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Evaluation of the Development of Intelligent-Construction Pilot Cities in China Based on the Entropy Method and TOPSIS

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Abstract: In order to encourage digital transformation in the traditional construction industry, the Chinese government has promoted 24 pilot cities to develop intelligent construction. The practices of intelligent construction are disparate in all 24 pilot cities. Given this context, it is important to effectively and comprehensively evaluate the level of intelligent construction in these pilot cities. This study thus evaluates the development of intelligent construction in different pilot cities. By conducting an in-depth analysis of the existing literature and policies, an evaluation system consisting of five dimensions and a total of 30 indicators is established. The entropy method and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are used to evaluate the development of intelligent construction in 23 pilot cities. The research findings indicate that the development of intelligent construction in different pilot cities is uneven, with clear gaps between first-tier cities and Western cities. The development of industries, the cultivation of talent, and economic growth are relatively satisfactory, while technological innovation and digital infrastructure are insufficient. Several suggestions are proposed to promote the development of intelligent construction, including expediting the construction of intelligent infrastructure, enhancing digital transformation, promoting technological innovation, and implementing talent cultivation strategies.

Keywords: intelligent construction; pilot cities; China; entropy method; TOPSIS

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1. Introduction

The construction industry, as a key driver of economic growth, is facing a range of challenges, including poor productivity, cost overruns, widespread safety risks, an increasingly acute shortage of labor, and energy-extensive consumption [1]. With the development of modern science and technology, the traditional construction industry is undergoing profound changes. The global construction industry is transforming into so-called intelligent construction, which integrates modern information technologies into construction industry processes, encompassing cyber–physical systems, robotics, artificial intelligence (AI), the Internet of Things (IoT), digital twin (DT), and big data [2–4]. The development of intelligent construction not only effectively improves project efficiency at various stages, such as the design, construction, and operation stages, but also demonstrates enormous potential in quality control, resource management, and risk prediction [5].

In order to promote the development of intelligent construction, many countries have put forward a series of supporting policies. For example, Construction 2025 proposed by the United Kingdom sets out a roadmap for digital innovation in the construction industry through the integration of construction processes, structural data, and AI [6]. The UK government set a goal to reduce 33% of lifecycle costs and 50% of carbon emissions in the construction industry, as well as increasing construction export production by 50%. In

Germany, the government has issued a roadmap for digital design and construction, encouraging the application of BIM in construction project processes [7]. An "i-Construction" strategy has been proposed by Japan in order to realize the digital transformation of the construction industry and increase production efficiency by 20% before 2025 [8]. In the Fourteenth Five-Year Plan and outline of vision goals for 2035 published by China, the development of intelligent construction through the application of 5G, AI, the IoT, and other information technologies is proposed [9].

In order to develop intelligent construction, a total of 24 pilot cities in China have been announced by the Ministry of Housing and Urban–Rural Development [10]. These pilot cities have published city-level implementation plans on smart construction and relevant standards. However, there is currently no unified framework or common paradigm for evaluating the development of intelligent construction across these cities. Despite the enormous potential demonstrated by smart building technology, its implementation still faces numerous challenges. Traditional construction companies often encounter difficulties in integrating intelligent technologies such as the IoT and AI into their existing processes, especially for small and medium-sized enterprises. These companies struggle with insufficient technological adaptability and face significant barriers to digitalization due to high infrastructure investment costs and the need for technological upgrades [5]. Additionally, the adoption rate of smart building technology is relatively slow in economically underdeveloped regions, primarily due to inadequate digital infrastructure and insufficient training for technical personnel [11]. Each pilot city has adopted a different approach to promoting intelligent construction, resulting in varying degrees of progress. Despite the importance of these initiatives, comprehensive assessments of intelligent construction development at the city level remain scarce. Existing studies have often focused on individual aspects of intelligent construction, such as specific technologies or policy impacts, without providing an evaluation of overall progress across cities. Therefore, this article aims to employ an entropy weight evaluation model to assess the developmental status of intelligent construction in different pilot cities. This approach allows for a multi-dimensional comparison of intelligent construction across different regions, providing a framework for evaluating progress and identifying key factors driving development. The findings are expected to aid the identification of influential factors for intelligent construction in these pilot cities, while formulating corresponding strategies to foster the advancement of intelligent construction and address any imbalances during the development stage.

2. Literature Review

Although the application of intelligent construction is flourishing, researchers have not reached a consensus regarding the definition of intelligent construction. Intelligent construction serves as a key driving force for the high-quality development of the construction industry, not only promoting its digital transformation and achieving improvements in efficiency but also fostering green and sustainable development [12]. Intelligent construction has accelerated the integration of the construction industry and the digital economy, providing a new impetus for overcoming development bottlenecks and enhancing core competitiveness in the field of architecture [13]. Several scholars have pointed out that intelligent construction integrates technologies such as smart computers and information communication into physical construction projects, enabling the management and control of the personnel, machinery, equipment, and facilities involved in the construction process [14]. Davila Delgado et al. [15] argue that intelligent construction transforms the construction industry through new technologies such as robotics, reducing excessive reliance on manual labor to improve precision in construction, reduce resource waste, and achieve higher efficiency in building projects.

With the increasing demand for intelligent construction technology in complex projects, there has been close integration of intelligent construction technology and engineering practices. For example, an IoT-based BIM platform has been developed to collect and analyze real-time data during the on-site assembly process of prefabricated components, thereby providing on-site assembly services for modular construction and improving site management efficiency [16]. In one study, an intelligent cloud platform was proposed for managing on-site operations in large-scale engineering projects [17]. Also, another cloud computing platform has been proposed in order to achieve intelligent control and provide services on construction sites [18]. The implementation of digital technology can enhance the efficiency of constructing intelligent buildings and mitigate energy consumption [2]. An intelligent framework has also been proposed to monitor personnel, machinery, and other risks on construction sites in real time [19].

Many researchers and practitioners have attempted to apply one or more information technologies in construction projects, including construction robots, AI, the IoT, and BIM. Robots have been adopted to drive transformation in the construction industry, reducing the reliance on scarce labor while improving accuracy, minimizing waste, and lowering project costs [15]. BIM technology combined with 3D laser scanning has been applied to inspect the appearance and quality of prefabricated components [20]. An unmanned driving compactor has been developed to improve the compaction quality of soil and rock dams [21]. By using artificial intelligence, control theory, and adaptive system technology, an intelligent observation platform framework has been developed to acquire real-time data from construction sites [22]. Further, an intrusion monitoring system based on IoT technology has been used to monitor construction sites in real time and prevent accidents related to building safety [23]. An AI-based computer vision technology has been proposed to improve the quality of construction projects [24]. An innovative BIM management model has also been developed to optimize the management of personnel, materials, machinery, and resource allocation with timely decisions [25]. Kochovski et al. [26] have also developed an Internet of Things application program to support high-quality service environments in smart buildings.

With these increasing applications, it is necessary to evaluate the performance of intelligent construction. There are several studies that have already evaluated the performance of intelligent construction techniques applied in construction projects, companies, and the whole industry. Zhang et al. [27] adopted diffusion of innovations (DOI) and technology–organization–environment framework (TOE framework) theories to identify influencing factors in the digital transformation of the construction industry and to evaluate different policies for supporting digital transformation. In terms of the evaluation of specific intelligent construction technologies, Oke et al. [28] assessed the application areas of IoT technology in the construction industry. Cong et al. [29] established specific evaluation indicators to evaluate the performance of blockchain technology. Meanwhile, several studies have shifted their focus to evaluating the application of intelligent construction technology at the project or enterprise level. Succar et al. [30] developed an evaluation model with twelve indicators (e.g., market, industry, and project team) and five levels of maturity for application in intelligent construction. However, none of the aforementioned technological research has been discussed in conjunction with the implementation of intelligent construction at the city level, and specific evaluation systems have not yet been established for this concept.

The construction sector plays an increasingly important role in bolstering the economy and stabilizing employment. Intelligent construction can bring new momentum to the development of the construction industry [31]. Hence, the development of intelligent construction tends to push the construction sector onto greener, smarter, and safer paths [32].

Intelligent construction leads to profound changes in the construction industry, including in regard to projects, employment opportunities, and construction enterprises [33]. The construction industry mainly provides pilot projects for intelligent construction. Intelligent construction not only introduces new requirements for construction professionals and employees but also increases the total profits and number of products of industrial companies [34].

Technological innovation also plays a vital role in the transformation of intelligent construction [35]. In order to promote intelligent construction, construction companies are encouraged to input research and development funds and employ R&D personnel so as to develop the systems and technologies required in intelligent construction [36].

Intelligent construction has also reshaped the demand for talent in the construction industry, resulting in a need for professionals with digital and intelligent skills [37]. Besides construction professionals, front-line construction personnel are also expected to adapt to digital transformation trends. Training for construction workers is essential in relation to operating construction-site robots and intelligent machines [38].

Digital transformation is indispensable for the development of intelligent construction and leads to advancements in the whole sector [12]. It not only greatly improves the efficiency and quality of construction, but also leads technological innovation and advancement within the industry. Digital infrastructure mainly involves the generation of new information and communication technologies, such as 5G, data centers, cloud computing, artificial intelligence, the IoT, blockchain, and various digital platforms formed based on these technologies to help people work and live better.

In order to develop intelligent construction, the Chinese government has announced 24 pilot cities, including Beijing, Shenzhen, and Guangzhou. This pilot-city program is used by the government to promote innovation and industrial transformation at the city or province level [39]. Yu et al. [40] conducted a comparative evaluation of citizens' perceptions of benefits in smart cities by combining the Analytic Hierarchy Process (AHP) method and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. Zhang et al. [41] evaluated new first-tier cities in China using the entropy method and the TOPSIS method. Li et al. [42] assessed the impact of low-carbon pilot-city projects on residents' carbon emissions by establishing a difference-in-differences model. Otay et al. [43] evaluated the sustainable energy system in a smart city using interval-valued Pythagorean fuzzy (IVPF) sets and conducted comprehensive optimization using the "best worst" method (BWM), also taking into account multiple experts' opinions and the TOPSIS method. Therefore, it is crucial to choose appropriate evaluation methods, with commonly used methods including the entropy method and the TOPSIS method. These methods are not influenced by subjective factors, they have simple calculation formulas, and they lead to accurate, stable, and consistent results. They can also consider the correlations and interactions between different indicators.

Although there are several investigations evaluating pilot smart cities and low-carbon communities, it is still rare for research to assess intelligent construction in pilot cities. There remains a lack of consensus on a standardized definition and a unified framework for evaluating its progress across different urban contexts. Therefore, in this work, in order to compare the development of intelligent construction in each pilot city, evaluation indicators are identified and evaluated using the entropy method and the TOPSIS method. The findings are expected to fill the current research gap in assessing intelligent construction at the urban level, provide valuable insights for policymakers aiming to accelerate intelligent construction development, and enhance the quality and efficiency of the construction industry.

3. Methodology

This study introduces a research framework with which it is possible to evaluate the development of intelligent-construction pilot cities, as shown in Figure 1. In this framework, first, evaluation indicators for the development of intelligent construction in pilot cities are identified. Second, an evaluation model is constructed using the entropy method and the TOPSIS method. The entropy method is employed to calculate indicator weights, while the TOPSIS method is applied to rank the pilot cities based on their performance. Relevant recommendations can thus be proposed.

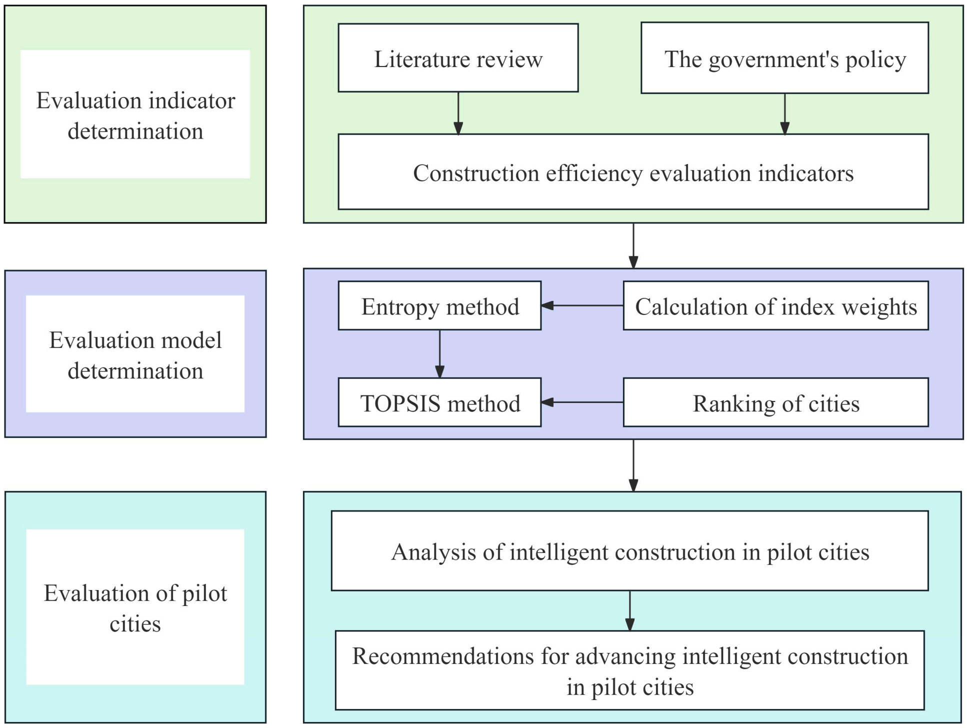

Figure 1. Methodological framework.

We selected the entropy and TOPSIS methods for their ability to handle multiple criteria objectively. Entropy minimizes subjectivity by assigning weights based on data variability, ensuring a fair and unbiased evaluation process. TOPSIS excels at ranking cities by evaluating their distance from an ideal solution, which is particularly useful for comparing diverse performance metrics across different cities. While other methods, such as multi-criteria decision analysis (MCDA) or regression models, could have been considered, they present certain limitations. MCDA methods often require subjective input to determine the importance of each criterion, which can introduce bias. Similarly, regression models assume predefined relationships between variables and are better suited for predictive analysis rather than ranking alternatives across multiple dimensions. In contrast, entropy and TOPSIS offer a more objective and comprehensive approach to evaluating intelligent construction development across regions with varying characteristics.

3.1. Evaluation Indicators

In order to establish a comprehensive and effective evaluation index system for the development of intelligent-construction pilot cities, we conducted an analysis of relevant works in the literature and government policies. The research on evaluation indicators is shown in Table 1. These studies provided a theoretical foundation by highlighting the key dimensions necessary for evaluating intelligent construction. Considering urban development policies and the challenges in data acquisition, a framework for evaluating indicators was established. Based on the development of Chinese cities, evaluation indicators with which to assess intelligent-construction pilot cities are illustrated in Table 2. The evaluation indicators consist of 5 primary indicators—industrial development (A), technical innovation (B), talent cultivation (C), economic growth (D), and digital transformation (E)—and 30 secondary indicators.

The level of development in the intelligent construction industry is evaluated based on industrial progress, which involves adopting intelligent construction processes in pilot projects, stimulating employment opportunities, enhancing income levels, and fostering social stability along with sustainable growth [33]. The corresponding secondary indicators include the number of pilot projects (A1), the number of large-scale industrial enterprises

(A2), the number of employees in the construction industry (A3), the total number of construction companies (A4), the total output value of the construction industry (A5), and the total profits of large-scale industrial enterprises (A6).

Technical innovation is utilized as a metric to assess the capacity and efficiency of converting technological achievements in the construction industry, which constitutes a pivotal factor in bolstering national competitiveness and fostering economic development [44]. The corresponding secondary indicators include the number of personnel engaged in R&D (B1), the total value of transactions for technology contracts (B2), the number of granted patents (B3), scientific and technological expenditure (B4), and internal R&D funds (B5).

Talent cultivation is adopted to evaluate the effectiveness of pilot cities in fostering and attracting talent within the field of intelligent construction, because human resources play an indispensable role in advancing research on, and promoting the application and dissemination of, intelligent construction technology. The corresponding secondary indicators include the number of higher-education institutions (C1), educational expenditure (C2), the total number of registered professionals (C3), the number of education practitioners (C4), the number of construction industry practitioners (C5), and the number of undergraduates and college students (C6).

The development of intelligent construction not only depends on economic growth and support, but also benefits economic development [31]. The secondary indicators under economic development include per capita GDP (D1), the proportion of the secondary industry to the GDP (D2), fixed-asset investment (D3), total retail sales of consumer goods (D4), residents' annual per capita disposable incomes (D5), completed real estate investments (D6), and the proportion of tertiary industries to the GDP (D7).

Digital transformation plays a crucial role in evaluating the future potential, competitiveness, and sustainability of pilot cities. The secondary indicators for this parameter include postal service revenues (E1), telecommunication service revenues (E2), the number of internet broadband access users (E3), the number of local telephone users at the end of the year (E4), the number of mobile phone users at the end of the year (E5), information transmission, and employment in the computer services and software industry (E6).

Table 1. Research on evaluation indicators.

Source / Index	Pan et al., 2023 [45]	Xu et al., 2018 [46]	Mao et al., 2023 [47]	Guo et al., 2022 [48]	Zhang et al., 2022 [41]	Ding et al., 2022 [49]	Shen et al., 2018 [50]
The number of large-scale industrial enterprises	√						
The total output value of the construction industry		√					
The total profits of large-scale industrial enterprises	√					√	
The number of personnel engaged in research and development (R&D)	√						
The number of granted patents	√			√	√		
Scientific and technological expenditure				√			
Internal research and development (R&D) funds	√				√	√	√
Educational expenditure							√
The number of education practitioners		√					
Per capita GDP	√		√	√	√	√	√
The proportion of secondary industries to GDP						√	
Residents' annual per capita disposable incomes					√	√	
The proportion of tertiary industries to GDP					√	√	
Postal service revenues		√					
The number of internet broadband access users	√		√		√		√
The number of local telephone users at the end of the year							√
The number of mobile phone users at the end of the year					√		√

Table 2. Evaluation indicators for assessing cities.

First-Level Indicator	Second-Level Indicators	Sources
Industrial development (A)	A1: The number of pilot projects (pieces)	Discussed in this work
	A2: The number of large-scale industrial enterprises (units)	Pan et al. (2023) [45]
	A3: The number of employees in the construction industry (10,000 people)	Xu et al. (2018) [46]
	A4: The total number of construction companies (units)	Discussed in this work
	A5: The total output value of the construction industry (CNY 100 million)	Discussed in this work
	A6: The total profits of large-scale industrial enterprises (CNY 10,000)	Pan et al. (2023) [45] Ding et al. (2022) [49]
Scientific and technological innovation (B)	B1: The number of personnel engaged in research and development (people)	Pan et al. (2023) [45]
	B2: The total value of transactions for technology contracts (CNY 100 million)	Discussed in this work
	B3: The number of granted patents (pieces)	Pan et al. (2023) [45] Guo et al. (2022) [48] Zhang et al. (2022) [41]
	B4: Scientific and technological expenditure (CNY 10,000)	Guo et al. (2022) [48]
	B5: Internal research and development funds (CNY 100 million)	Pan et al. (2023) [45] Zhang et al. (2022) [41] Ding et al. (2022) [49] Shen et al. (2018) [50]
Talent cultivation (C)	C1: The number of higher-education institutions (pieces)	Discussed in this work
	C2: Educational expenditure (CNY 10,000)	Shen et al. (2018) [50]
	C3: Total registered professionals (10,000 people)	Discussed in this work
	C4: The number of education practitioners (10,000 people)	Xu et al. (2018) [46]
	C5: The number of construction industry practitioners (10,000 people)	Guo et al. (2022) [48]
	C6: The number of undergraduates and college students (people)	Discussed in this work
Economic development (D)	D1: Per capita GDP (CNY)	Pan et al. (2023) [45] Guo et al. (2022) [48] Zhang et al. (2022) [41] Ding et al. (2022) [49] Shen et al. (2018) [50] Mao et al. (2023) [47]
	D2: The proportion of secondary industries to GDP (%)	Ding et al. (2022) [49]
	D3: Fixed-asset investment (CNY 100 million)	Discussed in this work
	D4: Total retail sales of consumer goods (CNY 10,000)	Discussed in this work
	D5: Residents' annual per capita disposable incomes (CNY)	Zhang et al. (2022) [41] Ding et al. (2022) [49]
	D6: Completed real estate investment (CNY 10,000)	Discussed in this work
	D7: The proportion of tertiary industries to GDP (%)	Zhang et al. (2022) [41] Ding et al. (2022) [49]

Table 2. *Cont.*

First-Level Indicator	Second-Level Indicators	Sources
Digital transformation (E)	E1: Postal service revenues (CNY 100 million)	Xu et al. (2018) [46]
	E2: Telecommunication service revenues (CNY 100 million)	Discussed in this work
	E3: The number of internet broadband access users (10,000 people)	Pan et al. (2023) [45] Zhang et al. (2022) [41] Shen et al. (2018) [50] Mao et al. (2023) [47]
	E4: The number of local telephone users at the end of the year (10,000 people)	Shen et al. (2018) [50]
	E5: The number of mobile phone users at the end of the year (10,000 people)	Zhang et al. (2022) [41] Shen et al. (2018) [50]
	E6: Information transmission and employment in the computer services and software industry (10,000 people)	Discussed in this work

3.2. Indicator Data Source

Following the evaluation indicators, relevant data were collected by consulting authoritative sources such as the *China Statistical Yearbook*, the *China City Statistical Yearbook*, and the *China Software Industry Statistical Yearbook*. Additionally, annual statistical yearbooks for provinces and cities, local statistical bulletins, and Government Work Reports were selected to ensure comprehensive data coverage. Considering the variations in data across different cities, all the data used were standardized, and the data used are from 2021. When cities report certain indicators using different units or metrics, they should be converted into a common unit to ensure data comparability across cities. In cases where data were missing, interpolation methods were employed. Specifically, missing values were replaced using the mean of the available data for each indicator. Mean imputation was selected because the amount of missing data was minimal. Mean imputation provided a straightforward and reliable way to maintain dataset integrity without introducing significant variance, making it an appropriate choice given the scope and goals of our analysis. Additionally, to control for potential biases in indicator selection, a standardized criterion was followed, prioritizing indicators relevant to intelligent construction and ensuring their availability across all cities. The entropy method, which is used to calculate the weights of each indicator, operates under the assumption that the indicators are independent of one another. The selected indicators were designed to represent distinct dimensions of intelligent construction. By ensuring that each indicator reflects a different aspect of development, we were able to reasonably maintain the independence assumption and preserve the overall reliability of the method. Due to the difficulty in obtaining relevant data on Xiong'an New Area, this article only presents evaluations for 23 intelligent-construction pilot cities in China (Table 3).

Table 3. Data sources for evaluation indicators.

Indicators		Data Sources	Websites
Industrial development (A)	A1	Ministry of Housing and Urban–Rural Development of the People's Republic of China	https://www.mohurd.gov.cn/gongkai/zhengce/zhengcefilelib/202211/20221109_768802.html (accessed on 17 June 2024)
	A2 A3	*China City Statistical Yearbook*	https://www.zgtjnj.org/navibooklist-n3023102607-1.html (accessed on 17 June 2024)
	A4 A5	The statistical yearbook of each city/local statistical bulletins	
	A6	*China City Statistical Yearbook*	https://www.zgtjnj.org/navibooklist-n3023102607-1.html (accessed on 17 June 2024)

Table 3. *Cont.*

Indicators		Data Sources	Websites
Scientific and technological innovation (B)	B1 B2	The statistical yearbook of each city/ local statistical bulletins	https://www.zgtjnj.org/navibooklist-n3023102607-1.html (accessed on 17 June 2024)
	B3 B4	*China City Statistical Yearbook*	
	B5	The statistical yearbook of each city	
Talent cultivation (C)	C1 C2	*China City Statistical Yearbook*	https://www.zgtjnj.org/navibooklist-n3023102607-1.html (accessed on 17 June 2024)
	C3 C4	The statistical yearbook of each city/ local statistical bulletins	
	C5 C6	*China City Statistical Yearbook*	https://www.zgtjnj.org/navibooklist-n3023102607-1.html (accessed on 17 June 2024)
Economic development (D)	D1 D2 D3 D4 D5 D6 D7	*China City Statistical Yearbook*	https://www.zgtjnj.org/navibooklist-n3023102607-1.html (accessed on 17 June 2024)
Digital transformation (E)	E1 E2 E3 E4 E5	*China City Statistical Yearbook*	https://www.zgtjnj.org/navibooklist-n3023102607-1.html (accessed on 17 June 2024)
	E6	*China Software Industry Statistical Yearbook* Government Work Report *China Statistical Yearbook* The statistical yearbook of each city	

3.3. Evaluation Model

To enhance the scientific and objective nature of the evaluation system, we established a multi-criteria evaluation model for intelligent-construction pilot cities using both the entropy method and the TOPSIS method.

The concept of entropy, originally developed in physics to quantify the level of disorder in a thermodynamic system, has been adapted in information theory as a measure of uncertainty [51]. In this study, entropy was used to calculate the weights of evaluation indicators, which were then applied in the TOPSIS stage. TOPSIS is a multi-criteria decision-making method that ranks alternatives based on their distance to an ideal solution and a negative ideal solution [52]. The entropy weights and TOPSIS rankings were calculated through the following steps.

(1) Establishing an evaluation system:

The characteristic value matrix of the evaluation system for the development of intelligent-construction pilot cities is shown in Equation (1), which uses n independent indicators to evaluate m intelligent-construction pilot cities:

$$R = \left(r_{ij}\right)_{n\times m} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix}_{n\times m} \quad (1)$$

where r_{ij} represents the score of city j for the evaluation indicator i, and a higher score indicates a greater development level of intelligent construction for that city in regard to this evaluation indicator.

(2) Standardization of data:

The characteristic values were standardized to eliminate differences caused by varying indicator dimensions, as shown in Equations (2) and (3):

$$x_{ij} = \frac{r_{ij} - \mathrm{Min}_i\{r_{ij}\}}{\mathrm{Max}_i\{r_{ij}\} - \mathrm{Min}_i\{r_{ij}\}} \quad (2)$$

$$x_{ij} = \frac{Max_i\{r_{ij}\} - r_{ij}}{Max_i\{r_{ij}\} - Min_i\{r_{ij}\}} \quad (3)$$

where $Max_i\{r_{ij}\}$ and $Min_i\{r_{ij}\}$ represent the maximum and minimum values under the same indicator i. x_{ij} is the value of the city i under the indicator i after unification, ranging from 0 to 1. With regard to the positive indicator in Equation (2), a higher value for this indicator corresponds to a better evaluation result. Conversely, for the negative indicator in Equation (3), a lower value for this indicator indicates a more favorable evaluation outcome.

(3) Determination of the entropy value of indicators:

The entropy weights of each indicator were calculated based on the matrix of standardized feature values. First, the entropy for each indicator was measured using Equation (4) [49]. Then, the entropy weights were calculated using Equation (5) [51]:

$$e_i = -k \sum_{j=1}^{m} p_{ij} \cdot \ln p_{ij} \quad (4)$$

Among these variables, $p_{ij} = \frac{x_{ij}}{\sum_{j=1}^{m} x_{ij}}$, $k = \frac{1}{\ln m}$, when $p_{ij} = 0$, $p_{ij} \cdot \ln p_{ij} = 0$.

$$w_i = \frac{1 - e_i}{\sum_{i=1}^{n} (1 - e_i)} \quad (5)$$

(4) Ideal solution and negative ideal solution:

The TOPSIS method was used to determine the ranking of the studied intelligent-construction pilot cities. First, the ideal solution and negative ideal solution were determined. Second, the distances between objective values and both the ideal solution and negative ideal solution in the objective space were measured [53]. Then, the value closest to the ideal solution was identified, while being furthest from the negative ideal solution, as the optimal solution. Finally, rankings were assigned based on distances to both the ideal and negative ideal solutions. The closer the distance to the ideal solution and the further the distance from the negative ideal solution, the higher the ranking [54].

According to the standardized characteristic values of the intelligent-construction pilot cities based on the evaluation indicators, the ideal solution and negative ideal solution were determined via Equations (6) and (7).

Ideal solution: $A^+ = \left(v_1^+, v_2^+, \cdots, v_n^+\right)$

$$v_i^+ = \begin{cases} Max_i\{v_{ij}\}, i \in J \\ Min_i\{v_{ij}\}, i \in J' \end{cases} \quad (6)$$

Negative ideal solution: $A^- = \left(v_1^-, v_2^-, \cdots, v_n^-\right)$

$$v_i^- = \begin{cases} Max_i\{v_{ij}\}, i \in J \\ Min_i\{v_{ij}\}, i \in J' \end{cases} \quad (7)$$

The expressions $Max_i\{v_{ij}\}$ and $Min_i\{v_{ij}\}$ indicate the respective maximum value and minimum value under indicator i. j represents the set of positive indicators, while j' represents the set of negative indicators.

(5) Distance calculation:

The distance from pilot city j to the ideal point and negative ideal point was determined according to Equations (8) and (9).

$$\theta_j^+ = \sqrt{\sum_{i=1}^n \left(v_i^+ - v_{ij}\right)^2} \tag{8}$$

$$\theta_j^- = \sqrt{\sum_{i=1}^n \left(v_i^- - v_{ij}\right)^2} \tag{9}$$

In these equations, θ_j^+ represents the distance from city j to the positive ideal solution, while θ_j^- represents the distance from city j to the negative ideal solution.

(6) Ranking the development performance of pilot cities:

We calculated the proximity coefficient θ_j for each pilot city and ranked the development performance of each intelligent-construction pilot city. The higher the value of θ_j, the higher the ranking of the city, indicating a greater level of development of intelligent construction within these pilot cities, as shown in Equation (10).

$$\theta_j = \frac{\theta_j^-}{\theta_j^+ + \theta_j^-} \tag{10}$$

4. Results

The traditional construction industry can no longer meet developmental needs and urgently requires transformation toward intelligence and informatization. To expedite this process, 24 pilot cities for intelligent construction have been unveiled, with the aim of driving transformative development in the building industry through technological innovation. Due to data collection difficulties in regard to Xiong'an New Area, an evaluation of 23 intelligent-construction pilot cities was conducted in this study, including Beijing, Tianjin, Baoding, Shenyang, Harbin, Nanjing, Suzhou, Wenzhou, Jiaxing, Taizhou, Hefei, Xiamen, Qingdao, Zhengzhou, Wuhan, Changsha, Guangzhou, Shenzhen, Foshan, Chongqing, Chengdu, Xi'an, and Urumqi. The geographical locations of the 23 pilot cities are shown in Figure 2.

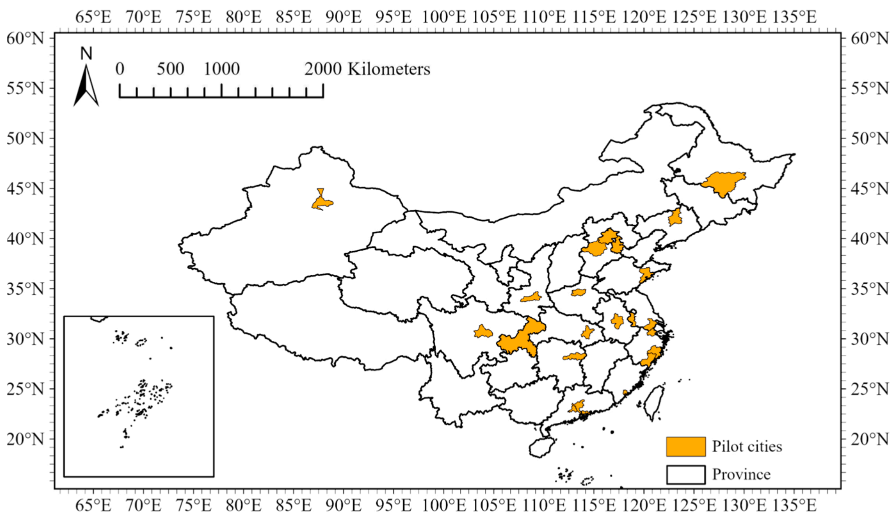

Figure 2. Geographical locations of the pilot cities.

By employing the entropy method to analyze data from 30 indicators across 23 cities, evaluation weights for each indicator were determined and are presented in Table 4. By employing the TOPSIS method, the weighted data were processed to obtain the final evaluation results. Among the 23 intelligent-construction pilot cities, the proximity coefficients of the indicators were calculated, and these are ranked in Table 5. The proximity coefficients of the five primary indicators (industrial development, scientific and technological innovation, talent cultivation, economic development, and digital transformation) are denoted as θ_j^A, θ_j^B, θ_j^C, θ_j^D, and θ_j^E. The cumulative proximity coefficient is represented as θ_j^T, which was calculated by summing up the coefficients of the five primary indicators.

Table 4. Weights of indicators.

Evaluation Goal	First-Level Indicator	Weight	Second-Level Indicators	Weight
Evaluation of the development of intelligent-construction pilot cities (T)	Industrial development (A)	0.1802	A1	0.0207
			A2	0.0236
			A3	0.0450
			A4	0.0223
			A5	0.0348
			A6	0.0338
	Scientific and technological innovation (B)	0.2105	B1	0.0342
			B2	0.0602
			B3	0.0285
			B4	0.0420
			B5	0.0455
	Talent cultivation (C)	0.1713	C1	0.0232
			C2	0.0342
			C3	0.0248
			C4	0.0326
			C5	0.0295
			C6	0.0269
	Economic development (D)	0.1118	D1	0.0121
			D2	0.0099
			D3	0.0192
			D4	0.0250
			D5	0.0123
			D6	0.0208
			D7	0.0124
	Digital transformation (E)	0.3262	E1	0.0629
			E2	0.0428
			E3	0.0516
			E4	0.0436
			E5	0.0530
			E6	0.0724

The TOPSIS ranking not only showcases the relative positions of cities in terms of smart building development but also directly reflects the disparities in their performance across different dimensions. For example, Beijing ranks highly due to its significant advantages in technological innovation and digital infrastructure construction, while Urumqi ranks relatively low due to insufficient resources and infrastructure in these areas. These rankings effectively demonstrate the variations among pilot cities in smart building development and highlight the key factors influencing these differences.

The performance of the 23 pilot cities in terms of industrial development is shown in Figure 3. Most cities have relatively low levels of industrial development, with proximity coefficients under 0.5. Beijing performs the best among these cities, with a proximity coefficient of 0.734, followed by Shenzhen, with a proximity coefficient of 0.6304, and

Guangzhou, with a proximity coefficient of 0.5419. Several pilot cities, including Harbin, Shenyang, Jiaxing, Xiamen, and Urumqi, perform poorly, with proximity coefficients below 0.2.

Table 5. Proximity coefficients and ranking results for the 23 studied cities.

City	θ_j^A	Rank	θ_j^B	Rank	θ_j^C	Rank	θ_j^D	Rank	θ_j^E	Rank	θ_j^T	Overall Rank
Beijing	0.7340	1	0.9179	1	0.6824	2	0.6885	2	0.6865	1	3.7093	1
Shenzhen	0.6304	2	0.5647	2	0.4553	5	0.6128	4	0.4710	3	2.7342	2
Guangzhou	0.5419	3	0.3866	3	0.5269	4	0.6213	3	0.4809	2	2.5576	3
Chongqing	0.4982	4	0.1696	10	0.7725	1	0.6898	1	0.3279	6	2.4580	4
Chengdu	0.4212	5	0.2403	6	0.5643	3	0.5375	7	0.3995	5	2.1628	5
Tianjin	0.3373	8	0.2345	7	0.3521	8	0.4603	9	0.4035	4	1.7877	6
Wuhan	0.4211	6	0.2181	8	0.4301	6	0.4860	8	0.1544	10	1.7097	7
Suzhou	0.4089	7	0.3501	4	0.2160	14	0.5403	6	0.1223	11	1.6376	8
Foshan	0.2772	10	0.1516	12	0.0800	22	0.3872	13	0.2991	7	1.1951	13
Xian	0.2467	13	0.2470	5	0.3506	9	0.3734	14	0.1939	8	1.4116	10
Nanjing	0.2822	9	0.1599	11	0.3155	11	0.5519	5	0.1552	9	1.4647	9
Zhengzhou	0.2528	12	0.1366	13	0.4005	7	0.4328	11	0.1002	13	1.3229	11
Hefei	0.2653	11	0.1836	9	0.3490	10	0.3445	15	0.0743	17	1.2167	12
Changsha	0.2357	14	0.1107	15	0.2961	12	0.4004	12	0.0862	14	1.1291	14
Qingdao	0.2215	16	0.1364	14	0.2021	15	0.4358	10	0.0744	16	1.0702	15
Wenzhou	0.1873	17	0.0814	17	0.1536	17	0.3042	16	0.0515	21	0.7780	16
Shenyang	0.1825	18	0.0445	21	0.1975	16	0.2422	19	0.0636	20	0.7303	18
Xiamen	0.1577	21	0.0873	16	0.1182	19	0.3009	17	0.0767	15	0.7408	17
Harbin	0.1283	22	0.0479	20	0.2380	13	0.1986	22	0.0644	19	0.6772	19
Baoding	0.1709	20	0.0540	19	0.0951	21	0.1490	20	0.0730	18	0.5420	22
Taizhou	0.2265	15	0.0218	22	0.1524	18	0.2420	23	0.0322	22	0.6749	20
Jiaxing	0.1749	19	0.0752	18	0.0376	23	0.2970	18	0.0234	23	0.6081	21
Urumqi	0.0311	23	0.0000	23	0.0962	20	0.2219	21	0.1067	12	0.4559	23

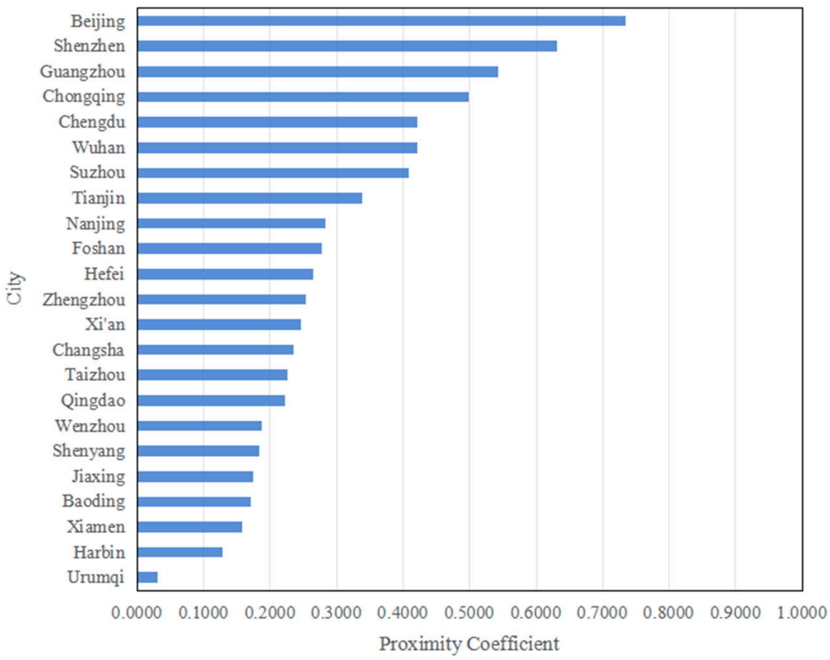

Figure 3. Performance of pilot cities in regard to industrial development.

The evaluation results regarding technical innovation indicate that the development level of intelligent construction technologies is unbalanced. Beijing has the highest performance, with a proximity coefficient exceeding 0.9, while most pilot cities demonstrate relatively low levels of technological innovation, with proximity coefficients under 0.2 (Figure 4).

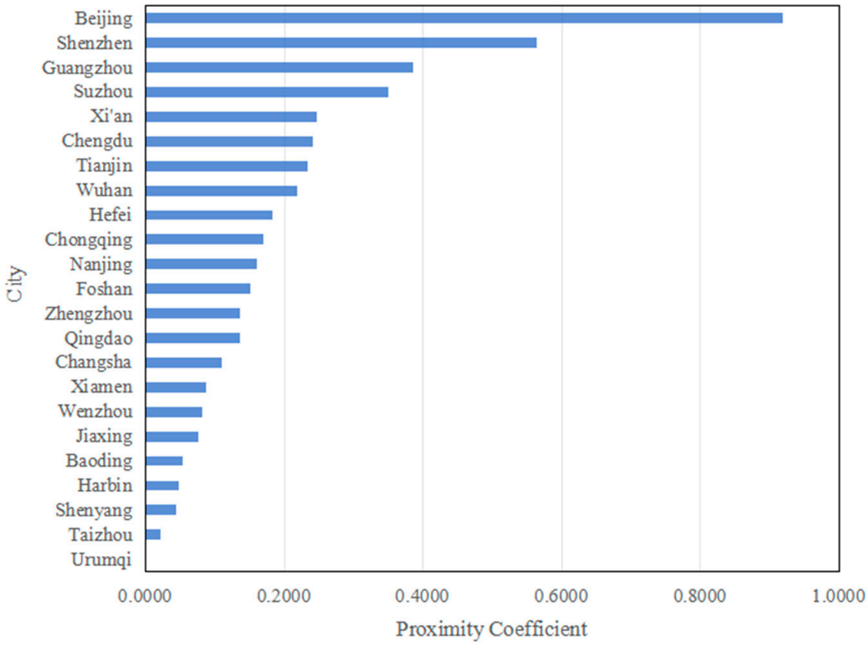

Figure 4. Performance of pilot cities in regard to scientific and technological innovation.

The performance of the 23 pilot cities in terms of talent cultivation is shown in Figure 5. These results reflect that megacities (e.g., Chongqing, Beijing, Guangzhou, Shenzhen, and Zhengzhou) with total populations greater than 12 million people perform significantly better in regard to talent cultivation than second-tier and third-tier cities, such as Baoding, Foshan, and Jiaxin. Chongqing has the highest performance among all cities, with a proximity coefficient of 0.77. This performance might be attributed to the high presence of both construction employees and universities in Chongqing.

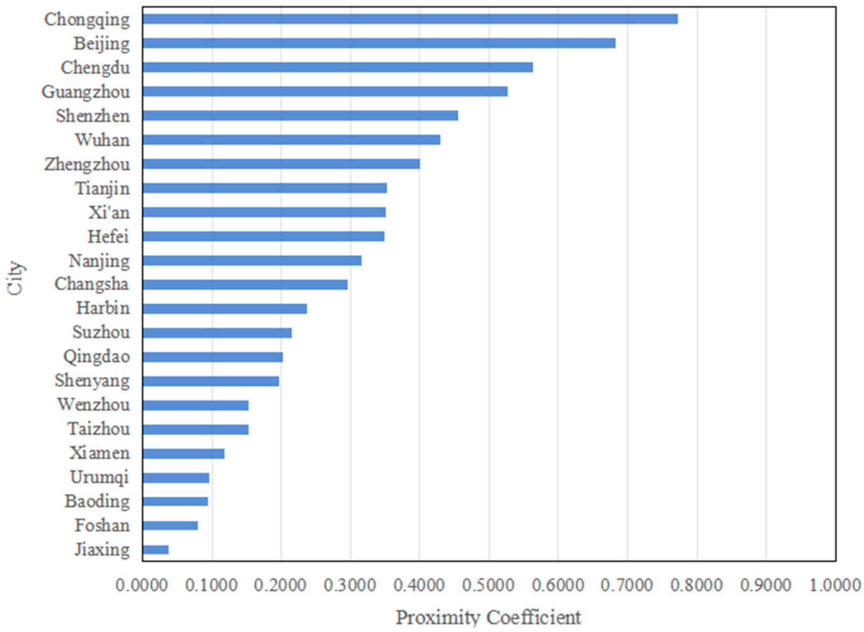

Figure 5. Performance of pilot cities in regard to talent cultivation.

The evaluation results regarding economic development in the 23 pilot cities are presented in Figure 6. The coefficients for different pilot cities were affected by economic development in different cities. The cities with a relatively strong performance include Chongqing, Beijing, Guangzhou, and Shenzhen, with each of their per capita GDP exceeding CNY 150,000. The remaining cities demonstrate proximity coefficients below 0.5, with Taizhou, Urumqi, and Harbin exhibiting the poorest performance in this respect.

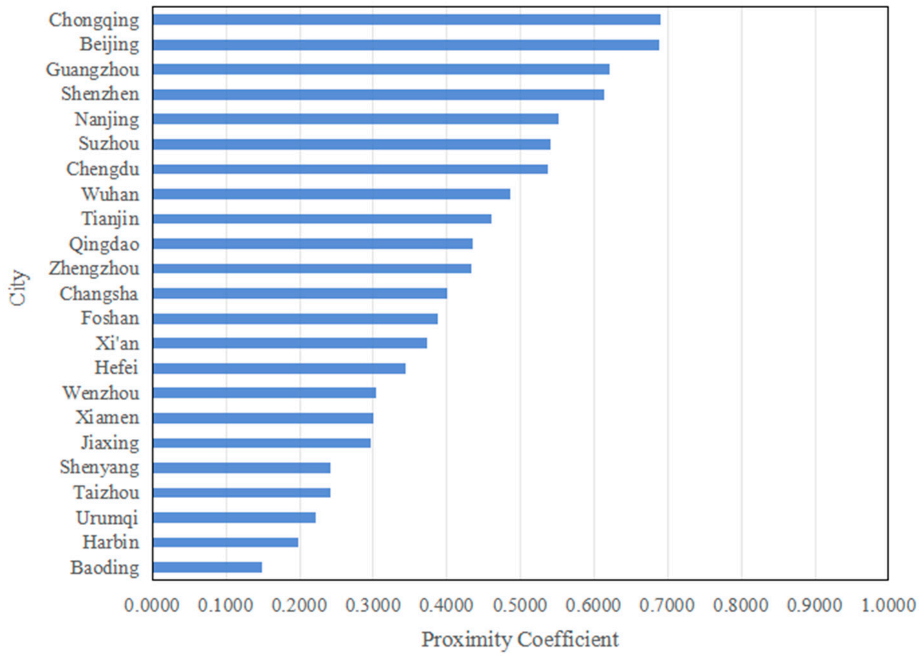

Figure 6. Performance of pilot cities in regard to economic development.

Only Beijing obtained a coefficient for digital infrastructure higher than 0.6, with all of the other cities achieving coefficients under 0.5 (Figure 7). These scores may reflect the ways in which current digital infrastructure is still not sufficient for the development of intelligent construction. More than 10 pilot cities even had coefficients for digital infrastructure under 0.1, which indicates an extremely poor performance.

Overall, as shown in Figure 8, Beijing performs the best among the pilot cities, followed by Shenzhen and Guangzhou. Urumqi, Baoding, and Jiaxing demonstrate a relatively poor performance. Not only does this reveal the relative strengths and weaknesses of each city in the development of smart buildings, but it also provides crucial evidence for studying our initial objective, which was to identify and quantify differences between cities in their development of smart buildings. In terms of the average performance across all five dimensions, as illustrated in Figure 9, relatively weaker levels of performance are seen in digital transformation and technological innovation, whereas economic development shows relatively stronger levels of performance. The performance in industrial development and talent cultivation is moderate. The average results not only evaluate the overall development performance of each city but also identify gaps between different dimensions, revealing distinct priorities and needs for smart building development in each city. Through these averages, this study is able to effectively identify key challenges that drive smart building development and provide more targeted guidance for future policy-making and practices.

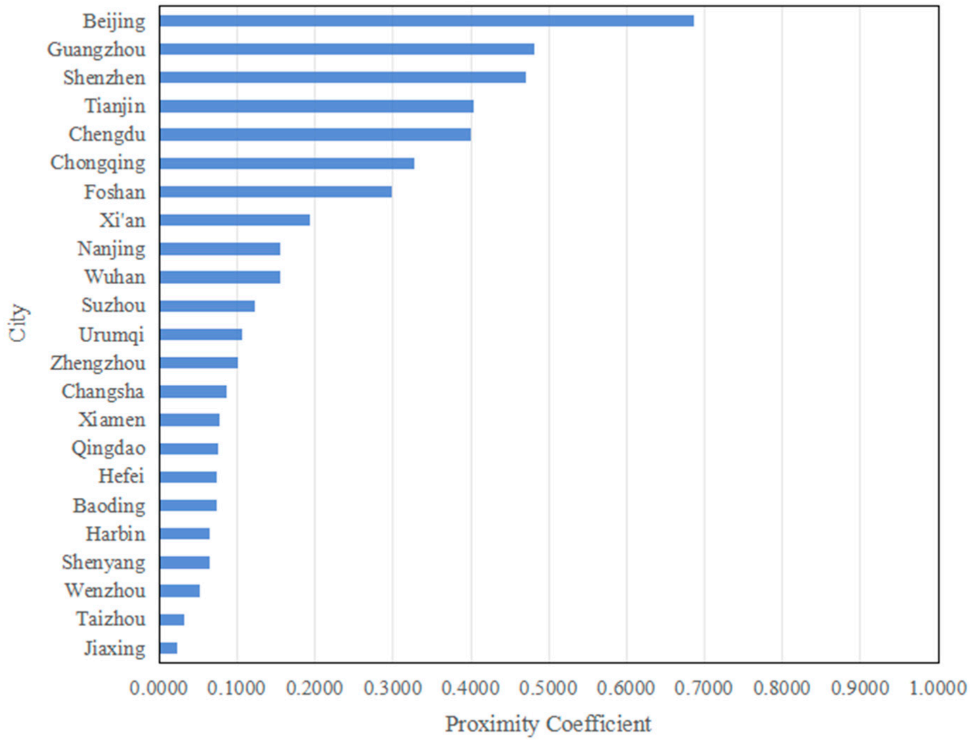

Figure 7. Performance of pilot cities in regard to digital transformation.

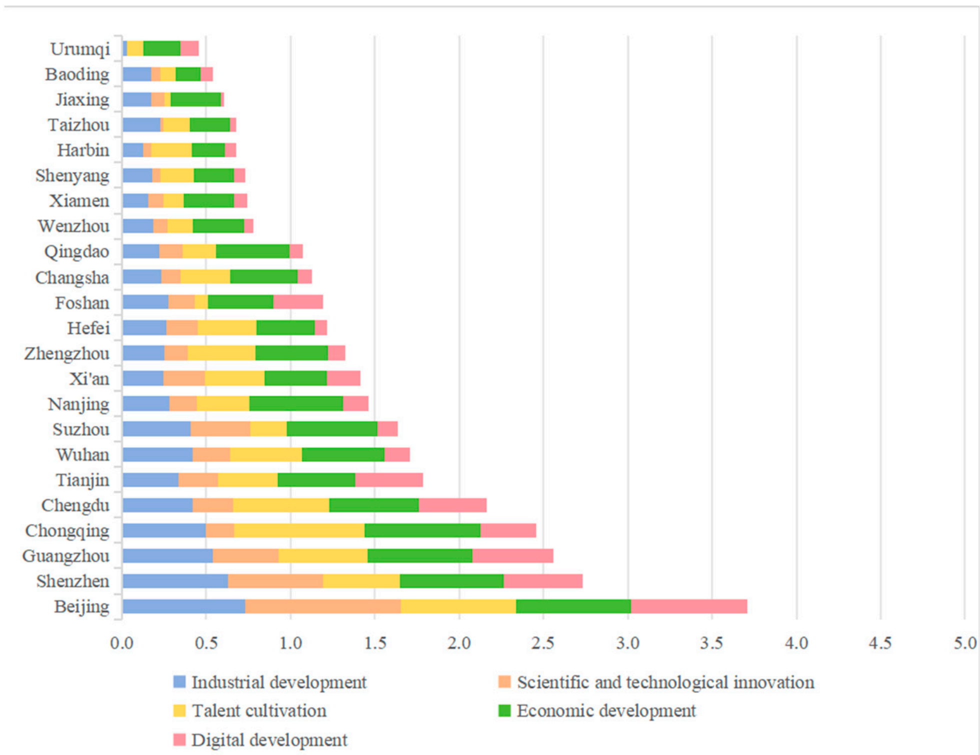

Figure 8. Overall performance of pilot cities.

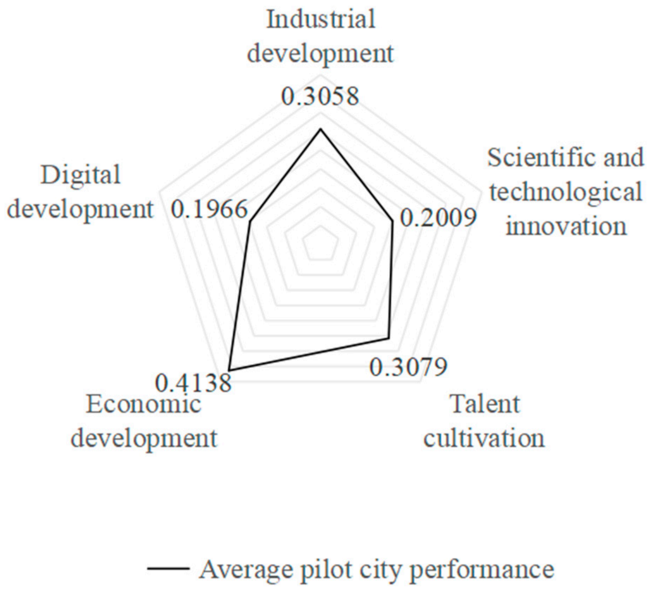

Figure 9. Average performance across the five primary indicators.

5. Discussion

According to the evaluation results, Beijing, Shenzhen, and Guangzhou are the most developed cities overall. These three cities, as examples of China's top-tier metropolises, not only have large populations and high levels of economic strength but also possess well-developed infrastructure and educational resources [55]. These cities have continuously invested in the field of technological innovation, constructing numerous 5G base stations as well as digital infrastructure, such as data centers and cloud computing platforms. Therefore, Beijing, Shenzhen, and Guangzhou have laid a solid foundation for the construction of smart cities and intelligent construction. Additionally, due to the presence of many large construction companies in these three megacities (e.g., the China Construction Second Engineering Bureau in Beijing, the China Construction Fourth Engineering Bureau in Guangzhou, and the China Construction Science & Industry Corporation LTD in Shenzhen), there has been an increase in mega-infrastructure, such as Beijing Daxing Airport, the Guangzhou International Financial Center, the Shenzhen Ping An International Finance Center, and Huaqiang's Fantawild Tower, in these cities. These projects provide abundant application scenarios for intelligent construction. In terms of higher education, many universities in Beijing, Shenzhen, and Guangzhou offer programs specializing in intelligent construction, which aim to cultivate a significant number of professionals in this field and promote its rapid development.

Urumqi obtained the lowest evaluation coefficient, which indicates a relatively poor performance among all of the intelligent-construction pilot cities. Urumqi faces challenges in regard to its undeveloped economy, incomplete digital infrastructure, and small population, which is in line with studies on regional imbalances in China [56]. Entry into the Urumqi market is quite difficult, because of the relatively poor industrial development and high logistical costs caused by the city's remote geographical location. Moreover, this city has a single-industry structure, with slow growth in high-tech industries and services. Therefore, the development of intelligent construction in Urumqi has been relatively slow.

Among the 23 pilot cities, Baoding and Jiaxing also displayed an unsatisfactory performance in regard to intelligent construction. Baoding relies heavily on traditional industries and lacks strong emerging sectors. In addition, Baoding is geographically adjacent to Beijing and Shijiazhuang, as well as Xiong'an New Area. This has led to a "siphon effect" from these major cities, where resources are easily attracted away, limiting Baoding's own development [57]. Similarly, Jiaxing is located in the economically active Yangtze River Delta region and is also affected by the siphon effect from other big cities such as Shanghai and Hangzhou. More talents tend to seek better opportunities in these cities. Moreover, Baoding currently relies primarily on traditional energy-intensive industries such as chemical engineering, textiles, clothing, and synthetic fibers, with a low proportion of high-tech industries, thus limiting employment attractiveness.

Apart from the aforementioned first-tier cities, there are some second-tier cities excelling in different respects. In terms of the cultivation of talent, Chongqing and Chengdu stand out. Both Chongqing and Chengdu possess abundant educational resources, with numerous universities offering programs in intelligent construction aiming to cultivate professional talents for the future of the construction industry. Additionally, due to their mountainous terrain, both of these cities often face greater challenges in construction that require project teams to possess higher levels of professional skills and innovation capabilities. The large scale of the construction industry also provides important support for local economic development and creates numerous job opportunities. As a result, there have been many remarkable construction projects in these areas, such as Chongqing's Land–Sea International Center and Chengdu's Tianfu International Airport. In terms of economic development, Chongqing's performance has increased rapidly due to the construction of the Chengdu–Chongqing dual-city economic circle, where cooperation between Chongqing and Chengdu mutually drives regional development [58].

Apart from the overall poor performance of these three cities (Urumqi, Baoding, and Jiaxing), there are also other cities that exhibit relatively weak performance across certain dimensions. Shenyang and Harbin, as traditional industrial cities in Northeast China, have a large proportion of traditional industries, which make it difficult for emerging high-tech industries to obtain sufficient development space and resource support. Many traditional industrial enterprises face challenges in regard to transformation, resulting in reduced employment opportunities and population outflow. Furthermore, Harbin is China's largest agricultural city and places a strong emphasis on agricultural development. However, due to the impact of transformation, its economic growth has been slow and there is a lack of funding for construction projects. In Shenyang, many research achievements are concentrated in traditional advantageous fields, while the proportion of awards for emerging industries is low, which hampers the development momentum of intelligent construction.

Xiamen's poor performance is mainly due to its economy being dominated by the service and tourism industries, which have high environmental requirements. Construction is not the major industry in Xiamen's economy, so it may not receive as many resources and policy support for construction compared to the service and tourism sectors, resulting in insufficient development of the construction industry. In order to achieve sustainable development and ecological construction goals, Xiamen encourages the use of advanced methods, such as smart construction, in project contracting. Although this construction method helps improve efficiency and quality, it may require more initial investment, research, and development costs, thereby affecting short-term profits in the construction industry and overall economic growth to some extent.

Across the five dimensions of intelligent construction development, technology innovation and digital infrastructure lag behind the other three primary factors. Regarding technology innovation, China's research focuses more on applying intelligence and automation in the design stage and emphasizes domain knowledge usage. In comparison, developed countries have conducted more extensive research on embodied intelligence, such as digital twins, artificial intelligence (AI), information integration, robotics, building information modeling (BIM), the Internet of Things (IoT), and virtual reality (VR) [59]. Technologies such as digital twins, AI, and the IoT enable real-time monitoring, predictive analytics, and automation, optimizing resource management and improving safety on construction sites [60]. BIM and information integration enhance design accuracy and collaboration, reducing errors and streamlining processes [61]. Robotics and VR further boost productivity and efficiency by automating tasks and providing immersive simulations for better planning and decision-making [62]. Digital infrastructure requires significant investment, and regional development imbalances are clearly evident. Economically advanced cities such as Guangzhou and Shenzhen are leading the way in technology innovation and the deployment of digital infrastructure, benefiting from stronger financial resources and more established industrial bases. In contrast, economically less developed cities such as Urumqi face significant gaps in both funding and infrastructure, which limit their ability to fully integrate and utilize digital technologies. In areas with weaker industrial foundations, the limited capacity to implement digital infrastructure restricts the level of intelligent construction application. As the scale of digital infrastructure expands, the amount of critical equipment that needs protection also increases; however, there may be vulnerabilities in software and hardware products related to digitization construction, which further raises network security risks. Ensuring security protection requires more financial support but funding shortages may further affect the development of digital infrastructure.

Intelligent construction technologies, such as AI, BIM, the IoT, and robotics, play a crucial role in modern building types like green buildings, energy-saving buildings, passive buildings, and prefabricated buildings. Green buildings utilize AI and IoT technologies to monitor energy consumption and resource usage in real time, combined with BIM to optimize lifecycle management, thereby minimizing carbon emissions and enhancing resource efficiency [63]. Energy-saving buildings employ automated control systems and Energy Management Systems (EMSs) to intelligently regulate lighting, Heating Ventilation Air Conditioning (HVAC) systems, and other equipment, reducing energy consumption and costs [64]. Passive buildings rely on smart shading systems and environmental control systems to optimize the use of natural light and ventilation through AI and sensor technologies, further decreasing the reliance on external energy sources [65]. Prefabricated buildings leverage robotic manufacturing technology and IoT-integrated design to ensure precise production and efficient assembly of modular components, significantly shortening the construction time and improving quality control [66]. The integration of these intelligent technologies not only makes buildings more efficient and environmentally friendly but also provides a pathway toward a more automated and sustainable future for the construction industry.

6. Recommendations

Due to significant regional development imbalances, pilot cities focusing on intelligent construction should formulate policies that align with their local characteristics. This will enable the creation of replicable and scalable models for intelligent construction, potentially serving as a reference for other countries that face similar urbanization challenges. Simultaneously, it is suggested that cities should establish a unique intelligent construction system with distinct local features by leveraging natural resources, talent reserves, or technological advantages available in the region, in order to foster an intelligent construction industry that reflects the city's specific characteristics. These locally tailored approaches may also offer valuable lessons for other countries seeking to implement intelligent construction technologies.

The construction of digital infrastructure in cities is crucial to enhancing the level of urban intelligent development. Therefore, it is recommended that cities increase their investment in digital infrastructure and promote the construction of new types of infrastructure, such as 5G base stations, data centers, artificial intelligence platforms, and the industrial internet. Emphasis should be placed on fundamental research and strengthening the application of key technologies such as artificial intelligence, big data, and the IoT in the construction field.

The development of intelligent construction in different pilot cities was evaluated in this study. However, there are also some limitations. Due to limitations in data collection channels, the evaluation indicator system we used may not be comprehensive. In the future, data collection methods can be optimized through web scraping and other means to obtain more effective data that reflect the efficiency of intelligence development. Additionally, with the integration and application of emerging technologies such as 5G, big data, and cloud computing, researchers can update and improve our evaluation indicator system in future studies. Currently, these 23 smart-construction pilot cities represent, to some extent, the direction of China's urban intelligent technology development. However, with economic growth, more cities are expected to become important platforms for smart construction and provide new cases for future research. Therefore, we suggest expanding the scope of research in future studies to include other cities, which would enable researchers to examine the development of intelligent buildings in different regions using innovative research methods such as a difference-in-differences (DID) methods. Moreover, the research methods used here are simple and can be improved upon in future evaluations. Future research could consider using more advanced methods, such as MCDA or regression models, to better capture the interrelated factors influencing smart construction development. Considering regional imbalances in development, it is recommended that future researchers use spatial economics to analyze and evaluate different pilot cities and to compare them with other cities worldwide.

7. Conclusions

With the emergence of intelligent construction, the transformation toward intelligence and informatization in the construction industry is an inevitable trend. However, implementing intelligent construction is a complex and challenging process that involves various elements, such as technological innovation, talent development, policy regulations, and data security. Therefore, it is particularly important to conduct a comprehensive evaluation of the level of intelligent construction in regard to urban development in China. The current research evaluates the performance of intelligent construction in 23 pilot cities with an evaluation index system that encompasses five dimensions: industrial development, scientific and technological innovation, talent cultivation, economic development, and digital transformation. The entropy method and the TOPSIS method were used to comprehensively assess these 23 pilot cities in regard to intelligent construction in China. The research findings indicate that the development of intelligent construction in different pilot cities is uneven. Three first-tier cities—Beijing, Shenzhen, and Guangzhou—performed relatively better than the remaining cities. Western cities performed poorly among all pilot cities. Across the five dimensions, the development of industries, talent cultivation, and economic growth are relatively satisfactory, while there is huge potential for improvements in technological innovation and digital infrastructure. This study offers an approach to understanding these disparities, enabling policymakers to tailor interventions that address specific regional challenges and promote balanced development.

According to the results of this study, it is recommended that pilot cities tailor their policies based on their own circumstances and establish replicable and scalable construction models. It is suggested that cities increase their investment in digital infrastructure and promote the development of new types of infrastructure. Additionally, accelerating technological research, strengthening basic research, and applying key technologies in the field of construction are recommended strategies. These strategies may offer valuable guidance for effectively addressing similar challenges in intelligent construction projects in other countries. However, there are limitations to the present research. First, the data collection from limited sources in this current study could be optimized through web scraping in future studies, although obtaining the most up-to-date data remains challenging due to the varying availability of data across different cities. Second, the number of cities evaluated in this work is small; therefore, expanding the scale in further research using a larger sample size would be beneficial. Future studies could explore how other countries are advancing in intelligent construction and learn from their experiences. Furthermore, this study did not fully account for other factors that could have influenced the results, such as differences in local policies or recent economic changes. Moreover, the research method used here is simple and could be improved upon in subsequent evaluations. Space economics could also be used to study and analyze the problem of unbalanced regional development. Finally, future studies could also focus on comparing China's intelligent construction development with approaches used by other countries.

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References

1. Sev, A. How Can the Construction Industry Contribute to Sustainable Development? A Conceptual Framework. *Sustain. Dev.* **2009**, *17*, 161–173. [CrossRef]
2. Asif, M.; Naeem, G.; Khalid, M. Digitalization for Sustainable Buildings: Technologies, Applications, Potential, and Challenges. *J. Clean. Prod.* **2024**, *450*, 141814. [CrossRef]
3. Bilal, M.; Oyedele, L.O.; Qadir, J.; Munir, K.; Ajayi, S.O.; Akinade, O.O.; Owolabi, H.A.; Alaka, H.A.; Pasha, M. Big Data in the Construction Industry: A Review of Present Status, Opportunities, and Future Trends. *Adv. Eng. Inform.* **2016**, *30*, 500–521. [CrossRef]
4. Yevu, S.K.; Owusu, E.K.; Chan, A.P.C.; Sepasgozar, S.M.E.; Kamat, V.R. Digital Twin-Enabled Prefabrication Supply Chain for Smart Construction and Carbon Emissions Evaluation in Building Projects. *J. Build. Eng.* **2023**, *78*, 107598. [CrossRef]
5. Ahn, H.; Lee, C.; Kim, M.; Kim, T.; Lee, D.; Kwon, W.; Cho, H. Applicability of Smart Construction Technology: Prioritization and Future Research Directions. *Autom. Constr.* **2023**, *153*, 104953. [CrossRef]
6. Dziekonski, K.; Mascarenhas, F.; Mahamadu, A.M.; Manu, P. Investigation into the Key Barriers to Achieving UK "Construction 2025" Strategy Targets. *Eng. Manag. Prod. Serv.* **2023**, *15*, 116–127. [CrossRef]
7. Borrmann, A.; Forster, C.; Liebich, T.; König, M.; Tulke, J. Germany's Governmental BIM Initiative—The BIM4INFRA2020 Project Implementing the BIM Roadmap. In Proceedings of the 18th International Conference on Computing in Civil and Building Engineering, São Paulo, Brazil, 18–20 August 2020; pp. 452–465.
8. Fujiwara, H.; Tamada, K.; Sadato, T.; Umeda, T.; Masaki, T.; Kumanaka, T.; Takee, H.; Hamada, K. An Approach to "i-Construction" of Chugoku Regional Development Bureau. *J. Jpn. Soc. Photogramm. Remote Sens.* **2018**, *57*, 57–64. [CrossRef]
9. Xue, H.; Chen, D.; Zhang, N.; Dai, H.-N.; Yu, K. Integration of Blockchain and Edge Computing in Internet of Things: A Survey. *Future Gener. Comp. Syst.* **2023**, *144*, 307–326. [CrossRef]
10. Ministry of Housing and Urban-Rural Development of the People's Republic of China. The Announcement of Intelligent Construction Pilot City. Available online: https://www.gov.cn/zhengce/zhengceku/2022-11/09/content_5725611.htm (accessed on 17 June 2024).
11. Abbott, C.; Ozorhon, B.; Aouad, G.; A Powell, J. *Innovation in Construction: A Project Lifecycle Approach*; Salford Centre for Reserach & Innovation: Salford, UK, 2009.
12. You, Z. Intelligent Construction: Unlocking Opportunities for the Digital Transformation of China's Construction Industry. *Eng. Constr. Archit. Manag.* **2024**, *31*, 1429–1453. [CrossRef]
13. Pachouri, V.; Singh, R.; Gehlot, A.; Pandey, S.; Vaseem Akram, S.; Abbas, M. Empowering Sustainability in the Built Environment: A Technological Lens on Industry 4.0 Enablers. *Technol. Soc.* **2024**, *76*, 102427. [CrossRef]
14. Zhang, L.; Li, Y.; Pan, Y.; Ding, L. Advanced Informatic Technologies for Intelligent Construction: A Review. *Eng. Appl. Artif. Intell.* **2024**, *137*, 109104. [CrossRef]
15. Davila Delgado, J.M.; Oyedele, L.; Ajayi, A.; Akanbi, L.; Akinade, O.; Bilal, M.; Owolabi, H. Robotics and Automated Systems in Construction: Understanding Industry-Specific Challenges for Adoption. *J. Build. Eng.* **2019**, *26*, 100868. [CrossRef]
16. Li, C.Z.; Xue, F.; Li, X.; Hong, J.; Shen, G.Q. An Internet of Things-Enabled BIM Platform for on-Site Assembly Services in Prefabricated Construction. *Autom. Constr.* **2018**, *89*, 146–161. [CrossRef]
17. Bucchiarone, A.; Sanctis, M.D.; Hevesi, P.; Hirsch, M.; Abancens, F.J.R.; Vivanco, P.F.; Amiraslanov, O.; Lukowicz, P. Smart Construction: Remote and Adaptable Management of Construction Sites through IoT. *IEEE Internet Things Mag.* **2019**, *2*, 38–45. [CrossRef]
18. Liu, T.; Hou, J.; Xiong, G.; Nyberg, T.R.; Li, X. Smart Cloud-Based Platform for Construction Sites. In Proceedings of the 2016 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), Beijing, China, 10–12 July 2016; pp. 168–173.
19. Jiang, W.; Ding, L.; Zhou, C. Cyber Physical System for Safety Management in Smart Construction Site. *Eng. Constr. Archit. Manag.* **2020**, *28*, 788–808. [CrossRef]
20. Kim, M.-K.; Cheng, J.C.P.; Sohn, H.; Chang, C.-C. A Framework for Dimensional and Surface Quality Assessment of Precast Concrete Elements Using BIM and 3D Laser Scanning. *Autom. Constr.* **2015**, *49*, 225–238. [CrossRef]

21. Zhang, Q.; Liu, T.; Zhang, Z.; Huangfu, Z.; Li, Q.; An, Z. Unmanned Rolling Compaction System for Rockfill Materials. *Autom. Constr.* **2019**, *100*, 103–117. [CrossRef]
22. Asgari, Z.; Rahimian, F.P. Advanced Virtual Reality Applications and Intelligent Agents for Construction Process Optimisation and Defect Prevention. *Procedia Eng.* **2017**, *196*, 1130–1137. [CrossRef]
23. Jin, R.; Zhang, H.; Liu, D.; Yan, X. IoT-Based Detecting, Locating and Alarming of Unauthorized Intrusion on Construction Sites. *Autom. Constr.* **2020**, *118*, 103278. [CrossRef]
24. Martinez, P.; Al-Hussein, M.; Ahmad, R. A Scientometric Analysis and Critical Review of Computer Vision Applications for Construction. *Autom. Constr.* **2019**, *107*, 102947. [CrossRef]
25. Yu, Z.; Peng, H.; Zeng, X.; Sofi, M.; Xing, H.; Zhou, Z. Smarter Construction Site Management Using the Latest Information Technology. *Proc. Inst. Civ. Eng. Civ. Eng.* **2019**, *172*, 89–95. [CrossRef]
26. Kochovski, P.; Stankovski, V. Supporting Smart Construction with Dependable Edge Computing Infrastructures and Applications. *Autom. Constr.* **2018**, *85*, 182–192. [CrossRef]
27. Zhang, J.; Zhang, M.; Ballesteros-Pérez, P.; Philbin, S.P. A New Perspective to Evaluate the Antecedent Path of Adoption of Digital Technologies in Major Projects of Construction Industry: A Case Study in China. *Dev. Built Environ.* **2023**, *14*, 100160. [CrossRef]
28. Oke, A.E.; Arowoiya, V.A. Evaluation of Internet of Things (IoT) Application Areas for Sustainable Construction. *Smart Sustain. Built Environ.* **2021**, *3*, 387–402. [CrossRef]
29. Cong, X.; Zi, L. Blockchain Applications, Challenges and Evaluation: A Survey. *Discret. Math. Algorithms Appl.* **2020**, *12*, 2030001. [CrossRef]
30. Succar, B. *Building Information Modelling Maturity Matrix*; Information Science Reference, IGI Publishing: Hershey, PA, USA, 2010.
31. Ghobakhloo, M. Industry 4.0, Digitization, and Opportunities for Sustainability. *J. Clean. Prod.* **2020**, *252*, 119869. [CrossRef]
32. Yan, J.; Zheng, Z.; Zhou, Y.; Lin, J.-J.; Deng, Y. A Review on Current Advances of Intelligent Construction Based on Bibliometric Analysis. In Proceedings of the International Conference on Construction and Real Estate Management 2022, Hong Kong, China, 17–18 December 2022.
33. Abioye, S.O.; Oyedele, L.O.; Akanbi, L.; Ajayi, A.; Davila Delgado, J.M.; Bilal, M.; Akinade, O.O.; Ahmed, A. Artificial Intelligence in the Construction Industry: A Review of Present Status, Opportunities and Future Challenges. *J. Build. Eng.* **2021**, *44*, 103299. [CrossRef]
34. Li, F.; Laili, Y.; Chen, X.; Lou, Y.; Wang, C.; Yang, H.; Gao, X.; Han, H. Towards Big Data Driven Construction Industry. *J. Ind. Inf. Integr.* **2023**, *35*, 100483. [CrossRef]
35. Ikudayisi, A.E.; Chan, A.P.C.; Darko, A.; Adedeji, Y.M.D. Integrated Practices in the Architecture, Engineering, and Construction Industry: Current Scope and Pathway towards Industry 5.0. *J. Build. Eng.* **2023**, *73*, 106788. [CrossRef]
36. Jia, M.; Komeily, A.; Wang, Y.; Srinivasan, R.S. Adopting Internet of Things for the Development of Smart Buildings: A Review of Enabling Technologies and Applications. *Autom. Constr.* **2019**, *101*, 111–126. [CrossRef]
37. Wang, S.; Li, J.; Yuan, Y. The Power of Convergence: STEM Education in the Era of Artificial Intelligence. In *Disciplinary and Interdisciplinary Education in STEM: Changes and Innovations*; Li, Y., Zeng, Z., Song, N., Eds.; Springer: Cham, Switzerland, 2024; pp. 63–80. ISBN 978-3-031-52924-5.
38. Barata, J.; Kayser, I. Industry 5.0—Past, Present, and Near Future. *Procedia Comput. Sci.* **2023**, *219*, 778–788. [CrossRef]
39. Xu, Y.; Wang, Z.-C.; Tao, C.-Q. Can Innovative Pilot City Policies Improve the Allocation Level of Innovation Factors?—Evidence from China. *Technol. Forecast. Soc.* **2024**, *200*, 123135. [CrossRef]
40. Yu, L.; Li, D.; Mao, L.; Zhou, S.; Feng, H. Towards People-Centric Smart Cities: A Comparative Evaluation of Citizens' Sense of Gain in Pilot Cities in China. *J. Clean. Prod.* **2024**, *434*, 140027. [CrossRef]
41. Zhang, Y.; Zhang, Y.; Zhang, H.; Zhang, Y. Evaluation on New First-Tier Smart Cities in China Based on Entropy Method and TOPSIS. *Ecol. Indic.* **2022**, *145*, 109616. [CrossRef]
42. Li, X.; Xing, H. Better Cities Better Lives: How Low-Carbon City Pilots Can Lower Residents' Carbon Emissions. *J. Environ. Manag.* **2024**, *351*, 119889. [CrossRef] [PubMed]
43. Otay, İ.; Çevik Onar, S.; Öztayşi, B.; Kahraman, C. Evaluation of Sustainable Energy Systems in Smart Cities Using a Multi-Expert Pythagorean Fuzzy BWM & TOPSIS Methodology. *Expert Syst. Appl.* **2024**, *250*, 123874. [CrossRef]
44. Tu, W.; Zhang, L.; Sun, D.; Mao, W. Evaluating High-Tech Industries' Technological Innovation Capability and Spatial Pattern Evolution Characteristics: Evidence from China. *J. Innov. Knowl.* **2023**, *8*, 100287. [CrossRef]
45. Pan, X.; Li, J.; Shen, Z.; Song, M. Life Cycle Identification of China's Regional Innovation Systems Based on Entropy Weight Disturbing Attribute Model. *Habitat Int.* **2023**, *131*, 102725. [CrossRef]
46. Xu, X.; Wang, Y.; Tao, L. Comprehensive Evaluation of Sustainable Development of Regional Construction Industry in China. *J. Clean. Prod.* **2019**, *211*, 1078–1087. [CrossRef]
47. Mao, C.; Wang, Z.; Yue, A.; Liu, H.; Peng, W. Evaluation of Smart City Construction Efficiency Based on Multivariate Data Fusion: A Perspective from China. *Ecol. Indic.* **2023**, *154*, 110882. [CrossRef]
48. Guo, Q.; Zhong, J. The Effect of Urban Innovation Performance of Smart City Construction Policies: Evaluate by Using a Multiple Period Difference-in-Differences Model. *Technol. Forecast. Soc.* **2022**, *184*, 122003. [CrossRef]
49. Ding, S.; Li, R.; Guo, J. An Entropy-Based TOPSIS and Optimized Grey Prediction Model for Spatiotemporal Analysis in Strategic Emerging Industry. *Expert Syst. Appl.* **2023**, *213*, 119169. [CrossRef]

50. Shen, L.; Huang, Z.; Wong, S.W.; Liao, S.; Lou, Y. A Holistic Evaluation of Smart City Performance in the Context of China. *J. Clean. Prod.* **2018**, *200*, 667–679. [CrossRef]
51. Li, J.; Chen, Y.; Yao, X.; Chen, A. Risk Management Priority Assessment of Heritage Sites in China Based on Entropy Weight and TOPSIS. *J. Cult. Herit.* **2021**, *49*, 10–18. [CrossRef]
52. Pandey, V.; Komal; Dincer, H. A Review on TOPSIS Method and Its Extensions for Different Applications with Recent Development. *Soft Comput.* **2023**, *27*, 18011–18039. [CrossRef]
53. Chen, P. Effects of Normalization on the Entropy-Based TOPSIS Method. *Expert Syst. Appl.* **2019**, *136*, 33–41. [CrossRef]
54. Behzadian, M.; Khanmohammadi Otaghsara, S.; Yazdani, M.; Ignatius, J. A State-of the-Art Survey of TOPSIS Applications. *Expert Syst. Appl.* **2012**, *39*, 13051–13069. [CrossRef]
55. Yi, P.; Li, W.; Zhang, D. Sustainability Assessment and Key Factors Identification of First-Tier Cities in China. *J. Clean. Prod.* **2021**, *281*, 125369. [CrossRef]
56. Zou, Y.; Zhao, W.; Zhong, R. The Spatial Distribution of Green Buildings in China: Regional Imbalance, Economic Fundamentals, and Policy Incentives. *Appl. Geogr.* **2017**, *88*, 38–47. [CrossRef]
57. Xu, Z.; Sun, T. The Siphon Effects of Transportation Infrastructure on Internal Migration: Evidence from China's HSR Network. *Appl. Econ. Lett.* **2021**, *28*, 1066–1070. [CrossRef]
58. Hu, R.; Xu, W. What's Going on? Urban Agglomerations and Firm Green Innovation: Evidence from Chengdu-Chongqing Economic Circle, China. *J. Clean. Prod.* **2023**, *414*, 137662. [CrossRef]
59. Pan, Y.; Zhang, L. Roles of Artificial Intelligence in Construction Engineering and Management: A Critical Review and Future Trends. *Autom. Constr.* **2021**, *122*, 103517. [CrossRef]
60. Park, J.; Lee, J.-K.; Son, M.-J.; Yu, C.; Lee, J.; Kim, S. Unlocking the Potential of Digital Twins in Construction: A Systematic and Quantitative Review Using Text Mining. *Buildings* **2024**, *14*, 702. [CrossRef]
61. Hauer, M.; Hammes, S.; Zech, P.; Geisler-Moroder, D.; Plörer, D.; Miller, J.; Van Karsbergen, V.; Pfluger, R. Integrating Digital Twins with BIM for Enhanced Building Control Strategies: A Systematic Literature Review Focusing on Daylight and Artificial Lighting Systems. *Buildings* **2024**, *14*, 805. [CrossRef]
62. Gharbia, M.; Chang-Richards, A.; Lu, Y.; Zhong, R.Y.; Li, H. Robotic Technologies for On-Site Building Construction: A Systematic Review. *J. Build. Eng.* **2020**, *32*, 101584. [CrossRef]
63. Yang, B.; Lv, Z.; Wang, F. Digital Twins for Intelligent Green Buildings. *Buildings* **2022**, *12*, 856. [CrossRef]
64. Han, K.; Zhang, J. Energy-Saving Building System Integration with a Smart and Low-Cost Sensing/Control Network for Sustainable and Healthy Living Environments: Demonstration Case Study. *Energy Build.* **2020**, *214*, 109861. [CrossRef]
65. Deb, C.; Lee, S.E.; Santamouris, M. Using Artificial Neural Networks to Assess HVAC Related Energy Saving in Retrofitted Office Buildings. *Sol. Energy* **2018**, *163*, 32–44. [CrossRef]
66. Zhong, R.Y.; Peng, Y.; Xue, F.; Fang, J.; Zou, W.; Luo, H.; Thomas Ng, S.; Lu, W.; Shen, G.Q.P.; Huang, G.Q. Prefabricated Construction Enabled by the Internet-of-Things. *Autom. Constr.* **2017**, *76*, 59–70. [CrossRef]