stronger. This supports that a "third-party data center" can shift the increased environmental emissions from the smart factory outside of the firm's boundaries.

On the other hand, firms can construct smart factory in two ways, i.e., retrofitting existing factory and building new factory. Based on the annual reports, we considered a firm with a "new smart factory" if it described the construction of new facilities like factories or production lines. If a firm mentioned adding equipment or technology to make existing factories smarter, we considered it to be a firm with a "retrofitting factory". We then analyzed the environmental emissions of the two groups. The results, as shown in Table 11, indicate that the "new smart factory" sample firms have a greater impact on environmental emissions. This suggests that managers should focus on retrofitting existing factories and reduces investment in building new factories.

**Table 10 The results of environmental emissions for group using third-party data center or local data center.**

| | Log GHG intensity | | Log Air pollutants intensity | | Log Waste intensity | |
|---|---|---|---|---|---|---|
| | **Model 8.1 Third part** | **Model 8.2 Local** | **Model 8.3 Third part** | **Model 8.4 Local** | **Model 8.5 Third part** | **Model 8.6 Local** |
| treat*period | 0.0457 | 0.1160*** | 0.0743** | 0.0535** | 0.0662 | 0.0741** |
| | (0.0591) | (0.0293) | (0.0364) | (0.0225) | (0.0728) | (0.0362) |
| *N* | 547 | 1269 | 547 | 1269 | 547 | 1269 |
| $R^2$ | 0.1010 | 0.1330 | 0.1080 | 0.1860 | 0.1080 | 0.0981 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed | Yes | Yes | Yes | Yes | Yes | Yes |

Robust standard errors are reported in brackets in the table.
*** and ** denote regression results passing significance tests at 1% and 5% confidence levels, respectively.

**Table 11 The results of environmental emissions for retrofitting existing factories and building new factories.**

| | Log GHG intensity | | Log Air pollutants intensity | | Log Waste intensity | |
|---|---|---|---|---|---|---|
| | **Model 9.1 Retrofitting** | **Model 9.2 New** | **Model 9.3 Retrofitting** | **Model 9.4 New** | **Model 9.5 Retrofitting** | **Model 9.6 New** |
| treat*period | 0.0865*** | 0.1290*** | 0.0646** | 0.0736** | 0.1270*** | 0.1310*** |
| | (0.0362) | (0.0392) | (0.0278) | (0.0308) | (0.0456) | (0.0464) |
| *N* | 1055 | 722 | 1055 | 722 | 1055 | 722 |
| $R^2$ | 0.0780 | 0.1520 | 0.1010 | 0.1330 | 0.0693 | 0.1170 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed | Yes | Yes | Yes | Yes | Yes | Yes |

Robust standard errors are reported in brackets in the table.
*** and ** denote regression results passing significance tests at 1% and 5% confidence levels, respectively.

## Conclusion and implications

**Study summary**. This study, based on all listed manufacturing enterprises in China, identified 144 firms that have implemented smart factory initiatives. Data on GHG emissions and pollution emissions were collected from these firms to analyze the relationship between smart factory construction and corporate environmental emissions. The research further explored the mediating effects of digital or physical technologies and the moderating role of corporate institutional environment. Several key findings emerged. First, the study provided empirical evidence supporting the potential of smart factories construction to increase environmental emissions in short term. Second, the research highlighted the mediating role of physical technology in smart factories construction to increase GHG emissions. Third, the study identified the industry with higher maturity of EMS can alleviate the negative impact of smart factory construction on GHG emissions.

**Theoretical implications**. This study makes several theoretical contributions. First, in contrast to existing qualitative research (e.g., Meng et al. 2018), this paper provides empirical evidence based on firm-level data from Chinese enterprises regarding the dialectical relationship between smart factories and corporate environmental emissions. Second, this study comprehensively measures the impact of smart factories on corporate environmental performance across various dimensions of environmental emissions. We identify variations in the value of digital or physical technologies in affecting corporate environmental emissions. We also provide insights for researchers to understand the mechanisms behind smart factory construction to affect environmental emissions. Third, while smart factories and environmental emissions are two critical themes in modern manufacturing, existing literature has not adequately addressed the impact mechanism between these two themes (Meng et al. 2018). Our results emphasize the importance of mimetic institution (industrial EMS maturity) on stimulating firm to influence environmental emissions by smart factory construction. This provides insights for researchers to adopt mimetic institutional force to study the relationship between smart manufacturing and environmental emissions.

**Practical implications**. This study offers practical insights for business managers. First, managers have been increasingly recognizing the close relationship between smart factories and environmental emissions. This study provides empirical evidence to support the idea that the construction of smart factories can damage environmental sustainability in short term. Managers need to be cautious as facilities of data management and significant use of physical robots or sensors are major energy consumers. Apart from focusing on efficiency gains from smart factories, managers should also prioritize GHG emission control as a primary goal of smart factory construction.

Second, the negative impact of smart factories on environmental emissions can be explained by increased adoption of physical technologies. Although such negative effect is only observed in the short term because most firms construed smart factories in recent years, managers are still suggested to focus on the potential long-term environmental impact of smart factories. Particularly, managers should not underestimate the additional negative impact of increasing physical foundations.

Third, managers need to be aware that an organization's environmental management and the maturity of its environmental systems favor the consideration of more environmental objectives in smart factory construction. Managers should realize that learning knowledge about EMS from the industry can benefit the environment when constructing smart factories. Meanwhile, governmental regulation and social media attention have no significant moderating effect on the relationship between smart factory construction and environmental emissions. This implies that the current policymakers may not realize the potential negative impact, but they should actively consider the negative impact and make relevant policy in the future.

**Limitations and future research**. This study also has certain limitations. First, constrained by the disclosure of corporate data, this study relied on pollution emission data and GHG emissions reported in annual reports. This may be subject to the influence and interference of GHG emissions from sources other than production (such as offices) and emission reduction measures. Although the study controlled for the effect of other environmental practices such as ISO certification and green innovation patents, it unavoidably remains susceptible to interference from other factors such as energy-saving and emission reduction initiatives. Future research should conduct factory-level studies based on more refined data. Second, since most firms constructed smart factory in recent years, we cannot observe the long-term effect of smart factory construction on corporate environmental performance. Future research can explore whether smart factories induce a positive impact on corporate environment performance in the long term as well as the potential mechanisms behind. Third, this study was based on Chinese smart factories and the context of carbon neutrality in China, focusing on listed manufacturing companies. Future research should extend the scope to a broader range of countries, allowing for the analysis of regional differences.

## Data availability

Data from Trucost can be accessed directly from the data providers with a fee. Other data analyzed can be made available upon reasonable request to the authors.

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## Notes

1 https://www.accenture.com/content/dam/accenture/final/a-com-migration/r3-3/pdf/Accenture-Centre-Sheffield-External-Digital-701.pdf#zoom=40
2 https://www2.deloitte.com/content/dam/insights/us/articles/4051_The-smart-factory/DUP_The-smart-factory.pdf
3 https://emt.gartnerweb.com/ngw/globalassets/en/supply-chain/documents/trends/smart-factory.pdf?_gl=1*1gj1968*_ga*MTM3MDEyNzc1Mi4xNjk0NjEwNjQz*_ga_R1W5CE5FEV*MTcwMTY3MTk5OC41LjEuMTcwMTY3MjM3MC41Ny4wLjA.
4 https://www.twi-global.com/technical-knowledge/faqs/what-is-a-smart-factory#TheFourLevelsofSmartFactories
5 https://iot-analytics.com/what-are-smart-factories/
6 https://www.advancedtech.com/blog/step-by-step-guide-to-building-a-smart-factory/
7 https://www.oracle.com/industrial-manufacturing/smart-factory-and-smart-manufacturing/
8 https://www.sap.cn/products/scm/what-is-a-smart-factory.html
9 Cloud China, Vision 2025. https://www.mckinsey.com.cn/wp-content/uploads/2022/08/Cloud-in-China-The-outlook-for-2025-vFF.pdf.
10 From "manufacturing" to "smart Manufacturing", Xinhua San Helps Great Wall Motor Address Data Challenges. https://www.h3c.com/cn/d_202206/1620026_30008_0.htm.

## References

Abell JA, Chakraborty D, Escobar CA et al. (2017) Big data-driven manufacturing—process-monitoring-for-quality philosophy. J Manuf Sci Eng 139(10):101009
Abubakr M, Abbas AT, Tomaz I et al. (2020) Sustainable and smart manufacturing: an integrated approach. Sustainability 12(6):2280
Akbar M, Irohara T (2018) Scheduling for sustainable manufacturing: A review. J Clean Prod 205:866–883
Ardia D, Bluteau K, Boudt K et al. (2023) Climate change concerns and the performance of green vs. brown stocks. Manag Sci 69(12):7607–7632
Bai C, Dallasega P, Orzes G et al. (2020) Industry 40 technologies assessment: A sustainability perspective. Int J Prod Econ 229:107776
Bai C, Li HA, Xiao Y (2022) Industry 40 technologies: Empirical impacts and decision framework. Prod Oper Manag Early view
Barreto I, Baden-Fuller C (2006) To conform or to perform? Mimetic behaviour, legitimacy-based groups and performance consequences. J Manag Stud 43(7):1559–1581
Cai X, Zhu B, Zhang H et al. (2020) Can direct environmental regulation promote green technology innovation in heavily polluting industries? Evidence from Chinese listed companies. Sci Total Environ 746:140810
Cenci S, Burato M, Rei M et al. (2023) The alignment of companies' sustainability behavior and emissions with global climate targets. Nat Commun 14(1):7831
Chen S, Mao H, Sun J (2022) Low-GHG city construction and corporate GHG reduction performance: evidence from a quasi-natural experiment in China. J Bus Ethics 180(1):125–143
Chen Y, Mai W (2024) Investor attention and environmental performance of Chinese high-tech companies: the moderating effects of media attention and coverage sentiment. Hum Soc Sci Commun 11(1):1–16
Chiarini A (2021) Industry 40 technologies in the manufacturing sector: Are we sure they are all relevant for environmental performance? Bus Strategy Environ 30(7):3194–3207
China SCIO (2024) China remains world's top manufacturing hub for 14 consecutive years. Available via DIALOG. http://english.scio.gov.cn/pressroom/2024-01/19/content_116952695.htm. Accessed 24 Aug 2024
Choi T M, Kumar S, Yue X et al. (2022) Disruptive technologies and operations management in the Industry 4.0 era and beyond. Prod Oper Manag 31(1):9–31
Clarkson P M, Li Y, Richardson G D et al. (2008) Revisiting the relation between environmental performance and environmental disclosure: An empirical analysis. Account Org Soc 33(4-5):303–327
Clemens B, Douglas TJ (2006) Does coercion drive firms to adopt 'voluntary'green initiatives? Relationships among coercion, superior firm resources, and voluntary green initiatives. J Bus Res 59(4):483–491
Cui D, Ding M, Han Y et al. (2023) Regulation-induced financial constraints, GHG emission and corporate innovation: Evidence from China. Energy Econ 127:107081
DiMaggio PJ, Powell WW (1983) The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. Am Sociol Rev 48(2):147–160
Du J, Shen Z, Song M et al. (2023) Nexus between digital transformation and energy technology innovation: An empirical test of A-share listed enterprises. Energy Econ 120:106572
Duanmu JL, Bu M, Pittman R (2018) Does market competition dampen environmental performance? Evidence from China. Strateg Manag J 39(11):3006–3030
Fang J, Gao C, Lai M (2020) Environmental regulation and firm innovation: Evidence from National Specially Monitored Firms program in China. J Clean Prod 271:122599
Fehr E, Schurtenberger I (2018) Normative foundations of human cooperation. Nat Hum Behav 2(7):458–468
Ferrell A, Liang H, Renneboog L (2016) Socially responsible firms. J Financ Econ 122(3):585–606
Gunasekaran A, Papadopoulos T, Dubey R et al. (2017) Big data and predictive analytics for supply chain and organizational performance. J Bus Res 70:308–317
Guo Q, Geng C, Yao N (2023) How does green digitalization affect environmental innovation? The moderating role of institutional forces. Bus Strategy Environ 32(6):3088–3105
Hanna B, Xu G, Wang X et al. (2023) Blockchain-enabled humanitarian supply chain management: sustainability and responsibility. In: Blockchain in a volatile-uncertain-complex-ambiguous world 251–276
Harwell MR, Rubinstein EN, Hayes WS et al. (1992) Summarizing Monte Carlo results in methodological research: The one-and two-factor fixed effects ANOVA cases. J Educ Stat 17(4):315–339
Hinings B, Gegenhuber T, Greenwood R (2018) Digital innovation and transformation: An institutional perspective. Inf Organ 28(1):52–61
Hu Y, Zou Z, Wu J (2024) Double-edged sword: China's free trade agreements reinforces embodied greenhouse gas transfers in agricultural products. Humanit Soc Sci Commun 11(1):1–13
Jaehn F (2016) Sustainable operations. Eur J Oper Res 253(2):243–264
Jeong S, Lee J (2022) Environment and energy? The impact of environmental management systems on energy efficiency. Manuf Serv Oper Manag 24(3):1311–1328
Kamble S, Gunasekaran A, Dhone NC (2020) Industry 40 and lean manufacturing practices for sustainable organisational performance in Indian manufacturing companies. Int J Prod Res 58(5):1319–1337

Kok R, Malkani H (2020) Impacting Energy Through Smart Manufacturing. Available via DIALOG. https://www.automation.com/en-us/articles/december-2020/impacting-energy-through-smart-manufacturing. Accessed 20 Sept 2023
Lee C M C, Qu Y, Shen T (2023) Gate fees: The pervasive effect of IPO restrictions on Chinese equity markets. Rev Financ 27(3):809–849
Li C, Wen M, Jiang S et al. (2024) Assessing the effect of urban digital infrastructure on green innovation: mechanism identification and spatial-temporal characteristics. Humanit Soc Sci Commun 11(1):1–14
Li Y, Dai J, Cui L (2020) The impact of digital technologies on economic and environmental performance in the context of industry 40: A moderated mediation model. Int J Prod Econ 229:107777
Lin B, Zhao H (2016) Technological progress and energy rebound effect in China' s textile industry: Evidence and policy implications. Renew Sust Energ Rev 60:173–181
Liu W, He Y, Dong J et al. (2023) Disruptive technologies for advancing supply chain resilience. Front Eng Manag 10(2):360–366
Lyu C, Xie Z, Li Z (2022) Market supervision, innovation offsets and energy efficiency: Evidence from environmental pollution liability insurance in China. Energy Policy 171:113267
Ma S, Huang Y, Liu Y et al. (2023) Edge-cloud cooperation-driven smart and sustainable production for energy-intensive manufacturing industries. Appl Energy 337:120843
Majeed A, Zhang Y, Ren S et al. (2021) A big data-driven framework for sustainable and smart additive manufacturing. Robot Comput Integr Manuf 67:102026
Masanet E, Shehabi A, Lei N et al. (2020) Recalibrating global data center energy-use estimates. Science 367(6481):984–986
Marquis C, Toffel MW, Zhou Y (2016) Scrutiny, norms, and selective disclosure: A global study of greenwashing. Organ Sci 27(2):483–504
Meng Y, Yang Y, Chung H et al. (2018) Enhancing sustainability and energy efficiency in smart factories: A review. Sustainability 10(12):4779
Mulusew A, Hong M (2024) A dynamic linkage between greenhouse gas (GHG) emissions and agricultural productivity: evidence from Ethiopia. Humanit Soc Sci Commun 11(1):1–17
Nasiri M, Saunila M, Ukko J (2022) Digital orientation, digital maturity, and digital intensity: determinants of financial success in digital transformation settings. Int J Oper Prod Manag 42(13):274–298
Nitlarp T, Kiattisin S (2022) The Impact Factors of Industry 40 on ESG in the Energy Sector. Sustainability 14(15):9198
Oláh J, Aburumman N, Popp J et al. (2020). Impact of Industry 4.0 on environmental sustainability, Sustainability 12(11):4674
Olsen T L, Tomlin B (2020) Industry 4.0: Opportunities and challenges for operations management. M&som-Manuf Serv Op 22(1):113–122
Osterrieder P, Budde L, Friedli T (2020) The smart factory as a key construct of industry 40: A systematic literature review. Int J Prod Econ 221:107476
Schniederjans DG, Hales DN (2016) Cloud computing and its impact on economic and environmental performance: A transaction cost economics perspective. Decis Support Syst 86:73–82
Scott WR (2010) Reflections: The past and future of research on institutions and institutional change. J Change Manag 10(1):5–21
Shahbaz M, Li J, Dong X et al. (2022) How financial inclusion affects the collaborative reduction of pollutant and GHG emissions: The case of China. Energy Econ 107:105847
Shen L, Wang Y (2018) Supervision mechanism for pollution behavior of Chinese enterprises based on haze governance. J Clean Prod 197:571–582
Strozzi F, Colicchia C, Creazza A et al. (2017) Literature review on the 'Smart Factory'concept using bibliometric tools. Int J Prod Res 55(22):6572–6591
Terry S, Lu H, Fidan I et al. (2020) The influence of smart manufacturing towards energy conservation: a review. Technologies 8(2):31
Tina Dacin M, Goodstein J, Richard Scott W (2002) Institutional theory and institutional change: Introduction to the special research forum. Acad Manag J 45(1):45–56
US Environmental Protection Agency (2017) Sustainable manufacturing. Available via DIALOG. https://www.epa.gov/sustainability/sustainable-manufacturing. Accessed 11 Nov 2023
Waibel MW, Steenkamp LP, Moloko N et al. (2017) Investigating the effects of smart production systems on sustainability elements. Procedia Manuf 8:731–737
Wang Q, Jiang S, Ngai EW et al. (2024) Vendor selection in the wake of data breaches: A longitudinal study. J Oper Manag 70(4):568–599
Wang S, Li J, Zhao D (2018a) Institutional pressures and environmental management practices: The moderating effects of environmental commitment and resource availability. Bus Strategy Environ 27(1):52–69
Wang W, Yang H, Zhang Y et al. (2018b) IoT-enabled real-time energy efficiency optimisation method for energy-intensive manufacturing enterprises. Int J Comput Integr Manuf 31(4-5):362–379
Wei S, Liu W, Choi T M et al. (2024) The influence of key components and digital technologies on manufacturer's choice of innovation strategy. Eur J Oper Res 315(3):1210–1220
World Economic Forum (WEF) (2022) Reducing the GHG footprint of the manufacturing industry through data sharing. Available via DIALOG. https://www.weforum.org/impact/carbon-footprint-manufacturing-industry/. Accessed 20 Sept 2023
Wu Q, Zhu J, Cheng Y (2023) The effect of cross-organizational governance on supply chain resilience: A mediating and moderating model. J Purch Supply Manag 29(1):100817
Xu S (2023) China's climate governance for carbon neutrality: regulatory gaps and the ways forward. Humanit Soc Sci Commun 10(1):1–10
Yadav PL, Han SH, Kim H (2017) Sustaining competitive advantage through corporate environmental performance. Bus Strateg Environ 26(3):345–357
Yang G, Nie Y, Li H et al. (2023) Digital transformation and low-GHG technology innovation in manufacturing firms: The mediating role of dynamic capabilities. Int J Prod Econ 263:108969
Yang MG, Kang M (2020) An integrated framework of mimetic pressures, quality and environmental management, and firm performances. Prod Plan Control 31(9):709–722
Yang Y, Jia F, Chen L et al. (2021) Adoption timing of OHSAS 18001 and firm performance: An institutional theory perspective. Int J Prod Econ 231:107870
Ye F, Ouyang Y, Li Y (2023) Digital investment and environmental performance: The mediating roles of production efficiency and green innovation. Int J Prod Econ 259:108822
Yiu L M D, Lam H K S, Yeung A C L et al. (2020) Enhancing the financial returns of R&D investments through operations management. Prod Oper Manag 29(7):1658–1678
Zhu Q, Ma D, He X (2023) Digital transformation and firms' pollution emissions. Technol Forecast Soc Change 197:122910

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## Author contributions

Weihua Liu: conceptualization, methodology, supervision. Jiahe Hou: writing—original draft preparation. Yang Cheng: introduction revision, methodology, manuscript polishing. Chaolun Yuan: literature searching, data collection. Rui Lan: conceptualization, data collection. Hing Kai Chan: final review and commenting.

## Competing interests

The authors declare no competing interests.

## Ethical approval

Ethical approval was not required as the study did not involve human participants.

## Informed consent

The study did not involve experimental subjects and therefore did not require an ethical review and informed consent statement.

## Additional information

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