

Article

Smart Lean in PC: Exploring Factors of Digitalization-Driven Lean in Chinese Prefabricated Construction Projects

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Abstract

The integration of digital technologies is increasingly recognized as a critical enabler of lean practices in prefabricated construction projects. However, a systematic understanding of the underlying factors that drive this lean–digital transformation remains limited. To address the gap, this study identified 18 factors through an in-depth review of 30 papers and a follow-up questionnaire survey. The factors are divided into five dimensions, i.e., organizational, social, technological, economic and environmental, according to an extended framework of the Socio-Technical Systems (STS) and Technology–Organization–Environment (TOE). These 18 factors were then analyzed via a back propagation (BP) neural network model. The empirical data were collected from 148 practitioners across 11 regions in China where PC industrialization, digital technology adoption, and lean-related practices are relatively mature. These regions were selected because digitalization-driven lean practices are more observable in such contexts, allowing the BP model to capture the comprehensive contribution of key factors more effectively. The findings reveal that the effective implementation of the smart lean practices via digitalization is primarily driven by a systematic process, where greater attention should be directed toward simulation-based process optimization, robust information management, integrated design and construction, lean management systems, and the workers’ digital skills. Although the empirical evidence is derived from relatively mature PC and digital construction markets in China, the identified factors provide reference insights for broader PC projects including less mature regions to make effective measures to improve lean implementation. This study contributes to the existing knowledge body of lean in PC by extending the theories of STS and TOE to advance the understanding of digital drivers. Additionally, the results serve as a reference for stakeholders by informing strategic priorities such as resource allocation for workforce development, advancing the realization of smart lean prefabricated construction.



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Keywords: prefabricated construction; lean construction; digitalization; STS-TOE framework; back propagation (BP) neural network model; driving factors

1. Introduction

Lean principles play a significant role in enhancing the efficiency of prefabricated construction (PC) projects [1]. Particularly speaking, PC projects are characterized by complex production workflows and longer production duration, which necessitate greater attention to production planning [2,3]. By optimizing construction processes, minimizing

waste, and emphasizing value creation, lean directly address core challenges in PC, particularly those arising during the production phase [4]. Parallel to the popularity of lean, the advancement of digital technologies under the Industry 4.0 has significantly transformed construction practices in PC projects [5]. Digital tools such as the Building Information Model (BIM), Artificial Intelligence (AI), and the Internet of Things (IoT) have been increasingly integrated into PC workflows. Digital technologies such as BIM, IoT, digital platforms, and data-driven management systems create new opportunities to support lean implementation by improving visualization, information sharing, process monitoring, and decision-making [6].

Despite existing studies having shed light on digitalization in lean-based PC projects [7–9], the existing literature has not yet provided a sufficiently systematic explanation of how digitalization drives lean implementation in PC projects. Without a clear understanding of the digitalization-driven factors that influence lean outcomes, it is difficult to formulate effective strategies to utilize digital tools to promote lean implementation [10,11]. Moreover, existing studies have rarely assessed these factors or identified clear directions for future research. Addressing this gap would not only provide a strategic map of key drivers but lay a solid foundation for policy development to support smart lean transformation.

The process of identifying influencing factors typically begins with a literature review to establish an initial pool, which is then refined through expert interviews [12]. Then, a questionnaire survey is used to empirically evaluate the factors and finalize the list by retaining those with higher average scores, alleviating the experts' subjectivity [13]. However, ranking factors only by average scores may not sufficiently reflect how strongly each factor is associated with the expected implementation outcome [14]. For digitalization-driven lean implementation in PC projects, different organizational, process, technological, economic, and institutional factors may jointly influence lean outcomes in a complex manner. Therefore, it is necessary to adopt an outcome-oriented weighting approach that links the identified factors with the perceived effectiveness of lean implementation. There are a series of studies by Gao, et al. [15], AlKheder, et al. [16], Chang [17], Dehdasht, et al. [18] and Dang, et al. [19] that have explored factors' significance with various methods like the Analytic Hierarchy Process (AHP), Decision-Making Trial and Evaluation Laboratory (DEMATEL), Analytic Network Process (ANP), and social network analysis (SNA). These methods provide useful tools for expert-judgment-based prioritization, causal-relationship analysis, interdependency modeling, and network-structure identification. However, the objective of this study is to calculate the relative contribution of each factor according to its relationship with the perceived lean implementation outcome. In this regard, the BP neural network model was adopted as an exploratory weighting tool. After learning the empirical input–output mapping between the identified factors and lean implementation effectiveness, the trained connection weights of the BP model can be further processed to estimate the relative contribution of each input factor to the output variable [20–22]. Furthermore, this capability is particularly suitable for exploring digitalization-driven factors in lean construction, as different digital and organizational factors may exert heterogeneous effects on lean outcomes.

The empirical samples collected through the questionnaire survey provide the necessary input–output structure for BP modeling, transforming subjective evaluations into quantitative inputs. By using region-specific observations as training samples, the BP model can reflect regional heterogeneity in estimating factor importance. Accordingly, this study does not use the BP model as a large-sample predictive model, but as an exploratory, outcome-oriented method for identifying key drivers of digitalization-driven lean implementation in PC projects. Thus, the paper's objectives are:

- (1) To identify a comprehensive set of factors that enable the integration of digital technologies into lean PC practices through a literature review, expert review, and questionnaire survey;
- (2) To calculate the outcome-oriented relative weights of these factors using a BP neural network model based on regional questionnaire data;
- (3) To develop strategic recommendations and mapping for enhancing digital–lean synergy in PC projects.

An integrated research framework combining an extended STS–TOE framework and a BP neural network model is constructed to explore digitalization-driven lean implementation in PC. To the best of our knowledge, this study is among the first to systematically investigate how digitalization enables lean construction in PC projects by integrating theoretical factor identification with outcome-oriented quantitative weighting. The findings yield twofold contributions. On the theoretical front, first, this study advances the understanding of digitalization-driven lean construction by developing an extended STS–TOE framework that incorporates organizational, process, technological, economic, and policy dimensions. Rather than merely classifying influencing factors, this framework explains smart lean implementation in PC as a multidimensional and interdependent system, in which digital technologies generate lean value through their alignment with organizational capabilities, process integration, economic feasibility, and institutional support. This enriches existing knowledge that has often examined lean construction, digitalization, and prefabricated construction separately. Second, this study provides a clearer understanding of the outcome-oriented importance of influencing factors by integrating the extended STS–TOE framework with a BP neural network model. This quantitative model moves beyond subjective factor ranking and enables the identification of key drivers according to their contribution to lean implementation outcomes. By capturing nonlinear relationships among factors and their impact on lean performance, the model enriches existing approaches for factor weighting and key driver identification in digital–lean construction research. On the practical front, the results provide evidence-based guidance for PC stakeholders to formulate more targeted digital–lean strategies. The identified key factors can support decision-makers in prioritizing digital technology investment, strengthening lean management systems, improving design–construction integration, enhancing informatization capability, and developing workers’ digital skills. Finally, this study offers practical directions for multiple stakeholders, including developers, designers, contractors, prefabrication manufacturers, technology providers, and policymakers, to optimize project activities and promote the high-quality transformation of PC through smart lean implementation.

2. Literature Review

This study examines existing research on lean practices and digitalization in the field of PC, as well as the application of the BP neural network model for determining factor weights. First, it explores lean principles in PC through a review of state-of-the-art studies, highlighting that effective implementation requires support from digital technologies. Then, digitalization is discussed, with a focus on its necessities and key factors driving lean practices in PC. Finally, methods are reviewed to assess the applicability of the BP neural network for determining factor weights, given the characteristics of the research objective.

2.1. Lean in Prefabricated Construction

PC involves the assembly of building components in a controlled manufacturing environment, followed by transportation and installation on site [23,24]. It has gained

widespread adoption due to its optimized use of limited construction space, reduced on-site construction time, minimized material waste, and enhanced quality [25,26]. However, common issues, such as high cost, shortage of specialized workforce, and logistical constraints continue to hinder productivity in PC projects [27,28]. Lean practices are thus applied throughout PC delivery systems, including a precast concrete manufacturing process [29–32]. At its core, lean implementation in PC aims to enhance efficiency by reducing waste and constraints while maximizing value to meet customer expectations [30].

A growing body of research has examined lean implementation in PC, with particular focus on three key themes: barriers and critical success factors (CSFs); lean tools and techniques; and lean frameworks [1,33]. In the area of CSFs, Negi, et al. [34] reviewed the lean implementation barriers in the Indian prefabrication sector, including understanding of lean construction, resistance to adopting better technologies, and insufficient funds; similarly, Ibrahim, et al. [35] categorized CSFs for lean adoption into six domains, highlighting strategic leadership as an emerging priority. These CSF studies offer a foundation for understanding the enablers of lean implementation and inform the identification of digital-relevant factors in our study. Regarding lean tools and techniques, Parameswaran, Tam, Geng and Le [31] reviewed 25 tools widely used in construction, identifying Value Stream Mapping (VSM) and just-in-time (JIT) as the most prevalent. Complementing this, Aslam, et al. [36] proposed a framework for selecting lean tools, such as Last Planner System (LPS), JIT, and pull scheduling, based on lean objectives. These lean tools are integral to lean implementation across various stages of PC projects. Furthermore, Gao and Low [37] extended the “Toyota Way” into a four-tier lean framework emphasizing process design, people and partner involvement, and systematic problem-solving. Together, these three themes of research provide a conceptual foundation for understanding lean in PC. However, PC involves different stages, spanning from design, manufacturing, and transportation to on-site assembly, which makes the construction process more fragmented [38]. How to integrate fragmented processes is also the key to achieving smooth lean project delivery.

Emerging digital technologies, e.g., BIM and IoT, present an opportunity to address process fragmentation by improving stakeholder coordination and process integration [39], which can support effective lean construction delivery. The integrated lean and digital technologies, such as BIM, in PC will significantly increase the value of the construction process [40]. However, most studies remain focused on lean tools and techniques alone [31,36,41–43]. This leaves comparatively limited attention to how emerging digital technologies can enhance lean, aside from a growing stream of research work on BIM–lean integration [44–46].

2.2. Digitalization in Lean Construction

The effective implementation of lean requires integration with modern digital tools, like BIM and IoT, bringing real-time visualization and stakeholder collaboration [47]. The application of digital technologies in lean construction has been as a popular research area in the development of PC [10,48,49]. Digital technologies are able to streamline drawings, facilitate the production process, and enhance lean outcomes [44,45,50]. For example, Altan and Işık [51] explored the interactions between digital twins and lean to analyze their benefits. Similarly, Liu, et al. [52] proposed a digital–lean platform to accelerate the transition toward smart lean, demonstrating its potential in the PC industry.

Given this growing interplay between digitalization and lean, it is essential to identify the key factors that drive the adoption of digital tools in lean construction. A clear understanding of these factors is critical for PC stakeholders to formulate effective strategies that leverage digital solutions for lean implementation [53]. There are

some studies focusing on the factors implementing BIM and lean construction. Evans, et al. [54] identified CSFs for integrating BIM and lean construction; Polat and Demirkesen [55] measured the impact of lean on BIM and project success. Current research largely focuses on BIM, with limited attention to the drivers of digitalization for lean construction, particularly in the PC context. This gap constrains stakeholders' ability to use digital technologies effectively in promoting lean construction, which hinders project performance and digital transformation. Therefore, there is a pressing need to systematically identify and examine the digitalization-related factors that drive lean adoption in PC. Such insights are essential for developing targeted strategies that not only optimize lean adoption but also support digital transformation [56].

In this regard, STS theory and the TOE framework provide foundations. STS theory emphasizes the interdependence between social, e.g., people, roles, organizational structures, and technical systems, e.g., processes and information, highlighting how organizational structure, human behavior, and technological tools co-evolve to enable systemic change [57,58]. This perspective is relevant to PC projects because digital tools such as BIM, IoT, digital platforms, and process simulation need to be embedded into lean routines, workforce capabilities, and cross-functional coordination mechanisms. However, STS mainly focuses on internal socio-technical alignment and pays less attention to the external conditions that shape technology adoption. The TOE explains technology adoption as a function of the technological context, organizational context, and environmental context [59]. In PC projects, the technological context reflects the availability and maturity of digital tools; the organizational context concerns managerial support, workforce capability, and internal coordination; and the environmental context captures external influences such as policy support, institutional standards, and industry requirements. For examining the impacts of digitalization-driven factors on lean implementation in PC, integrating STS and TOE helps explain both the internal implementation mechanism and the external adoption environment of digitalization-driven lean practices, providing a more comprehensive analytical approach [60].

Additionally, we extend this integrated framework to include an economic dimension. The economic dimension is necessary because digitalization-driven lean implementation requires investment in digital platforms, BIM/IoT systems, process simulation tools, training, data management, and workflow reconfiguration. These changes can only be sustained when economic feasibility, return on investment, cost allocation, and resource availability are sufficiently considered. In this sense, the economic dimension bridges the internal socio-technical transformation emphasized by STS and the external adoption conditions emphasized by TOE, because economic feasibility is shaped by both internal resource allocation and external market or policy conditions [54,61,62].

Hence, this study conceptualizes the factors across five dimensions: organizational, social, technological, economic, and environmental. This extended STS-TOE framework could enable a holistic examination of how digitalization supports lean construction in PC. Furthermore, it provides a theoretical criterion for selecting digitalization-related drivers and designing measures to enhance lean implementation through digital technologies.

2.3. Methods for Selecting and Weighting Factors

While identifying influencing factors, a literature review is commonly used to establish an initial factor pool, and expert interviews are then conducted to refine the factors through adding, deleting, and adjusting items [12,63]. However, relying only on a small expert panel may introduce instability and limited representativeness [64]. Therefore, questionnaire surveys are further introduced to empirically evaluate the initial factors and retain items with sufficiently high average scores, thereby removing marginal or less salient factors [13,65].

Although ranking factors by average scores can reflect their perceived importance, it does not directly explain how each factor contributes to the expected outcome. This distinction is particularly relevant to digitalization-driven lean implementation in PC projects, where organizational, process, technological, economic, and institutional factors may jointly affect lean implementation effectiveness [14,66]. Therefore, beyond identifying and screening factors, this study further requires an outcome-oriented weighting method that links the identified factors with the perceived effectiveness of lean implementation [12,67].

There are a series of studies by [18,68–70] that have explored factors' significance with various methods like Analytic Hierarchy Process (AHP), Decision-Making Trial and Evaluation Laboratory (DEMATEL), Analytic Network Process (ANP), Entropy, and social network analysis (SNA). For example, Li, et al. [71] used the ANP-Fuzzy comprehensive evaluation mode to assess the lean construction performance; Dang, et al. [72] integrated the entropy and FAHP to weight the factors influencing the sustainable construction capability in Chinese prefabrication enterprises. These methods are effective in revealing relative importance or structural relationships among factors; however, they are generally limited in quantifying the magnitude of each factor's contribution to the outcome variable [73]. As a result, the identified key factors may not necessarily be the most effective leverage points for improving the target outcome [73]. In fact, the driving factors are interactive, with their importance varying across different regions [14,66]. Therefore, when determining the driving factors of digital technologies in lean PC projects, it is essential to not consider their relative influence, but their effects on the implementation outcomes of lean. In this regard, the BP neural network model is able to learn the mapping from multiple input variables to the output variable through iterative training and is capable of quantifying each factor's impact on the final outcome [20,21,74]. Notably, the BP neural network model stands out for its ability to capture and quantify the magnitude of each factor's influence between input variables and output outcomes [20,22]. This is because BP neural network models are capable of learning complex relationships between the input variables and output results through iterative training [74,75]. More importantly for this study, after the network is trained, the connection weights between the input layer, hidden layer, and output layer can be further processed to estimate the relative contribution of each input factor to the output variable [76]. This capability is particularly suitable for exploring digitalization-driven factors in lean construction, as different digital and organizational factors may exert heterogeneous effects on lean outcomes. As such, the BP neural network model offers a comprehensive approach to determine factor weights, leading to a deeper understanding of complex systems [77]. The BP neural network model has been widely applied in engineering, finance, energy, and communication fields, and has continued to evolve through optimization and refinement [78,79].

Importantly, the questionnaire survey also provides an empirical dataset that links influencing factors to project outcomes [12,63]. Specifically, the retained factors constitute the input variables (X), while the overall performance or target evaluation score constitutes the output variable (Y). This empirical input–output structure enables subsequent data-driven modeling and transforms subjective questionnaire-based evaluations into analyzable quantitative inputs [80]. Moreover, the empirical samples were collected across different regions or projects where the maturity levels of digitalization and lean implementation vary [81–84]. By using these region-specific observations as training samples, the BP neural network can reflect such spatial heterogeneity when estimating factor importance [85,86]. In summary, the questionnaire-based empirical model provides the necessary input–output evidence, and the BP neural network operationalizes this evidence to quantify factor contributions and identify key drivers of digitally driven lean construction in prefabricated projects [87,88]. Accordingly, this study adopts

the BP neural network to address the methodological need for outcome-oriented and data-driven identification of critical influencing factors in digitalization-driven lean prefabricated construction projects.

Given that the impact of digital technologies on lean implementation in PC projects is not uniform across regions, this study employs BP neural networks to assess the factor significance, ensuring a more accurate and context-sensitive evaluation of driving factors.

3. Methodology

To achieve the research objective, a mixed method that integrates qualitative and quantitative analyses is adopted. Specifically, the method comprises a comprehensive literature review, a questionnaire survey, and a BP neural network analysis, as shown in Figure 1. These processes can be divided into four parts, which includes (1) the primary identification of driving factors through the literature review based on the extended STS-TOE framework, (2) the determination of driving factors based on the questionnaire survey, (3) the construction of a weight calculation model based on BP neural networks, and (4) the determination of critical factors and their influences on lean practice in PC.

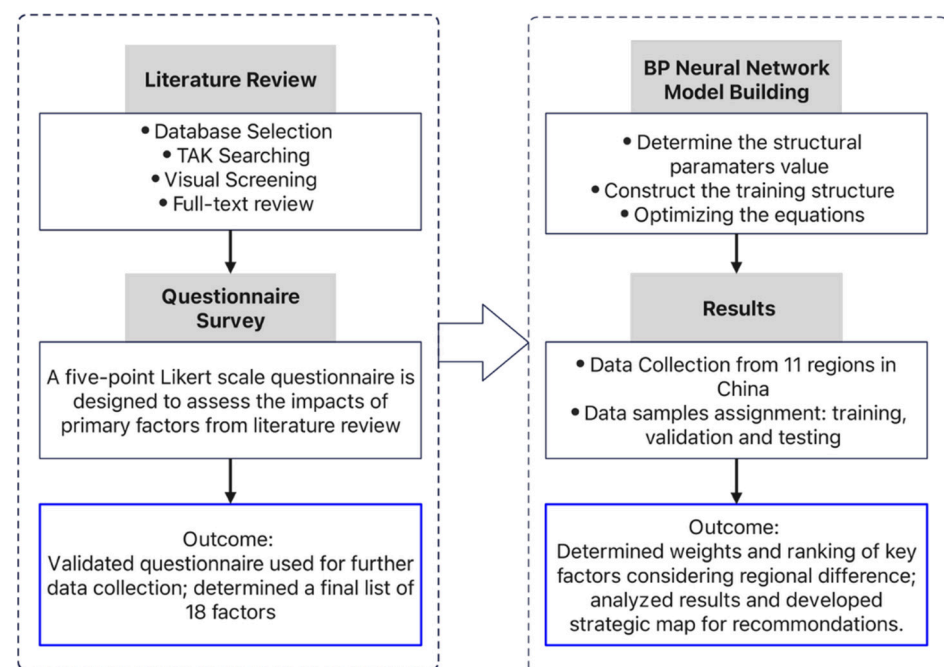


Figure 1. Research design.

3.1. Identifying Primary Factors Under Extended Sts-Toe Framework

This study identified digitalization-driven factors with the extended STS-TOE framework. Accordingly, the factors can be identified from five key dimensions: (1) organization-based, e.g., culture, capability, and coordination, (2) social-based, e.g., process, planning, workflows, and interoperability, (3) technology-based, e.g., tools, maturity, and platforms, (4) economy-based, e.g., investment, cost, and benefits, and (5) environment-based, e.g., standards, support, and incentives. Then, an in-depth literature review was conducted to identify the primary factors of digitalization-driven lean in PC projects from the five dimensions. Searches were performed across global databases, i.e., “Google Scholar”, “Web of Science”, “Scopus”, as well as the Chinese database, i.e., “CNKI”. The search strategy used Boolean string: Title/Abstract/Keyword = (“lean” OR “just-in-time”) AND (“prefabricated construction/buildings” OR “prefabrication” OR “precast” OR “off-site construction” OR “industrial building system”) AND (“BIM” OR “digitalization” OR

“information technology”). Time restrictions were not set to cover a full list of relevant studies. To ensure methodological rigor, only peer-reviewed articles were included, as they undergo a more rigorous review process than conference papers [89,90]. The search was further refined by selecting articles as the “document” type and limiting language to “English”. The search initially yielded around 80 papers. Studies that were not directly relevant to the research scope, lacked factor-related evidence, or were not peer-reviewed journal articles were excluded. After removing duplicates and excluding non-SCI journal articles through visual inspection, 30 high-quality and highly relevant papers were selected for full-text review. Similar factor-identification studies have also used a focused corpus of high-relevance papers rather than a large but weakly related literature pool, as the quality and relevance of sources are more critical than the absolute number of papers for thematic factor extraction.

These 30 papers formed the basis for identifying preliminary factors, while the initial broader set of 80 papers was also referred to ensure comprehensive coverage. During the literature-reviewing process, particular attention was paid to avoiding conceptual redundancy among the extracted factors. Similar or overlapping expressions identified from different studies were compared, merged, and standardized according to their theoretical meanings and practical implications. This coding and refinement process helped avoid repeated counting of semantically similar items and ensured that each preliminary factor represented a relatively distinct aspect of digitalization-driven lean implementation. From these, a total of 27 preliminary factors relating to organizational, social, technological, economic and environmental dimensions were identified. To further enhance objectivity, only factors that appeared in at least three reviewed papers were retained as preliminary factors, ensuring that the selected items reflected recurring themes in the literature rather than isolated or repetitive expressions.

3.2. Data Collection Through a Questionnaire Survey

To refine the 27 preliminary factors, a structured questionnaire survey was conducted targeting construction practitioners in China who have working experience with prefabricated, off-site, or modular construction projects. Additionally, the questionnaire survey should be used to calculate the factors’ weights based on BP neural networks [84]. The questionnaire was divided into two sections: Part 1 gathered demographic and professional profile information, including gender, age, position, and years of experience. Part 2 asked respondents to rate the importance of each identified factor and the overall effectiveness of lean implementation in PC projects, using a five-point Likert scale, ranging from 1 (minimal impact) to 5 (very high impact). The overall effectiveness of lean implementation is the output variable of the BP model. This item was designed to capture the overall outcome of lean implementation as perceived by practitioners, rather than to measure each sub-dimension of lean performance separately. Before distributing, a pilot study was conducted with 6 experts working on PC projects to ensure that the wording and phrasing of the 27 factors and the overall evaluation of lean implementation were clear and easy to understand. Based on their feedback, minor adjustments were made. Then, the survey was administered online via the Wenjuanwang platform using a combination of random and convenience sampling to enhance representativeness.

Notably, to thoroughly consider the impact of regional difference in construction management practices, technical standards, and economic conditions on digitalization-driven lean implementation in PC, the different regions should be considered [82]. This not only ensures the reliability of the data but also considers the influence of regional differences. Therefore, the data collected from the questionnaire survey should cover various regions. Regions with a higher level of PC development and lean–digital application can more

comprehensively reflect the driving role of digital tools in lean implementation, thereby enabling the identification of effective and representative influencing factors. This is because regions with higher levels of development possess richer experience, which allows for more comprehensive evaluations. Since the study aims to identify how digital technologies support lean implementation in PC projects, regions with more mature PC and digital construction practices provide a more suitable empirical context, as digitalization-driven lean practices are more observable and practitioners are more likely to evaluate the relevant factors based on actual project experience. Moreover, according to the “Guidelines on Vigorously Developing Prefabricated Buildings” issued by the General Office of the State Council [91], Beijing–Tianjin–Hebei, the Yangtze River Delta, and the Pearl River Delta are designated as priority regions for PC advancement. Consequently, PC in these areas is relatively mature, and, combined with their advanced economic conditions, the level of digital technology application and lean is relatively higher. Therefore, this study selects these regions and China’s eastern coastal regions as the focus areas for analysis. As a result, 11 regions are selected as the survey regions, i.e., Beijing City, Tianjin City, Hebei Province, Shanghai City, Jiangsu Province, Zhejiang Province, Anhui Province, Guangdong Province, Fujian Province, Shandong Province and Liaoning Province. Therefore, data from these regions can support the identification of key factors that are meaningful for PC projects seeking to advance lean implementation through digital technologies.

Over a two-week period, 148 valid responses were collected from 11 regions. Respondent profiles are summarized in Table 1. The respondents covered different professional roles in PC projects, including production managers, construction managers, project managers, cost managers, and chief engineers. This multi-role respondent structure was adopted to obtain a more comprehensive professional evaluation of digitalization-driven lean implementation, rather than relying on a single stakeholder perspective. In addition, many respondents had participated in multiple lean and digital PC projects, indicating that they were able to evaluate the identified factors based on practical project experience. Therefore, the questionnaire data provide a professional basis for constructing regional-level evaluations of lean implementation effectiveness.

Descriptive statistical analyses were conducted via SPSSPRO for the reliability of the results. Cronbach’s alpha coefficient is $0.949 >$ the standardized threshold of 0.948 , indicating excellent internal consistency of the questionnaire. To evaluate the construct validity, a factor analysis was performed. The Kaiser–Meyer–Olkin test has a value of 0.927 , while Bartlett’s test of sphericity has p -value < 0.05 , confirming the suitability of the data for factor analysis.

Table 1. The basic information for the 148 valid responses.

Items	Profile	NO.	Percentage (%)
Main position	Production manager	35	23.65%
	Construction manager	29	19.59%
	Project manager	36	24.32%
	Cost manager	24	16.22%
	Chief engineer	24	16.22%
Education level	Bachelor or below	73	49.32%
	Master	57	38.51%
	Ph.D.	18	12.16%
Years of experience	<5	57	38.51%
	5–10	46	31.08%
	11–20	30	20.27%
	20<	15	10.14%

Table 1. Cont.

Items	Profile	NO.	Percentage (%)
Numbers of lean and digital PC projects	1–3	39	26.35%
	4–6	55	37.16%
	7–9	39	26.35%
	10≤	15	10.14%
Region distribution	Beijing City	13	8.78%
	Tianjin City	15	10.14%
	Hebei Province	12	8.11%
	Shanghai City	15	10.14%
	Jiangsu Province	12	8.11%
	Zhejiang Province	12	8.11%
	Anhui Province	13	8.78%
	Guangdong Province	18	12.16%
	Fujian Province	11	7.43%
	Shandong Province	15	10.14%
	Liaoning Province	12	8.11%

3.3. Determining Final Factors Through a Questionnaire Survey

A questionnaire survey was conducted to evaluate the perceived importance of the 27 preliminary factors. Respondents used a five-point Likert scale (1 = minimal impact, 5 = very high impact). To retain factors with relatively clear importance, a mean-score threshold of 3.4 was adopted. The 3.4 threshold represents a pragmatic selection criterion, retaining approximately two-thirds of the maximum score, reflecting the majority of respondents' perception of importance, while excluding less important factors. This is commonly used as selection criteria for identifying relevant factors. Factors with mean scores below 3.4 were considered less salient and were removed. Accordingly, 18 factors with mean scores above 3.4 were retained for subsequent BP neural network analysis. The 9 removed factors included "Skilled workers knowing PC and BIM" [44], "Clear organizational boundaries and responsibilities" [6], "Development of lean construction technics" [92], "Change control based-digitalization" [93], "Plan management based digitalization", "Cost-benefit analysis based digitalization" [94], "Promotion and application of emerging informational technologies" [95,96], "Cost of application and management" [97,98] and "Investment of software and hardware" [6,98]. These final factors, listed in Table 2, were deemed relatively important by respondents, thereby enhancing the robustness of the subsequent BP neural network analysis process.

Table 2. Final 18 factors of digitalization-driven lean in PC projects.

Category	Code	Factors	Definitions	Relevant Models/Framework
Organization-based	X ₁	Workers' skill in digital technologies	The extent to which workers possess the knowledge and operational capability to use digital tools in PC projects	Guideline for BIM–lean integration [99]; digital twin-based on lean thinking [98]
	X ₂	Stakeholder's' attitudes of information share	The willingness of participants to use digital information collaboratively across the life cycle of PC projects	Factors of lean and BIM [40]; BIM–lean framework [6,44,97,100,101]
	X ₃	Organization structure	The extent to which the organizational arrangement and coordination mechanisms support digital–lean implementation in PC projects	BIM–lean framework [6,97,101]

Table 2. Cont.

Category	Code	Factors	Definitions	Relevant Models/Framework
Process-based	X ₄	Construction of lean management system (LMS)	The establishment of systematic lean management routines, such as value stream management, just-in-time coordination, and continuous improvement	Guideline for BIM and lean integration [99]; workflow based on BIM and lean [102]
	X ₅	Digitalization of processes and workflows	The transformation of traditional construction processes and workflows into digital, traceable, and data-supported procedures across the PC project life cycle	Lean construction principles [45]; BIM–lean framework [6,44,97,100,101]; workflow based on BIM and lean [102]
	X ₆	Data consistency and compatibility	The degree to which project data are accurate, standardized, interoperable, and compatible across different stakeholders and project stages	Digital transformation maturity model [103]; BIM–lean framework [6,97,100,101]
	X ₇	Improvement in construction efficiency	The extent to which digital technologies contribute to reducing rework, process delays, and improving productivity in PC project delivery	Workflow based on BIM and lean [102]
Technology-based	X ₈	Level of informatization	The maturity of digital information systems and data management capability supporting real-time monitoring and decision-making	Digital twins based on lean thinking [98]
	X ₉	Effective implementation of lean construction tools	The effective use of lean tools and methods, such as JIT, VSM, and LPS, supported or enhanced by digital technologies	Guideline for BIM and lean integration [99]; lean practices using BIM and digital twinning [92]
	X ₁₀	Integration of design and construction	The degree of coordination and information integration between design and on-site construction to reduce fragmentation and rework	Lean construction principles [45,104]
	X ₁₁	Quality control-based digitalization	The application of digital technologies to monitor, evaluate, trace, and improve quality control during construction processes	Lean construction principles [45,104]; digital twins based on lean thinking [98]; 3D digital framework [105]
	X ₁₂	Efficiency control-based digitalization	The use of digital technologies to monitor and control schedule, productivity, resource utilization, and workflow efficiency in PC projects	Lean construction principles [45,104]; workflow based on BIM and lean [102]; lean practices using BIM and digital twinning [92]
	X ₁₃	Simulation and optimization of processes	The use of digital simulation tools, such as BIM-based simulation to optimize workflows and improve construction planning	Lean construction principles [45,104]; lean production strategies with virtual reality and BIM [96]
	X ₁₄	Digital platform of collaboration	The use of integrated digital platforms that support multi-stakeholder collaboration, information sharing and coordinated decision-making	Digital transformation maturity model [103]; guideline for BIM and lean integration [99]; factors of lean and BIM [40]; lean production strategies with virtual reality and BIM [96]
	X ₁₅	Customization of digital technologies	The tailoring of digital systems to fit the specific needs, processes, organizational conditions, and project characteristics of PC projects	Digital transformation maturity model [103]; lean production strategies with virtual reality and BIM [96]

Table 2. Cont.

Category	Code	Factors	Definitions	Relevant Models/Framework
Economy-based	X ₁₆	Economic benefit of lean digitalization	The perceived economic value generated by integrating digital technologies with lean construction, such as cost reduction and return on investment	Digital transformation maturity model [103]; BIM–lean framework [6,44,97,100,101]
Policy-based	X ₁₇	Support of government policy	The extent to which governmental policies, incentives, regulations, and development strategies support lean digitalization in PC	Digital transformation maturity model [103]; BIM–lean framework [6,44,97,100,101]
	X ₁₈	Publication of institution and standard	The availability of industry standards, technical guidelines, and institutional regulations that guide digital–lean integration in PC projects	Digital transformation maturity model [103]; guideline for BIM and lean integration [99]; lean management tool [106]

Among the 18 factors, the organization-based factors emphasize digital skills, stakeholder attitudes, and organization structures, while the social-based factors concern lean management systems, workflows, and data consistency. Technology-based factors address informatization, design–construction integration, quality control, simulation, and digital platforms. In addition, economy- and environment-based factors highlight economic benefits, government support, and institutional standards. Together, these factors form a comprehensive framework grounded in established literature and models.

3.4. Bp Neural Network Analysis

(1) Constructing the structure of the BP neural network model.

The BP neural network model consists of an input layer, hidden layers, and an output layer [20]. The parameters including the number of nodes in each layer were determined to set the BP network structure. One feature is that the neuron nodes are fully connected to adjacent layers but not within the same layer [107]. While multiple hidden layers can model complex relationships, more layers do not improve performance. The hidden layer captures nonlinear relationships, but an imbalance in node count can lead to underfitting, i.e., too few nodes, or overfitting, i.e., too many nodes, reducing predictive accuracy. To optimize performance, the BP neural network model was designed with a compact structure, selecting the minimum necessary nodes while maintaining accuracy [77]. The number of input layer nodes is 18, corresponding to the total number of influential factors, while the number of output layer nodes is 1, representing the goal of lean implementation in PC [108]. The number of hidden layer nodes can be determined with reference to Equation (1) to enhance selection effectiveness [74,108].

$$m = \sqrt{nk} + a \quad (1)$$

where m is the number of nodes of the hidden layer, n is 18, representing the number of nodes of the input layer, and k is 1, representing the number of nodes of the output layer. a is a constant belonging to 1–10. In order to determine the node number of the hidden layer, training experiments are carried out for the network model with different numbers of neurons in the hidden layer respectively, and a comparative analysis is conducted for the mean square error (MSE) [109]. The MSE calculation formula is as Equation (2) [109].

$$MSE = \frac{1}{m} \sum_{i=1}^m (y_i - \hat{y}_i)^2 \quad (2)$$

where y_i is the true value, $\hat{y}_i$ is the estimated value, and m is the number of hidden layer nodes. After multiple trials, this study determined that a BP neural network with one hidden layer and 6 nodes in the hidden layer achieved the lowest *MSE* [77].

The model structure of the BP neural network model with three layers is shown in Figure 2. The figure illustrates the structure of the BP neural network model used to evaluate the impact of digitalization-related factors on lean construction. The input layer consists of 18 driving factors, which are processed through 6 neurons in the hidden layer to capture their nonlinear interactions. The output layer represents the overall effectiveness of lean construction. This structure enables the model to simulate and quantify how each factor contributes to lean implementation by learning the underlying relationships between inputs and outputs through iterative training.

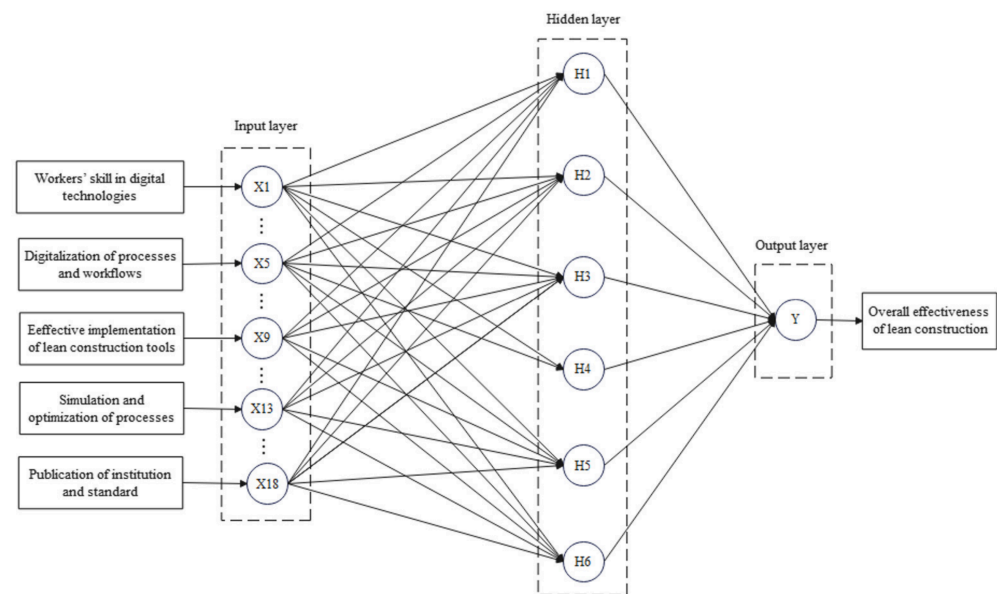


Figure 2. The structure of the BP neural network.

(2) The working principle of the BP neural network.

The learning process of the BP neural network model consists of two directions: (1) feedforward, i.e., input data from the 18 factors are processed via weighted connections in the hidden layer, transformed via the activation function, and passed to the output layer; (2) back propagation, i.e., the error inverse transfer algorithm iteratively adjusts weight and bias to minimize the difference between expected and actual outputs, ensuring convergence to the optimal solution. The hyperbolic tangent sigmoid transfer function was selected as the activation function for the neurons in the hidden layer, while a purely linear activation function was selected in the output layer. The model consists of a summation unit computing the weighted sum of inputs and a nonlinear activation function within a defined threshold. They are mathematically formulated in Equation (3).

$$u_k = \sum_{j=1}^p \omega_{kj} x_j, v_k = u_k - \theta_k, y_k = \varphi(v_k) \quad (3)$$

p is the number of nodes of the input layer; k is the number of nodes of the input layer; w represents the weight; θ is the threshold; and φ is the activation function in the hidden layer.

(3) The learning and training of the Bp model.

The Levenberg–Marquardt algorithm is widely used for training BP neural network models, particularly with small training datasets [110]. As an iterative optimization

method, it integrates the strengths of the steepest descent and Gauss–Newton methods, making it highly effective for nonlinear least squares problems and function parameter fitting [111,112]. The training steps of the BP neuron network model can be found in Rumelhart, Hinton and Williams [21,77].

In this study, training parameters were set to balance computational efficiency and convergence accuracy. Usually, the learning rate of the network is set to 0.01 [77,113], the maximum training number is 1000 [80,88], and the training requirement accuracy is 0.001 [108,114]. Other parameters are set by default settings, and training is performed until the network automatically converges, that is, the BP neural network model construction is completed. In order to ensure the reliability of the training results, 30 samples were taken randomly as training samples, and the remaining 5 samples were chosen as a test group [108]. The normalized index data are input into the constructed neural network model, and the output rural vulnerability rank index is between $[-1$ and $1]$ [113].

(4) Calculating factors' weights using the Bp model.

Note that the weight of the hidden layer is w_{ij} in Equation (4), and the weight of the output layer is w_{jk} in Equation (4) [77]. Then, the factors' final weights S_i can be calculated through combining w_{ij} and w_{jk} . The input data matrix is $n \times m$ dimensional: m is the amount of data. There are 6 hidden layer neurons, so the hidden layer weight w_{ij} is an $n \times 6$ dimensional matrix, and the output layer weight w_{jk} is a 6×1 dimensional matrix.

$$\begin{cases} w_{ij} = \text{net.IW}\{1,1\} \\ w_{jk} = \text{net.LW}\{2,1\} \end{cases} \quad (4)$$

The BP neural network modeling and analysis aim to determine the weight values of the influencing factor indices for digitally driven lean construction in PC. To evaluate the extent to which input variables affect the output variable, it is necessary to analyze and process the weights between neurons in the input layer, hidden layer, and output layer [77,111]. The influence of the i_{th} input variable relative to all units in the input layer on the j_{th} hidden layer unit is expressed as

$$F_{ij} = \frac{|\omega_{ij}|}{\sum_i |\omega_{ij}|} \quad i = 1, 2, \dots, n; j = 1, 2, 3, \dots, m \quad (5)$$

Similarly, the influence of unit j relative to all units in the hidden layer on the k_{th} output is expressed as

$$F_{jk} = \frac{|w_{jk}|}{\sum_j |w_{jk}|} \quad j = 1, 2, \dots, m; k = 1, 2, 3, \dots, p \quad (6)$$

Furthermore, the influence of the i_{th} input variable on the k_{th} output variable is expressed as

$$F_{ik} = \sum_j F_{ij} \cdot F_{jk} \quad (7)$$

Therefore, the weights among the input layer indicators can be expressed as

$$S_i = \frac{F_{ik}}{\sum_{i=1}^n F_{ik}} \quad (8)$$

where i represents the input variables of the neural network, $i = 1, 2, \dots, n$; j represents the hidden layer units, $j = 1, 2, 3, \dots, m$; k represents the output variables, $k = 1, 2, 3, \dots, p$; w_{ij} is

the weight coefficient between i and j ; w_{jk} is the weight coefficient between j and k ; and S_i is the final weight of the factors.

3.5. Importance Evaluation Based on the Bp Neural Network Model

(1) The data source of the input and output layer.

It should be noted that the BP neural network model in this study was used to calculate the relative weights of the identified factors rather than to conduct large-sample prediction. Existing studies indicated a limited number of representative analytical units can be used in BP-based exploratory evaluations such as 10 and 11. Therefore, the 11 region-level observations were used as representative analytical units for exploratory factor-weight calculation. Considering the regional differences in PC development, digital technology adoption, and lean implementation practices in China, the individual questionnaire responses were aggregated at the regional level for BP neural network analysis. These 11 regions have been identified as key areas for promoting PC in China due to their relatively mature industrial foundation, policy support, and practical experience in construction industrialization. For the input layer of the BP neural network, the average scores of the 18 identified key factors were calculated for each region, which served as the input variable, denoted as $X_1, X_2, \dots, X_{18}$.

For the output layer, the regional average score of the perceived overall effectiveness of lean implementation in PC projects was used as the output variable, denoted as Y . As mentioned in Section 3.2, respondents' qualitative assessments of perceived overall effectiveness of lean implementation are collected. It should be emphasized that the output variable represents an overall professional evaluation of lean implementation effectiveness, rather than a multidimensional latent construct scale. This design is consistent with the exploratory purpose of the BP model in this study, which is to calculate the relative contribution of digitalization-driven factors to the perceived lean implementation outcome. These scores were aggregated at the regional level to generate comparable regional input–output observations, rather than to represent the perception of every individual respondent or project. It should be noted that regional aggregation may reduce within-region variance. The purpose of the BP neural network analysis is to calculate exploratory, outcome-oriented factor weights at the regional level, rather than to explain individual-level differences. Moreover, the respondents covered multiple professional roles in multiple lean and digital PC projects as detailed in Table 1, providing a more comprehensive professional evaluation of the overall implementation level within each region. In summary, the correspondence between input variables (X_i), i.e., the regional averages of the 18 factors, and the output variable (Y), i.e., the composite lean effectiveness score, is presented in Table 3.

Table 3. Data source of input and output layer of BP neural network model.

	Beijing	Tianjin	Hebei	Shanghai	Jiangsu	Zhejiang	Anhui	Guangdong	Fujian	Shandong	Liaoning
X_1	4.07	4.00	4.00	3.93	3.89	4.00	4.00	3.75	3.75	4.00	3.65
X_2	3.80	4.00	3.67	3.60	4.11	4.00	3.86	3.75	3.75	3.79	3.55
X_3	4.00	4.00	4.33	3.80	3.22	3.95	3.62	3.58	4.75	3.83	3.40
X_4	3.73	4.25	3.00	3.87	3.89	3.68	3.81	3.58	3.25	3.75	3.70
X_5	3.93	3.75	3.33	3.87	3.33	3.58	4.33	3.67	3.00	3.75	3.60
X_6	4.13	3.75	4.33	3.80	4.00	3.74	4.00	4.00	3.75	4.00	3.65
X_7	3.87	4.25	3.00	3.73	4.22	3.95	3.62	3.58	3.25	3.79	3.60
X_8	3.60	3.75	4.00	3.80	3.56	3.84	3.86	3.83	4.00	3.67	2.90
X_9	3.67	3.25	4.00	3.60	4.11	3.53	3.76	3.83	3.75	3.92	3.55
X_{10}	3.73	4.00	3.00	3.93	3.67	3.47	3.76	3.75	3.25	3.71	3.15
X_{11}	3.87	3.75	4.33	3.80	4.00	3.95	3.86	3.58	3.75	3.54	3.85

Table 3. Cont.

	Beijing	Tianjin	Hebei	Shanghai	Jiangsu	Zhejiang	Anhui	Guangdong	Fujian	Shandong	Liaoning
X ₁₂	4.13	3.50	4.33	4.20	3.78	3.58	3.86	3.58	3.75	3.75	3.20
X ₁₃	3.80	3.50	3.67	3.80	3.89	3.84	3.62	3.58	3.25	4.25	3.45
X ₁₄	3.93	3.75	3.00	2.87	3.56	3.63	3.48	3.25	2.50	3.71	3.30
X ₁₅	3.73	3.00	4.00	2.67	3.56	3.53	3.48	3.58	1.75	3.67	3.55
X ₁₆	3.73	3.75	2.33	3.47	3.44	3.37	3.43	3.50	2.50	3.50	3.45
X ₁₇	3.73	4.00	3.00	2.93	3.33	3.79	3.24	3.25	2.25	3.50	3.45
X ₁₈	3.60	2.75	2.67	2.93	3.11	3.68	3.48	3.33	2.75	3.63	3.50
Y	4.20	3.75	5.00	3.87	3.89	4.26	3.86	3.58	3.25	4.00	3.85

(2) Data processing.

Data normalization and partitioning are necessary for the BP neural network model. Normalization forms the foundation of model training by transforming the data into the range of $[-1, 1]$. This can be done with the toolbox of BP neural networks in MATLAB (R2019b). Data partitioning is critical for preventing overfitting in BP neural networks. Typically, the data is divided into three subsets: training, validation, and testing. The model was trained using the training data, while the validation data was used to ensure that the model did not overfit the training dataset. The test dataset was finally applied to assess the final performance of the model. The data of training, validation, and testing datasets were set as 70%, 15%, and 15%, which is a balanced approach commonly used in neural network models [115]. However, because the analysis was based on 11 region-level observations, the *MSE* values were interpreted only as internal fitting indicators rather than as evidence of strong predictive accuracy or generalization capability. Similar BP-based evaluation studies have also used a limited number of evaluation objects when the purpose was model-based evaluation or factor-weight identification rather than large-sample prediction.

The training set *MSE* results indicate that the trained network achieved an acceptable internal fit to the aggregated regional dataset. Nevertheless, the interpretation of the BP neural network results focuses on the relative ranking and managerial implications of the derived factor weights rather than on predictive performance. Accordingly, the subsequent analysis uses the trained network weights to calculate the relative contribution of each digitalization-driven factor to lean implementation effectiveness in PC projects.

Furthermore, the trained BP neural network model was applied to generate fitted values for five selected regions, namely Anhui, Shandong, Liaoning, Zhejiang, and Shanghai. The fitted values were compared with the observed regional values using a discrepancy rate metric, as shown in Table 4. The discrepancy rates were all below 10%, suggesting that the fitted values were generally consistent with the observed regional scores. This comparison provides a descriptive check of internal consistency, while the main purpose of the BP model remains the calculation of factor weights for identifying the key drivers of digitalization-driven lean implementation.

Table 4. Comparison between predicted and actual values using BP neural network model.

Region	Anhui	Shandong	Liaoning	Zhejiang	Shanghai
Ideal values	3.94	4.06	3.61	3.94	3.83
Actual values	3.86	4.00	3.85	4.26	3.87
Discrepancy rate	2.08%	1.41%	6.36%	7.62%	0.93%

4. Results

To assess the impact of each input variable on the output variable, a three-layer BP neural network with an “18-6-1” configuration was employed, comprising 18 input neurons,

six hidden neurons, and one output neuron. As mentioned before, this configuration was selected based on empirical rules for optimizing predictive performance. To calculate the weights of each factor, the weight matrices according to Equation (4) were achieved by directly accessing the properties of the neural network object in MATLAB. The weight w_{ij} matrix from the input layer to the hidden layer represents the connection strengths between the 18 factors and six neurons in the hidden layer, as detailed in Table 5.

Table 5. The weight matrix between the input layer and hidden layer.

Input Layer	Hidden Layer					
	Node 1	Node 2	Node 3	Node 4	Node 5	Node 6
Shield	1.4208	−1.1356	0.4808	0.0766	0.8799	1.4507
X_1	−0.2775	0.2357	−0.2882	0.2485	0.2238	0.7562
X_2	0.1588	−0.0934	0.2078	0.6958	0.5261	−0.5135
X_3	−0.5649	−0.4542	0.1865	−0.4902	0.5306	0.2497
X_4	−0.2472	0.5309	0.6822	0.7074	0.2400	0.0401
X_5	−0.3493	0.1765	0.0232	−0.3854	0.0679	0.1641
X_6	−0.6533	0.6764	−0.8305	−0.2596	0.0221	−0.0392
X_7	0.4216	−0.1652	−0.2283	0.6477	0.3448	0.1394
X_8	0.0515	−0.1015	0.4387	−0.1185	−0.5861	−0.2059
X_9	0.3306	−0.0423	−0.1977	0.5618	0.3827	−0.3836
X_{10}	1.0871	−0.1736	0.1935	−0.2017	0.0563	−0.5757
X_{11}	−0.4357	−0.0409	0.1871	−0.1305	−0.3162	−0.1480
X_{12}	−0.4748	−0.0276	−0.8197	−0.0535	−0.3482	0.5950
X_{13}	0.0395	0.4153	0.4601	0.3273	−0.4653	0.6794
X_{14}	0.2941	0.4655	−0.0471	0.1966	−0.4418	0.6500
X_{15}	−0.0118	−0.5507	0.0745	−0.0827	−0.6078	−0.1744
X_{16}	−0.0405	−0.1283	0.5692	0.2842	0.2607	0.0398
X_{17}	0.2493	0.3222	0.1322	0.2503	0.5479	0.2109
X_{18}	0.0370	0.2006	0.1055	0.1602	0.3860	0.2678

Similarly, the weight w_{jk} matrix from the hidden layer to the output layer captures the connections between the six hidden neurons and the output neuron, as shown in Table 6.

Table 6. The weight matrix between the hidden layer and output layer.

Output Layer	Hidden Layer						
	Shield	Node 1	Node 2	Node 3	Node 4	Node 5	Node 6
Y	0.0326	−0.5473	0.0662	−0.3274	0.3744	−0.3564	0.6344

In Tables 5 and 6, there are some negative weight values. In BP neural networks, the connection weights between layers are not normalized importance coefficients, but multiplicative parameters that determine the direction and magnitude of signal transmission during nonlinear mapping. These weights can take positive, negative, or zero values, enabling the network to model synergistic, inhibitory, and neutral interactions among influencing factors [74]. The existence of negative weights therefore does not indicate irrational results; rather, it reflects the realistic situation where certain factor combinations may suppress lean performance under specific conditions. This mechanism is precisely what allows BP neural networks to represent complex nonlinear relationships that cannot be captured by linear weighting or simple additive models. If all weights were constrained to positive values, the expressive capacity of the network would be severely limited, and important interaction effects among digitalization-driven factors would be lost. Meanwhile, these final weights are positive and directly reflect each factor's contribution to the

target objective, thereby translating the complex internal interactions into interpretable managerial insights.

To assess the impact of input variables on the output variable, the final weights S_i between neurons were analyzed and processed using Equations (5)–(8). By substituting the weight matrices from Tables 5 and 6 into the equations, the total influence of each input variable on the output was calculated. The influence was derived by aggregating the contributions from all hidden neurons and normalizing the results to obtain the relative weight percentages of each factor. The final computed weights, as shown in Table 7, highlight the relative importance of each influencing factor, providing valuable insights for prioritizing key factors in lean construction practices.

Table 7. The final factors' weights between the input and output layer.

Category	NO	Factors	Weights	Rank
Organizational management	X_1	Workers' skill in digital technologies	0.0682	5
	X_2	Stakeholders' attitudes of information share	0.0616	9
	X_3	Organization structure	0.0319	17
Process management	X_4	Construction of lean management system (LMS)	0.0688	4
	X_5	Digitalization of processes and workflows	0.0363	15
	X_6	Data consistency and compatibility	0.0573	11
	X_7	Improvement in construction efficiency	0.0682	6
Technological application	X_8	Level of informatization	0.0692	3
	X_9	Effective implementation of lean construction tools	0.0580	10
	X_{10}	Integration of design and construction	0.0784	2
	X_{11}	Quality control-based digitalization	0.0620	8
	X_{12}	Efficiency control-based digitalization	0.0410	14
	X_{13}	Simulation and optimization of processes	0.0851	1
	X_{14}	Digital platform of collaboration	0.0631	7
	X_{15}	Customization of digital technologies	0.0413	13
Economic and cost	X_{16}	Economic benefit of lean digitalization	0.0329	16
Policy and institution	X_{17}	Support of government policy	0.0310	18
	X_{18}	Publication of institution and standard	0.0458	12

Shown as Table 7, these weights, ranked from highest to lowest, are as follows: X_{13} (0.085), X_{10} (0.078), X_8 (0.069), X_4 (0.068), X_1 (0.068), X_7 (0.068), X_{14} (0.063), X_{11} (0.062), X_2 (0.061), X_9 (0.058), X_6 (0.057), X_{18} (0.045), X_{15} (0.041), X_{12} (0.041), X_5 (0.036), X_{16} (0.033), X_3 (0.032), and X_{17} (0.031). Among these, the top five factors are “simulation and optimization of processes (X_{13})”, “integration of design and construction (X_{10})”, “level of informatization (X_8)”, “construction of lean management system (X_4)”, and “workers' skill in digital technologies (X_1)”. Specifically, X_{13} , X_{10} and X_8 belong to technological application, X_4 pertains to the domain of process management, and X_1 relates to workforce capability. These factors exert a significant influence on leveraging digital tools to facilitate the implementation of lean construction. The result further indicates that successful digitalization-driven lean in PC projects relies on a combination of advanced technological application, effective process management, and skilled workforce. The results' in-depth analysis and implementation are discussed as below in Section 5.

5. Discussion and Managerial Implications

This study employed a BP neural network model to identify and quantify the key factors of digitalization-driven lean, named smart lean, in PC. Compared with relevant methodologies, such as AHP, FAHP, and ANP, the BP neural network model can uncover factors' importance on the expected outcome through adapting to specific project contexts. This provides a more accurate and comprehensive understanding of how driving factors interact and influence the implementation of lean practices, further promoting digital transformation.

5.1. Key Digital Enablers for Lean Implementation

Technology-based management acts as a key strategic area for optimizing lean practices in PC projects, particularly through “simulation and optimization of processes”, “integration of design and construction”, and “level of informatization”. These findings are strongly supported by prior studies. For example, Wang, Thangasamy, Tiong and Zhang [102] examined the role of BIM in optimizing workflows, reducing inefficiencies, and supporting lean principles such as waste reduction and value maximization. Similarly, Barkokebas, Khalife, Al-Hussein and Hamzeh [44], Gusmao Brissi, Wong Chong, Debs and Zhang [104] and Tortorella, G. [116] proposed frameworks to integrate BIM, IoT, a robotic system and lean to improve construction workflow in prefabrication projects. Digital simulation via 4D BIM and VR, in particular, allows practitioners to improve usability, accuracy and construction speed [117]. It enhances communication and coordination by facilitating seamless integration between design and construction phases [44]. Additionally, this would be directly relevant to the physical realization of lean and digital goals in underground PC projects, such as material management, construction processes, risk management and data-based decisions [118–121].

The integration of lean practices and digital tools in PC reflects not merely a technological shift, but a transformation toward digitally enabled a lean management system (LMS). An LMS refers to a structured approach to implementing lean principles, like VSM and JIT, at an organizational level [122]. While it originated in the manufacturing sector and has been adopted in the healthcare area [123,124], its application in the context of PC remains underexplored. Recent research work by Dang, Geng, Niu, Jiang and Sun [33] is among the first to conceptualize LMS as a strategic vehicle for enhancing lean performance in PC projects. In practice, an LMS involves routines, i.e., value identification, mapping value streams, scheduling workflows, establishing pull-based traction systems, and initiating continuous improvement [122]. When embedded in digital environments, these routines become digitally enabled, allowing data-driven adjustments and collaborative learning across teams and project stages. Critically, this relationship suggests that digitalization and LMS are not substitutes but mutually reinforcing complements. This finding is consistent with previous studies by Aziz and Zainon [53] and Schimanski, et al. [125], which emphasize effective lean management for realizing the full benefits of digitalization.

Moreover, “Workers' skills in digital technologies” falling within organization management was identified as a critical factor in enhancing lean PC projects. This finding reveals the critical role of human capital in the successful implementation of lean construction, and the importance of digital readiness at the workforce level. Since construction projects can operate within project-based organizational structures [126], the effective utilization of digital tools relies on the human capital available to use them. As evidenced by STS and TOE theory, tools like BIM, IoT, and AI can only deliver value when project teams have the necessary training and competence. A digitally skilled workforce is crucial for maximizing the potential of these tools and ensuring their proper integration into the con-

struction process. This adds an important dimension to the literature, which often focused on technical capabilities while overlooking human factors in the digital transformation of the PC industry.

In summary, digital tools serve as augmentative systems that enhance lean implementation such as coordination and visualization through technology-based optimization, social-based LMS, and organization-based workforce capability. The broader implication for the transition is that digital transformation should be approached not only through technological investment, but as an organizational capability-building process grounded in LMS with digital upskilling in the PC field.

5.2. Strategic Mapping of Smart Lean in PC

The BP-weighted results provide the empirical basis for constructing a strategic mapping of smart lean implementation in PC projects. The identified five key factors in Table 7 are covered in the aspects of technological, social and organizational management, in the ways of “simulation and optimization of processes”, “integration of design and construction”, “level of informatization”, “construction of lean management system”, and “workers’ skill in digital technologies”. These factors constitute the main empirical pillars of the proposed strategic “House” for smart lean implementation, as shown in Figure 3.

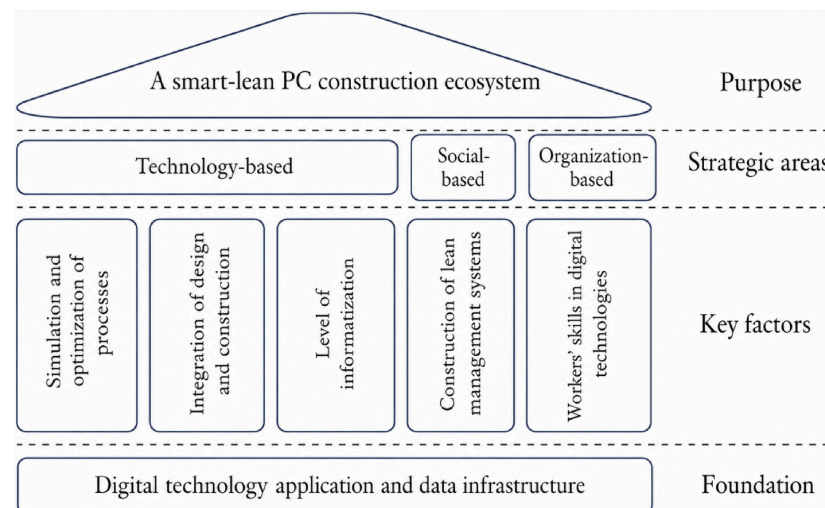


Figure 3. Strategic “House” of smart lean in PC.

Figure 3 presents a strategic “House” that conceptualizes the hierarchical logic of how digital technologies drive lean implementation in PC. The model establishes a multi-layer architecture that maps the transformation pathway from foundational enablers to strategic outcomes. The foundation represents the digital enabling environment, the pillars represent the empirically identified key factors, and the roof represents the expected outcome of digitalization-driven lean implementation in PC projects. This structure clarifies how digital technologies can support lean implementation through technological optimization, process-based lean management, and organizational capability building.

The digitalization foundation refers to the broader enabling condition for applying digital technologies in PC projects, including data collection, information sharing, digital platforms, BIM/IoT-supported monitoring, and data-supported coordination [127]. It represents the basic digital environment through which the weighted key factors can operate. This foundation is consistent with the role of digital technologies discussed in the Introduction, where BIM, IoT, digital platforms, and data-driven management systems were identified as enabling visualization, information sharing, process monitoring, and decision-making in PC projects.

The middle tier identifies five critical factors divided into technological–social–organizational strategic areas deriving from the extended STS-TOE framework: (1) technology-based management, optimizing processes-based simulation, integrating design and construction and improving the information level; (2) social-based management, constructing LMS; and (3) organization-based management, pertaining to workers’ skills in digital technologies. These factors represent the operational mechanisms through which digital technologies translate into lean outcomes, bridging the gap between technological capabilities and organizational performance. Then, the factors delineate the key domains where digital–lean synergies manifest, ultimately converging toward the overarching purpose of creating a smart lean PC ecosystem. By mapping relationships between foundation, critical factors, and strategic outcomes, this “House” offers insights for PC stakeholders seeking to leverage digitalization for lean transformation, thereby supporting both operational excellence and industry-wide digital advancement.

Therefore, the strategic “House” is not a generic conceptual diagram, but a synthesis of the BP-weighted key factors and the theoretical structure of the extended STS-TOE framework. These findings reflect a socio-technical logic of complementarity, where human expertise and digital technologies co-evolve rather than compete, in realizing smart lean in PC [128]. Likewise, the level of informatization can be understood as the maturity of an organization’s digital information system, highlighting that technological gains depend on human capabilities to interpret [129]. This aligns with STS theory, which suggests organizations comprise mutually interdependent social and technical subsystems. According to this theory, optimal performance requires the joint optimization of human and technological components [130,131]. In the context of PC, this means that technology-based management should be integrated with organization development to fully realize the benefits of lean–digital integration.

5.3. Managerial Implication

Based on the preceding discussion, this study provides evidence-informed guidance for stakeholders seeking to overcome challenges in promoting lean implementation through digitalization and to prioritize key resources in PC projects. Five managerial implications can be summarized. First, the five dimensions derived from the extended STS-TOE framework—organizational, social/process, technological, economic, and environmental/institutional aspects—are all relevant to digitalization-driven lean implementation. Among them, technological, process-oriented, and organizational resources should receive particular attention, as they are closely associated with the most influential factors identified in this study. Strengthening the digitalization foundation is fundamental to lean implementation, especially through data collection, information sharing, BIM/IoT-supported process monitoring, and collaborative digital platforms. This foundation supports the operation of the BP-weighted key factors, including process simulation and optimization, design–construction integration, informatization capability, lean management systems, and workers’ digital skills. Accordingly, managers may assess and invest in digital technologies such as BIM, IoT systems, and collaborative information platforms to support simulation-based process adjustment, real-time information sharing, and stakeholder coordination. Third, constructing a lean management system supported by digital tools is essential for sustaining continuous improvement. For example, just-in-time coordination, as a key pillar of lean management, can be enhanced through BIM-based visualization and IoT-enabled data collection. Fourth, improving workers’ digital skills and competencies is necessary to ensure that the benefits of digitalization are effectively realized. Industry stakeholders may therefore develop digital upskilling programs for employees and site supervisors, particularly focusing on data interpretation, real-time monitoring, and the integration of lean tools

with digital platforms. Finally, although policy and institutional support were not among the five highest-ranked factors, their relative importance suggests that supportive policies, industry standards, and incentive mechanisms could provide an enabling environment for accelerating digital–lean integration, particularly during the early stages of lean and digital application in PC projects.

6. Conclusions

This study adopted a BP neural network model to analyze the underlying factors demonstrating how digitalization drives smart lean construction in the PC context. The factors are identified based on an extended STS–TOE theoretical framework. Then, this study utilized a quantitative BP analysis to determine their weights. Furthermore, strategic mapping and practical measures of how to improve lean implementation were provided. The results revealed that:

1. The influencing factors consist of organizational, social–technological, economic, and environmental aspects, reflecting that digitally driven lean implementation is a systematic process, not a one-sided approach.
2. The importance of driving factors should sufficiently consider regional variance on the outcome.
3. Efficient measures of lean implementation are the simulation and optimization of processes, the integration of design and construction and the level of informatization, the construction of lean management systems, and workers’ skills in digital technologies.

From a theoretical view, first, this study contributes to the literature by developing an extended STS–TOE framework for understanding digitalization-driven lean implementation in prefabricated construction. The framework advances existing knowledge by explaining smart lean as a multidimensional system shaped by the interaction of technological, process, organizational, economic, and policy conditions. Second, by integrating the extended STS–TOE framework with a BP neural network model, this study provides an outcome-oriented approach for identifying the key drivers of digitalization-enabled lean construction. Lastly, the proposed strategic map prioritizes key areas, i.e., process simulation and optimization, design–construction integration, information management, LMS, and workforce competency, offering practical direction for both researchers and industry stakeholders. From a practical perspective, the identified key factors may serve as evidence-informed references for stakeholders seeking to use digital technologies to support lean implementation in PC projects. Specifically, the findings suggest that stakeholders could consider prioritizing resources toward process simulation, digital coordination between design and construction, information management capability, lean management system development, and workforce digital upskilling.

Admittedly, although the study has addressed several gaps in PC development, there are several limitations that present opportunities for future research. First, the data were collected in China, which may limit the generalizability of the findings to international contexts. Future research could include cross-country comparisons to broaden the applicability. Second, the study relies mainly on perceptual questionnaire data from practitioners, which are useful for capturing professional judgments but may be affected by respondents’ subjective perceptions and project experiences. Further research should collect objective data such as panel data to increase the persuasive power of the results. Third, the sample size used for BP neural network modeling is relatively limited. Larger project-level datasets would be helpful for improving model robustness, generalization ability, and cross-validation. Fourth, although this study explains the suitability of the BP model in the literature review, further comparative analysis with other MCDM methods, such as AHP and entropy weighting, could be conducted to verify the consistency and robustness of the weighting

results. Finally, the analysis in this study is based on a static model, whereas the influence of digitalization-related factors on lean performance in PC projects may evolve dynamically over time. Future studies could adopt longitudinal research designs to better capture the changing relationships between lean construction practices and digital technologies.

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