# EMBODIED INTELLIGENCE AND ECOLOGICAL WELFARE PERFORMANCE: EVIDENCE FROM CHINESE CITIES

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**Abstract.** Amid the growing global climate crisis and the urgent need for coordinated international action to combat global warming, embodied intelligence (EI), a cutting-edge technology that integrates perception, cognition and decision-making, presents an innovative approach to overcoming the constraints of traditional eco-governance and improving ecological welfare performance (EWP). Using a panel dataset from 280 Chinese prefecture-level cities, we construct a composite EI indicator and apply a fixed-effects model to evaluate the impact of EI on EWP and its mechanisms. Our results demonstrate that EI has a significant positive effect on EWP. The mechanism analysis shows that EI enhances EWP mainly through promoting green innovation, boosting green total factor productivity and advancing financial development. Moderating effect analysis highlights that industrial structure upgrading, human capital and digital technology development significantly strengthen these effects. Heterogeneity analysis reveals that EI has a more pronounced ecological empowerment effect in western, northern, non-coastal and resource-based cities. Spatial effect analysis indicates that while EI boosts local EWP, spatial competition and resource diversion may lead to negative externalities for neighboring regions. This study deepens our understanding of the role of intelligent technologies in environmental governance, offering valuable policy and practical insights for sustainable development and ecological civilization goals.
**Keywords:** *embodied intelligence, ecological welfare performance, green innovation, green total factor productivity, financial development level, industrial structure upgrading, human capital, digital technology development*

## Introduction

Accelerating global climate change is one of the most urgent challenges that contemporary society faces. As highlighted in the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report, the global average temperature for the decade 2011–2020 was approximately 1.09°C above the pre-industrial baseline, leading to unprecedented climatic changes worldwide. In the absence of urgent and comprehensive mitigation efforts, global warming is projected to exceed the critical 1.5°C threshold, potentially triggering irreversible ecological disruptions and incurring substantial economic costs (Hoegh-Guldberg et al., 2019). Consequently, an increasing number of countries has pledged to achieve stringent climate goals in alignment with the Paris Agreement, representing a crucial turning point in international policy (Wei et al., 2022). Strengthening ecological welfare performance (EWP) to foster synergy between


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economic expansion and ecological preservation has therefore become a key priority on governmental and academic agendas (*Table 1*).

***Table 1.*** *Acronyms*

| Full term | Abbreviation |
|---|---|
| Ecological welfare performance | EWP |
| Embodied intelligence | EI |
| Green innovation | GI |
| Green total factor productivity | GTFP |
| Financial development level | FD |
| Industrial structure upgrading | ISU |
| Human capital | HC |
| Digital Technology Development | DT |

As digital technology evolves rapidly worldwide, deploying intelligent tools like AI and big data has become fundamental to environmental management (Song et al., 2024). As an emerging paradigm, embodied intelligence (EI) is fundamentally a 'think–act' system that interacts with and dynamically adapts to the physical environment, ensuring intelligence is not confined to algorithms but is optimized through physical embeddedness and synergy (Shen et al., 2024). Unlike disembodied AI that operates in the digital realm, EI's key characteristic is its physical agency, allowing it to process data and execute real-world tasks. This characteristic makes it highly applicable to ecological governance and sustainable development (Tripaldi, 2025). Specifically, through mechanisms such as intelligent sensing, real-time monitoring and feedback-based regulation, EI can enhance resource allocation efficiency, optimize pollutant emission management and mitigate negative environmental externalities. Concurrently, EI can enhance social welfare. For instance, in fields such as ophthalmology, EI exemplifies its capabilities by integrating perception, logic and physical response to facilitate adaptive learning with real-time feedback. This synergy dramatically enhances the customization and precision of medical procedures, including diagnostics, surgery and therapy (Qiu et al., 2025). Consequently, extensively implementing EI fosters sustainable economic restructuring and greater societal well-being, in turn boosting comprehensive EWP.

Recent literature in environmental economics explores the digital economy's impact on ecological well-being. Existing studies indicate that the digital economy creates new pathways for promoting sustainable urban development (Liu et al., 2024b), encouraging sustainable urban consumption (Jiang et al., 2024) and accelerating renewable energy innovation (Yi et al., 2024). Within this context, digital technologies such as AI, big data, cloud computing and blockchain—which are the foundational pillars of the digital economy—have become key research directions (Lee et al., 2024). However, EI, a next-generation intelligent technology, has received limited scholarly attention and lacks a comprehensive theoretical framework. Unlike traditional digital technologies, EI demonstrates that intelligent behavior emerges from integrating the brain, body and environment (Liu et al., 2025). This intrinsic integration allows EI systems to adapt more effectively to complex, dynamic environments, enhancing EWP. Systematically examining the mechanisms through which EI influences EWP offers major theoretical and practical insights. Advancing this research is important for leveraging the digital


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economy's green potential and promoting the integrated development of social, economic and environmental systems.

Compared with existing research, our primary contributions are as follows. First, this study uniquely integrates AI and robotics within a unified research framework, comprehensively evaluating EI across three dimensions, which are hardware infrastructure, software capabilities and the degree of hardware–software synergy. Second, this paper extends the theoretical perspective on the EI–EWP relationship. While a growing literature has focused on the impact of digital technologies like AI, big data and blockchain in environmental governance (Wang and Guo, 2024), the specific impact of EI on EWP remains underexplored. Third, this research reveals the intrinsic mechanisms through which EI influences EWP. This study theoretically posits and empirically verifies that EI enhances EWP by promoting green innovation (GI), increasing green total factor productivity (GTFP) and strengthening the financial development level (FD). Our findings deepen the understanding of intelligent technologies' role in high-quality economic development, moving beyond the scope of traditional digital technology research in environmental governance. Finally, this study examines the varied effects of EI on EWP across geographical, urban and coastal contexts, offering robust evidence to support global green digital transformation and enhance ecological governance.

This paper proceeds as follows: Section II reviews the relevant literature and develops the theoretical framework. Section III outlines the empirical methodology, covering data sources, variable selection and model specification. Section IV reports and interprets the empirical results. Section V discusses the findings. Section VI concludes and presents policy recommendations. Finally, Section VII outlines limitations and proposes future research directions.

## Literature review and theoretical analysis

### *Literature review*

The concept of EWP was initially proposed by Daly (1974), but its application was limited due to challenges in quantification. Subsequently, the Human Development Index (HDI) and the ecological footprint concept (Rees, 1992) provided a new methodological foundation and conceptual support for measuring EWP (Common, 2007). Expanding upon this earlier work, Zhu et al. (2015) formally defined EWP as the efficiency of converting ecological resources into human welfare. As a central concern in sustainable development, EWP seeks to minimize environmental externalities and maximize human well-being through strategic allocation of ecological and economic resources (Wang et al., 2023). Research on EWP primarily concentrates on three aspects: indicator systems, measurement methodologies and influencing mechanisms. Regarding indicator systems, evaluations typically cover three dimensions (Wang et al., 2023). Approaches for the resource and environmental dimensions include indicators based on resource consumption and pollution emissions (Frugoli et al., 2015) or the ecological footprint method (Strezov et al., 2017). The social dimension is often measured using multivariate indicator systems of subjective, objective, or combined well-being, such as the 'Happiness or Happy Life Years' index (Zhang et al., 2018). In terms of measurement methodologies, early studies often relied on a simple indicator defined as the ratio of human welfare to ecological resource use (Abdallah et al., 2009). However, the focus has recently shifted to more comprehensive and dynamic measures, such as comprehensive index methods (Yao et al., 2021) and Data Envelopment Analysis (DEA) frameworks


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(Chen et al., 2023). Ecological welfare performance is shaped by multiple interconnected factors, including policy systems, economic structures and ecological efficiency. Han et al. (2025) find that low-carbon city pilot policies improve the EWP not only in host cities but also in neighboring jurisdictions. Zhu and Zhang (2014) reveal an inverted U-shaped relationship between economic growth and EWP. Furthermore, Feng et al. (2019) point out that the primary driver of China's EWP has gradually shifted from green industrial restructuring to improved GTFP. Existing research clarifies macro-level ecological welfare trends and informs strategies for optimizing micro-level sustainable development.

Turing first proposed the concept of EI, emphasizing that machines, through the integration of hardware and software, can create intelligent entities capable of autonomous learning and evolution to interact with the physical world (Turing, 2021). This form of intelligence is widely regarded as the ultimate manifestation of artificial intelligence (Ren et al., 2024). While technical bottlenecks slowed the development of EI for decades, recent cross-disciplinary synergies between robotics, Deep Learning, Reinforcement Learning, Large Language Models (LLMs), Computer Graphics and Cognitive Science are now driving significant breakthroughs (Shen et al., 2024). Particularly with the advent of the 'LLM + robot' paradigm, EI has achieved significant breakthroughs across both academia and industry. LM-Nav, proposed by the University of California, Berkeley, innovatively fuses three models—ViNG, GPT-3 and CLIP—to enable robots to perform map-less navigation tasks based solely on verbal commands (Shah et al., 2023). EI technology is currently applied primarily in sectors such as smart healthcare, advanced manufacturing, autonomous driving and smart aging services (Zhao and Yuan, 2025). However, the impact of EI in environmental economics remains largely unexamined. As an advanced technology combining perception, cognition and intelligent decision-making, EI shows significant potential for green intelligence applications. Existing intelligent technologies like artificial intelligence have shown a direct, significant positive impact on EWP (Liu et al., 2023). These technologies can also improve resource utilization by enhancing GTFP (Yang and Liu, 2024), indirectly optimizing EWP (Feng et al., 2019). As a next-generation intelligent technology, EI is positioned to be a critical driver of EWP improvement, given its considerable potential in ecological governance.

Existing studies have systematically developed indicators, assessment methods and mechanisms for analyzing EWP, focusing primarily on macro policies, traditional green technologies and digital intelligence. However, they have largely overlooked the potential of convergent smart technologies like EI. EI, an advanced AI modality, shows considerable promise in high-tech manufacturing, medical care and elder care services, but its mechanisms for impacting EWP remain theoretically unframed and empirically unverified. To address this gap, this study constructs a comprehensive evaluation index for EI across three dimensions: software capabilities, hardware infrastructure and hardware–software synergy. Using this framework, we expand the theoretical understanding of and empirically test the intrinsic mechanisms through which EI affects EWP, thereby addressing a critical gap in the literature.

## *Theoretical analysis*

### *Embodied intelligence and ecological welfare performance*

EI's direct positive impact on EWP stems from its distinctive features that set it apart from traditional AI, including physical embeddedness, adaptive learning and real-time feedback. Unlike traditional AI that optimizes processes through data analysis, EI can


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physically interact with its environment, creating a direct pathway to enhance EWP. First, through high-precision execution and rapid response capabilities, EI can minimize non-linear errors arising from human operation in traditional production processes and enable rapid resource scheduling during emergencies. These actions reduce pollution and resource waste, mitigating environmental negative externalities. For example, Dekanovsky et al. (2020) designed an intelligent, chemically-coded microrobot that effectively removes hormonal pollutants. Second, by leveraging its capabilities for embodied sensing, execution and evolution (Shen et al., 2024), EI can generate transparent and traceable environmental and production data in real time. This real-time data enhances public trust in environmental governance and provides governments and enterprises with robust feedback. This information helps convert environmental and economic activities into social welfare, supporting collaborative governance and shared benefits. Finally, EI can be deeply integrated into intelligent manufacturing systems, promoting the industry's transformation towards greater intelligence, flexibility and human-centric design (Xu et al., 2025), while also displacing human labor in high-risk, high-intensity occupations (Li et al., 2024). Therefore, EI can directly enhance EWP. We hypothesize that:

H1: EI significantly enhances EWP.

*The mediating effect of embodied intelligence and ecological welfare performance*

GI is widely recognized as a key driver of ecological improvement and sustainable economic development (Sun et al., 2024). EI can indirectly enhance EWP by promoting GI, which in turn strengthens the sustainability of enterprises and industries. On the one hand, EI promotes GI by restructuring firms' R&D resource allocation. Traditional technological R&D models often face high trial-and-error costs, whereas EI enables innovation in virtual simulation environments, allowing iterative optimization in a safe and efficient manner (Kaur et al., 2023). On the other hand, GI exerts a positive impact on EWP. GI significantly improves the efficiency of ecological resource utilization (Hossain et al., 2024), thereby optimizing overall environmental performance. At the same time, GI promotes the economic transition from high-pollution industries to low-carbon and green sectors, mitigating environmental externalities (Takalo and Tooranloo, 2021), and consequently enhancing EWP. We propose the following hypothesis:

H2a: GI mediates the relationship between EI and EWP.

The growth of GTFP fundamentally relies on technological progress as a core driver (Chen et al., 2025) and is also a significant factor in enhancing EWP (Feng et al., 2019). As an advanced form of AI, EI can affect EWP by promoting enhancements in GTFP. Specifically, the advancement of EI spurs the adoption of smart technologies, enabling firms to leverage tools like big data and AI to shape more environmentally benign industrial patterns and effectively reduce ecological pressures (Chen et al., 2025). Furthermore, due to its real-time feedback mechanisms and efficient resource allocation capabilities, EI promotes digital transformation. Digital transformation, in turn, enhances resource utilization efficiency and fosters green technological innovation, thereby increasing GTFP (Gao and Huang, 2024). The improvement of GTFP further contributes to the enhancement of EWP. On the one hand, rising GTFP may drive the transition toward a low-carbon energy structure, improving environmental quality at its source (Zhang et al., 2024a). On the other hand, as a comprehensive measure of economic efficiency, rising GTFP signifies that economic growth and environmental protection can


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be synergistically achieved, enhancing local well-being (Xia and Xu, 2020). Based on the preceding analysis, this paper posits the following hypothesis:

H2b: GTFP mediates the relationship between EI and EWP.

Economic growth is the foundation for improving well-being (Yang et al., 2023), whereas a robust financial system is a critical enabler of high-quality economic development (Shen and He, 2022). In the digital economy era, technological innovation has emerged as a primary driver of economic growth (Si et al., 2023). As a next-generation intelligent technology, EI can indirectly enhance EWP by accelerating the intelligent digitalization of the financial system. EI in the form of robotic process automation can streamline banking operations, enhance customer service responsiveness and reduce operational costs, thereby enhancing the overall efficiency of financial services. EI can also harness technologies like big data and cloud computing to make financial services considerably more accessible and convenient. This is particularly beneficial for populations previously excluded from financial markets, thus promoting inclusive FD (Zhang et al., 2024b). Enhanced FD further contributes to improved EWP. First, a robust financial system stimulates digital economy expansion, which can directly enhance EWP (Yang et al., 2023). Second, green finance improves resource allocation by channeling funds to green and low-carbon sectors. These effects promote efficient resource use and improve environmental quality, thereby indirectly enhancing ecological welfare (Lv et al., 2021). Thus, EI can indirectly improve EWP by strengthening FD. Building on the preceding theoretical analysis, this paper advances the primary hypothesis as follows:

H2c: FD mediates the relationship between EI and EWP.

*Moderating effect of embodied intelligence and ecological welfare performance*

Industrial structure upgrading (ISU) involves more productive, technologically advanced industries gradually replacing outdated, low-value-added sectors. This evolution creates a favorable market environment for EI's implementation and use. First, the proliferation of high-value-added industries enhances the capacity of firms to absorb and integrate advanced intelligent technologies, improving resource utilization efficiency and GI capabilities (Chen et al., 2025). Second, ISU helps establish unified data standards and network infrastructure. This development enables EI to transcend the limitations of a single factory and realize 'group intelligence' (Ichihashi et al., 2024), thus reinforcing its positive effect on EWP. Finally, during industrial upgrading, advancing digital technology profoundly reshapes production models, breaking traditional industrial boundaries and fostering a transition from labor-intensive to knowledge-intensive sectors. This transformation encourages industries to adopt cleaner, high-output, low-emission production methods, effectively reducing carbon emission intensity (Chang et al., 2023) and enhances EWP. ISU is therefore expected to reinforce EI's positive effect on EWP. Thus, this study formulates the following hypothesis:

H3a: ISU positively moderates the relationship between EI and EWP.

Human capital (HC) is a core and active production factor in socioeconomic development. Professional training cultivates high-quality talent, creating a skilled workforce with the innovative capacity to apply EI technology and enhance production efficiency and environmental welfare performance. First, a high level of HC equips employees with superior problem-solving and task-completion skills (Cui and Diwu, 2024), enhancing firms' absorptive capacity to introduce and integrate EI technologies. Second, the accumulation of HC stimulates corporate innovation (Liu et al., 2024a),


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enabling innovations driven by EI to be more rapidly converted into tangible productivity gains. Finally, a high concentration of HC can also foster a more favorable institutional environment and inform policymaking, creating positive externalities for applying EI to enhance EWP. HC can therefore positively moderate the relationship between EI and EWP.

H3b: HC positively moderates the relationship between EI and EWP.

Ongoing advances in digital technology have markedly enhanced capacities for information exchange, data analysis and intelligent decision-making, facilitating the deployment of EI in ecological governance. First, digital technology development (DT) narrows the digital divide (Yang et al., 2024), facilitates cross-sectoral information sharing and collaboration and dismantles geographic and administrative barriers. This enables EI to assume a broader and more effective role in ecological governance. Second, advances in digital technology have offered new momentum to local governments throughout the policy cycle of environmental governance, including formulation, implementation and feedback (Wang and Guo, 2024), in turn fostering an institutional setting conducive to the adoption of EI. DT can therefore positively moderate the relationship between EI and EWP. This study formulates the following hypothesis:

H3c: DT positively moderates the relationship between EI and EWP (*Fig. 1*).

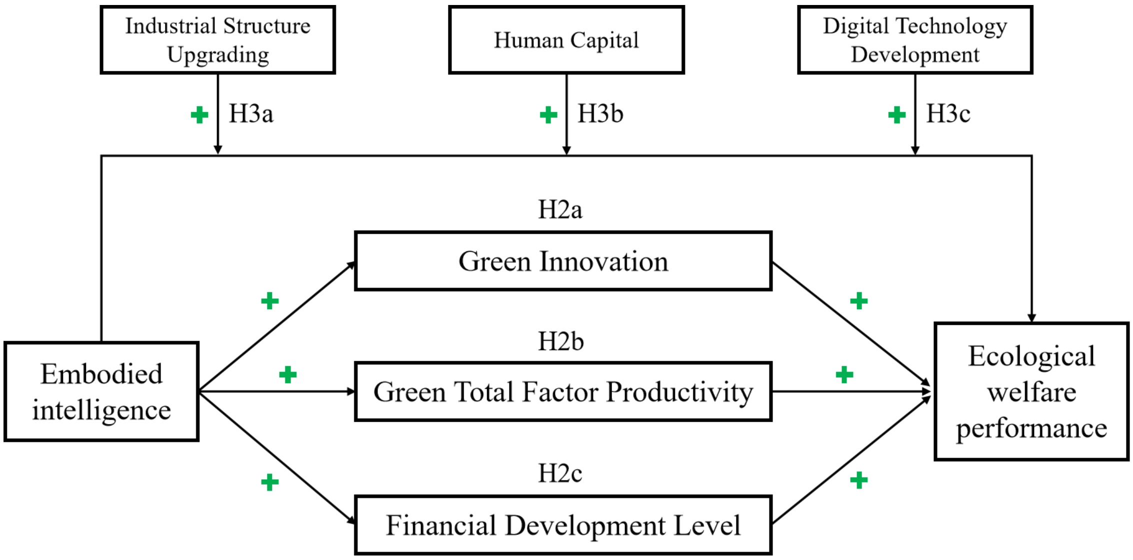


***Figure 1.*** *Framework for research*

## Research design

### *Sample selection and data sources*

This study uses a panel dataset of Chinese prefecture-level cities from 2012 to 2022. After excluding cities with significant missing values for key variables, we obtained a final sample of 280 cities, yielding 3080 city-year observations. Data on AI enterprises and AI patents are sourced from the China Research Data Service Platform (CNRDS). Data on AI technology word frequency are from the Digital Economy Policy Database (DEPD), and data on industrial robots are from China Stock Market and Accounting Research Database (CSMAR). Other data are collected from the China Statistical Yearbook, China Science and Technology Statistical Yearbook, China Environmental Statistics Yearbook, China


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Energy Statistical Yearbook, the Statistical Report on China's Internet Development, the National Bureau of Statistics website and the statistical yearbooks of various provinces. Any remaining minor gaps in the data were filled using interpolation.

## *Definition of variables*

### *Explained variables*

EWP denotes the efficiency in transforming natural resources into human well-being with minimal environmental impact (Zhang et al., 2021). It underscores the coordinative enhancement of economic, social and environmental welfare with minimal resource input and environmental cost, consistent with the 'input–output' analytical framework of the DEA method. Building on the methodologies of Zhang et al. (2021) and Bian et al. (2020), this study develops a comprehensive framework for evaluating EWP. Considering the limitations of conventional DEA models in addressing input–output slack, this study employs a two-stage super-efficiency network SBM-DEA model to measure EWP.

This two-stage framework offers a more granular analysis by disaggregating the EWP generation process, moving beyond the limitations of a single-stage 'black box' model. Stage 1, referred to as Economic Production, models the efficiency of converting initial inputs into economic welfare. Following existing literature (Yang and Zhang, 2018; Mavi et al., 2019), the inputs include natural resource consumption such as water, energy and land, and socioeconomic inputs including labor, capital and fiscal spending. The desirable output is economic welfare, measured by indicators such as GDP and income, while the undesirable outputs are the environmental pollutants generated during production, including wastewater, $SO_2$ and industrial dust (Wang et al., 2019). Stage 2, referred to as Welfare Conversion, treats the economic welfare generated in Stage 1 as an intermediate input and models its efficiency in being converted into final social and environmental well-being outputs. The stage's outputs reflect a high quality of life, encompassing social welfare indicators like consumption, healthcare and culture, and environmental welfare measures including clean water, waste treatment and air quality, consistent with UNDP indicators (Zhang et al., 2018). This network structure distinguishes between the efficiency of generating economic prosperity and translating that prosperity into tangible well-being. We structure the model as follows.

We assume $n$ Decision-Making Units (DMUs), each of which consists of $k$ stages, where $k = 1,2,3,\dots,K$. For each stage $k$, the input is denoted by $m_k$, the output by $u_k$, and $\psi_k$ represents the number of intermediate indicators between stages. The input vector for the $j$-th DMU in the $k$-th stage is $x_k^j$, satisfying $\left\{x_k^j \in R_+^{m_k}\right\}$. Let $\lambda^k \in R_+^n$ be the weight vector for the stage-k model and $w^k$ be the stage importance weights. The desirable and undesirable outputs are represented by the matrices $Y^d = [y_l^d, L, y_N^d] \in R^{s_l \times N}$ and $Y^b = [y_l^b, L, y_N^b] \in R^{s_l \times N}$, respectively. The intermediate products are represented by $z_j^{(k,h)} \in R_+^{t(k,h)} (j = 1,2,\cdots,n; (q,h) \in L)$ and $s_i^{k-}$ represents the input slack variable. Then the overall efficiency of a specific decision-making unit, $DMU_0$, can be formulated as follows:

$$\rho_0 = \min \frac{\sum_{k=1}^{K} w^k \left(1 + \frac{1}{m_k} \sum_{i=1}^{m_k} \frac{s_i^{k-}}{x_{i0}^k}\right)}{\sum_{k=1}^{K} w^k \left[\left(1 - \frac{1}{u_{1k}+u_{2k}} \left(\sum_{r=1}^{u_{1k}} \frac{s_r^{dk}}{y_{r0}^{dk}} + \sum_{r=1}^{u_{2k}} \frac{s_r^{bk}}{y_{r0}^{bk}}\right)\right)\right]}$$


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$$s.t.\, x_0^k \geq \sum_{j=1,\neq 0}^{n} \lambda_j^b\, x_j^k + s^{k-}, y_0^{dk} \leq \sum_{j=1,\neq 0}^{n} \lambda_j^b\, y_j^{dk} + s^{dk}, y_0^{bk} \geq \sum_{j=1,\neq 0}^{n} \lambda_j^b\, y_j^{bk} - s^{bk}$$

$$\mathcal{E} \leq 1 - \frac{1}{u_{1k}+u_{2k}}\left(\sum_{r=1}^{u_{1k}} \frac{s_r^{dk}}{y_{r0}^{dk}} + \sum_{r=1}^{u_{2k}} \frac{s_r^{bk}}{y_{r0}^{bk}}\right), z^{(k,h)}\lambda^h = z^{(k,h)}\lambda^k, \sum_{j=1,\neq 0}^{N} \lambda_j^k = \sum_{k=1}^{K} w^k = 1$$

$$\lambda^k \geq 0, w^k \geq 0, s^{k-} \geq 0, s^{dk} \geq 0, s^{bk} \geq 0$$

In this study, we conceptualize the EWP framework as a two-stage process ($K$=2). The efficiency for each phase is formulated as follows:

$$\rho_0^1 = \frac{1+\frac{1}{m_1}\sum_{i=1}^{m_1}\frac{s_i^{l-}}{x_{i0}^k}}{1-\frac{1}{\psi}\sum_{r=1}^{\psi}\frac{s_r^{l+}}{z_{r0}}}$$

$$\rho_0^2 = \frac{1+\frac{1}{\psi}\sum_{r=1}^{\psi}\frac{s_r^{1+}}{z_{r0}}}{1-\frac{1}{u_{12}+u_{22}}\left(\sum_{r=1}^{u_{12}}\frac{s_r^d}{y_{r0}^d}+\sum_{r=1}^{u_{22}}\frac{s_r^b}{y_{r0}^b}\right)}$$

In this model, $s_r^d$ represents the slack for desirable outputs, while $s_r^b$ is the slack for undesirable outputs. Specifically, $u_{12}$ denotes the number of desirable outputs and $u_{22}$ indicates the count of undesirable outputs. Furthermore, $\rho_0$, $\rho_0^1$ and $\rho_0^2$ denote the overall EWP, the first-stage EWP and the second-stage EWP, respectively. See *Table 2* for details.

*Explanatory variables*

EI, as a core paradigm that characterizes the dynamic interaction between artificial intelligence and the physical environment, necessitates a multi-dimensional indicator framework for comprehensive evaluation. Accordingly, this paper develops an aggregate measure incorporating three fundamental elements: the hardware level, the software level and hardware–software synergy. (1) The hardware level is designed to capture the physical ‘body’ of EI. We measure this dimension using three city-level indicators. First, industrial robot installation density is a direct proxy for the physical deployment of intelligent agents. Second, the number of industrial robot patents reflects the innovative capacity in hardware technology. Third, the word frequency related to ‘AI hardware’, derived from analyzing government work reports via the Digital Economy Policy Database (DEPD) using a specialized AI dictionary, captures governmental focus and policy attention on the physical carriers of intelligence. (2) The software level captures the ‘intelligence’ or cognitive core of EI through three indicators. The number of AI enterprises reflects the industrial scale of AI algorithms, while AI patent counts represent their innovative output. Word frequency of ‘AI software’ in government work reports, analyzed using an AI keyword list from the DEPD, indicates the development and policy discourse of the software ecosystem. (3) After calculating the hardware and software levels using the entropy weight method, we calculate their synergy using the coupling coordination degree evaluation model, as follows:

$$C = \left\{[E \times F]\left[\frac{E+F}{2}\right]^2\right\}^{1/2}$$


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Within the given formula, the overall assessment values for the hardware and software sub-indices are represented by $E$ and $F$ respectively, while $C$ stands for the level of coupling between these two dimensions. We then introduce a coupling coordination degree model to assess their synergistic relationship more holistically. The model is specified as

$$T = \alpha E + \beta F$$

$$\mathrm{D} = \sqrt{\mathrm{C} \times \mathrm{T}}$$

In this formulation, let $D$ be the coupling coordination degree and $T$ be the integrated coordination index measuring the alignment of the hardware and software subsystems. The parameters $\alpha$ and $\beta$ are the weight coefficients corresponding to the hardware and software subsystems, respectively. Grounded in the assumption that the hardware and software levels are of equal importance, this study assigns equal weight to both coefficients, setting $\alpha = \beta = 0.5$.

Finally, we use the entropy weight method to objectively weight each sub-indicator and construct the comprehensive EI index as follows:

$$EI = \sum_{i=1}^{n} \omega_i \, x_i$$

Here, $\omega_i$ represents the weight of the $i$-th indicator, and $x_i$ denotes its corresponding standardised value. This comprehensive system not only captures the physical foundations and algorithmic capabilities of EI but also reveals the effectiveness of its technological integration via a dynamic synergistic mechanism, providing rigorous data for analyzing EI's impact pathways on EWP. *Table 3* details the specific indicators of the evaluation system, where Weight1 denotes the first-stage entropy weights for the sub-indicators within the hardware and software levels. Weight2 denotes the second-stage entropy weights for the three primary dimensions: the hardware level, the software level and the software–hardware synergistic development degree.

*Mediating variables*

The analysis above shows that EI may indirectly affect EWP through GI, GTFP and FD. Here, drawing on the methodology of Sun et al. (2024), GI is quantified using the number of green patent applications filed per 1000 individuals. Following the research of Gao and Huang (2024), GTFP is calculated using the SBM model, which allows for the inclusion of undesirable outputs. Following the study by Yang and Ni (2022), FD is measured using a composite index constructed from regional gross product, total loans and total deposits of financial institutions.

*Moderating variables*

The measurement of ISU, following the research of Zheng et al. (2021), is done by weighting the per capita output of each of the three industries by its respective share of the total output value. HC is defined by the share of the regional population undertaking regular undergraduate or junior college programs. DT is measured by the number of digital patents per 10,000 residents.


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***Table 2.*** *Measurement indicator system for EWP*

| Category | Primary indicator | Secondary indicator | Indicator definition | Unit |
|---|---|---|---|---|
| First-Stage Input | Resource Consumption | Water Resource Input | Daily water consumption per capita | Liters/person |
| | | Energy Input | Annual electricity consumption per capita | 10 kWh/person |
| | | Land Input | Land area per capita | km²/person |
| | | Fiscal Input | Local fiscal expenditure within the general budget /regional GDP | - |
| | | Labor Input | Number of year-end employees in units | Ten thousand people |
| | | Capital Input | Capital stock | 10,000 yuan |
| First-Stage Desirable Output | Welfare Level | Economic Welfare | Per capita GDP | 100 million yuan |
| | | | Per capita disposable income of urban residents | 10,000 yuan |
| | | | Per capita disposable income of rural residents | 10,000 yuan |
| First-Stage Undesirable Output | Environmental Pollution | Wastewater Pollution | Industrial wastewater discharge volume | 10,000 tons |
| | | Waste Gas Pollution | Industrial sulfur dioxide emissions | tons |
| | | Solid Waste Pollution | Industrial smoke and dust emissions | tons |
| Second-Stage Input | Economic Input | Economic Welfare (First-Stage) | Per capita GDP | 100 million yuan |
| | | | Per capita disposable income of urban residents | 10,000 yuan |
| | | | Per capita disposable income of rural residents | 10,000 yuan |
| Second-Stage Output | Social Welfare | Per Capita Consumption Welfare | Total retail sales of consumer goods/resident population | 10,000 yuan/person |
| | | Per Capita Medical Welfare | Number of beds in hospitals and health centers/resident population | Beds/10,000 persons |
| | | Per Capita Cultural Welfare | Total collection of books in public libraries/resident population | 1000 volumes/person |
| | Environmental Welfare | Clean Water Accessibility | Sewage treatment rate | % |
| | | Waste Harmlessness | Harmless disposal rate of domestic waste | % |
| | | Healthy Air Welfare | Proportion of days with air quality at or better than grade | % |


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***Table 3.*** *Measurement indicator system for EI*

<table>
<tr><th>Variable</th><th>Primary indicator</th><th>Secondary indicator</th><th>Weight1</th><th>Weight2</th></tr>
<tr><td rowspan="7">EI</td><td rowspan="3">Hardware level</td><td>AI hardware word frequency</td><td>0.0838</td><td rowspan="3">0.2962</td></tr>
<tr><td>Industrial robot installation density</td><td>0.1105</td></tr>
<tr><td>Number of industrial robot patents</td><td>0.8057</td></tr>
<tr><td rowspan="3">Software level</td><td>AI software word frequency</td><td>0.1335</td><td rowspan="3">0.5670</td></tr>
<tr><td>Number of AI companies</td><td>0.3857</td></tr>
<tr><td>Number of AI patents</td><td>0.4808</td></tr>
<tr><td>Software-hardware synergistic development degree</td><td>Software-hardware coupling coordination degree</td><td></td><td>0.1369</td></tr>
</table>

*Control variables*

To control for potential confounding influences on EWP, we incorporate the following control variables, summarized in *Table 4*. Population density (PD) is defined as the number of urban residents per unit of regional area. GDP per capita (GDPPC) is defined as regional gross domestic product divided by the total resident population. urbanization rate (UR) is measured as the proportion of the urban population to the year-end total population. Government intervention (GOV) is captured by the ratio of local government general budget expenditure to regional GDP. Internet development level (IDL) is proxied by the natural logarithm of (1 + the number of fixed broadband subscriptions). Per capita consumption level (PCCL) is defined as total retail sales of consumer goods per capita.

***Table 4.*** *Definitions of major variables*

| | Variable | Definition |
|---|---|---|
| Explained variables | EWP | Calculated using the two-stage super-efficiency network SBM-DEA model |
| Explanatory variables | EI | Calculated using the entropy weight method and the coupling coordination degree evaluation model |
| Mediating variables | GI | Defined as the number of green patent applications filed per 1000 individuals |
| | GTFP | Calculated based on the SBM model considering undesirable outputs |
| | FD | Defined as the ratio of the balance of deposits and loans of financial institutions to the Gross Regional Product |
| Moderating variables | ISU | Measured as: (Proportion of primary industry × 1) + Proportion of secondary industry × 2) + (Proportion of tertiary industry × 3) |
| | HC | Defined as the number of students enrolled in regular undergraduate and junior college programs divided by the regional population |
| | DT | Defined as the number of digital patents per 10,000 residents |

## Model design

To examine the mechanism through which EI influences EWP, this study establishes the following baseline regression model, which is empirically tested using panel data covering 280 prefecture-level cities in China over the period 2012–2022.


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$$EWP_{it} = \alpha_0 + \alpha_1 EI_{it} + \alpha_2 Control_{it} + \mu_i + \sigma_t + \varepsilon_{it}$$

The subscripts $i$ and $t$ denote cities and years, respectively. $EWP_{it}$ is the dependent variable, and $EI_{it}$ is the key independent variable. The coefficient of interest, $\alpha_1$, measures the effect of EI on EWP. $Control_{it}$ represents a vector of control variables, with $\alpha_2$ being the corresponding coefficient vector. $\mu_i$ denotes city fixed effects controlling for time-invariant unobserved heterogeneity across cities, and $\sigma_t$ denotes year fixed effects accounting for common shocks or temporal trends. Finally, $\varepsilon_{it}$ represents the idiosyncratic random error term.

Potential endogeneity in the baseline model may lead to biased and inconsistent estimates. To address this potential endogeneity, we employ a two-stage least squares (2SLS) instrumental variables approach. Given that the second-stage 2SLS model is identical to the baseline model, we present only the first-stage regression:

$$EI_{it} = \delta_0 + \delta_1 IV_{it} + \mu_i + \sigma_t + \varepsilon_{it}$$

where the regression coefficient $\delta_1$ reflects the effect of the instrumental variable on EI in the first-stage model.

To examine the moderating effects on the EI-EWP relationship, we specify the following interactive model:

$$EWP_{it} = \phi_0 + \phi_1 EI_{it} + \phi_2 W_{it} + \phi_3 EI_{it} \times W_{it} + \phi_4 Control_{it} + \mu_i + \sigma_t + \varepsilon_{it}$$

In this model, $W_{it}$ is the moderating variable (i.e., ISU, HC, or DT). The statistically significant coefficient $\phi_3$ on the interaction term $EI_{it} \times W_{it}$ provides evidence of a moderating effect. The sign of $\phi_3$ determines whether the moderating variable strengthens or weakens the effect of EI on EWP.

Furthermore, to test the indirect effects of EI on EWP, we employ the following mediation analysis:

$$M_{it} = \beta_0 + \beta_1 EI_{it} + \beta_2 Control_{it} + \mu_i + \sigma_t + \varepsilon_{it}$$

$$EWP_{it} = \gamma_0 + \gamma_1 EI_{it} + \gamma_2 M_{it} + \gamma_3 Control_{it} + \mu_i + \sigma_t + \varepsilon_{it}$$

In this model, $M_{it}$ is the mediating variable (i.e., GI, GTFP, or FD). The coefficient $\beta_1$ represents the effect of EI on the mediating variable, $\gamma_1$ represents the direct effect of EI on EWP after controlling for the mediator, and $\gamma_2$ represents the mediator's effect on EWP.

## Results and analysis

### *Descriptive statistics of variables*

*Table 5* presents the descriptive statistics for the variables used in this study. Our analysis is based on a balanced panel dataset of 280 prefecture-level cities in China from 2012 to 2022, comprising 3080 city-year observations. EWP has a mean of 0.336 (SD = 0.198) and ranges from 0.019 to 1.378. The EI index averages 0.056 (SD = 0.068), with values between 0 and 0.959. Furthermore, we conducted a multicollinearity test to


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ensure the robustness of our estimates. The variance inflation factors (VIFs) for all variables are below the standard threshold of 10, indicating no significant multicollinearity.

***Table 5.*** *Descriptive statistics of variables*

| Variable name | Obs | Mean | SD | Min | Median | Max | VIF |
|---|---|---|---|---|---|---|---|
| EWP | 3080 | 0.336 | 0.198 | 0.019 | 0.287 | 1.378 | - |
| EI | 3080 | 0.056 | 0.068 | 0.000 | 0.042 | 0.959 | 2.25 |
| PD | 3080 | 0.045 | 0.036 | 0.001 | 0.037 | 0.329 | 1.70 |
| GDPPC | 3080 | 5.826 | 3.443 | 0.816 | 4.861 | 25.691 | 3.32 |
| UR | 3080 | 0.573 | 0.145 | 0.181 | 0.553 | 1.007 | 2.60 |
| GOV | 3080 | 0.203 | 0.0961 | 0.044 | 0.178 | 0.741 | 1.90 |
| IDL | 3080 | 13.636 | 0.9023 | 9.210 | 13.605 | 16.599 | 2.22 |
| PCCL | 3080 | 0.278 | 0.1943 | 0.003 | 0.234 | 1.890 | 2.83 |

*Figure 2* presents the correlation matrix. The correlation between GDPPC and UR is relatively large at 0.73 but still within an acceptable range, indicating a strong yet reasonable positive linear relationship between the two variables. Overall, all correlation coefficients remain within a reasonable range, suggesting that multicollinearity is not a significant concern.

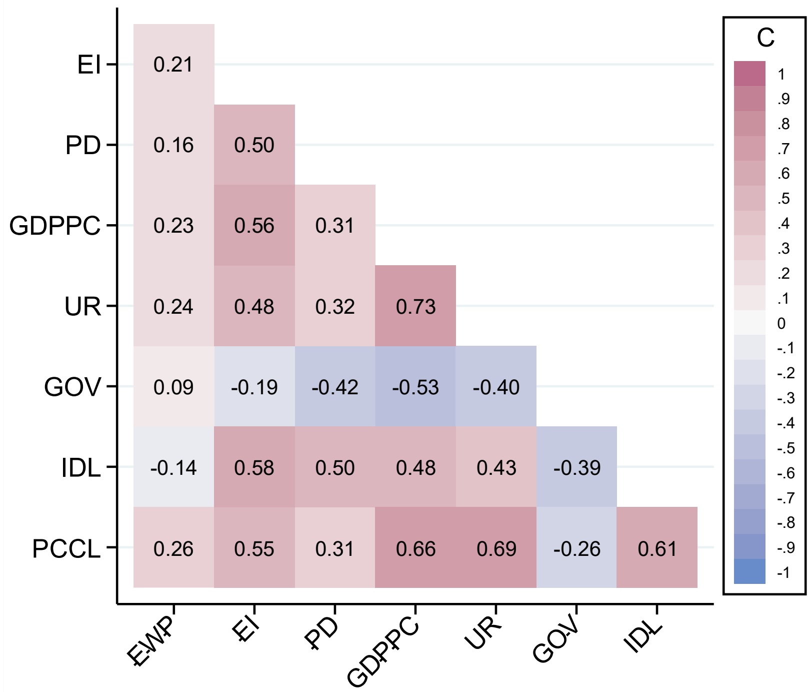


***Figure 2.*** *Correlation coefficient matrix of variables*

## ***Baseline regression results***

To determine the appropriate specification for controlling time and individual heterogeneity and avoiding potential estimation bias, we conducted a Hausman test to


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compare the random-effects and fixed-effects models. The test results (chi2 (7) = 75.67, Prob > chi2 = 0.000) permit the rejection of the null hypothesis. This outcome validates the selection of the fixed-effects model, which serves to control for unobserved heterogeneity and mitigate potential estimation bias.

*Table 6* presents the baseline regression results using a two-way fixed-effects model. Column (1) presents results from a model with city fixed effects, while Column (2) adds year fixed effects to the specification. Across both specifications, the estimated coefficient for EI is consistently positive and statistically significant ($p < 0.01$), strongly indicating that EI significantly improves EWP. Columns (3) and (4) extend the models from Columns (1) and (2) by including control variables. Although its magnitude decreases slightly with the inclusion of controls, the EI coefficient remains positive and significant ($p < 0.01$). The estimate in Column (4) implies that a one-unit increase in EI is associated with a 0.368-unit rise in EWP, equivalent to approximately 1.86 standard deviations of the dependent variable, indicating substantial economic significance. These results provide robust support for H1. Column (5) presents the SYS-GMM results, which address endogeneity and dynamic effects. The AR (2) and Hansen tests are not rejected ($p = 0.122$ and $p = 0.100$, respectively), and the coefficient on EI remains positive and significant at the 5% level, confirming the robustness of the main finding to potential endogeneity and dynamic persistence. Our findings extend the work of Wang et al. (2024), who showed that AI development reduces a region's ecological footprint. However, their study primarily measured environmental impacts from the 'cost side' through the lens of ecological footprints, without fully considering the 'benefit side', the capacity of technological progress to advance economic and social well-being. As a result, the comprehensive social value of advanced technologies like EI may have been underestimated. By employing EWP as the dependent variable, this study offers a more holistic perspective. It reveals that EI not only contributes to environmental improvements but also fosters sustainable economic and social development, thereby realizing synergistic gains across the environmental, economic and social dimensions.

### *Robustness test*

To further substantiate the empirical findings, robustness checks were undertaken using three distinct approaches.

First, we use an instrumental variable (IV) approach to address potential endogeneity. To begin, we utilize the interaction term of 'year-end number of post and telecommunication offices' and 'national count of internet broadband subscribers' as the instrumental variable for EI. The instrument satisfies the relevance condition because historical communication infrastructure and digital adoption predict EI's development potential. It also satisfies the exogeneity condition because these historical variables likely affect current EWP only through their influence on modern technology and are uncorrelated with the error term. Second, we use the lagged value of EI as an instrumental variable. This instrument is valid because lagged EI is highly correlated with its current value but is unaffected by current EWP. On this basis, this study applies the 2SLS method with panel fixed effects for estimation. The results in Columns (1) and (2) show that the EI coefficient remains positive and significant ($p < 0.01$). These findings suggest our main result is robust. In Columns (1) and (2), the Kleibergen–Paap rk LM statistic indicates that the instruments are well-identified. Furthermore, the Cragg–Donald Wald F-statistics are 517.832 and 3,401.013, respectively, both strongly rejecting the null hypothesis of weak instruments.


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***Table 6.** Baseline regression results*

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | **EWP** | **EWP** | **EWP** | **EWP** | **SYS-GMM** |
| L.EWP | | | | | 0.517***<br>(2.869) |
| L.EI | | | | | 0.218**<br>(2.202) |
| EI | 0.323***<br>(5.827) | 0.584***<br>(8.894) | 0.303***<br>(3.929) | 0.368***<br>(4.622) | |
| PD | | | 1.540***<br>(2.814) | 1.194**<br>(2.234) | 0.632*<br>(1.872) |
| GDPPC | | | 0.011***<br>(4.418) | 0.011***<br>(4.267) | 0.019<br>(1.122) |
| UR | | | -0.070<br>(-1.131) | -0.083<br>(-1.222) | 0.061<br>(1.265) |
| GOV | | | -0.093<br>(-1.430) | 0.149**<br>(2.083) | 0.152<br>(1.000) |
| IDL | | | -0.099***<br>(-9.515) | -0.070***<br>(-5.800) | -0.051**<br>(-2.341) |
| PCCL | | | 0.251***<br>(6.609) | 0.161***<br>(4.266) | 0.192***<br>(2.963) |
| _cons | 0.318***<br>(83.260) | 0.303***<br>(71.387) | 1.529***<br>(12.480) | 1.124***<br>(6.784) | 0.703***<br>(2.619) |
| Year | No | Yes | No | Yes | Yes |
| Ind | Yes | Yes | Yes | Yes | Yes |
| N | 3080 | 3080 | 3080 | 3080 | 2800 |
| Adj. $R^2$ | 0.615 | 0.649 | 0.634 | 0.656 | |
| AR (1) | | | | | 0.001 |
| AR (2) | | | | | 0.122 |
| Hansen test (p) | | | | | 0.100 |

t-statistics are in parentheses; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The same applies to the tables below

Second, we test the robustness of our main conclusion by using an alternative measure for the core independent variable. The entropy weight method is one of several possibilities, so we reconstruct the EI index using Principal Component Analysis (PCA). We first conduct KMO and Bartlett's sphericity tests on the EI indicators. The KMO test yields a value of 0.774, and Bartlett's test significance is P = 0.000***, indicating that the data are suitable for PCA. We then construct the alternative EI score by weighting the principal components by their variance contribution, yielding weights of 0.395 for the Hardware Level, 0.375 for the Software Level, and 0.330 for Hardware–Software Synergy. The results in Column (3) of *Table 7* show that the coefficient on the PCA-derived EI index is positive and significant ($p < 0.01$). This result confirms that our main finding is robust to the choice of measurement for the independent variable.


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Finally, considering the political status and unique administrative advantages of municipalities, this study further tests the robustness of the model by excluding the four municipalities of Beijing, Shanghai, Tianjin and Chongqing to eliminate potential bias arising from their special status. In addition, to examine whether the results remain consistent across different time periods, the analysis is re-estimated using the post-2015 sub-sample. Furthermore, to mitigate the influence of potential outliers, we winsorize all continuous variables at the 1% level and re-estimate the baseline model. As shown in Columns (4), (5) and (6), the coefficient of EI remains significantly positive at the 1% level across these tests, further confirming the robustness of the empirical results.

***Table 7.*** *Robustness test results*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | **IV1** | **IV2** | **Alt. EI** | **No Munic.** | **Post-2015** | **Winsor 1%** |
| EI | 0.822***<br>(4.067) | 0.475***<br>(4.512) | 0.027***<br>(4.595) | 0.270***<br>(2.715) | 0.256***<br>(2.751) | 0.313***<br>(2.955) |
| _cons | | | 1.141***<br>(6.901) | 1.124***<br>(6.763) | 0.770***<br>(3.486) | 1.234***<br>(6.173) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes | Yes |
| Ind | Yes | Yes | Yes | Yes | Yes | Yes |
| Kleibergen-Paap rk LM statistic P-val | 483.188*** | 1612.670*** | | | | |
| Cragg-Donald Wald F static | 517.832*** | 3401.013*** | | | | |
| N | 3080 | 2800 | 3080 | 3036 | 2240 | 2751 |
| Adj. $R^2$ | -0.063 | -0.069 | 0.656 | 0.653 | 0.675 | 0.622 |

## Further analysis

### *Mediating effects test*

Based on the theoretical framework, this study tests the mediating mechanisms through GI, GTFP and FD, as proposed in H2a–H2c. *Table 8* reports the results of the mediation analysis. For the GI pathway, EI significantly promotes green innovation (Column 2). When GI is included in the regression model (Column 3), it exerts a significant positive effect on EWP, while the coefficient of EI decreases to 0.267 ($p < 0.01$) but remains significant, indicating a partial mediating effect of GI. This finding confirms H2a. For the GTFP pathway, EI has a significant positive impact on green total factor productivity (Column 4). In the full model (Column 5), GTFP positively affects EWP, and the coefficient of EI decreases to 0.208 ($p < 0.01$) while remaining significant, suggesting that GTFP also serves as a partial mediator, validating H2b. For the FD pathway, the results in Columns (6) and (7) show that EI significantly enhances financial development. When FD is incorporated as a mediator, its effect on EWP remains positive and significant, while the coefficient of EI slightly declines but stays significant at the 1% level, indicating that FD partially mediates the relationship between EI and EWP. This confirms H2c.


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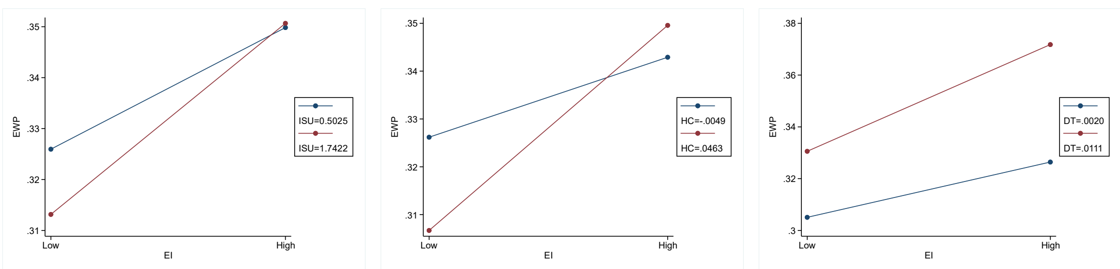
***Table 8.*** *Mediating effects test results*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | **EWP** | **GI** | **EWP** | **GTFP** | **EWP** | **FD** | **EWP** |
| EI | 0.368***<br>(4.622) | 1.590***<br>(38.370) | 0.267***<br>(2.717) | 2.214***<br>(11.840) | 0.208***<br>(2.584) | 1.364***<br>(4.217) | 0.356***<br>(4.462) |
| GI | | | 0.063*<br>(1.738) | | | | |
| GTFP | | | | | 0.072***<br>(9.094) | | |
| FD | | | | | | | 0.009*<br>(1.847) |
| _cons | 1.124***<br>(6.784) | 0.203**<br>(2.354) | 1.111***<br>(6.703) | 1.637***<br>(4.209) | 1.005***<br>(6.138) | 3.894***<br>(5.787) | 1.090***<br>(6.546) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Ind | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3080 | 3080 | 3080 | 3080 | 3080 | 3080 | 3080 |
| Adj. $R^2$ | 0.656 | 0.913 | 0.656 | 0.760 | 0.666 | 0.854 | 0.657 |

## ***Moderating effect test***

*Table 9* presents the results for the moderating effects analysis, which tests whether ISU, HC and DT positively moderate EI's effect on EWP. Specifically, In Column (1), the $EI \times ISU$ interaction term is significantly positive, supporting H3a. This indicates that ISU enhances EI's effect on EWP, likely because industrial upgrading fosters high-value-added industries with greater technological absorption capacity, enables 'group intelligence' through unified standards and promotes cleaner production. Similarly, the $EI \times HC$ interaction term (Column 2) is significantly positive, suggesting that higher HC levels bolster EI's positive impact, thus supporting H3b. This finding is attributable to a skilled workforce improving EI integration and absorptive capacity, while HC accumulation accelerates the conversion of EI innovation into productivity. Finally, Column (3) reveals a significantly positive $EI \times DT$ interaction term, confirming H3c. This finding indicates that digital technology development exerts a significant positive moderating effect, likely by enhancing information sharing, dismantling barriers for broader EI application in governance and fostering a conducive institutional environment (*Fig. 3*).




(a) ISU (b) HC (c) DT

***Figure 3.*** *Marginal effects of moderating variables*

***Table 9.*** *Moderating effect test results*

| | (1) | (2) | (3) |
|---|---|---|---|
| | **EWP** | **EWP** | **EWP** |
| EI×ISU | 0.081**<br>(2.014) | | |
| EI×HC | | 3.758**<br>(2.572) | |
| EI×DT | | | 16.037**<br>(2.097) |
| EI | 0.135<br>(0.952) | 0.141<br>(1.211) | 0.126<br>(0.842) |
| ISU | -0.009<br>(-0.903) | | |
| HC | | -0.336<br>(-0.688) | |
| DT | | | 2.990<br>(0.782) |
| _cons | 1.130***<br>(6.826) | 1.103***<br>(6.446) | 1.091***<br>(6.537) |
| Controls | Yes | Yes | Yes |
| Time Fixed | Yes | Yes | Yes |
| Individual Fixed | Yes | Yes | Yes |
| N | 3080 | 3058 | 3080 |
| Adj. $R^2$ | 0.657 | 0.641 | 0.657 |

### *Heterogeneity effect test*

To explore potential regional heterogeneity in the effect of EI on EWP, this paper conducts heterogeneity regression analyses from the dimensions of geographical region, city type and coastal characteristics, with the results presented in *Figure 4*. The results show that the positive impact of EI on EWP remains significant across multiple sub-samples, but the magnitude of this effect varies markedly. Geographically, EI's effect is most pronounced in the western and northern regions compared to their eastern, central and southern counterparts (*Figs. 4a–b*). This disparity likely arises because these regions face more severe environmental challenges from fragile ecosystems and a legacy of heavy industry, giving them greater potential to improve through EI. Similarly, EI exerts a stronger impact in non-coastal and resource-based cities (*Figs. 4c–d*), likely due to their 'latecomer advantage'. Their urgent need for industrial upgrading and less developed environmental governance systems enable EI to exert a stronger influence through resource optimization and green transition, whereas coastal or non-resource-based cities may experience diminishing returns under already advanced systems. *Table 10* shows details.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### *Spatial spillover effect test*

To examine whether the driving effect of EI on EWP exhibits spatial spillover characteristics, further testing is necessary. This study constructs a Spatial Durbin Model (SDM) to test the spatial spillover effect of EI on EWP, with the results presented in *Table 11*. Model (1) utilizes a geographical adjacency 0-1 matrix to set the spatial weight matrix $\omega_{ij}$, considering that geographically adjacent regions have a certain correlation in government policy formulation. Model (2) employs the inverse of the absolute difference in economic development levels between different regions as economic distance. Model (3) uses the inverse of the geographical distance between city centroids as the spatial matrix. Model (4) calculates economic-geographical distance weights by multiplying economic distance and geographical distance. The results across all four models consistently show that the direct coefficient of EI is significantly positive ($p < 0.01$), indicating that local EI development significantly enhances local EWP. However, the coefficient of the spatially lagged EI term (Wx:EI) is significantly negative in all specifications ($p < 0.01$ or $p < 0.05$). This suggests the presence of significant negative spatial spillover effects, meaning that the development of EI in neighboring cities may inhibit the EWP of the local city. The spatial autocorrelation coefficient (rho) is also significantly positive across models, confirming the overall spatial dependence in EWP. These findings indicate that while EI boosts local ecological welfare, spatial competition or resource diversion effects might lead to negative externalities for neighboring regions.

***Table 10.*** *Heterogeneity effect test*

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | **East** | **Middle** | **West** | **Source** | **North** |
| EI | 0.249*** | 0.389** | 0.653** | 0.174* | 0.583*** |
| | (2.595) | (2.004) | (2.420) | (1.700) | (4.645) |
| _cons | 1.314*** | 0.809** | 0.670** | 1.818*** | 0.287 |
| | (4.190) | (2.461) | (2.201) | (7.987) | (1.165) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes | Yes |
| Ind | Yes | Yes | Yes | Yes | Yes |
| N | 1100 | 1100 | 869 | 1694 | 1386 |
| Adj. $R^2$ | 0.672 | 0.619 | 0.664 | 0.667 | 0.656 |

***Table 10. cont.*** *Heterogeneity effect test*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | **Coastal** | **Non-Coastal** | **Resource** | **Non-Resource** |
| EI | 0.101 | 0.621*** | 0.558** | 0.301*** |
| | (0.925) | (5.427) | (2.153) | (3.496) |
| _cons | 1.535*** | 0.556** | 0.944*** | 1.209*** |
| | (5.629) | (2.530) | (3.704) | (5.266) |
| Controls | Yes | Yes | Yes | Yes |
| Year | Yes | Yes | Yes | Yes |
| Ind | Yes | Yes | Yes | Yes |
| N | 1243 | 1837 | 1243 | 1837 |
| Adj. $R^2$ | 0.667 | 0.657 | 0.623 | 0.678 |


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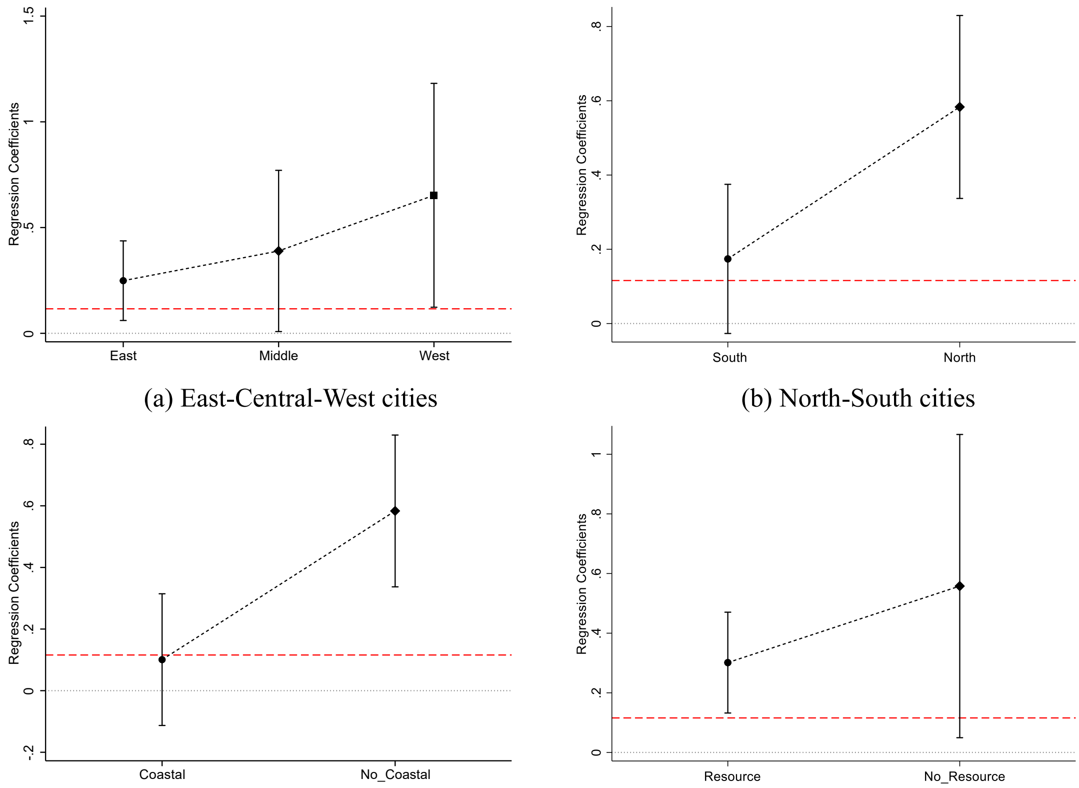


(a) East-Central-West cities

(b) North-South cities

(c) Coastal and Non-Coastal cities

(d) Resource and Non-Resource cities

***Figure 4.*** *Heterogeneity effect test*

***Table 11.*** *Spatial Durbin model regression results*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | **Proximity distance** | **Geographical distance** | **Economic distance** | **Economic geographical distance** |
| main | | | | |
| EI | 0.359*** | 0.345*** | 0.374*** | 0.399*** |
| | (5.699) | (5.496) | (5.783) | (6.281) |
| Controls | Yes | Yes | Yes | Yes |
| Wx | | | | |
| EI | -0.301*** | -2.680*** | -0.357** | -0.773*** |
| | (-3.382) | (-6.060) | (-2.264) | (-5.730) |
| Spatial | | | | |
| rho | 0.188*** | 0.678*** | 0.096*** | 0.197*** |
| | (8.381) | (8.482) | (2.810) | (6.483) |
| Variance | | | | |
| sigma2_e | 0.024*** | 0.025*** | 0.025*** | 0.025*** |
| | (39.178) | (39.091) | (39.198) | (39.103) |


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| | | | | |
|---|---|---|---|---|
| N | 3080 | 3080 | 3080 | 3080 |
| Within $R^2$ | 0.035 | 0.006 | 0.035 | 0.041 |

## Discussion

This study systematically evaluates the impact of EI on EWP and examines its mechanisms, moderating pathways, regional heterogeneity and spatial spillovers. The results demonstrate that EI significantly enhances EWP. This positive effect operates primarily through three mediating channels: promoting GI, enhancing GTFP and strengthening FD. Furthermore, ISU, HC and DT significantly and positively moderate the relationship between EI and EWP. Moreover, EI's effect varies significantly across geographic regions and city types. Spatial effects analysis also indicates that while EI boosts local ecological welfare, spatial competition or resource diversion effects might lead to negative externalities for neighboring regions.

This study confirms a significant positive correlation between EI and EWP, revealing the substantial potential of EI in enhancing environmental governance and public welfare. These results align with previous work that highlights how AI and digital technology contribute to advancing sustainability goals (Wang et al., 2021; Zeng and Zhang, 2024). Our distinctive contribution, however, is pioneering the integration of the emerging EI concept into the EWP framework and developing a multi-dimensional indicator system. This approach not only moves beyond the traditional focus on individual digital technologies but also highlights EI's efficiency in specific ecological governance scenarios, including resource allocation, pollution monitoring and real-time response. In doing so, this study offers a novel technological pathway for improving urban ecological wellbeing.

Our finding that EI enhances EWP through GI, GTFP and FD extends existing research on intelligent technologies in ecological governance by offering a more nuanced theoretical perspective. Specifically, our finding for the GI pathway corroborates Yin et al. (2023), who find that intelligent technologies promote green transformation by reshaping knowledge acquisition and innovation experimentation. The GTFP mechanism aligns with the findings of Feng et al. (2019) that GTFP has become a key driver of EWP. Similarly, the FD channel resonates with the findings of Huang et al. (2022), who argue that digital finance can optimize resource allocation, a principle this study shows is also applicable to the advanced capabilities of EI.

Analysis of the moderating effects indicates that ISU, HC and digital technology jointly amplify the positive influence of EI on ecological wellbeing performance. This finding complements and extends the work of Cheng et al. (2024), who explored AI's impact on corporate pollution emission intensity. Their study showed AI reduces corporate emissions by channels such as improving total factor productivity, increasing pollution control investments and optimizing input allocation. Unlike their micro-level firm analysis, this research identifies macro-level conditions that enhance EI's eco-welfare effects.

EI's effect is more pronounced in Western, Northern, non-coastal and resource-based urban areas, as indicated by the heterogeneity analysis. This suggests a stronger marginal effect and greater response elasticity in regions characterized by higher ecological pressures and weaker economic foundations. This finding is consistent with the proposition by Luo and Wang (2025) that 'the emission reduction effect of AI is more


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evident in western and northern regions', and provides empirical evidence and policy implications for regionally differentiated intelligent eco-governance.

The negative spatial spillovers reveal complexity in EI's benefits. Positive local impacts of EI development may not translate into broader regional improvements and could potentially intensify inter-city disparities if not carefully managed. Potential explanations from regional science and environmental economics include increased competition for scarce resources, aligning with theories of agglomeration shadows and backwash effects (Partridge et al., 2009; Chen and Partridge, 2013). Another possibility relates to the potential displacement of polluting activities from technologically advancing cities to their neighbors, echoing concerns raised in the 'pollution haven' literature (Saleem and Gozgor, 2025). This finding underscores the critical need for coordinated regional development strategies and inter-city cooperation mechanisms to manage such spatial externalities and ensure that the benefits of EI are shared more broadly, preventing a 'beggar-thy-neighbor' scenario in the pursuit of localized green growth.

## Conclusions and policy recommendations

Amidst the global movement towards carbon neutrality and an accelerated digital transformation, the integration of intelligent technology and robotics is emerging as a critical pathway for developing new, high-quality productive forces. While digital technologies have been widely recognized for their potential in advancing environmental governance, a gap exists in the literature regarding systematic empirical research on the mechanisms through which EI enhances EWP. To address this gap, this study empirically investigates the mechanisms and heterogeneous effects of EI on EWP by constructing a panel dataset for 280 prefecture-level cities, with data drawn from CNRDS, CSMAR, DEPD, and various Chinese statistical yearbooks.

The main findings of this study are presented below. First, EI has a significant positive relationship with urban EWP. Second, a mechanism analysis reveals that EI enhances EWP by stimulating GI, increasing GTFP and strengthening FD. Furthermore, ISU, HC and DT each play a significant positive moderating role on the relationship between EI and EWP. Third, the results of the heterogeneity analysis reveal that the impact of EI on EWP is more pronounced in Western regions, Northern cities, non-coastal cities and resource-based cities. Finally, spatial effects analysis indicates that while EI boosts local ecological welfare, spatial competition or resource diversion effects might lead to negative externalities for neighboring regions.

The foregoing findings contribute to the literature on intelligent technology and high-quality development, offer a novel perspective on how digital technologies can enhance EWP and hold significant theoretical value for expanding future research into EI-enabled environmental governance. We can therefore derive several key policy recommendations.

First, the government should accelerate the deployment of EI infrastructure to strengthen the technological foundation for ecological governance. Our core finding that EI directly improves EWP provides a clear mandate for prioritizing investment in this area. Government departments should prioritize establishing EI-based environmental monitoring networks within smart city pilot programs, integrating IoT and edge computing technologies to enable real-time tracking and dynamic management of pollution sources. Additionally, national science and technology projects should be established that focus on lowering EI's application barriers by developing low-energy


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sensors and advanced autonomous decision-making algorithms, facilitating its widespread implementation.

Second, the government should establish a 'Smart-Green-Financial' collaborative innovation system. Given that our results show that EI operates through GI, GTFP and FD, policy should focus on maximizing the throughput of these channels. On the innovation side, governments should support EI-driven virtual simulation platforms to lower the cost of green R&D, incentivized by green patent tax credits. On the production side, policymakers should promote EI-based optimization systems in energy-intensive industries to boost GTFP. On the financial side, a specialized green credit certification system for EI projects can pioneer an 'intelligent perception for precision financing' model, ensuring capital flows to the most impactful green projects.

Third, the government should simultaneously promote the upgrading of industrial structure, talent reserve and technological support. Our finding that ISU, HC and DT amplify EI's benefits means that isolated technology policy is suboptimal. Policymakers should integrate 'digital + green' metrics into government performance evaluations. To foster HC, governments should support joint university-enterprise projects focused on 'EI + Ecological Welfare' to cultivate interdisciplinary talent. To advance DT, collaboration with industry associations is needed to formulate technical specifications and certification systems for EI applications, promoting the widespread adoption of mature technologies.

Finally, the government should implement differentiated regional support and establish cross-regional coordination mechanisms tailored to local conditions. Our results indicate that EI delivers the highest marginal returns in less-developed regions. This calls for a tailored, two-pronged strategy. For Western, Northern, non-coastal and resource-based cities, policy should focus on foundational investment to leverage their 'latecomer advantage'. Instruments like 'Special Subsidies for Eco-Intelligent Development' and 'Green Transformation Loans' can help these cities use EI as a primary engine for industrial upgrading and to leapfrog directly to greener development models. By contrast, or more developed Eastern and coastal cities with smaller EI marginal effects, policy should prioritize advanced integration. These regions can use EI to optimize sophisticated governance systems, refine resource management and develop next-generation environmental technologies, maintaining their competitive advantage. An 'East–Middle–West EI Collaborative Innovation Alliance' could accelerate best practice dissemination across regions. Given the negative spatial spillovers identified, the alliance and regional policies must address inter-city resource competition and prevent pollution displacement. Potential mechanisms include joint planning, shared infrastructure investments and cross-regional compensation schemes to ensure EI development promotes regionally balanced ecological welfare improvements.

## Limitations and further research

Despite its contributions to the theoretical framing and empirical validation of the topic, this study is subject to several limitations that warrant consideration. First, while this paper constructs an EI indicator system encompassing hardware, software and their synergistic interaction to reflect the essential feature of 'AI-environment integration', the operationalization of EI remains limited by direct measurement and concreteness, potentially affecting the precision of empirical analysis. Second, because the study uses Chinese city-level panel data, although the sample coverage is extensive, its institutional environment and policy system has unique characteristics; the applicability of the


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research conclusions in an international context requires further validation. Furthermore, the mechanistic pathways focused on in this paper are mainly limited to GI, GTFP and FD, and a detailed identification of more complex indirect mechanisms such as institutional adaptation, organizational behavior and social acceptance is still lacking.

Addressing the limitations identified in this study, we propose three primary directions for future research: First, a more precise operationalization of EI could be achieved by developing a multi-level, multi-dimensional measurement framework to enhance indicator precision. Second, subsequent research should investigate the mediating pathways across institutional, organizational and behavioral levels to better elucidate the underlying causal mechanisms. Finally, the research scope could be broadened by utilizing cross-national data or conducting longitudinal studies to examine the influence of EI on ecological performance and its evolutionary trajectories within diverse institutional contexts.

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