Analyzing Critical Influencing Factors of the Maturity of Smart Construction Site Applications

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Abstract: The burgeoning application of advanced information technology in the construction industry has led to the widespread adoption of smart construction sites (SCSs) in recent years. As a novel concept, smart construction site application maturity (SCS-AM) aims to identify the pivotal factors impeding the current progression of SCSs and foster the metamorphosis of the construction sector. Through a meticulous review of the existing literature, this study delineates 14 fundamental factors influencing SCS-AM. Employing both Exploratory Factor Analysis (EFA) and confirmatory factor analysis (CFA), alongside the acquisition of 217 valid questionnaires, practitioners’ perceptions regarding these factors within the smart construction domain were examined. This study initially categorized the 14 factors into four dimensions by utilizing the EFA method: technological innovation and integration (TII), project management and implementation (PMI), collaboration mechanism and information sharing (CMIS), and standardization and compliance (SC). Subsequently, a first-order CFA was employed to elucidate the correlations between the observed variables and latent factors, while a second-order CFA was employed to delve into the interplay among the first-order factors and their collective influence on SCS-AM. The results underscore the paramount impact of standardization and compliance (SC) and technological innovation and integration (TII) on SCS-AM. By meticulously analyzing the key influencing factors, this study offers theoretical underpinnings for bolstering SCS-AM, thereby providing stakeholders such as governments and construction enterprises with strategic insights for future development endeavors.

Keywords: smart construction sites; application maturity; factor analysis; influencing factors

1. Introduction

The traditional construction industry has long been criticized for its high accident rates, low production efficiency, high resource consumption, and minimal use of technology [1]. Consequently, there is an urgent need for the transformation and modernization of the construction sector within both academia and industry [2]. In recent years, with the advancement of information technology and the increasing need for sustainable development, the demand for intelligent and information-based management in the construction industry has become more prominent [3]. Construction sites, as primary production sites where various resources are integrated to produce finished products such as buildings and urban infrastructure, represent some of the most critical components of the construction industry and are a vital area to be optimized [4]. Therefore, the transformation and upgrading of construction sites are seen as key levers for the overall transformation of the industry [5,6].

In recent years, the concept of smart construction sites (SCSs) has been introduced in academia and has been widely mentioned in industrial and government documents. Essentially, SCSs use information and intelligent technologies (such as big data, the IoT,
blockchain, and building information modeling (BIM)) to build an intelligent platform that supports site management, networked collaboration, intelligent decision making, and knowledge sharing throughout the lifecycle of a construction project [7–9]. The aim of implementing an intelligent site system is to improve the level and efficiency of site management through information technology, thereby better achieving the overall objectives of quality, schedule, cost, occupational health and safety, and environmental protection throughout the project lifecycle [10].

Maturity models (MMs) were first proposed by the Software Engineering Institute (SEI) in the 1980s to assess the maturity of software development processes [11]. Since then, the concept has been extended to various domains, including information technology, smart cities, smart grids, safety, health, and environmental management [12,13]. Maturity models use a series of pre-defined maturity levels to represent the evolution of the subject from nonexistent, initial, unstructured stages to highly mature optimized processes [14]. Each maturity level represents a specific phase in the subject’s capability, efficiency, and complexity within the relevant domain [15]. The model is designed to help institutions identify their current level of capability, identify opportunities for improvement, and, by implementing appropriate actions, increase their overall maturity to improve their effectiveness and competitive advantage [14]. Therefore, conducting maturity research on the application of smart construction sites is of significant importance in identifying the key factors limiting current development and facilitating the transformation and upgrading of the construction industry.

Currently, the academic exploration of maturity models for smart construction site (SCS) applications is still in its infancy, with the predominant literature focusing on technological implementation, management optimization, and efficiency improvements. This body of work includes the applications of Internet of Things (IoT) technology in construction sites, as well as the use of big data and artificial intelligence (AI) in project management and decision support systems [16]. However, research on maturity models specific to SCS applications is particularly scarce, which limits the theoretical development and practical application of such models, particularly in assessing and strategizing the advancement of smart construction sites. Identifying and analyzing key influencing factors for maturity models is critical for guiding practical applications and facilitating development in the field. Therefore, advanced research on maturity models for SCS applications, especially research clarifying model definitions, establishing evaluation standards, and identifying key influencing factors, is urgently needed to advance the practical application of project management in smart construction sites and promote the transformation and upgrading of the construction industry.

To address the shortcomings of the aforementioned studies and to achieve the objectives of this research, a systematic and comprehensive review of the existing studies was first conducted to identify the key factors affecting the maturity of smart construction site applications. Based on this, a questionnaire was developed to assess the importance of these factors for the maturity of smart construction site applications, gathering insights into the importance of each factor from the academics and practitioners in the field of smart construction sites. Following data collection and screening, Exploratory Factor Analysis (EFA) was used to explore the latent factor structure within the data, while confirmatory factor analysis (CFA) was used to verify the accuracy and stability of the structure. Ultimately, the critical factors influencing the maturity of smart construction site applications were identified, providing a reference for industrial transformation and upgrading.
2. Literature Review

2.1. Smart Construction Sites

Smart construction sites leverage advanced technologies, such as the Internet of Things (IoT) and big data, to automate site management and make it “intelligent” [17,18]. These technologies facilitate enhanced productivity, safety management, and quality control on construction sites while optimizing resource allocation and minimizing environmental impact [19]. IoT technology enables the efficient management of resources through the real-time monitoring of equipment, personnel, and materials on site [17]. The application of big data and artificial intelligence (AI) provides robust data support and predictive analytics capabilities for construction sites [20,21]. The integration of these technologies not only solves the complexity of site management but also improves the efficiency and safety of construction projects [17,18].

The technological framework of smart construction sites typically encompasses a data acquisition layer, a network transmission layer, a data processing and storage layer, and an application service layer. The data acquisition layer is principally tasked with collecting different on-site information via sensors and other devices [22]. The network transmission layer is responsible for transmitting the gathered data to a cloud platform or data center. The data processing and storage layer analyzes and processes the data, rendering them usable [20]. The application service layer, which is based on the processed data, provides decision support for aspects such as progress management, quality control, and safety monitoring [21].

Smart construction sites, which are grounded in cutting-edge information technologies such as the Internet of Things (IoT), big data, building information modeling (BIM), and artificial intelligence (AI), strive for the automation and intelligent management of construction sites. Wu et al. (2022) focused on the current state and future directions of Natural Language Processing (NLP) within smart construction, examining how NLP can enhance project management and communication efficiency, thereby offering innovative approaches to human–machine interaction on smart construction sites [20]. Sarkar et al. (2023) provided an overview of IoT security intelligence, including machine learning solutions and research directions, offering guidance on data security for smart construction sites [18]. Lv et al. (2022) explored the construction and management of smart cities in the context of COVID-19 through digital twins and big data in building information modeling (BIM), offering new perspectives and technical support for smart construction sites [23].

2.2. Application of Smart Construction Sites

In recent years, the application of intelligent construction site technology has gradually expanded to encompass site management, safety and activity monitoring, real-time tracking systems, and the recognition of construction equipment activities. Márquez Sánchez et al. (2021) investigated the BeSafe B2.0 intelligent multi-sensor platform, which significantly reduces the incidence of accidents and occupational diseases by monitoring the health status of workers in real-time using smartwatches and sensors (such as helmets or belts) at construction sites [24]. Jiang et al. (2021) described a cyber–physical system that synchronizes risk data with both virtual and actual construction sites, enhancing site safety and risk management through improved data perception and processing [25]. Jin et al. (2020) developed an IoT-based intrusion monitoring system that uses smart helmets and portable RFID triggers to monitor site personnel in real-time, providing effective, convenient, and safe intrusion detection and location solutions [26]. By integrating artificial intelligence and Internet of Things technologies, Lee et al. (2023) developed an intelligent monitoring platform for construction safety. This platform actively ensures the safety of management personnel and others by monitoring construction site activities in real-time, not only preventing workers from entering hazardous areas but also swiftly detecting and responding to emergencies [27]. Relevant research indicates that the intelligent
construction sites that are enhanced with advanced technologies not only improve the efficiency and quality of projects but also ensure the safety and health of on-site personnel.

2.3. Maturity Models

Maturity models (MMs) are tools used to assess and enhance the development level and maturity of organizations within specific domains or industries. They define a series of incremental stages, helping organizations identify their current maturity level and providing clear pathways and recommendations for improvement. The fundamental concept of maturity models is that by progressively elevating the capabilities and practices of an organization, continuous improvement and optimization can be achieved, thereby enhancing the overall performance and competitiveness [28]. Paulk et al. (1993) introduced the Capability Maturity Model (CMM) for the improvement of software development processes, providing an early framework for the application of maturity models [29]. The CMM defines five incremental maturity levels (initial, managed, defined, quantitatively managed, and optimizing), aiding software development organizations in identifying and improving their development processes. Subsequently, the application of maturity models has expanded to other fields, such as project management, knowledge management, and IT service management. Wendler (2012) conducted a systematic review of maturity models, exploring their applications across different domains, and provided robust theoretical support for the cross-disciplinary application of maturity models [30]. The core dimensions in constructing maturity models include capabilities, processes, technologies, and organizational aspects. Specific research tools involve surveys, expert interviews, and data analysis methods [30,31].

In recent years, maturity models have also been applied in the construction sector. Demirdöğen et al. (2021) proposed a maturity framework that integrates lean management, value engineering, BIM, and big data analytics. This framework includes key elements such as data management, human resources and culture, leadership and strategy, automation, collaboration and communication, and innovation. They validated the feasibility and practicality of this assessment system through the maturity evaluations of two construction enterprises and proposed improvement methods to enhance intelligent construction management capabilities at various maturity levels [32]. Das et al. (2023) conducted a systematic review of the existing maturity models, identifying key process categories such as data management, personnel and culture, leadership and strategy, automation, collaboration and communication, change management, and innovation. Through two rounds of expert interviews, they developed a maturity model named the Smart Modern Construction Enterprise Maturity Model (SMCeMM) to guide construction enterprises [33]. Yusof et al. (2018) conducted a systematic literature review that analyzed the literature related to BIM maturity and proposed a maturity analysis framework encompassing information, personnel, policies, processes, technology, organizations, and deliverables [34]. Lin et al. (2022) systematically reviewed existing intelligent construction management (ICM) research and proposed a maturity model evaluation framework that included five dimensions: data management, personnel and culture, policies and regulations, technology and tools, and processes and methods [35].

The conclusions from these studies provide the theoretical foundation for identifying the influencing factors of the SCS-AM framework in this study.

In summary, the rapid development of information technology has significantly impacted the construction industry, catalyzing the advancement of smart construction site (SCS) technologies. Extensive research has demonstrated the widespread application of cutting-edge technologies such as the Internet of Things (IoT), artificial intelligence (AI), and big data within smart construction sites, highlighting their notable benefits in enhancing productivity, safety, and efficiency in resource allocation. Additionally, the existing studies suggest that research on maturity models can elevate system capability levels, thereby facilitating the optimization of smart construction sites’ advantages. However, despite considerable progress in smart construction site research, notable deficiencies
remain. Primarily, most studies focus narrowly on the development, application, and evaluation of the technological aspects of smart construction sites, with few incorporating technical factors into a comprehensive framework for assessing application maturity. Moreover, the predominant focus on technological factors has led to a paucity of research on non-technical aspects, such as management processes, organizational structures, and legal regulations, resulting in an incomplete research framework. These limitations restrict the holistic identification of factors impeding the development of smart construction site application maturity. To address these research gaps, this study introduces the concept of smart construction site application maturity (SCS-AM), which is aimed at reflecting the progress and efficiency of construction sites in adopting smart construction technologies and advanced management practices. This study focuses on identifying and analyzing the influencing factors of SCS-AM, and it constructs a comprehensive and complete framework for factor analysis through an extensive literature review. The research provides theoretical support for identifying the critical factors that constrain the application of smart construction sites and clarifies directions for improvement.

2.4. Critical Influencing Factors of the Maturity of Smart Construction Site Applications

In this study, a bibliometric analysis was conducted to determine the critical influencing factors of the maturity of SCS applications using the Web of Science (WOS) as the core database for data collection. The advanced search strategy employed was as follows: TS = ("smart construction" OR "intelligent construction" OR "digital construction") AND ("factors" OR "influences" OR "maturity" OR "assessment" OR "evaluation") AND PY = (2014–2024). This strategy aimed to retrieve the studies published between 2014 and 2024 that addressed various aspects impacting the maturity of smart construction site applications. The initial search yielded 136 journal articles. To further refine the literature list and facilitate the identification of key influencing factors, a second round of screening was conducted. The specific criteria for this screening included selecting high-level journal studies that made substantial contributions to the influencing factors of SCS-AM in terms of technology, organizational structure, management processes, and legal regulations. Based on these criteria and the removal of duplicates, 70 journal articles were ultimately selected. Based on a comprehensive literature review and expert interviews, the influencing factors of SCS-AM identified in this study are shown in Table 1.

<table>
<thead>
<tr>
<th>NO.</th>
<th>Key Factor</th>
<th>Description</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
<td>Advanced Technology Adoption and Application</td>
<td>The incorporation and utilization of cutting-edge technology enable enhanced efficiency, productivity, and quality in SCS-AM</td>
<td>[19,25,36–38]</td>
</tr>
<tr>
<td>F2</td>
<td>Technology Platform Integration Capacity</td>
<td>The seamless integration of various technology platforms ensures optimal functionality and interoperability in SCS-AM</td>
<td>[36,39–42]</td>
</tr>
<tr>
<td>F3</td>
<td>Data Processing and Analysis Technology</td>
<td>Efficient data handling and interpretation facilitate real-time decision making and problem solving in SCS-AM</td>
<td>[36,43–45]</td>
</tr>
<tr>
<td>F4</td>
<td>Technological Innovation Atmosphere</td>
<td>A culture that encourages technological innovation to drive the continuous improvement and adoption of advanced methods in SCS-AM</td>
<td>[46–48]</td>
</tr>
<tr>
<td>F5</td>
<td>Leadership in Smart Construction Site Strategy</td>
<td>Strong leadership provides vision and guidance for the effective implementation and scaling of smart construction technologies in SCS-AM</td>
<td>[16,44,49]</td>
</tr>
<tr>
<td>F6</td>
<td>Multi-Party Information and Data Sharing</td>
<td>Effective data-sharing systems promote collaboration and efficiency among stakeholders in SCS-AM projects</td>
<td>[50–52]</td>
</tr>
<tr>
<td>F7</td>
<td>Smart Construction Site Technical Talent Development</td>
<td>Developing professionals skilled in smart construction technologies ensures successful adoption and innovation in SCS-AM</td>
<td>[43,53,54]</td>
</tr>
</tbody>
</table>
3. Methodology

3.1. Research Framework

The research framework is shown in Figure 1. The findings from this analytical process are expected to elucidate the key determinants of SCS application maturity and their interrelationships, thus enabling the adoption of effective strategies.

![Figure 1. Research framework.](image-url)

3.2. Questionnaire Design

3.2.1. Expert Interviews

In this research, the questionnaire design process was segmented into two critical phases: the verification of indicator validity and the validation and optimization of questionnaire content by utilizing expert interviews to ensure comprehensiveness, accuracy, and effectiveness. A total of 28 experts and scholars in the field of smart construction sites...
were invited to participate, all of whom were from China. These experts represented a diverse range of affiliations, including universities, government agencies, and construction companies. Through a combination of online and offline discussions, two rounds of deliberations were conducted. During the first round of discussions, the experts extensively reviewed a set of influencing factors for the smart construction site (SCS) application maturity model derived from the literature review. This phase aimed at validating and optimizing the initially identified factors to ensure comprehensive and non-overlapping coverage, culminating in the confirmation of a specified set of 14 influence factors. Subsequently, in the second round, which was focused on the validation and optimization of the questionnaire content, the experts meticulously examined the questionnaire’s structure and content. This step was intended to refine the questionnaire based on expert feedback, ensuring the comprehensiveness of the content, clarity of questions, and logical coherency, thereby enhancing the scientific rigor and practical applicability of the questionnaire design.

3.2.2. Questionnaire Design

The questionnaire was divided into two modules, with the first encompassing basic information about the respondents and the second containing a scoring section that evaluated the importance of the factors affecting the maturity level of smart construction site applications. The first module was designed to gather details such as the respondents’ work experience to discern whether they had substantial practical or academic research experience relevant to the application of smart construction sites, thereby ensuring the accuracy of their responses. The second module utilized a seven-point Likert scale to assess the importance of the influencing factors. This scale was chosen because it provided a balance between the sufficient differentiation of responses and the ease of use for the participants, facilitating a comprehensive quantification and analysis of the respondents’ attitudes. The scale was delineated as follows: “No influence at all”, “No influence”, “Minimal influence”, “Neutral”, “Moderately influential”, “Influential”, and “Highly influential”.

3.3. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA)

Exploratory Factor Analysis (EFA) constitutes a pivotal statistical approach that was ingeniously devised for the identification of latent structures obscured within observed variables. This methodology empowers investigators to examine potential underlying dimensions within datasets that are notably devoid of predetermined hypotheses. Through EFA, observed variables are efficiently condensed into a succinct array of factors that encapsulate their shared variance, thereby facilitating subsequent analytical endeavors such as confirmatory factor analysis (CFA) or related statistical methodologies [66]. Confirmatory factor analysis (CFA) is primarily aimed at validating the congruence between hypothesis models constructed based on theoretical grounds and actual empirical data. Unlike the exploratory nature of Exploratory Factor Analysis (EFA), CFA mandates that researchers predefine the model structure. This structure includes the anticipated number of factors and the relationships between observed variables and factors and then employs statistical techniques to assess the fit of this a priori model [67].

In the current research, the methodology integrating Exploratory Factor Analysis (EFA) and confirmatory factor analysis (CFA) is extensively applied in the development of scales and the validation of theoretical models. This approach is divided into two main phases: initially, EFA is deployed to unearth the latent factor structure within the data, followed by the application of CFA to confirm and validate this structure [68]. The amalgamation of EFA and CFA not only facilitates the exploration of factor structures on a data-driven basis but also permits their rigorous validation under theoretical guidance, thereby enhancing the scientific robustness and precision of the research. This methodology has gained widespread acceptance and application across various fields, including
4. Data Collection and Results

4.1. Data Collection

This research utilized an online questionnaire to gather the necessary data for the study. The questionnaire was distributed via the Wenjuanxing platform. The target respondents were from a construction company in Shenzhen and its associated partners, including six enterprises, one university, and governmental agencies. Specifically, the questionnaires were distributed to 542 employees across the six enterprises, 28 practitioners within the university, and 9 government officials, totaling 579 individuals. The selection of the sample size was based on the estimated number of potential respondents in the total population to ensure the statistical significance and representativeness of the study results. Considering the accuracy requirements of factor analysis, where the sample size should be 10–15 times the number of factors [69], and anticipating a 50% response rate, distributing 579 questionnaires was deemed appropriate. The questionnaire was designed to assess the perceived importance of the key factors influencing the application maturity in the smart construction site application. To ensure the accuracy and professionalism of the responses, the questionnaire was distributed specifically to the researchers and practitioners engaged in smart construction sites. To further ensure the reliability of the data, the questionnaire included queries regarding the respondents’ experience in smart construction site research or practice. The responses of the participants who had been involved in fewer than three smart construction site projects were excluded from the analysis. The demographic details of the valid respondents are depicted in Table 2. All the participants originated from China.

Table 2. Survey population information.

<table>
<thead>
<tr>
<th>Category</th>
<th>Sub-Category</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration of Participation in Work or</td>
<td>0–5 years</td>
<td>54%</td>
</tr>
<tr>
<td>Academic Research</td>
<td>5–10 years</td>
<td>34%</td>
</tr>
<tr>
<td></td>
<td>Over 10 years</td>
<td>12%</td>
</tr>
<tr>
<td>Type of Employment</td>
<td>Owner</td>
<td>5%</td>
</tr>
<tr>
<td></td>
<td>Construction enterprise</td>
<td>62%</td>
</tr>
<tr>
<td></td>
<td>Design enterprise</td>
<td>11%</td>
</tr>
<tr>
<td></td>
<td>Supervision enterprise</td>
<td>5%</td>
</tr>
<tr>
<td></td>
<td>Consulting enterprise</td>
<td>4%</td>
</tr>
<tr>
<td></td>
<td>Software enterprise</td>
<td>2%</td>
</tr>
<tr>
<td></td>
<td>Government regulatory department</td>
<td>4%</td>
</tr>
<tr>
<td></td>
<td>Universities and other scientific institutions</td>
<td>5%</td>
</tr>
<tr>
<td></td>
<td>Others</td>
<td>2%</td>
</tr>
<tr>
<td>Professional Rank</td>
<td>None</td>
<td>14%</td>
</tr>
<tr>
<td></td>
<td>Junior</td>
<td>27%</td>
</tr>
<tr>
<td></td>
<td>Intermediate</td>
<td>38%</td>
</tr>
<tr>
<td></td>
<td>Senior</td>
<td>21%</td>
</tr>
<tr>
<td>Number of Smart Construction-Related Projects in Which They Were Involved</td>
<td>3–5</td>
<td>55%</td>
</tr>
<tr>
<td></td>
<td>5–10</td>
<td>34%</td>
</tr>
<tr>
<td></td>
<td>More than 10</td>
<td>11%</td>
</tr>
</tbody>
</table>
4.2. Data Screening

(1) Questionnaire Screening
A total of 579 questionnaires were distributed in this study, and 296 were received. Of these, 34 questionnaires were excluded due to consistent results for all the options in the second part of the questionnaire and a significantly shorter completion time than that of the other respondents. Additionally, the results of 45 respondents with experience in less than three smart site projects were also excluded. In conclusion, a total of 217 questionnaires that met the requisite criteria were received, with a response validity rate of 37.38%.

(2) Variable Measurement
The results of the questionnaire collection were initially evaluated using Kaiser–Meyer–Olkin (KMO) followed by Bartlett’s test of sphericity (see Table 3). The results are presented in Table 2, and the KMO value was greater than 0.8, which fulfilled the prerequisites of the factor analysis. In addition, the p-value of Bartlett’s test of sphericity was less than 0.05, which was suitable for factor analysis [70].

Table 3. KMO and Bartlett’s test.

<table>
<thead>
<tr>
<th></th>
<th>KMO Value</th>
<th>0.846</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Approximate Chi-Square</td>
<td>1859.412</td>
</tr>
<tr>
<td>Bartlett’s Test of Sphericity</td>
<td>df</td>
<td>91</td>
</tr>
<tr>
<td></td>
<td>p-value</td>
<td>0</td>
</tr>
</tbody>
</table>

(3) Normality test
The values of the skewness index (SI) ranged from −1.441 to −0.734, with absolute values that were all less than three. Similarly, the kurtosis index (KI) ranged from −0.829 to 1.643, with absolute values that were all less than 10. Therefore, the 14 factors in this study can be considered to have a normal distribution [71].

(4) Multicollinearity test
To ensure the clarity and interpretability of the factor analysis, this study utilized the variance inflation factor (VIF) to test for multicollinearity. The VIF values for the 14 factors ranged from 4.06 to 9.72, indicating that no significant covariance existed [72].

4.3. Exploratory Factor Analysis (EFA)
This research employed the Varimax rotation method, which is a maximum variance technique, to rotate the data with the aim of revealing the associations between each factor and the research variables. Table 4 extensively outlines the amount of information that each factor extracted from the research variables, as well as the corresponding relationships between the factors and variables. The examination of the data in the table indicates that the commonalities of all the research variables exceeded 0.4, signifying significant correlations between each variable and its respective factor, thereby demonstrating the efficacy of factor analysis in extracting crucial information [71].

Table 4. Factor structure and variance explained.

<table>
<thead>
<tr>
<th>Name</th>
<th>TII</th>
<th>PMI</th>
<th>CMIS</th>
<th>SC</th>
<th>Commonalities</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
<td>0.831</td>
<td>0.145</td>
<td>0.080</td>
<td>0.161</td>
<td>0.743</td>
</tr>
<tr>
<td>F2</td>
<td>0.802</td>
<td>0.022</td>
<td>0.179</td>
<td>0.199</td>
<td>0.715</td>
</tr>
<tr>
<td>F3</td>
<td>0.847</td>
<td>0.115</td>
<td>0.098</td>
<td>0.140</td>
<td>0.759</td>
</tr>
<tr>
<td>F4</td>
<td>0.798</td>
<td>0.019</td>
<td>0.060</td>
<td>0.146</td>
<td>0.661</td>
</tr>
<tr>
<td>F8</td>
<td>0.034</td>
<td>0.888</td>
<td>0.125</td>
<td>0.112</td>
<td>0.817</td>
</tr>
<tr>
<td>F9</td>
<td>0.148</td>
<td>0.879</td>
<td>0.001</td>
<td>0.075</td>
<td>0.800</td>
</tr>
<tr>
<td>F10</td>
<td>0.066</td>
<td>0.857</td>
<td>0.122</td>
<td>0.038</td>
<td>0.756</td>
</tr>
</tbody>
</table>
4.4. Confirmatory Factor Analysis (CFA)

The empirical findings from the EFA suggested several hypotheses concerning the quantity and characteristics of the factors within the SCS-AM framework. Subsequently, the proposed measurement model underwent evaluation for its fit and validity through a first-order confirmatory factor analysis (CFA). Further analysis was conducted on the overarching SCS-AM construct, encompassing four factors, using a second-order CFA.

(1). First-order Confirmatory Factor Analysis

Based on the results from the Exploratory Factor Analysis (EFA), the a priori hypothesized model suggested that SCS-AM was a four-factor structure composed of technological innovation and integration (TII), project management and implementation (PMI), collaboration mechanism and information sharing (CMIS), and standardization and compliance (SC), as depicted in Figure 2.

The specifics of the model and its components are as follows:

a. The responses to the SCS-AM measurement tool can be explained by four factors, namely, TII, PMI, CMIS, and SC.

b. These factors are interrelated.

c. Each observed variable is associated with only one factor, and the error terms associated with each observed variable are uncorrelated.

Figure 2. Hypothesized first-order model of the factorial structure for SCS-AM.
Various goodness-of-fit (GOF) indicators are employed to assess the representativeness and accuracy of models from diverse perspectives. The current research utilized several key metrics to evaluate the applicability of the models: the standardized chi-square ($\chi^2$) measures the absolute fit of the model; the Goodness-of-Fit Index (GFI) and the Root Mean Square Error of Approximation (RMSEA) reflect the consistency between the model and the data and between the model and the estimation error, respectively [73]; additionally, the Comparative Fit Index (CFI) and the Adjusted Goodness-of-Fit Index (AGFI) assess the improvement of the model relative to a baseline model and the fit quality considering the model’s complexity. Collectively, these indicators provide a comprehensive overview to determine the adaptability and effectiveness of statistical models. The fit indices suggest that the model is well supported ($\chi^2$/df = 1.061, GFI = 0.952, RMSEA = 0.017, CFI = 0.998, NFI = 0.96, and NNFI = 0.997) [74]. The standardized output of the first-order confirmatory factor analysis measurement model is shown in Figure 3. Table 5 enumerates the eight largest modification index (M.I.) values, each of which is less than 20, suggesting negligible correlations between the factors and the explicit variables.

![Figure 3](image.png)

**Figure 3.** Standardized output of the first-order model of the factorial structure for SCS-AM.

**Table 5.** Eight largest modification indices (first order).

<table>
<thead>
<tr>
<th>Path</th>
<th>M.I.</th>
<th>Par Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>F14</td>
<td>3.235</td>
<td>0.142</td>
</tr>
<tr>
<td>F8</td>
<td>9.853</td>
<td>-0.251</td>
</tr>
<tr>
<td>F5</td>
<td>5.219</td>
<td>-0.19</td>
</tr>
<tr>
<td>F6</td>
<td>3.924</td>
<td>0.105</td>
</tr>
<tr>
<td>F9</td>
<td>4.11</td>
<td>-0.124</td>
</tr>
<tr>
<td>F14</td>
<td>4.955</td>
<td>0.136</td>
</tr>
<tr>
<td>F14</td>
<td>3.235</td>
<td>0.142</td>
</tr>
<tr>
<td>F4</td>
<td>9.853</td>
<td>-0.251</td>
</tr>
</tbody>
</table>
(2). Second-order Confirmatory Factor Analysis

To facilitate a theoretical understanding of the multidimensional nature of SCS-AM, we transformed the first-order measurement model into a second-order measurement model. The difference between the two models lies in the imposition of a structure on the correlational pattern among the first-order factors by the second-order model. In this study, SCS-AM was defined as the overarching construct underlying the four first-order factors, as depicted in the schematic diagram presented in Figure 4.

The CFA model to be tested postulated the following priorities:

a. The response to the SCS-AM tool can be explained through the four first-order factors, namely, TII, PMI, CMIS, and SC, and one second-order factor (SCS-AM).

b. Each observed variable is associated with only one first-order factor.

c. The error terms of each observed variable are uncorrelated.

d. The covariation among the four first-order factors is entirely explained by their regression relationships with the second-order factor (SCS-AM).

Based on the results of the model fit indices ($\chi^2$/df = 1.056, GFI = 0.952, RMSEA = 0.016, CFI = 0.998, NFI = 0.997, and NNFI = 0.998), the model is well supported. The standardized output of the second-order confirmatory factor analysis measurement model is shown in Figure 5. Table 6 enumerates the eight largest modification index (M.I.) values, each of which is less than 20, suggesting negligible correlations between the factor and the explicit variables. Conclusively, the robust model fit validates that the current second-order model is the optimal representation for analyzing the factors influencing SCS-AM [71].

![Figure 4. Hypothesized second-order model of the factorial structure for SCS-AM.](image)

In the analysis of the key influencing SCS-AM, four primary factors were scrutinized: technological innovation and integration (TII), project management and implementation (PMI), collaboration mechanisms and information sharing (CMIS), and standardization and compliance (SC). Among these, SC exhibited the highest standardized estimate, which was quantified at 0.70, demonstrating its pivotal role. Following SC, TII recorded a
value of 0.65, indicating its substantial impact. Meanwhile, the estimates for CMIS and PMI were comparatively lower at 0.55 and 0.51, respectively. These findings underscore the predominance of standardization and compliance, alongside technological innovation and integration, over project management and execution, as well as collaboration mechanisms and information sharing, positioning the former two as the critical influencers within the SCS-AM framework.

Figure 5. Standardized output of the second-order model of the factorial structure for SCS-AM.

Table 6. Eight largest modification indices (second order).

<table>
<thead>
<tr>
<th>Path</th>
<th>M.I.</th>
<th>Par Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>e14 --&gt; e17</td>
<td>4.282</td>
<td>0.172</td>
</tr>
<tr>
<td>e9 --&gt; e16</td>
<td>6.462</td>
<td>0.207</td>
</tr>
<tr>
<td>e9 --&gt; e14</td>
<td>4.907</td>
<td>0.136</td>
</tr>
<tr>
<td>e6 --&gt; e17</td>
<td>6.226</td>
<td>−0.185</td>
</tr>
<tr>
<td>e6 --&gt; e15</td>
<td>4.377</td>
<td>0.182</td>
</tr>
<tr>
<td>e6 --&gt; e10</td>
<td>4.090</td>
<td>−0.124</td>
</tr>
<tr>
<td>e4 --&gt; e9</td>
<td>5.178</td>
<td>−0.190</td>
</tr>
<tr>
<td>e4 --&gt; e5</td>
<td>9.800</td>
<td>−0.251</td>
</tr>
</tbody>
</table>

5. Discussions

5.1. Construction of the Analytical Framework for the Influencing Factors of SCS-AM

Utilizing Exploratory Factor Analysis (EFA), this study classified the fourteen determinants into four distinct factors, as illustrated in Figure 6. By examining the commonalities and interconnections among the determinants within each factor, the factors were accordingly designated as technological innovation and integration (TII), project management and implementation (PMI), collaboration mechanism and information sharing (CMIS), and standardization and compliance (SC). Specifically, the factor of technological innovation and integration encompasses Advanced Technology Adoption and Application (F1), Technology Platform Integration Capacity (F2), Data processing and analysis
technology (F3), and technological innovation atmosphere (F4). Collaboration mechanism and information sharing includes Leadership in Smart Construction Site Strategy (F5), multi-party information and data sharing (F6), and Smart Construction Site Technical Talent Development (F7). Project management and implementation comprises project management processes (F8), quality control processes (F9), Safety Management Processes (F10), and Environment Management Processes (F11). Standardization and compliance consist of laws and regulations (F12), Workflow and Technology Application Standardization (F13), and System Evaluation and Improvement (F14).

From the perspective of theoretical analysis, the research framework constructed in this study identified 14 key influencing factors through a comprehensive and systematic literature review. Based on the data from the questionnaire surveys, the 14 factors selected in this study passed the KMO and Bartlett’s sphericity tests, and they exhibited good normality and multicollinearity, providing a statistical basis for the validity and scientific nature of the framework’s construction. The SCS-AM research framework, which was proposed based on EFA and comprised the four categories of factors, offers a method for simplifying the data structure. This framework demonstrated excellent goodness of fit in the first-order confirmatory factor analysis, indicating strong support for the constructed model.

From the perspective of the existing research, this study presents a research framework that includes four categories of influencing factors: technological innovation and integration (TII), project management and implementation (PMI), collaboration mechanisms and information sharing (CMIS), and standardization and compliance (SC). The factors within these four categories exhibit significant inter-factor correlations, and the results of factor analysis and conceptual analysis show consistency. Additionally, this research framework aligns well with the existing studies. Xiahou et al. (2022) utilized the DEMATEL-ISM method to propose a research framework for key influencing factors in smart construction site applications, including technical systems, organizational systems, and management systems [43]. Zhou et al. (2021) proposed a research framework based on the SWOT and principal component analysis methods, identifying six key factors influencing the sustainable development of smart construction enterprises: technological products, policies and regulations, talent and innovation, internal management, multi-party collaboration, and project management [75]. Wernicke et al. (2021) proposed a framework for assessing the operational maturity of smart construction sites, identifying organizational structure, technology, external environment (including partners, policies and regulations, and innovation atmosphere), and talent as important influencing factors and evaluation criteria [76]. Das et al. (2023) proposed the Smart Modern Construction Enterprise Maturity Model (SMCeMM), which includes seven aspects: data management, people and culture, leadership and strategy, technology, collaboration and communication, management, and innovation and change [33]. The analytical framework proposed in this study not only encompasses aspects frequently addressed in the existing literature, such as technological innovation and integration, and project management, but also places special emphasis on the critical importance of data elements in smart construction sites and the demands for standardization, compliance, and collaborative information sharing [77]. Particularly, the framework highlights two key modules: standardization and compliance (SC) and collaboration mechanism and information sharing (CMIS), which bring innovative insights into the maturity of smart construction site applications. Consequently, the smart construction site application maturity (SCS-AM) framework introduced in this research demonstrates significant theoretical and practical validity and innovation. The framework provides a theoretical basis for exploring the main influencing factors of SCS-AM, contributing to the advancement of the development of SCS-AM.
5.2. Analyzing the Critical Influencing Factors of SCS-AM

The research findings indicate that in the second-order confirmatory factor analysis (CFA), the path coefficients of SC and TII are relatively high, demonstrating their significant impact on SCS-AM. Conversely, the path coefficient of PMI is lower, suggesting that the influence of project management and implementation on SCS-AM is relatively small. The following were the specific findings:

(1) Standardization and compliance (SC) emerged as the predominant factor influencing SCS-AM, with laws and regulations (F12) exhibiting the highest first-order path coefficient, indicating a strong correlation, followed by Workflow and Technology Application Standardization (F13) and System Evaluation and Improvement (F14). The findings emphasize the pivotal role of SC in ensuring operational consistency, efficiency enhancement, and adherence to legal and industrial standards [31]. Particularly notable is the strong emphasis on compliance with laws and regulations, reflecting the respondents’ prioritization of compliance with the legal and industrial standards in smart construction site operations [61,76]. Furthermore, given the intricate requirements of technology integration, data management, and the high standards of safety and quality control within smart construction sites, the importance of standardized workflows and technology applications is highlighted [55].

(2) Technological innovation and integration (TII) was identified as the second most influential factor, highlighting the significant dependence of smart construction sites on integrating and applying advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and big data analytics [77]. These technologies notably improve operational efficiency and enhance resource management while facilitating data-driven decision-making processes. Specifically, the adoption and application of advanced technologies (F1), including IoT, AI, and big data analytics, markedly enhance operational efficiency and resource allocation [78]. The ability to integrate technology platforms (F2) is crucial for coordinating complex construction activities and ensuring timely project completion [56]. Data processing and analysis technology (F3) plays a pivotal role in smart construction sites by supporting risk management, progress monitoring, and quality control, thereby enhancing operational efficiency and decision-making quality [79]. While the
technological innovation atmosphere (F4) is a critical factor in long-term technological advancements, its direct influence is relatively minor and challenging to measure through immediate indicators [80].

(3) Collaborative mechanisms and information sharing (CMIS) stands as the third most crucial factor impacting SCS-AM, as the complexity of smart construction sites demands elevated levels of team collaboration and seamless information exchange, directly affecting project management efficiency and outcomes [80]. However, compared with the direct contributions of technological innovation and standardization, CMIS seems to rely more on the maturity of organizational culture and communication processes, offering an indirect yet equally significant impact [49]. Notably, the strong correlations between smart construction sites’ strategic leadership (F5), multi-party information and data sharing (F6), and technical talent development (F7) with CMIS underscores their pivotal role in elevating the maturity of smart construction site applications.

(4) Project management and implementation (PMI) exhibit the least influence on SCS-AM. Although it is a foundational component of any construction project, the significance of PMI is considered to be slightly less in smart construction sites [41]. This may be attributed to the fact that SCS-AM is more dependent on the aforementioned factors, such as standardized processes and technology integration, as well as effective information sharing and collaboration mechanisms [31].

6. Conclusions and Implications

6.1. Conclusions

This study performed a comprehensive literature review to identify the 14 key factors affecting the maturity of smart construction site applications (SCS-AM). These factors were then categorized into four principal factors using Exploratory Factor Analysis (EFA). The subsequent application of first-order confirmatory factor analysis (CFA) confirmed the associations between the observed variables and these latent factors. Second-order confirmatory factor analysis (CFA) was employed to further explore the interrelations among the first-order factors and their collective representation of the second-order latent variable, SCS-AM. The investigation categorized the 14 influential factors (F1–F14) into four domains: technological innovation and integration (TII), project management and implementation (PMI), collaborative mechanisms and information sharing (CMIS), and standardization and compliance (SC). Notably, technological innovation and integration (TII) and standardization and compliance (SC) were found to exert significantly pronounced effects on SCS-AM.

In both theoretical and practical domains, this study bears significance for stakeholders engaged in SCS-AM. Theoretically, the introduction of the smart construction site application maturity (SCS-AM) model presents a novel theoretical framework for research on smart construction sites. From a practical perspective, this research offers actionable strategies for industry practitioners; for instance, policymakers can leverage the study’s findings to formulate comprehensive regulations and policies that are conducive to SCS advancement, thereby perpetually elevating the maturity of smart construction site applications.

6.2. Implications

In the application of smart construction sites, standardization and compliance should be prioritized. Standardization not only enhances the efficiency of data management but also improves the safety and quality of the construction site. Establishing unified data interfaces and formats, building standardized systems, and formulating detailed technical guidelines, site management norms, and standardized personnel allocation can significantly enhance the level of standardization at smart construction sites [78]. Moreover, a robust legal framework provides solid institutional support for the promotion and application of smart construction sites.
Technological innovation and integration are key factors in the successful implementation of smart construction site management systems. The integrated application of advanced technologies such as the Internet of Things, blockchain, artificial intelligence, and big data is crucial for enhancing automation and intelligence levels [79]. The convergence of these technologies provides the necessary technical support for the enhancement of SCS-AM. Therefore, emphasis should be placed on the development and integrated application of these advanced technologies, promoting their acceptance and innovative management at smart construction sites.

Although this study shows that the importance of collaborative mechanisms, information sharing, and project management processes is lower, these factors should not be overlooked in the practical application of smart construction sites. They directly affect the management efficiency and operational quality of sites. Optimizing organizational structures and workflows, strengthening strategic enterprise planning and talent development, and enhancing project management levels are all crucial for enhancing the implementation and effectiveness of SCS-AM [80].

Finally, establishing a comprehensive evaluation system for the effectiveness of SCS-AM is essential. This system will help governments or other relevant departments to monitor and evaluate the development of smart construction sites in real-time. Through this system, the dynamic evaluations of the optimization effects of the key influencing factors can be conducted, ensuring the timeliness and effectiveness of policymaking.

7. Limitations

Currently, research on SCS-AM is still in its nascent stage, and there is an inadequate understanding of SCS-AM. Therefore, this study, as an exploratory endeavor related to SCS-AM, inevitably possesses certain limitations. For instance, the 14 influencing factors identified in this study may not be comprehensive enough. Furthermore, with the advancement of cutting-edge technologies, the connotations of SCS-AM will involve greater complexity, necessitating further refinement and enhancement of the evaluation indicator system in the future.

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