Decoding High-Quality Urban Development: Evaluating the Short- and Long-Term Effects of AI Penetration and Green Finance on China's Socioeconomic Transformation

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Abstract

Currently, over 60% of China's population resides in urban areas, contributing nearly 80% to the nation's GDP, creating an urgent and undeniable need for high-quality urban development (HQUD) to secure China's future economic stability, social equity, and environmental resilience in the face of rapid urbanization. Addressing this imperative, this paper explores the dynamic role of artificial intelligence (AI) and green finance (GF) using the panel dataset of 31 provinces of China from 2007 to 2022. This study makes a novel contribution by jointly estimating the short- and long-run effects of artificial intelligence (AI) and green finance (GF) on a multidimensional high-quality urban development (HQUD) index—an intersection that prior studies have not modelled in a single dynamic framework. We measure HQUD using the entropy method with 12 key indicators of economic, social, environmental, and infrastructure dimensions, AI development using industrial robot penetration rate, and GF through a Global Principal Component Analysis (GPCA)-based index encompassing green credit, investment, and carbon finance. Based on the results of rigorous pre-diagnostic tests, we apply the advanced Autoregressive Distributed Lag (ARDL) model - Pooled Mean Group (PMG) estimation, known for its robustness in handling mixed-order integration in large datasets. The baseline results employing PMG estimation approach show that long-run effects are positive and statistically significant: GF: +2.797 and AI: +0.580 on HQUD. The short-run results show a small yet significant immediate effect for GF (ΔGF: +0.068) but not for AI, while the error-correction term indicates rapid adjustment to equilibrium. The robustness estimates (DFE) confirm the long-run positives (GF: +2.202; AI: +0.352). Regional heterogeneity is pronounced: impacts are larger in central/eastern regions (GF: +3.038; AI: +0.493) than in western provinces (GF: +1.520; AI: +0.395). Policy should expand GF instruments nationwide and close AI infrastructure gaps in lagging regions to accelerate HQUD.

Keywords: Artificial intelligence; Entropy method; Green finance; High-quality urban development; Regional heterogeneity; Sustainable development.

Introduction

On January 1, 2016, the United Nations adopted "Transforming our World: The 2030 Agenda for Sustainable Development", which is an effort to achieve 17 Sustainable Development Goals (SDGs). Promoting sustainable development has become a critical need for the world with the rapid pace of global social and economic development. It has the potential to address the global challenges of climate change, border security, poverty, and infrastructural damages(Carleton & Hsiang, 2016). Sustainable development policies are aimed at creating synergies through the systematic promotion of mutually reinforcing policy actions among government departments and agencies to achieve set goals, which emphasizes balancing the institutional, temporal, geographical, and sectoral differences among countries while striving for common targets (Sinha et al., 2020). The successful attainment of the SDGs is based on the enhancement of three fundamental components: economic, social, and environmental.

China, an emerging industrial economy, has the dual responsibility to boost the national economy without compromising on ecological resources. Since 1992, sustainable development has been a crucial aspect of China's national strategy. Nevertheless, environmental pollution and ecological degradation remain significant challenges in the country, which posit a negative impact on China's economy and quality of life (Fang et al., 2007). At the beginning of the 21st century, China strictly focused on mixed policies of growing rapid economic development, intensifying environmental pollution efforts, and mitigating pollution(Bawa et al., 2010; Riedel et al., 2007). In the economic domain, China grapples with numerous challenges, such as unproductive nature of enterprises and social overcapacity (Riedel et al., 2007). Moreover, China is also facing a difficult international trade environment, with restrictions on technology, tariffs, and other areas. In addition to this, the economic structure of China does not keep pace with economic development, and posits serious challenges with supply structure. In this context, advancements in artificial intelligence, high-end manufacturing, clean energy, and biotechnology are new avenues through which these issues can be tackled effectively (Lu et al., 2019). In the social domain, challenges of social equity, unequal urban development, border stability, and social harmony have been examined previously. A significant gap exists between urban and rural incomes, and this gap shows a tendency to widen in the future (Chauvin et al., 2017; Zhu et al., 2020). On the environmental front, industrial emissions that result in water, air, and marine pollution have remained serious challenges in the country (Zhou et al., 2021).

As the world's largest developing economy, China has a crucial role in framing environmental preservation and sustainability policies, not only for itself but also for the global community (Zhang & Wen, 2008). In response to the environmental, economic, and social pressure, China's government is actively promoting the concept of high-quality urban development (HQUD) across all the provinces(Luo, 2003). HQUD emphasizes leveraging the benefits across multiple dimensions, including social equity, economic growth, ecological environment, and modern industrial structure. It aims at fostering a more balanced and adequate development, regulating the economic structure, achieving a dynamic balance between supply and demand, boosting productivity, and addressing income disparities and other equity issues. Moreover, HQUD supports sustainable economic development where economic growth is not at the cost of environmental damage (Li et al., 2012). This paper employs entropy method because it objectively assigns weights to each indicator based on their intrinsic information contribution, avoiding subjective biases common in other composite indices. This approach enhances the robustness and comparability of our HQUD measurement across provinces. China made significant efforts to influence regional economies through the promotion of artificial intelligence and the introduction of green finance policies to support HQUD (Liang and Langbein, 2015). However, there is limited empirical evidence on how AI and green finance jointly contribute to HQUD in China, especially at the regional level. This paper addresses this critical research gap by investigating their combined influence using a comprehensive panel dataset spanning 31 provinces over 16 years.

Artificial intelligence (AI) accelerates efficiency and capacity with the introduction of smart manufacturing, aids enterprises in their operational transformation and upgrading, and optimizes industrial structure (Zheng et al., 2021). The manufacturing industry, as the backbone of China's economy, is the future battleground for China's "innovation-driven, transformation, and upgrading" economic strategy(Han, 2019; Yan et al., 2022). To achieve SDGs, the state council signed and endorsed the policy of "Made in China", which advocates the establishment of intelligent and innovative manufacturing cities across China. In this regard, China's economic development is now based on shifting the focus of manufacturing industries from quantity to quality, aimed at developing a competitive edge in manufacturing operations (Xie et al., 2019). Artificial intelligence, integrated with biodiversity objectives, emphasizes sustainable economic growth and industrial innovations, improved public welfare, increased infrastructural investments, and employs new technology to achieve sustainable economic development, social and infrastructure development, and address climate change challenges (Küfeoğlu, 2022).

Green finance (GF), characterized by the promotion of green bonds, green insurance policies, and green investments, can support high-quality urban development in China by fostering sustainable economic growth and environmental preservation. Specifically, the green bond market in China has reached $30.1 billion in 2020, ranking China as the second-largest green bond economy (Lin & Hong, 2022). This financial mechanism significantly supports urban projects that emphasize pollution control, energy efficiency, and sustainable infrastructural development. In the Beijing-Tianjin-Hebei region, green finance has reduced air pollution levels by 25% over the last five years through funding renewable energy projects and electric vehicles (Papapanou, 2020). Additionally, green finance initiatives enable the construction of eco-friendly buildings, with over 6.6 billion square meters of green buildings constructed across China by 2020 (Zhang & Wang, 2021). Green finance guidelines introduced in 2017 drive 60% of total green loans towards urban infrastructure projects (Macaire & Naef, 2023), thereby significantly supporting the HQUD. By channelling funds into green urban development, China addresses not only environmental concerns but also ensures sustainable economic growth that is in line with the goals of HQUD (Liu & Wang, 2022).

Despite these developments, the spatially differentiated impact of AI and GF on HQUD remains underexplored, particularly across eastern, central, and western regions with varying economic maturity and policy capacities. This paper fills that gap through a regionally disaggregated heterogeneity analysis. Using panel data on 31 provinces of China from 2007 to 2022, this study investigates the role of artificial intelligence (AI) and green finance (GF) in promoting high-quality urban development (HQUD) in China. We employed advanced econometric techniques of the Pedroni co-integration test, PMG estimation approach, and dynamic fixed effects to present the long-term and short-term associations between the variables of study. The use of the PMG-ARDL model is particularly justified in this study due to the presence of mixed integration orders among variables, making it a robust choice for distinguishing long-run equilibrium relationships from short-run dynamics in large provincial panels. Despite rapid growth in the separate literatures on AI and GF, the combined transmission of AI and GF to multidimensional HQUD has not been modelled within a single dynamic panel. Studies on AI typically trace productivity and industrial upgrading, while GF studies link to environmental outcomes and green innovation; none jointly estimate long- and short-run effects on a composite HQUD index and report region-disaggregated results. We address this gap by (i) constructing an entropy-weighted HQUD index (12 indicators), (ii) building a GPCA-based GF index, and (iii) estimating PMG-ARDL with DFE robustness and regional heterogeneity.

This paper is structured as follows: Section (1) introduces the research problem and sets the scene for further analysis; Section (2) covers literature reviews and presents the research gaps; Section (3) explains methodology, data, variables, and descriptive statistics; Section (4) covers empirical results of pre-diagnostics tests, PMG estimation approach, DFE model, and heterogeneity analysis; Section (5) concludes the paper and presents policy implications.

Literature review

High-quality urban development (HQUD)

High-quality urban development (HQUD) is framed as a comprehensive initiative with its unique and multidimensional paradigm. It supports the notion of prosperity and inclusive welfare of people, economic growth boost, and bridging the gaps between communities with a more balanced economic, social, and ecological policy mix (Jiang & Liu, 2021). Fostering HQUD is an inevitable outcome that adheres to natural laws of economic progress, ensures equal distribution of benefits throughout communities and people, and is a necessary pathway for modern society (Zhang et al., 2025; Zhao et al., 2025). Since its economic reforms, China, as the global manufacturing player, is increasingly aware of the need for HQUD (Wang et al., 2022). To support sustainable economic growth, it is crucial to upgrade and transform the industrial structures. This process helps in addressing the structural imbalances in a systematic manner, accelerates competitive growth, and promotes the building of a robust industrial foundation (Hui et al., 2024; Nassar et al., 2024). Such changes optimize production, distribution, and consumption patterns and thus aid industrial sectors to be aligned with the changing market demands to create a dynamic equilibrium where supply and demand drive each other (Jiang et al., 2020). It is required to build the industrial chain around the industrial chain by enhancing the innovative capabilities of industrial sectors and improving their mechanism for transformation (Ali & Jamal, 2024; Sun et al., 2025). This can drive high internal growth and provide primary incentives to lead development across various sectors. The Made in China 2025 initiatives underscore the importance of HQUD to achieve inclusive and significant sustainable economic development within China's economy. Sustainable development is framed by efficient resource utilization, strong innovation capacity, environmental sustainability, and balanced social welfare across communities and people (Jahanger, 2021). Previous studies either focused on specific aspects of high-quality urban development such as economic, environmental, social, and others, or they rely on aggregate indicators that may not capture all crucial aspects of HQUD (Tao et al., 2022). Jiang and Liu (2021) developed an agricultural HQD assessment index by expanding the original upgrade assessment system with a greater focus on HQD. Jahanger (2021) explains the direct impact of foreign direct investment on the quality of China's economic development within the context of the country's economic reforms. Following (Jiang et al., 2022; Li & Wang, 2023; Luo et al., 2024), this study employs entropy method to measure the HQUD index across all provinces of China, which accounts for economic, social, environmental, and infrastructural aspects, and thereby representing a broader measure of high-quality urban development.

Artificial intelligence (AI)

With the rapid growth of globalization, traditional manufacturing processes encounter new challenges, with positive support from stable economic growth beginning to wane (Simmert et al., 2019). The growing need for faster delivery, customized and personalized products, automated efficiency, and high quality is putting substantial pressure on traditional manufacturing enterprises. Consequently, these enterprises are keen to leverage the benefits of the fourth industrial revolution, also known as Industry 4.0 (Candau & Dienesch, 2017; Zheng et al., 2021). This revolution is primarily aimed at harnessing technological innovation to increase economies of scale, redesigning industry efficiency models, and reorganizing production processes. Specifically, this revolution has transformed the operations of manufacturing firms via the integration of numerous technologies into their production processes(Gao et al., 2022). The emergence of artificial intelligence is closely linked with the Internet of Things (IoT), which is a crucial driver of the Industry 4.0 revolution's goals. Artificial intelligence can aid in modernizing production systems through enabling the large-scale production of highly customized products across various manufacturing sectors. Some researchers investigate the technical development of artificial intelligence (Buckholtz et al., 2015), while others focused on investigating the impact of artificial intelligence on narrow aspects such as economic, social, environmental, and infrastructural development (Buckholtz et al., 2015; Meng et al., 2022). However, its impact on broader high-quality urban development remains unexplored.

Green finance (GF)

Green finance has emerged as the crucial mechanism to address environmental concerns through providing required fundings for green projects within private and public sectors. The concept of green finance gained special attention in the early 21st century as governments, financial institutions, and international organizations realize the need to finance environmentally sustainable projects (Buckholtz et al., 2015; Dong & Yu, 2024). Chinese government embraced this concept at the same time and pushed its financial institutions to embark on green finance throughout the country. Green finance has the ability to mitigate climate change effects, promote renewable energy, and support the transition to a green economy(Campiglio, 2016). Additionally, green finance has encouraged innovation in sustainable technologies and fostered economic growth through the creation of new markets and job opportunities(Idasz-Balina et al., 2020). Green bonds, as the popular instrument of green finance, facilitate funding of large-scale infrastructure projects that directly contribute to environmental sustainability (Shen et al., 2024). The ongoing evolution of green finance in China emphasizes its role in fostering sustainability targets(Campiglio, 2016; Cheng et al., 2014) and thus can support high-quality urban development.

AI and HQUD

In the developing and developed world, economic growth is largely driven by industrialization, a primary source of environmental pollution (Duzgoren-Aydin, 2007). National Bureau of Statistics (2016) reports that almost 70% to 90% of the emissions came from industrial activities. China, as an emerging industrial economy, is facing the dual challenge of sustainable economic growth and managing industrial pollution emissions to achieve the objective of high-quality urban development (HQUD) (Zheng et al., 2017). In response to this, the Chinese government implemented numerous environmental regulations and protection policies to counteract environmental challenges coming from industrialization. In addition to this, the government is focused on fostering innovation in production technologies and enhancing industrial structures, which shows its commitment to environmental protection. Previous studies show that artificial intelligence adoption contributes to sustainable and stable economic growth (Lu & Zeng, 2022; Luo et al., 2024; Wu et al., 2023)**.** Most of the studies have focused on the relationships of artificial intelligence with industrial structures, green development, and economic growth. Although AI has been linked to productivity and industrial upgrading (Damioli et al., 2021; Gao & Feng, 2023), its role in shaping HQUD through multidimensional socioeconomic and environmental pathways remains largely unexplored, especially in a joint framework with green finance.

GF and HQUD

Green finance can be a crucial tool to promote sustainable urban development through addressing environmental challenges, fostering economic growth, and counteracting social challenges. The instruments of green finance, including green bonds, green loans, green insurances, and green investments, establish necessary financial mechanisms to fund projects that prioritize environmental sustainability (Flammer, 2021). These instruments support renewable energy transition, energy efficiency, pollution control, and sustainable infrastructure, which could be crucial to support high-quality urban development(Campiglio, 2016). Particularly, green bonds enabled regional governments to finance large-scale green projects such as waste management, clean public transport, and green infrastructure, thereby contributing to social, economic, and environmental welfare (Duzgoren-Aydin, 2007). In addition to this, green finance encourages the adoption of technologies that could improve resource productivity, thus supporting the notion of a green economy (Zhang & Wang, 2021). Green finance can help to create an urban environment that is more inclusive, equitable, and resilient (Cheng et al., 2014) by aligning funding flows with the environmental, social, and economic challenges. In this way, the integration of green finance into urban planning can support the development of green infrastructure, reduce urban pollution, and enhance public health, all of which are key drivers of high-quality urban development. The components of high-quality urban development – economic, environment, social, and infrastructure – are studied separately with the impact of green finance on them (Citaristi, 2022; Ghosh & Hajra, 2023; Lee, 2020). However, green finance's impact on high-quality urban development is still unexplored.

Research Summary

Previous studies on artificial intelligence, green finance, and high-quality urban development have contributed significantly to the field, yet there are certain limitations. Many of these studies primarily focused on the individual aspects of urban development (Wang et al., 2015), or they relied on a traditional econometric approach that might not fully capture the dynamic effects of artificial intelligence and green finance. The present study addresses these limitations in several ways. First, we employ a multidimensional approach that incorporates economic, social, environmental, and infrastructural aspects into our analysis, reflecting the comprehensive nature of high-quality urban development. This broader perspective enables us to examine the diverse impacts of artificial intelligence and green finance on high-quality urban development in China (Gao et al., 2022).

Second, we use advanced econometric techniques, including the Pedroni co-integration test to explain the long-term relationship between variables, Panel Autoregressive Distributed Lag (ARDL) - Pooled Mean Group (PMG) estimator as the benchmark approach to explain short-term and long-term effects of AI and GF on HQUD, and Dynamic Fixed Effects (DFE) as the robustness test. This methodology allows us to identify the dynamic effects more accurately and determine the causal relationship of AI and GF with HQUD. Finally, this study contributes to the existing literature by evaluating the effectiveness of AI and GF on HQUD with consideration of regional development across provinces (Sun et al., 2025). It is shown how the effects of AI and GF vary across the provinces of China to support high-quality urban development in the short run and long-run (Gao et al., 2022). With these advancements, this study not only extends the literature by offering a more comprehensive understanding of the interaction of AI and GF with HQUD but also addresses the shortcomings of previous studies by considering multiple dimensions of high-quality urban development to present specific policy implications.

Data and Methodology

Description of variables

Dependent variables

High-quality urban development (HQUD): This study measures high-quality urban development following the framework proposed by prior literature(Jiang et al., 2022; Li & Wang, 2023; Lu & Zeng, 2022; Luo et al., 2024; Wang et al., 2015). HQUD index is constructed by considering the development principles of coordination, innovation, sharing, development, and openness. These principles are measured across four key dimensions: economic, social, environmental, and infrastructure. Environmental pressure and exposure pathways are central to urban quality (e.g., groundwater contaminants and indoor BTEX exposures (Abdipour et al., 2025; Abdipour et al., 2024; Ma et al., 2019). To create a comprehensive measure of high-quality urban development, we further broke down these dimensions into 12 fundamental measures such as industrial output, first-class highway length, treatment capacity of industrial water and others. Each dimension's index, weighting, and property details are given in Table 1. Using the entropy value method of weighting, it is ensured that variation across the indexes is minimal. construct High-Quality Urban Development (HQUD) index, this study employs entropy weight method, a widely recognized objective weighting technique that minimizes subjectivity by leveraging the intrinsic variability of each indicator. This method is chosen because it allows us to consider various factors that could shape the high-quality urban development in China. This approach weighs the factors as per their importance to support the HQUD in various Chinese provinces. This method ensures that indicators having greater informational contribution would be given more weight in composite index of HQUD. Using the entropy value method of weighting, it is ensured that variation across the indexes is minimal. The condition of HQUD in China in 2007 and 2022 is visually presented in figure 1. This figure shows that HQUD is exclusively reached across all the Chinese provinces, and there could be different drivers to support this development including green finance and artificial intelligence.

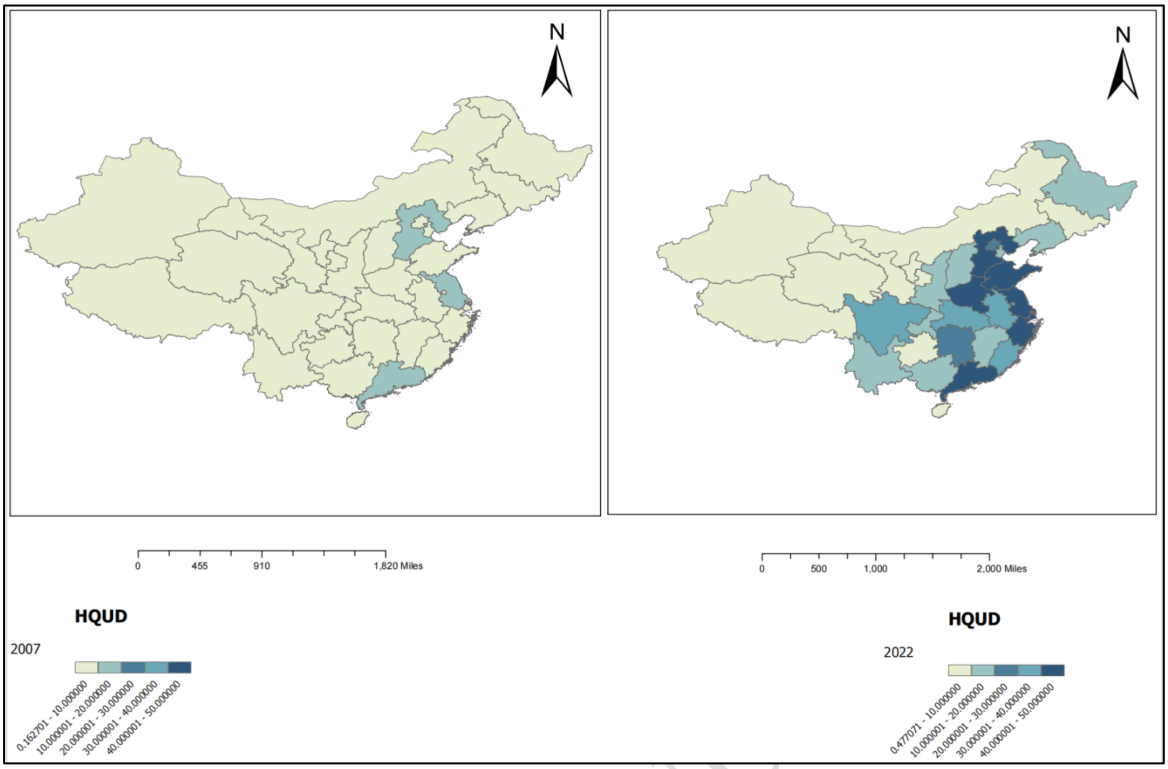

Figure 1: High-quality urban development across 31 provinces of China (2007 and 2022)

Table 1: High-quality urban development evaluation index system.

Target level	Guideline level	Weighting	Index layer	Weighting	Property
High Quality-Urban Development	Economic Growth Momentum	0.2558	GDP growth rate (%)	0.3231	+
			Total industrial output value (100 million yuan)	0.3541	+
			Commodity retail price index ((previous year=100))	0.3228	+
	Social Support Function	0.2408	Number of hospital beds (beds)	0.358	+
			Number of public libraries (number)	0.3367	+
			Number of personnel involved in scientific and technological activities (person)	0.3053	+
	Ecological and Environmental Efficiency	0.2627	Green coverage rate of organized towns (%)	0.3274	+
			Harmless treatment rate of domestic waste (%)	0.3357	+
			Urban harmless treatment volume (10,000 tons)	0.3369	+
	Infrastructure Potential	0.2407	Total postal business volume (10,000 yuan)	0.2972	+
			First-class highway mileage (km)	0.3629	+
			Urban gas penetration rate (%)	0.3389	+

Independent variables

Artificial intelligence (AI): Following (Graetz & Michaels, 2018; Liang et al., 2023; Zhang et al., 2024), we measure the level of AI development within a specific province using the industrial robot penetration rate across all the enterprises, based in that province. The raw data regarding the number of robots is sourced from the IFR (International Federation of Robotics) database. Robots stand as the tangible manifestation, reflecting the practical implementation of AI within geographical locations. The development of AI across 31 provinces of China in 2007 and 2022 is shown in Figure 2. It is shown in figure 2 that AI development was not much in 2007 across all the provinces of China, but in 2022, this development has been extensively expanded across all the Chinese provinces.

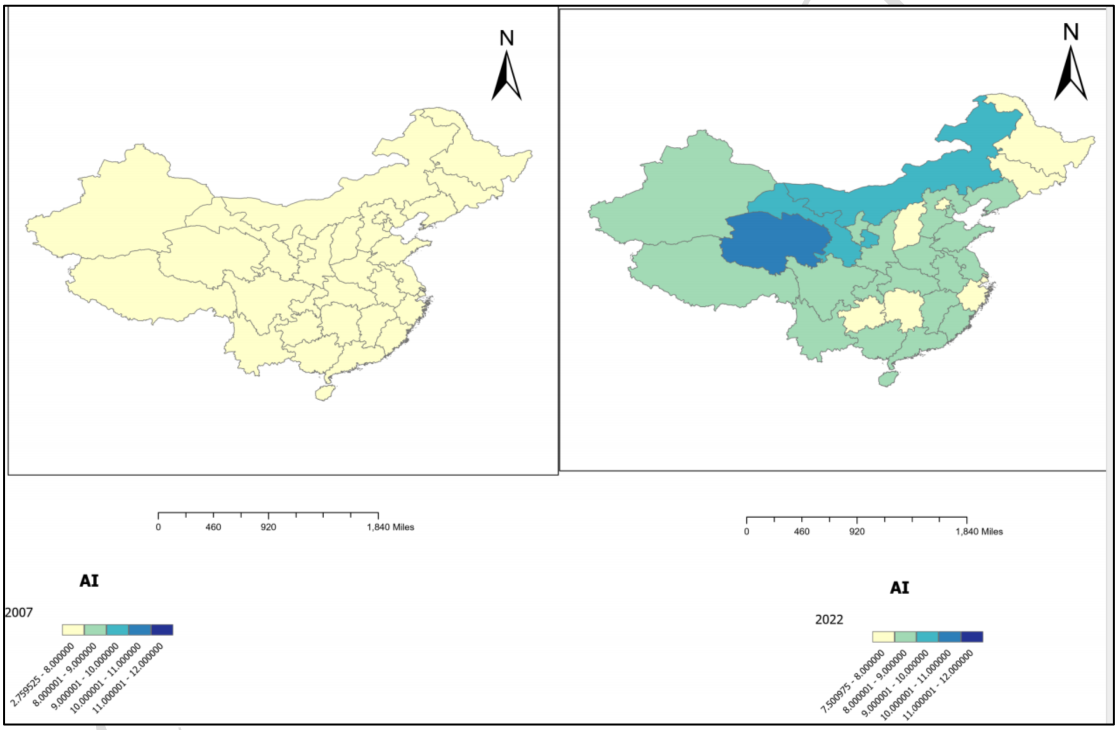

Figure 2: AI development across 31 Provinces of China (2007 and 2022)

Green Finance (GF): This study employs the Global Principal Component Analysis (GPCA) method to construct a green finance development index to measure the green finance development across 31 provinces of China(Zhou et al., 2020). This index includes green finance components of green credit, green investment, green securities, and carbon finance (Wang & Zhi, 2016). The mentioned approach captures regional differences and temporal dynamics in green finance development in China (Zhang et al., 2022). Figure 3 shows the development of green finance in 2007 and 2022. It can be seemed that green finance development was relatively low in 2007, and in 2022 it has been reached at moderate level across Chinese provinces.

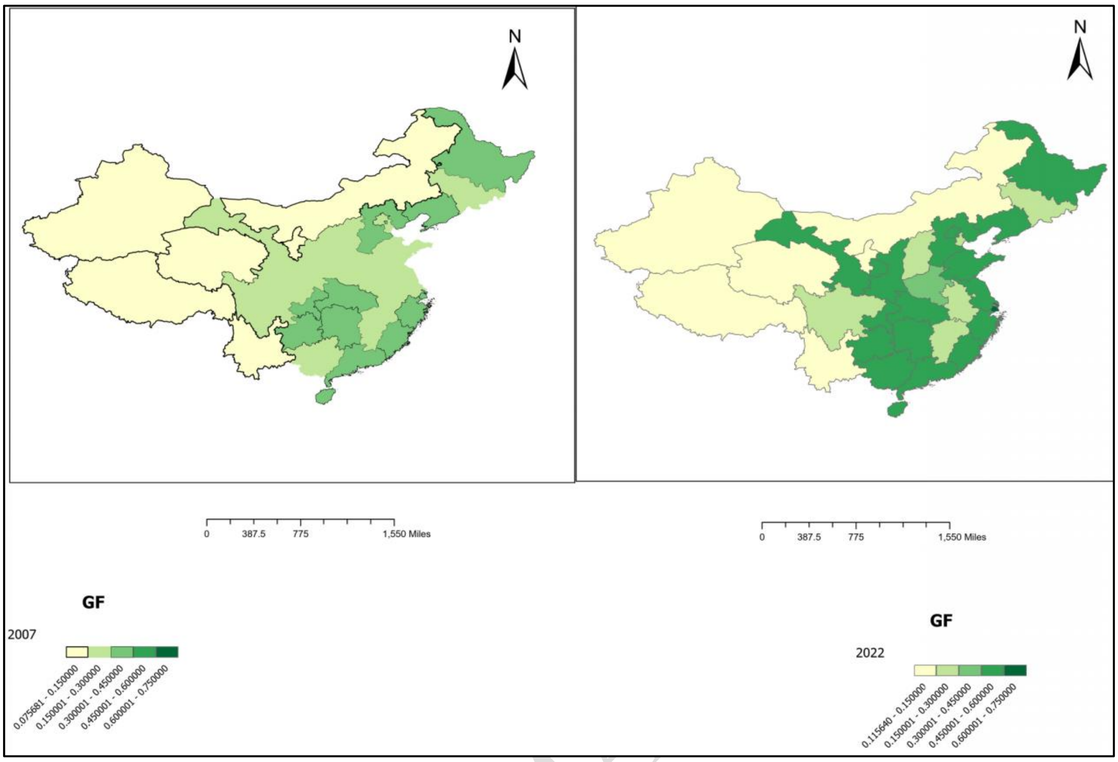

Figure 3: Green finance development across 31 provinces of China (2007 and 2022)

Control variables

Following existing literature (Angelidou, 2017; Haarstad & Wathne, 2019; Xie et al., 2019), this study selects four control variables that might influence the quality of urban development. The level of innovation (INOV) is an essential driver of high-quality urban development, which increases the efficiency of processes, measured by the number of patents granted. The economic development level in a particular province (GDP) is a crucial factor in urban growth and significantly influences the ecological environment of provinces. This is measured as the log of GDP per capita. The level of investment in a region (Capital) could influence its social and economic progress, and it is measured as the fixed capital formation (%) of a province in a particular year. Finally, Educational (Edu) is another important factor that provides the necessary talent, innovation, technology, and intelligence resources to drive high-quality urban development. It is measured as the volume of educational expenditures in a province in a year.

Data and descriptive statistics

This study uses data from 31 provinces of mainland China. The data on HQUD indicators and other variables are primarily sourced from the China City Statistical Yearbook and the China Statistical Yearbook, covering the years 2007 to 2022. Any missing data are supplemented using either the mean imputation method or statistical bulletins of the individual provinces. The descriptive statistics for the variables of this study are presented in Table 2. The mean value for HQUD is 13.05313, with a standard deviation of 14.17526, which reflects the variation of high-quality urban development across provinces of China. For all explanatory and control variables, the descriptive statistics are within acceptable range. Figures 4 and 5 present the dynamic changes in patterns of variables for 2007-2022. Figure 5 shows the mean trend of all variables over the sample period, indicating the development phases of HQUD, GF, and AI over 2007-2022. This shows that during the sample period, there is significant improvement in HQUD, AI, and GF, and there could be chances of having the influence posited by the independent variables toward dependent variables in further analysis. Figure 5 presents the nexus between key variables of this study. It can be seemed that there is a certain nexus exists between HQUD, AI, and GF over the sample period.

Table 2: Variables and descriptive statistics.

Variables	Symbol	Obs.	Mean	St. Dev	Min	Max
High-quality urban development	HQUD	496	13.05313	14.17526	0.1627011	50.59818
Green finance	GF	496	0.3006372	0.1247783	0.075681	0.6317453
Artificial intelligence	AI	496	6.150376	1.35545	2.759525	10.40267
Innovation	INOV	496	3.695177	1.624654	0.02171	5.94062
Economic Growth	GDP	496	4.626967	0.2559628	3.890868	5.279469
Government investments	Capital	496	4.844347	3.26319	1.09811	8.583808
Education	Edu	496	6.843171	0.3845474	5.62383	7.77951

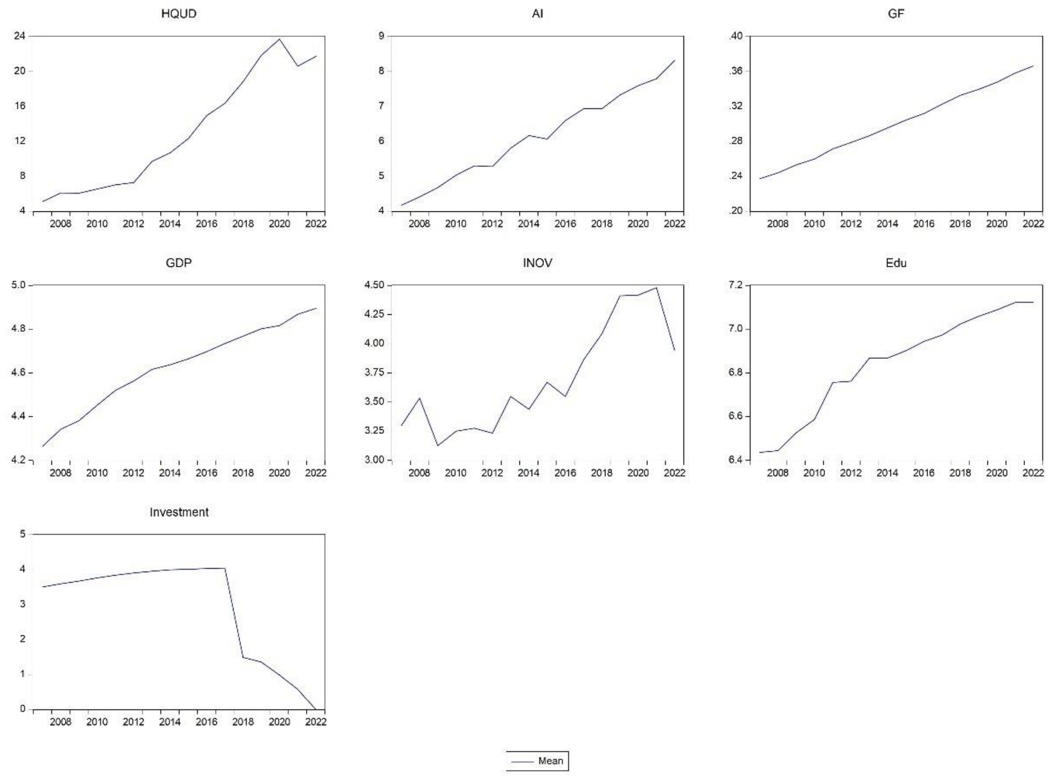

Figure 4: Mean trend of the key variables across the sample period.

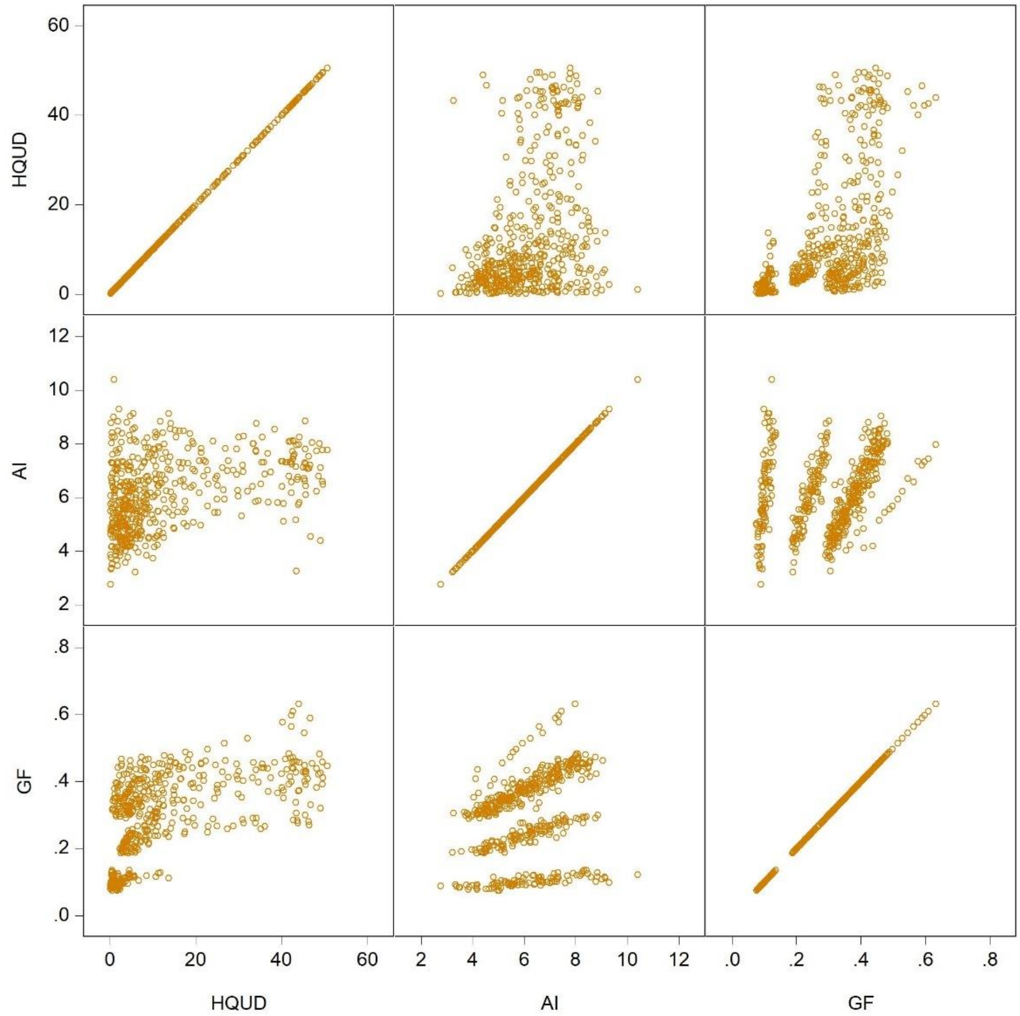

Figure 5: The nexus between HQUD, AI, and GF

Methodology

Pre-diagnostics

This study utilizes the Panel Autoregressive Distributed Lag (ARDL) - Pooled Mean Group estimator model to examine the short- and long-term effects of AI and GF on HQUD in China. The PMG estimator is developed by Pesaran et al. (1999), and it is particularly suitable for dynamic heterogenous panels where long-run relationships among the variables could be assumed to be homogenous, but short-run dynamics and error variances could differ across the cross-sectional units. Before moving toward estimations, panel unit root tests could be conducted to confirm that variables are integrated of order I(0) or I(1), as the ARDL framework has not the strict requirement of all variables to be stationary, and thus making it flexible to handle the mixed integration orders (Asafu-Adjaye et al., 2016; Zaman et al., 2020). The PMG model is preferred over dynamic fixed effects and mean group estimators due to several reasons.

While dynamic fixed effects approach imposed the homogeneity in both short- and long-term coefficients across all the cross-sectional units, and mean group approach allows full heterogeneity which may results in inefficiency and overfitting in small samples (Lee et al., 1997). On the other side, PMG offers a middle ground by allowing the short-term heterogeneity while also maintaining the long-run equilibrium constraints, thereby we can achieve more efficient and theoretical grounded estimates. To further validate the choice of PMG, we performed a Hausman test to compare PMG and MG estimators. The test results did not reject null hypothesis of long-term homogeneity, thereby confirming that PMG model is fully suitable for current study. This advanced econometric approach ensures the robustness of our findings and accounts for the economic, institutional, and development diversity across the Chinese provinces.

Before estimating ARDL, we first determine whether each series is integrated of order 0 or 1. If the variables present integration of higher orders, the ARDL bounds testing approach does not provide robust results, leading to exclude those variables from the dataset. To test for unit roots in the panel data, we employ the Im, Pesaran, and Shin (IPS) test and the Levin, Lin, and Chu (LLC) test, as introduced by Im et al. (2003) and Levin et al. (2002), respectively. These first-generation unit root tests, based on the Augmented Dickey-Fuller (ADF) regression for panel data, are applied to assess the stationarity of the panel data series.

$$\Delta y_{it} = \gamma_i y_{i,t-1} + \sum_{j=1}^{P} \varphi_j \Delta y_{i,t-j} + \varepsilon_{it} \tag{1}$$

Where$\gamma_i = \rho_i - 1$ both tests are employed to examine the null hypothesis of unit root existence $H_0 = \gamma_i = 0$ $(\rho_i = 1)$ against the alternative hypothesis of the existence of stationarity H_1: $\gamma_i < 0$ $(\rho_i < 1)$. LLC test has the assumption that parameters being tested are equal across all panels of study, and thus $\rho_i = \rho$ for all i countries in panel data. However, the IPS test is relatively less restrictive than the LLC test as it obtains the average of ADF statistics and shows that parameters may vary across panels. IPS and LLC tests are classified as the first-generation unit root test, as they don't account for cross-sectional dependence, which could be a crucial issue when all panels are from a single economy, such as in our case, 31 provinces of China. To identify the existence of cross-sectional dependence, we employed the cross-sectional dependence CD test, proposed by Pesaran (2004), which examines the nexus of residuals across cross-sections and can be specified as:

$$CD = \frac{\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N}\hat{\rho}_{ij}}{\frac{1}{N(N-1)}\sum_{i=1}^{N}\sum_{j=1}^{N}\hat{\rho}_{ij}} \tag{2}$$

where N is the number of cross-sections, and $\hat{\rho}_{ij}$ denotes the residual correlation between cross sections i and j. Additionally, to evaluate whether there is a multicollinearity issue or not, this study estimates variance inflation factors for all explanatory and control variables. Following the existence of cross-sectional dependence via the CD test, this study uses the Pesaran (2007) cross-sectional Augmented Dickey-Fuller (CADF) test to address the existence of cross-sectional dependence between variables.

After diagnosing the order of integration, the second stage involves the testing for long-run cointegration of AI and GF with HQUD. Pedroni (2004) panel cointegration test is used for this purpose as it examines panel-specific cointegrating vectors. This test has its basis on the panel-data model for an *I(1)*explained variable y, and tests the null hypothesis of no integration exists between variables. This test is constructed as follows:

$$y_{it} = x'^{it}\beta_i + z'_{it}\tau_i + e_{it} \tag{3}$$

where x^{it} denotes the covariables for each panel *i,* and this test requires that covariates are not integrated.

Inferential analysis approach

After confirming the appropriate order of integration and long-run relationship through unit root and cointegration tests, we move forward to estimate the PMG-ARDL model. This model presents short and long-term coefficients and is also reliable when the sample period and/or sample size is short Pesaran and Shin (1998). The Pool Mean Group (PMG) model is utilized to estimate the long-run and short-run association of high-quality urban development with artificial intelligence and green finance in China for the period of 2007-2022. Model 4 is built as the panel ARDL equation where *p* represents the number of lags of dependent variables, and *q* is the lag length of explanatory variables, and it is specified as:

$$HQUD_{it} = \alpha_i + \sum_{j=1}^{p} \alpha_{1,ij} AI_{i,t-j} + \sum_{j=0}^{q_1} \alpha_{2,ij} GF_{i,t-j} + \sum_{j=0}^{q_4} \alpha_{3,ij} \mathrm{control}_{i,t-j} + \epsilon_{it} \tag{4}$$

where i is the province, t is the time, αi denotes the constant effect, α1 −α3 represent the lagged coefficient of explanatory variables and regressors, and ϵ_{it} is the error term. In panel error correction (ECM), the model will be constructed as:

$$\Delta HQUD_{it} = \alpha_i + \sum_{j=1}^{p} \alpha_{1,ij} \Delta AI_{i,t-j} + \sum_{j=0}^{q_1} \alpha_{2,ij} \Delta GF_{i,t-j} + \sum_{j=0}^{q_1} \alpha_{3,ij} \ln\, \Delta control_{i,t-j} + \beta_{2,ij} AI_{i,t-1} + \beta_{3,ij} GF_{i,t-1} + \beta_{3,ij} control_{i,t-1} + \varepsilon_{it} \tag{5}$$

where Δ is the first difference of the variables in the study, α1 − α5 indicate short-run coefficients, while β1 −β5 indicate long-run coefficients of AI, GF, and control variables, respectively. For estimating the short-run relationship, Hendry (1995)'s approach is followed to estimate the short-term effects as $\frac{\sum_{j=1}^{q_1} \alpha_{2,ij}}{\left(1-\sum_{j=0}^{p} \alpha_{1,ij}\right)}$. Once long-run relationship is established between independent and dependent variables, the panel ECM model will be expressed as follows:

$$\Delta HQUD_{it} = \alpha_i + \sum_{j=1}^{p} \alpha_{1,ij} \Delta AI_{i,t-j} + \sum_{j=0}^{q_1} \alpha_{2,ij} \Delta GF_{i,t-j} + \sum_{j=0}^{q_1} \alpha_{3,ij} \Delta control_{i,t-j} + \theta_i ECM_{i,t-1} + \varepsilon_{it} \tag{6}$$

where θ_i is the coefficient of ECM, which measures the adjustment speed that is made every year toward long-run equilibrium. The optimal lag length is chosen by Akaike's lag selection criteria, and the maximum lag length chosen in this study is two due to the limited number of annual observations.

Empirical results

Pre-diagnostic results

Unit-root test results

The results of first-generation unit root tests LLC and IPS (reported in table 3) show important insights into the stationarity of the variables of this study. LLC test results at levels show that many variables are non-stationary, which indicates the existence unit root for these variables. These results remain consistent when considering the trends with a constant for the LLC test. Similarly, the majority of the variables are non-stationary at levels for the IPS test for both constant and constant-trend patterns. This non-stationary nature of variables can be problematic for regression analysis because of the spurious relationship when correlations between variables could be misleading. This nature of panel data can be due to the macroeconomic factors of inflation, policy changes, or technological progress. To address this problem, we transform the variables by taking their first differences. The results of the LLC and IPS test show that at first differences, all variables become stationary, and this behavior remains consistent when both constant and trend patterns are included in the models. This transformation addressed the unit-root problem and made variables suitable for further regression analysis.

Table 3: First-generation unit root tests

	LLC Test				IPS test			
	At Levels		At First difference		At Levels		At First difference	
Variable	(Constant)	(Constant, trend)	(Constant)	(Constant, trend)	(Constant)	(Constant, trend)	(Constant)	(Constant, trend)
HQUD	-1.8532	-13.2279	-13.1589***	-13.4378***	7.1584	-5.3120***	-14.9982***	-10.7911***
GF	-1.0760	-18.8182***	-25.8734***	-26.9191***	5.4391	-4.6910***	-15.3084***	-11.1550***
AI	-2.3443	-18.9479***	-26.9054***	-27.5395***	2.-7899	-12.3451	-14.8101***	-12.4271***
INOV	-6.4824***	-13.0949***	-21.1746***	-25.9265***	-2.1116	2.8369	-2.0760***	-3.8863***
GDP	-11.8506***	-9.3535	-10.2826***	-18.6097***	4.0419	2.3443	-6.2816***	-2.6928***
Capital	-4.5734	-11.7618***	-17.0343***	-18.0489***	-6.7424	5.4941	-1.3038***	-4.8548***
Edu	-16.0693***	-7.6228	-10.5359**	-20.9585***	7.1584	-5.3120***	-14.9982***	-10.7911***

Note: *, **, and *** represent the significance level at 10%, 5%, and 1% respectively.

The first-generation unit root tests don't account for cross-sectional dependence and their results could not be accepted if cross-sectional dependence exists across panels of study. For this purpose, we employed Pesaran CD test to check whether cross-sectional exists among variables or not. The results of cross-sectional dependence are shown in Table 4, and it is apparent that cross-sectional dependence exists for all variables of the study. This suggests that shock to one unit may have a significant impact on other units. This study is based on China's provinces, so there could have been strong inter-connectedness across all the regions of the economy. Additionally, we also test for multicollinearity utilizing the variance inflation factor (VIF) values. VIF values for all explanatory and control variables are also reported in Table 4. The VIF values ranged from 1.51 to 2.52, indicating that VIF values for all variables are below the common threshold of 10. It confirms that multicollinearity is not the major concern in our analysis.

Table 4: Cross-sectional dependence and VIF tests

Variable	CD	VIF
HQUD	73.53***	
	(0.000)	
GF	81.41***	1.59
	(0.000)	
AI	74.01***	2.47
	(0.000)	
INOV	28.72***	1.51
	(0.000)	
GDP	84.39***	2.52
	(0.000)	
CAPITAL	72.90***	1.62
	(0.000)	
EDU	84.81***	2.23
	(0.000)	

Note: *, **, and *** represent the significance level at 10%, 5%, and 1% respectively. p-values in brackets.

Based on the results of the Pesaran CD test, we need to employ a second-generation unit-root test, Pesaran CADF (Cross-Sectionally Augmented Dickey-Fuller). This test assesses the stationarity of the variables in the presence of cross-sectional dependence. The results of the Pesaran CADF test (reported in Table 5) show that at levels, most variables are not stationary when only constant or constant with trend pattern is included in models. However, after transforming into first differences, the majority of variables demonstrate stationarity, as evidenced by highly significant results for all variables. This finding leads us to use variables at first differences for further econometric analysis to ensure the reliability and validity of the subsequent analyses.

Table 5: Cross-Sectional Augmented Dickey-Fuller (CADF) Test

Variable	At level		At first difference	
	(Constant)	(Constant, trend)	(Constant)	(Constant, trend)
HQUD	-1.285	-1.867	-2.338***	-1.628***
	(0.992)	(0.990)	(0.001)	(0.009)
GF	-2.723***	-2.652**	-3.392***	-3.386***
	(0.000)	(0.023)	(0.000)	(0.000)
AI	-2.427***	-2.119	-3.069***	-2.970***
	(0.000)	(0.826)	(0.000)	(0.000)
INOV	-2.205**	-1.828	-2.485***	-2.764***
	(0.005)	(0.995)	(0.000)	(0.006)
GDP	-1.965	-2.443	-2.896***	-3.442***
	(0.100)	(0.199)	(0.000)	(0.000)
Capital	-2.142**	-1.948	-1.948***	-1.781***
	(0.012)	(0.970)	(0.000)	(0.001)
Edu	-2.076**	-2.472	-2.896***	-3.121***
	(0.029)	(0.157)	(0.000)	(0.000)

Note: *, **, and *** represent the significance level at 10%, 5%, and 1% respectively. p-values in brackets.

Co-integration test results

The Pedroni co-integration test results (reported in Table 6) present comprehensive insights into the long-term relationship among the variables of this study. The Modified Phillips-Perron t statistic value is significant and positive with and without trend, which indicates the existence of robust co-integration across the panels. The Phillips-Perron t statistic values are also significant with and without trends, indicating the existence of long-term relationships among variables. The Augmented Dickey-Fuller (ADF) t statistic values suggest that the relationship across panels is complex and dependent on trend factors. Finally, the variance ratio statistic, with its significant positive values, confirms the existence of long-term co-integrated relationships among variables. These results indicate short-term fluctuation in the association of variables; however, there is the existence of long-term co-integration among all these variables. These findings imply us to move further to check the short-term and long-term associations between variables of the study.

Table 6: Pedroni cointegration test

Test Statistic	(Without Trend)	(With Trend)
Panel Test Statistics		
Modified Phillips-Perron t	7.9237***	9.8478***
	(0.0000)	(0.0000)
Phillips-Perron t	-0.2270**	0.5999**
	(0.0412)	(0.0274)
Augmented Dickey-Fuller t	-3.7014***	-1.4693*
	(0.0001)	(0.0709)
Variance Ratio	8.7342***	11.3333***
	(0.0000)	(0.0000)

Note: *, **, and *** represent the significance level at 10%, 5%, and 1% respectively. p-values in brackets.

Panel ARDL test results

The PMG estimations results (reported in Table 7) present benchmark insights into the long-run and short-run effects of green finance and artificial intelligence on high-quality urban development. In the long run, the coefficients for the variables GF (green finance) and AI (artificial intelligence) are positive and highly significant. This indicates that accelerating the development of green finance and AI across China's provinces significantly promotes high-quality urban development. Specifically, the coefficient for GF is 2.79730, indicating that a unit increase in green finance tends to promote high-quality urban development by 2.79730. AI's coefficient of 0.58047 suggests that an increase in one unit of artificial intelligence accelerated high-quality urban development by 0.58047. Additionally, the coefficients for AI, GDP, and Edu are positive and significant, indicating their positive role in fostering high-quality urban development across the provinces of China. However, Capital's (government investment) coefficient is negative and shows that an increase in government investments could lead to negative long-term effects on high-quality urban development.

Table 7: PMG estimations

Variable	Coefficient	Standard Error
Long-Run Coefficients		
GF	2.79730***	0.81855
AI	0.58047***	0.15423
INOV	1.75533***	0.66064
GDP	5.20155***	1.77181
Capital	-0.20604**	0.09594
Edu	2.61500*	1.70277
Short-Run Coefficients		
EC Term	-0.70687***	0.046299
D_GF	0.067811***	0.000422
D_AI	0.00088	0.00062
D_INOV	0.02038***	0.00497
D_GDP	0.03192*	0.01930
D_CAPITAL	0.00026	0.00032
D_EDU	0.02321***	0.00481
Constant	4.10038**	1.95555

Note: *, **, and *** represent the significance level at 10%, 5%, and 1% respectively.

In the short run, the error correction term (EC Term) is negative and highly significant, which reflects a strong adjustment speed toward long-term equilibrium after the short-term shocks to the explanatory variables. The results show that green finance's impact on high-quality urban development is small in the short run, indicated by a coefficient of 0.067811. In the short run, artificial intelligence does not support high-quality urban development, as indicated by its insignificant value. The short-run effects of control variables are also small, suggesting that all these factors support high-quality urban development in the long run. Overall, these results suggest that green finance fosters high-quality urban development in both time zones, short-run and long-run; however, AI's impact on high-quality urban development can be leveraged only in the long run.

In summary, these baseline results are also in line with recent work on China. Using the green-finance reform pilot as a quasi-natural experiment, Xu et al. (2025) report sustained improvements in inclusive green growth, which supports our large long-run GF effect and the small short-run movement. For spatial conditions, evidence from Beijing shows that mobility constraints at metropolitan margins weaken the translation of policy into development gains (Zhao et al., 2025), consistent with our finding that effects strengthen as capacity accumulates. At the network level, research on air–rail intermodal development finds cooperative, long-run payoffs where connectivity is higher (Sun et al., 2025), which matches our result that structural improvements—finance depth, technology, and transport links—raise HQUD over the long run. Furthermore, our study's findings support the view presented by Rieder et al. (2022) that artificial intelligence fosters the sustainable urban development.

Dynamic fixed effects test results

To confirm the robustness of PMG estimations, this study employs the dynamic-fixed effects (DFE) model, which is a robust econometric approach to account for individual heterogeneity and dynamic adjustments across panels (Pesaran et al., 1999; Sarafidis & Wansbeek, 2012). The DFE model is particularly useful in scenarios where the relationship between variables is relatively stable across units, as shown by CD test results. This is a robust alternative to the PMG estimator as it reduces potential biases caused by the cross-sectional dependence or variations in adjustment speed across panels of a study. The DFE model assumes homogeneity in the slope coefficients across provinces, which contrasts with the PMG's allowance for heterogeneous short-run dynamics. This comparison helps confirm whether the key long-term relationships—especially those between AI, GF, and HQUD—hold under more restrictive assumptions. Additionally, the DFE model controls for unobserved province-level effects and dynamic adjustments, further validating our findings. The results of the DFE model (reported in Table 8) present the positive and significant coefficients for GF and AI, validating the long-term effects of artificial intelligence and green finance on high-quality urban development across provinces of China. The magnitude of the long-term effects of GF and AI is generally lower compared to PMG estimation, which could be due to dynamic adjustments across the entire panel. In the short run, the error correction (EC) term is negative and significant, which is smaller in magnitude compared to PMG estimations, suggesting a consistent adjustment speed towards equilibrium. The

Table 8: Dynamic fixed effects test results

Variable	Coefficient	Standard Error
Long-Run Coefficients		
GF	2.20233***	0.30109
AI	0.35186**	0.16494
INOV	0.10707***	0.02326
GDP	0.70066*	0.36313
Capital	-0.29479**	0.11213
Edu	1.73656*	0.94275
Short-Run Coefficients		
EC Term	-0.50341**	0.25088
D_GF	0.07015***	0.00065
D_AI	0.04465	0.21539
D_INOV	0.01416**	0.00778
D_GDP	1.48165	5.269163
D_CAPITAL	0.03506	0.12324
D_EDU	1.81212	5.82434
Constant	6.82366***	1.53227

Note: *, **, and *** represent the significance level at 10%, 5%, and 1% respectively.

positive immediate impact of green finance on high-quality urban development is validated by the DFE model. The impact of AI on HQUD remains insignificant in the short run, as shown in Table 8. These robustness results are also consistent with recent evidence from China that considers finance and technology together. Using the green-finance reform pilot, Xu et al. (2025) show that the growth and environmental gains remain when alternative estimators and controls are used, which matches our positive long-run GF effect under DFE. At the mechanism level, Dong and Yu (2024) find that green bond issuance raises real green innovation, helping explain why GF retains significance even when short-run gains are small. On the technology side, city-scale work that applies multimodal, AI-based urban analytics reports improvements in urban safety and amenity as digital capacity deepens (Zhang et al., 2025). This aligns with our result that AI contributes in the long run while its short-run effect is limited. Overall, these results support the robustness of benchmark findings by showing the positive role of green finance in fostering high-quality urban development in the short-run and long-run. However, artificial intelligence's positive role in promoting high-quality urban development is proven only in the long run.

Regional heterogeneity

To explore regional disparities, provinces are grouped into eastern, central, and western categories based on China's National Bureau of Statistics classifications, which reflect economic maturity, innovation capacity, and infrastructure readiness. This study delves into the effects of AI and GF on HQUD across central, eastern and western regions of China. Central and eastern regions are classified as developed regions, while western regions are classified as under-developed regions. The heterogeneity results are shown in Table 9, which suggests that in the central and eastern regions, there is a greater and significant effect of artificial intelligence and green finance to boost high-quality urban development. The impact of both green finance and artificial intelligence on high-quality urban development is found to be significant and positive in the short run. These results imply that in central and eastern regions, the effects of both GF and AI on HQUD are highly significant and positive in the short run and long run, indicating their robust role in developed regions. This could be due to the developed infrastructure, technological integrations, and greater innovations across these regions.

The results for the western regions show significant differences from the central and eastern regions. The coefficients for GF and AI are still positive but lower in magnitude for the western regions, indicating that green finance and artificial intelligence are supporting these provinces to foster high-quality urban development, but the impact is smaller. This could be due to ineffective infrastructure, challenges in financial inclusion, and the limited presence of industries across these provinces. The short-term impact of green finance is also found within western regions, and we find that AI does not support HQUD in the short run in these provinces. Overall, these results suggest that there is the existence of heterogeneity effects of GF and AI on HQUD across the provinces of China. These results confirm that provinces with advanced industrial ecosystems and better digital-financial integration experience more immediate gains from AI and GF. Western regions, facing resource and structural limitations, require tailored strategies to fully benefit.

Table 9: PMG estimations across regions

Variable	Eastern and Central Regions	Western regions
Long-Run Coefficients		
GF	3.03847***	1.51999**
	(0.72012)	(0.84372)
AI	0.49301***	0.39455*
	(0.049092)	(0.21083)
INOV	0.48496	0.32409**
	(0.78986)	(0.15037)
GDP	3.57497***	5.84049
	(1.21848)	(5.342732)
CAPITAL	-0.46717	-0.20715**
	(0.28922)	(0.07778)
EDU	2.55531**	2.32631***
	(1.20409)	(0.41093)
Short-Run Coefficients		
EC Term	-0.17724***	-0.74291***
	(0.01437)	(0.08376)
D_GF	0.08901***	0.05501***
	(0.00237)	(0.00128)
D_AI	0.05774***	0.04016
	(0.00162)	(0.07675)
D_INOV	0.02554*	0.02643
	(0.01471)	(0.04899)
D_GDP	1.12372***	0.30730**
	(0.31605)	(0.122371)
D_CAPITAL	0.01082	-0.00918
	(0.02382)	(0.01615)
D_EDU	0.71576	-0.03872
	(1.33034)	(0.64538)

Variable	Eastern and Central Regions	Western regions
Constant	7.42648***	8.47998***
	(1.35336)	(2.42213)

Note: *, **, and *** represent the significance level at 10%, 5%, and 1% respectively.

Conclusion and Policy implications

In the context of China's accelerating urbanization, widening regional inequalities, and growing ecological pressures, achieving high-quality urban development (HQUD) has emerged as a central policy goal for this country. However, the complex interplay between financial innovation, digital technologies, and multidimensional development outcomes remains insufficiently understood. This study contributes to filling this gap by providing new empirical evidence on how artificial intelligence (AI) and green finance (GF) influence HQUD across China's provinces. By integrating AI and GF in one dynamic panel and reporting region-specific long- and short-run effects on a composite HQUD index, we provide evidence the prior literature lacks: the combined and heterogeneous transmission of technology and green finance to high-quality urban development. Using panel data from 31 provinces of China for the period 2007-2022, this study examines the role of artificial intelligence (AI) and green finance (GF) in promoting high-quality urban development (HQUD) in China. A co-integration test is employed to identify the long-term association between the variables. Based on the results of unit root tests, we use the Pooled Mean Group (PMG) estimation approach to assess the short-term and long-term effects of AI and GF on HQUD. The benchmark results indicate that green finance significantly fosters high-quality urban development in both the short run and the long run. However, artificial intelligence contributes to high-quality urban development only in the long run. The dynamic fixed effects approach is further employed as a robustness check, and its results validate the benchmark findings. Furthermore, the heterogeneity analysis reveals that green finance and artificial intelligence have immediate and long-term effects on high-quality urban development in the central and eastern regions. In the case of the western regions, the impact of artificial intelligence on high-quality urban development is observed only in the long run, while green finance influences both the short run and the long run.

The findings of this study present several policy implications to promote high-quality urban development across all regions of China. Based on the short and long-term positive effects of green finance, First, policymakers should promote the expansion and deepening of green financial instruments, particularly in underdevelopment regions where the impact is a little lower. Regional governments should provide targeted incentives, subsidies, and grants to support the development of green financial infrastructure across all the provinces. Second, to extend the impact of AI development, policymakers should focus on closing the digital infrastructure gap and ensuring equitable access to AI-enabling technologies in western provinces. Specifically, it is suggested to promote AI education across all cities and provinces of China, which will not only upgrade people's skills but will also enable them to support high-quality urban development. Third, there is need to foster innovation ecosystems to accelerate the adoption and integration of AI technologies across all industries. The local innovation ecosystems—particularly in western China—must be strengthened through AI incubators, public-private partnerships, and regional innovation hubs. Such efforts can help translate long-run AI investments into tangible development outcomes in the medium term. Last, there is a need for tailored governance approaches that could be accountable for the specific needs and development levels of different regions to leverage the benefits of green finance and AI development in China to foster their role in high-quality urban development. This study is subject to limitations. First, while the panel captures provincial-level dynamics, it may not reflect intra-provincial variations. Second, endogeneity concerns—especially reverse causality between HQUD and AI/GF—may persist despite methodological precautions. Future work could employ instrumental variable techniques or natural experiments.

Competing interest statement:

The authors declare that they have no known competing financial interests or personal relationships which could have appeared to influence the work reported in this paper.

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Data availability statement

Data will be made available on reasonable request.

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