



Article Study on the Influencing Factors of Digital Transformation of Construction Enterprises from the Perspective of Dual Effects—A Hybrid Approach Based on PLS-SEM and fsQCA

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Abstract: The digital transformation of Chinese construction enterprises is crucial for achieving sustainable and high-quality development in the construction industry. However, there is still a lack of in-depth research on the impact mechanism of digital transformation in construction enterprises. The purpose of this study is to explore the multiple influencing factors and complex causal relationships of digital transformation in construction enterprises and promote the deep integration of digitalization and construction enterprises. To this end, based on the dual-effect perspective (net effect perspective of a single influencing factor and configuration effect perspective of multiple influencing factors), using the "technology-organization-environment" framework (TOE framework) to construct a research model of influencing factors for digital transformation in construction enterprises. A sample of 236 construction enterprise managers was surveyed, and partial least squares structural equation modeling (PLS-SEM) and fuzzy set qualitative comparative analysis (fsQCA) methods were used to empirically analyze the dual effects of influencing factors for digital transformation in construction enterprises. The results show that: (1) from the net effect perspective, there are seven factors that significantly impact digital transformation in construction enterprises; (2) from the configuration effect perspective, there are three paths that can achieve high-level digital transformation in construction enterprises, and one path that leads to low-level digital transformation; (3) from the dual-effect perspective, top management support and policy support are key factors for digital transformation in Chinese construction enterprises. The research results enrich the relevant research on digital transformation in construction enterprises and provide a reference basis for promoting digital transformation in construction enterprises.

Keywords: digital transformation; influencing factors; dual effects; construction enterprises; PLS-SEM and fsQCA methods

1. Introduction

With the arrival of the fourth industrial revolution, digitalization is accelerating profound changes in various industries [1,2], and digital transformation has been recognized by many countries as the key to ensuring the competitiveness of traditional industries [3,4], including the construction industry. As a resource- and labor-intensive traditional industry, the construction industry faces more severe sustainability issues due to problems such as dispersed and outdated project management methods, low production efficiency, frequent safety accidents, serious resource waste, and environmental pollution [1,5,6]. Digital transformation has been proven to be an effective way to address sustainability issues in construction projects [6,7], and construction enterprises urgently need to undergo digital



Citation: Zhang, G.; Wang, T.; Wang, Y.; Zhang, S.; Lin, W.; Dou, Z.; Du, H. Study on the Influencing Factors of Digital Transformation of Construction Enterprises from the Perspective of Dual Effects—A Hybrid Approach Based on PLS-SEM and fsQCA. *Sustainability* **2023**, *15*, 6317. https://doi.org/10.3390/ su15076317

Academic Editors: Albert P. C. Chan, Emmanuel Kingsford Owusu and Ting Wang

Received: 6 February 2023 Revised: 25 March 2023 Accepted: 4 April 2023 Published: 6 April 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). transformation to respond to this critical issue. With the application and development of digital technologies such as artificial intelligence (AI) [8], building information modeling (BIM) [9,10], the Internet of Things (IoT) [11], blockchain (DT) [12], big data (BD) [13], and cloud models (CM) [14] in the construction industry, a series of problems and challenges encountered in traditional construction have been improved [15], providing crucial technology and basic platforms for construction enterprises to achieve digital transformation and sustainable development [2,7].

Despite the active promotion of digital transformation in the construction industry, the overall level of digitization in the construction industry is still at the bottom compared to other industries due to the complexity, fragmentation, and extensive production methods of the construction process [1,16]. In addition, construction enterprises also face the dilemma of a slowdown in industry growth, declining profits, increasing competition, insufficient attractiveness to new employees, exacerbation of aging of the workforce, and a lack of digital professionals [1]. Traditional production and operation models can no longer meet the requirements of intelligent construction under digitalization [17]. Therefore, accelerating the promotion of digital transformation is also an inevitable requirement for construction enterprises to transform their production and operation methods, improve construction project efficiency, enhance core competitiveness, optimize the structure of the construction industry, and achieve sustainable and high-quality development. To this end, the Chinese Ministry of Housing and Urban-Rural Development has successively released relevant policies to incorporate digitization into the development strategic planning of the construction industry [2]. Subsequently, the 20th National Congress of the Communist Party of China also proposed accelerating the construction of a digital China, developing a digital economy, creating new opportunities for the digital transformation and high-quality development of construction enterprises in China.

However, the current research on digital transformation in the construction industry is still in its early stages, and there is no consensus on the definition of digital transformation [1]. Nonetheless, there is already literature on digital transformation that can provide a certain research foundation for the digital transformation of construction enterprises. For example, Vial [18] define digital transformation as triggering significant changes to entities through the integration of digital technology to improve processes. Based on this, the digital transformation of construction enterprises is summarized as process reengineering caused by the integration of digital technology into the entire process of enterprise production, operation, project design, construction, and maintenance, leading to organizational change activities for achieving profitability and competitive advantage. This also reflects that existing research mostly focuses on defining digitalization from the perspectives of technology-driven and organizational change [19], which may be determined by the process of digital transformation, where the adoption of digital technology and organizational change are essential parts of the digital transformation content.

Most scholars also explore the digital transformation of construction enterprises based on these two aspects. Specifically, the first aspect is the changes in construction management brought about by digital technology [17,20]. For example, artificial intelligence (AI) can model, predict, and optimize the problems that arise throughout the entire construction process through data-driven methods [8]. The second aspect is the process of organizational adaptation to digital transformation [21,22]. For example, the formal and informal organizational structures of large construction enterprises will be profoundly affected by digital technology [22], and enterprise digital transformation can enhance organizational resilience [23], etc. However, in the process of triggering multilevel changes within organizations, digital technology may lead to disruptive innovation within the organization and have positive or negative impacts on enterprise digital transformation [19]. Therefore, scholars have also begun to turn to the study of the impact mechanism of digital transformation on construction enterprises, exploring which factors are related to the digital transformation of construction enterprises. For example, Li et al. [1] explored the key factors of digital transformation in the construction industry based on the LDA topic model and constructed a comprehensive evaluation system for the digitalization of the construction industry by combining the DEMATEL and AHP methods.

Although many scholars have conducted research on the digital transformation of construction enterprises, there are still some shortcomings. Firstly, previous literature has mostly focused on specific aspects of the digital transformation of construction enterprises from a single perspective. However, digital transformation is a complex system engineering project [24] that is influenced by multiple factors such as technology, environment, and organization [25]. Therefore, it is necessary to explore the mechanisms of different influencing factors on the digital transformation of construction enterprises from a comprehensive perspective that considers multiple contexts. Secondly, the digital transformation of construction enterprises involves many stakeholders [7], and its transformation is affected by the interaction of internal and external factors, which requires further research [26]. However, studies on the digital transformation of construction enterprises mostly focus on the net effect of transformation on individual factors, making it difficult to explain the logical relationship between many internal and external influencing factors within organizations [26]. This approach fails to effectively reveal the configuration effects of different factors that impact the digital transformation of construction enterprises. Lastly, existing research on the digital transformation of construction enterprises mainly focuses on qualitative research and lacks quantitative and empirical research on the impact mechanisms of digital transformation on construction enterprises. Therefore, clarifying the net effect of factors that influence the digital transformation of construction enterprises, as well as the configuration effects between these factors, is essential for the successful implementation of digital transformation in the construction industry. To address these issues, this study conducts a deep-level investigation into the factors that influence the digital transformation of construction enterprises.

The structure of this study is as follows: the introduction in Section 1 provides a context for the research and highlights the existing research gaps, explaining the necessity of this study. Section 2 focuses on model construction and research hypotheses, outlining the study's research model and hypotheses. Section 3 discusses the research methods and data collection. Section 4 is the empirical analysis of this study. Section 5 discusses the results of the empirical research. Finally, the study concludes with a summary of its findings, limitations, and future prospects.

2. Research Model and Hypothesis

2.1. Research Model

The technology–organization–environment (TOE) framework, which is a comprehensive theoretical framework that analyzes the adoption of innovation technology in organizations based on their technological, organizational, and environmental contexts [27], has been widely used to explore the factors that influence the adoption of innovation technology in organizations [28]. This framework is highly applicable because it allows for the selection of influencing factors based on different research scenarios [29], rather than specifying specific explanatory variables in different contexts. Different factors in the technological, organizational, and environmental contexts have been shown to have an impact on the digital transformation of firms [30]. However, since the digital transformation of construction firms is subject to synergistic effects from multiple factors within and outside the organization, these influencing factors cannot be considered in isolation [26]. Therefore, it is necessary to further explore the combined effects of these factors in various contexts.

Given the research context of this paper, the TOE framework is chosen to analyze the influencing factors of digital transformation in construction companies. Building on the previous TOE framework and the actual situation of digital transformation in construction enterprises, this study proposes a research model of digital transformation influencing factors in construction enterprises (as shown in Figure 1). This model encompasses 10 measurement constructs, namely, use of digital technology (UDT), relative advantage

(RA), and digital employees (DE) in the technological context; digital cost (DC), organizational readiness (OR), digital transformation strategy (DTS), and top management support (TMS) in the organizational context; and competitive pressure (CP), partner pressure (PP), and policy support (PS) in the environmental context. The findings of this study will shed light on which factors have a significant impact on digital transformation in construction firms and how these factors interact to shape the process of digital transformation.

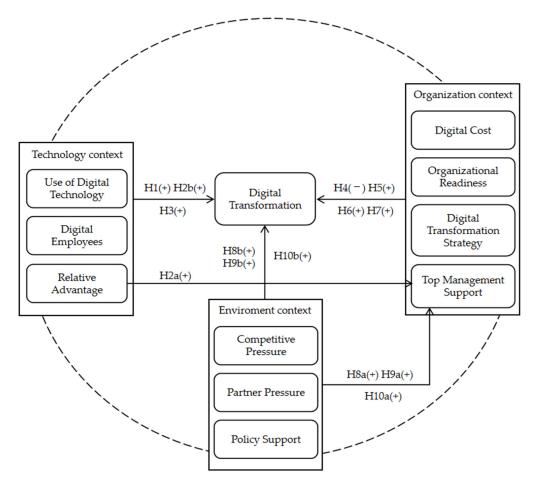


Figure 1. Research model of factors influencing digital transformation of construction enterprises.

2.2. Research Hypothesis

2.2.1. Technical Context

(1) Use of Digital Technology. As the technological foundation driving digital transformation in enterprises, digital technology has the potential to bring about systemic changes and achieve digitalization [31] and is considered a key factor in facilitating digital transformation [32]. The extent of digital technology utilization reflects a company's attitude towards these technologies and their ability to utilize them [33]. In general, companies with higher levels of digital technology usage possess a better technological foundation for digital transformation and are more likely to accept and implement digitalization. Despite the fact that digital technologies such as BIM [34], the Internet of Things [11], big data [35], social media [18], and network security technology [36] have played important roles in promoting digital transformation in enterprises [17], the utilization of digital technology in the construction industry is still relatively low, and it has not fundamentally changed the production mode of engineering projects [1]. This hinders construction enterprises from digital transformation. Li et al. [1] also pointed out that construction enterprises urgently need to deeply integrate data technology to promote digital technology innovation and enhance the core competitiveness of construction enterprises, thereby promoting digital transformation. Therefore, this study proposes the following hypothesis:

Hypothesis 1 (H1). *The use of digital technology has a positive impact on the digital transformation of construction companies.*

(2) Relative Advantages. Relative advantage generally refers to the benefits that a company gains from adopting innovative technology that exceeds the current state [37]. Previous studies have shown that digital transformation can transform organizational business models [38], help companies save costs, improve operational efficiency [39], achieve better corporate performance, and, thus, bring competitive advantages to companies [40]. For example, the integration of Building Information Modeling (BIM) and Information and Communication Technology (ICT) in construction companies can simplify project processes to improve productivity and efficiency [41]. With the widespread use of digital technology in the construction industry [1], data resources are effectively integrated to enhance traceability and transparency in the project construction process, promoting collaborative cooperation among stakeholders in construction companies. For example, blockchain technology is believed to achieve this function [42]. In addition, the competitive advantage brought by digital transformation through digital technology may drive top managers' willingness to support the digital transformation of construction companies. Therefore, this study proposes the following hypotheses:

Hypothesis 2a (H2a). *Relative advantage has a positive impact on top management support for digital transformation of construction companies.*

Hypothesis 2b (H2b). *Relative advantage has a positive impact on the digital transformation of construction companies.*

(3) Digital Employee. Digital employees are considered to be the digital skill talents needed to support a company's digital transformation [31], and they are an important production factor in digital transformation [1]. Digital employees can promote the process of digital transformation in enterprises by enhancing digital awareness and skills [43]. Although more and more companies are aware of the important role of digital employees in digital transformation [31], the shortage of digital talent is still one of the main factors restricting the digital transformation of the construction industry [44]. At the same time, the lack of digital learning resources provided by enterprises for employees has led to a lack of digital skills [45], which also hinders the process of digital transformation in enterprises [46]. Organizational preparation for digitalization also requires employees to have digital transformation capabilities [47]. To achieve digital transformation in the construction industry, it is necessary to strengthen the construction of digital talent, especially to improve the digital level of employees who already possess good business abilities within the enterprise. Therefore, we propose the following hypothesis:

Hypothesis 3 (H3). *Digital employees have a positive impact on the digital transformation of construction companies.*

2.2.2. Organizational Context

(4) Digital Costs. Digital costs refer to the expenses incurred by enterprises in adopting measures related to digital transformation, primarily including the costs generated by adopting digital technologies. Typically, higher costs will decrease the willingness of enterprises to adopt new technologies [48], and digital costs will also affect the adoption of digital technologies by enterprises, thus impeding digital transformation. Although digital technologies can help the construction industry integrate dispersed knowledge and information and improve organizational collaboration and communication [49], there are many benefits, the expensive costs associated with the adoption of digital technologies,

such as high costs of technical learning and management [50], hardware facilities, and operational maintenance costs, may be a limiting factor. Currently, the adoption rate of digital technologies in construction enterprises remains low [51]. Previous studies have shown that costs are a significant obstacle to the adoption of digital technologies such as blockchain in construction enterprises [12]. For digital transformation in construction enterprises, digital costs may also be an important influencing factor. Therefore, this study proposes the following hypothesis:

Hypothesis 4 (H4). Digital costs have a negative impact on the digital transformation of construction companies.

(5) Organizational Readiness. Organizational readiness reflects the available resources within an organization to support digital transformation, including existing infrastructure, related personnel, and available funding [52]. Numerous scholars have found through research that organizational readiness has a positive impact on the adoption of new technologies by businesses [52,53]. For instance, organizational readiness is a key driving factor for businesses to adopt big data [54]. Wang et al. [12] also suggest that the adoption of new technologies by organizations is influenced by the resources invested in them, showing a positive correlation. The construction industry is no exception, as the application of technologies such as BIM, IoT, big data, and prefabrication can establish the necessary information collaboration data foundation and platform for the industry's digital transformation. In general, the more abundant the existing resources are invested, and the higher the level of digital foundation, the stronger its adaptability to digital transformation, thus increasing the likelihood of achieving it. Therefore, this study proposes the following hypothesis:

Hypothesis 5 (H5). Organizational readiness has a positive impact on digital transformation in construction companies.

(6) Digital transformation strategy. As a guideline for enterprises to implement digital measures [33], digital transformation strategy is considered a prerequisite for the success of digital transformation [31]. Digital strategy involves using digital resources to create value and influence enterprise operational strategies [55]. The digital transformation of enterprises is driven by enterprise strategies [31], and it is required to create new models that conform to the enterprise's business strategy to gain greater competitive advantage [56]. If digital transformation is solely dependent on the use of digital technology and lacks a cohesive digital transformation strategy, enterprises often face failure in their digital transformation [57]. Therefore, the formulation and implementation of a digital transformation strategy have become the primary issue for current enterprises [58]. Kane et al. [59] also believe that digital strategy plays an important role in the digital transformation of enterprises. Research conducted by Ghobakhloo et al. [60] found that developing a digital strategy is crucial for small and medium-sized enterprises to succeed in the transformation to Industry 4.0. In the case of project-based construction enterprises, the level of digital transformation usually depends on whether the digital transformation strategy is effectively formulated and implemented. Therefore, this study proposes the following hypothesis:

Hypothesis 6 (H6). *Digital transformation strategy has a positive impact on the digital transformation of construction companies.*

(7) Top Management Support. The support of top management refers to the degree to which the leadership of an enterprise accepts and drives digital transformation. While most industries and enterprises can benefit from digital transformation, the leadership's role in the success of an enterprise's digital transformation remains critical [61,62]. This is because the effect of digital transformation on reshaping an enterprise largely depends on the leadership's response to digital transformation also affects the process, as it influences the development and implementation of digital strategy [59]. For example, Wrede et al. [62] found that top management can respond to enterprise digital transformation by understanding the digital process and taking supportive action. In addition, during the process of adopting digital technology for digital transformation, enterprises cannot avoid obstacles and require the support of leadership to provide necessary resources and funds to encourage the implementation of digital transformation. At the same time, facing the uncertainties and risks in the process of digital transformation in the construction industry, leadership support is also needed [57]. Therefore, this study proposes the following hypothesis:

Hypothesis 7 (H7). Top management support has a positive impact on digital transformation in construction companies.

2.2.3. Environmental Context

(8) Competitive Pressure. Competition pressure refers to the degree to which companies are influenced by their competitors in the competitive market to adopt new technologies [63]. Specifically, in order to gain a competitive advantage, companies are usually required to adopt innovative methods and further optimize the allocation of production factors [12], such as improving production quality and efficiency, and reducing costs under the pressure of competition from peers. The perception of top management on the level of competition pressure is also reflected in the organization of the enterprise. As the competition in the construction market intensifies, especially with the rise of digital technology, traditional business and production methods of construction enterprises are facing both opportunities and challenges. Enterprises are also undergoing transformations to adapt to the fierce competition pressure [64] and avoid being eliminated from the market. Relevant studies have shown that competition pressure may prompt enterprises to transform and ultimately achieve digital transformation [63]. Singh et al. [65] also found that competition pressure has a significant impact on the digital transformation of Indian manufacturing companies. Therefore, this study proposes the following hypotheses:

Hypothesis 8a (H8a). *Competitive pressure has a positive impact on top management support for digital transformation of construction companies.*

Hypothesis 8b (H8b). *Competitive pressure has a positive impact on digital transformation of construction companies.*

(9) Partner Pressure. Partner pressure may be an important factor influencing the digital transformation of enterprises. Construction companies may be encouraged and required by partners to adopt new technologies, such as BIM and other digital technologies, through project construction. Previous studies have confirmed that the pressure from partners is also a major factor influencing enterprises to accept new technologies [66]. This may be because enterprise leaders strengthen their relationship with partners and encourage the adoption of mature technologies that partners have applied [67], and digital transformation is no exception. If a partner's digital technology is widely used, construction companies are more likely to adopt it to enhance collaboration among project stakeholders, improve construction efficiency, and save costs, thereby promoting digital transformation. Therefore, this study proposes the following hypotheses:

Hypothesis 9a (H9a). *Partner pressure has a positive impact on top management support for digital transformation of construction companies.*

Hypothesis 9b (H9b). Partner pressure has a positive impact on digital transformation in construction companies.

(10) Policy Support. Policy support refers to the assistance provided by governments or regulatory agencies to encourage businesses to achieve digital transformation. In terms of policy, governments and regulatory bodies can encourage or prohibit businesses from adopting innovative technologies by implementing relevant policies [54]. For example, research by Luo et al. [61] found that government policy support has a positive effect on digitization and can promote the digital transformation of pharmaceutical companies. As digital transformation is relatively new in the construction industry, most construction companies may have a low level of understanding of digital transformation and lack the necessary conditions and motivation to promote it [31]. At the same time, enterprise digital transformation also requires support in terms of financial, material, human, and other resources. If the government supports enterprise digital transformation in terms of finance and technology standards, top management of companies often respond positively, increasing the possibility of promoting digital transformation. Therefore, this study proposes the following hypotheses:

Hypothesis 10a (H10a). *Policy support has a positive impact on top management support for digital transformation of construction companies.*

Hypothesis 10b (H10b). *Policy support has a positive impact on the digital transformation of construction companies.*

3. Research Methodology and Data

3.1. Research Design

Questionnaires have the advantages of being easy to implement and scientific and have been widely used in research in the field of architecture [30]. In this study, data were collected through a questionnaire survey. To ensure that the research variables and measurement questions are consistent with the context of this study, the scales used in this study were all based on mature scales from relevant foreign literature. Combined with the research hypotheses and the results of enterprise digital transformation research, a preliminary questionnaire was designed for this study. Based on the suggestions of experts and scholars in the construction industry, the questionnaire measurement questions were adjusted and revised. To ensure that the questionnaire was scientific and reliable, a pre-test adjustment of the measurement questions was conducted on a small scale before the formal questionnaire survey was conducted, resulting in the final questionnaire.

The questionnaire consists of 42 measurement questions used to measure the variables within the TOE framework. To facilitate participants' judgment and completion, a 5-point Likert scale (from 1 indicating completely inconsistent to 5 indicating completely consistent) was used in this study to measure different variables. Before construction industry practitioners filled out the questionnaire, they were first explained what digital transformation of construction enterprises means and informed that they can make judgments and decisions based on their own experience, and that there are no right or wrong answers. These answers are only used for academic research. Technical context includes use of digital technology, relative advantage, and digital employees. Organizational context includes digital cost, organizational readiness, digital transformation strategy, and top management support. External environmental context includes competitive pressure, partner pressure, and policy support.

3.2. Data Collection

Due to the impact of the COVID-19 pandemic, this study adopted an online questionnaire distributed via the "Wenjuanxing" platform to professionals in the construction industry through relevant professional WeChat and QQ groups, forums, and conferences, and forwarded to some experts in the field. In order to improve participants' enthusiasm, the research team promised to provide a research report to interested participants after the study to help them better understand the digital transformation process of construction enterprises. A total of 310 questionnaires were collected in this study, and after removing invalid questionnaires with completely identical or excessively high response rates, 236 valid questionnaires were obtained, resulting in an effective rate of 76.13%. According to Chin [68], a minimum sample size in PLS-SEM should satisfy the 10-times rule of thumb. Specifically, this means choosing the maximum value between (1) ten times the number of measurement items for the construct with the largest number of items in the measurement model and (2) ten times the number of exogenous variables for the endogenous variable with the most exogenous variables. In this study, the construct with the most measurement items is the use of digital technology (UDT), with five measurement items, and digital transformation (DT) (endogenous variable) has ten exogenous variables. Therefore, the 236 samples in this study meet the requirement of a minimum sample size greater than 100.

In this study, basic information of the questionnaire respondents can be found in Table 1. Firstly, in terms of gender, there were 195 male respondents and 41 female respondents, with males accounting for the absolute majority, which is consistent with the basic situation of the construction industry where men outnumber women. Secondly, more than 60% of the respondents had an undergraduate degree or below, while less than 40% had a master's degree or above, reflecting the emphasis on practical experience in the construction industry. Thirdly, the age of the respondents was concentrated in the range of 25–30 years old, with more than 60% having less than five years of work experience, which may be due to the high staff turnover rate in the construction industry. Finally, the respondents' work units included owners, construction companies, survey and design institutes, consulting firms, and supervision companies, with state-owned units accounting for more than 60%, which is consistent with the fact that state-owned units dominate the construction market in China.

Basic Information	Category	Frequency	Percentage (%)	
	Men	195	82.63	
Gender	Female	41	17.37	
	College and below	21	8.90	
	Undergraduate	121	51.27	
Education	Master	90	38.14	
	PhD	4	1.69	
	<25 years	23	9.75	
	25–30 years	128	54.24	
Age	31–35 years	50	21.19	
-	36–40 years	17	7.20	
	>40 years	18	7.63	
	<3 years	93	39.41	
Years of work in the	3–5 years	62	26.27	
construction industry	6–10 years	44	18.64	
construction moustry	11–15 years	21	8.90	
	>15 years	16	6.78	
	Owner	94	39.83	
	Construction company	76	32.20	
Work units	Reconnaissance and design institutes	29	12.29	
	Consulting organization	23	9.75	
	Supervision company	14	5.93	
	Government/Institutions	30	12.71	
Theit shaws star	State-owned enterprises	117	49.58	
Unit character	Private enterprises	85	36.02	
	Foreign-funded enterprises	4	1.69	

Table 1. Basic information of questionnaire participants.

Since the questionnaire data were collected from a single source, there is a risk of common method bias (CMB) [63]. To evaluate the impact of CMB on this study, the

Harman's single-factor identification method was used to test for CMB before data analysis, which is widely used in detecting CMB [69]. The results showed that the first factor explained only 47.70% of the total variance, which was less than 50%, indicating that CMB did not have a substantial impact on this study [63,70]. In addition, the correlation coefficients of each variable were all less than 0.90, which also indicates that CMB was not a serious problem [63,70]. At the same time, the variance inflation factor (VIF) of this study was less than the threshold of 5 proposed by Hair et al. [71], indicating that multicollinearity would not affect this study.

3.3. Analysis Method

This study adopted a combined approach of partial least squares structural equation modeling (PLS-SEM) and fuzzy set qualitative comparative analysis (fsQCA) to verify the proposed theoretical model. Firstly, PLS-SEM, as a modern multivariate analysis technique, has many advantages over CB-SEM, such as being more suitable for non-normal distribution data, small sample size data, complex structure models with many measurement variables, and not requiring high data requirements [72,73]. It has been widely used in the field of construction management [74] and has gradually received widespread attention in research related to digital technology and digital transformation [23,65]. Smart-PLS 3.3.9 software was used to analyze the questionnaire data in this study to test the constructed research model and hypotheses and explore the "net effect" of different influencing factors on the digital transformation of construction enterprises.

fsQCA, as an analysis method based on set theory and fuzzy theory [75], is particularly suitable for studying complex causal relationships caused by multiple antecedents [76]. It can use Boolean logic to reveal different paths leading to common results [77] and has causal asymmetry. Unlike traditional symmetric methods such as regression and structural equation modeling, which only allow the analysis of the impact factors of a single path, it can determine the necessary conditions for achieving success [77]. Therefore, fsQCA needs to be used to explore the "configurational effect" of different influencing factors on the digital transformation of construction enterprises from an overall perspective, in order to seek paths that affect the level of digital transformation in construction enterprises. Based on the above analysis, combining these two methods is in line with the data and model testing requirements of this study.

4. Data Analysis and Results

4.1. PLS-SEM Analysis

4.1.1. Measurement Model

In PLS-SEM, the quality of the research model is evaluated through the examination of the reliability, convergent validity, and discriminant validity of the measurement model [71]. Firstly, with regard to reliability, as shown in Table 2, the Cronbach's alpha coefficient and composite reliability (CR) values of all constructs in this study are above 0.80, which meets the standard requirements suggested by Hair et al. [71]. This indicates that the constructs in this study have good reliability. Secondly, in terms of convergent validity, all external model factor loadings of the measurement items in the questionnaire are above 0.70, and the average variance extracted (AVE) of all constructs is above the recommended value of 0.50, indicating that there is convergent validity among all constructs [71].

Constructs	Items	Loadings	Cronbach's α	CR	AV	
	CP1	0.891				
Competitive Pressure	CP2	0.889	0.841	0.893	0.67	
(CP)	CP3	0.717	0.041			
	CP4	0.784				
	DC1	0.955				
Digital Cost	DC2	0.901	0.861	0.907	0.76	
(DC)	DC3	0.761				
	DE1	0.870				
Digital Employees	DE2	0.891	0.000	0.000	0.75	
(DE)	DE3	0.892	0.903	0.932	0.77	
	DE4	0.869				
	DT1	0.909				
Digital Transformation	DT2	0.908			0.83	
(DT)	DT3	0.917	0.933	0.952		
	DT4	0.915				
	DTS1	0.930				
Digital Transformation Strategy	DTS2	0.923	0.917	0.947	0.85	
(DTS)	DTS3	0.924	00011			
	OR1	0.895				
Organizational Readiness	OR2	0.932				
(OR)	OR3	0.893	0.925	0.947	0.81	
	OR4	0.896				
	PP1	0.941				
Partner Pressure	PP2	0.913	0.902	0.939	0.83	
(PP)	PP3	0.889	0.002	0.707		
	PS1	0.827				
Policy Support	PS2	0.880			0.71	
(PS)	PS3	0.859	0.868	0.910		
	PS4	0.819				
	RA1	0.904				
Relative Advantage	RA2	0.916				
(RA)	RA3	0.930	0.931	0.951	0.82	
	RA4	0.890				
	TMS1	0.933				
Top Management Support	TMS2	0.848				
(TMS)	TMS3	0.932	0.931	0.951	0.83	
	TMS4	0.928				
	UDT1	0.813				
	UDT2	0.853				
Use of Digital Technology (UDT)	UDT3	0.860	0.862	0.900	0.64	
	UDT4	0.774				
	UDT5	0.703				

Table 2. Reliability and convergence validity indices.

Finally, the Fornell–Larcker criterion and cross-loading were used to evaluate the discriminant validity of each construct in the measurement model [74]. As shown in Table 3, the square root of the AVE on the diagonal of each construct is greater than

the absolute value of the Pearson correlation coefficient between the construct and other potential constructs. In addition, the cross-loading of each construct is higher than that of the remaining constructs, meeting the standard requirements for discriminant validity [71]. This indicates that all constructs have discriminant validity.

Constructs	СР	DC	DE	DT	DTS	OR	РР	PS	RA	TMS	UDT
СР	0.823										
DC	0.213	0.876									
DE	0.559	0.175	0.880								
DT	0.691	0.119	0.611	0.912							
DTS	0.663	0.155	0.693	0.751	0.926						
OR	0.587	0.125	0.780	0.680	0.769	0.904					
PP	0.711	0.112	0.524	0.625	0.548	0.534	0.915				
PS	0.666	0.128	0.586	0.670	0.601	0.601	0.724	0.847			
RA	0.434	0.289	0.530	0.606	0.524	0.606	0.344	0.403	0.910		
TMS	0.694	0.177	0.685	0.777	0.831	0.782	0.572	0.636	0.604	0.911	
UDT	0.511	0.295	0.543	0.652	0.557	0.577	0.436	0.451	0.762	0.639	0.803

Table 3. Fornell-Larcker criterion for discriminant validity results.

4.1.2. Structural Model

The evaluation of PLS-SEM structural models requires the consideration of three indicators: Coefficient of determination (\mathbb{R}^2), Construct Cross-validated Redundancy (\mathbb{Q}^2), and effect size f² [78]. R² measures the precision of the model prediction, representing the amount of explained variance of the endogenous constructs by the exogenous ones [78]. Chin [68] suggests that \mathbb{R}^2 values close to 0.670 indicate high explanatory power. In this study, the R^2 for DT was 0.736, adjusted R^2 was 0.724, and for TMS, R^2 was 0.627, adjusted R^2 was 0.620, indicating a high level of explanation of the intermediate variables of top leadership support and digital transformation (as shown in Figure 2). Hair et al. [71] state that the prediction correlation Q^2 of the structural model should be greater than 0, and the higher the model's predictive accuracy, the greater the Q^2 [78]. The Q^2 values of this study were 0.599 and 0.510, respectively, indicating good predictive correlation of the model. Chin [68] and Hair et al. [78] suggest using Cohen's Effect size (f²) to determine the size of the influence of each path in the structural equation model, with f^2 values between 0.02 and 0.15, between 0.15 and 0.35, and greater than 0.35, indicating low, moderate, and high effects, respectively. In this study, all constructs had f² values less than 0.15 for DT. The f^2 values of CP, PS and RA on TMS were 0.162, 0.063 and 0.243, respectively, indicating that CP and RA had moderate and high effects on TMS, respectively.

Smart-PLS software usually estimates path significance levels using the Bootstrapping method in 5000 repeated samples [68]. As shown in Table 4, the digital employees, organizational readiness, and partner pressure are non-significant at the 0.05 level. Among the 10 accepted hypotheses, use of digital technology, relative advantage, digital transformation strategy, top management support, competitive pressure, and policy support have a positive impact on digital transformation in construction enterprises, while digital costs have a negative impact. In addition, relative advantage, competitive pressure, and policy support have a positive impact on top management support. Regarding the mediating effect, as shown in Table 5, top management support partially mediates the relationship between relative advantage and competitive pressure and digital transformation, but there is no significant mediating effect between partner pressure and policy support and digital transformation.

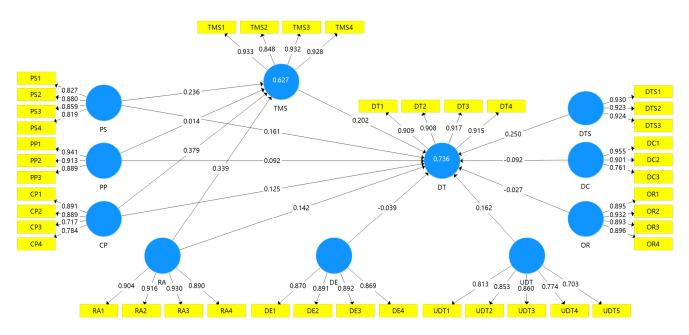


Figure 2. Study model path.

Table 4.	Hypothesis	testing result	lts.
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Hypotheses	Relationship	Path Coefficients	T Statistics	p Values	Result
H1	$UDT \rightarrow DT$	0.162	2.679	0.007	Supported
H2a	$RA \rightarrow TMS$	0.339	5.433	0.000	Supported
H2b	$RA \rightarrow DT$	0.142	2.120	0.034	Supported
H3	$DE \rightarrow DT$	-0.039	0.693	0.488	Not Supported
H4	$DC \rightarrow DT$	-0.092	2.032	0.042	Supported
H5	$OR \rightarrow DT$	-0.027	0.405	0.686	Not Supported
H6	$DTS \rightarrow DT$	0.250	3.075	0.002	Supported
H7	$TMS \rightarrow DT$	0.202	2.377	0.017	Supported
H8a	CP→TMS	0.379	4.475	0.000	Supported
H8b	$CP \rightarrow DT$	0.125	1.995	0.046	Supported
H9a	PP→TMS	0.014	0.182	0.855	Not Supported
H9b	$PP \rightarrow DT$	0.092	1.304	0.192	Not Supported
H10a	PS→TMS	0.236	2.582	0.010	Supported
H10b	PS→DT	0.161	2.332	0.020	Supported

Table 5. Specific indirect effect.

Relationship	Original Sample	T Statistics	p Values	Mediation Effect
RA→TMS→DT	0.068	2.105	0.035	Partial Mediation
$CP \rightarrow TMS \rightarrow DT$	0.076	2.095	0.036	Partial Mediation
$PP \rightarrow TMS \rightarrow DT$	0.003	0.171	0.864	No Mediation
$PS {\rightarrow} TMS {\rightarrow} DT$	0.048	1.747	0.081	No Mediation

4.2. fsQCA Analysis

4.2.1. Calibration

Before analyzing the configurational effects, data calibration must be performed first. fsQCA requires converting the raw variable data into a range of 0 to fuzzy set 1 (0 denotes no membership, 0.5 represents the crossover point, indicating the maximum fuzzy point, and 1 denotes complete membership) [26]. To calibrate the data, not only should direct or indirect calibration methods be considered in the study, but for scale data, the relationship between the measurement scale and the actual sample distribution should also be taken into

account [79]. Therefore, based on the data situation, this study adopts a direct calibration method. First, the scores of different measurement questions under different facets are added and averaged. Then, in the means of different facets, the mean values corresponding to the 95%, 50%, and 5% percentile, which have been used more frequently in previous studies, are selected as anchors [80] to distinguish the degree of membership between facets. Finally, all the original data are calibrated using the "calibration" function in the fsQCA software.

4.2.2. Analysis of Necessary Conditions

The necessity test for antecedent conditions is also a necessary procedure before conducting configurational analysis. If the consistency of the system is greater than 0.9, it is generally considered that the antecedent conditions are necessary for the outcome [81]. As shown in Table 6, under the results of high and low levels of digital transformation in construction enterprises, the consistency levels of all individual conditions are not higher than 0.9, indicating that none of the single conditions have sufficient explanatory power for digital transformation and are not necessary conditions for digital transformation in construction enterprises. This suggests that digital transformation in construction enterprises is influenced by various conditions in a coordinated manner and needs to be explored from the perspective of configurational effects.

Table 6. Necessity analysis of single conditions.

Conditions -	High-Level Digita	l Transformation	Low-Level Digital	Transformation
conditions	Consistency	Coverage	Consistency	Coverage
UDT	0.823139	0.802374	0.548858	0.513682
~UDT	0.501096	0.536361	0.788841	0.810693
CA	0.825980	0.804635	0.587733	0.549719
~CA	0.537774	0.576019	0.791125	0.813604
DC	0.708970	0.717806	0.664221	0.645689
~DC	0.650050	0.668472	0.709706	0.700723
DE	0.790424	0.829646	0.544602	0.548837
~DE	0.570166	0.565973	0.830960	0.791965
OR	0.861080	0.824033	0.602024	0.553154
~OR	0.533065	0.582474	0.808487	0.848203
DTS	0.883887	0.839778	0.589178	0.537459
~DTS	0.513165	0.565404	0.824360	0.872067
TMS	0.876379	0.872026	0.556332	0.531500
~TMS	0.529161	0.554014	0.866047	0.870573
СР	0.797541	0.842611	0.529325	0.536943
~CP	0.561711	0.554163	0.844844	0.800262
PP	0.805938	0.836321	0.548590	0.546575
~PP	0.563048	0.565048	0.835718	0.805250
PS	0.871130	0.801364	0.603729	0.533236
~PS	0.492600	0.564214	0.775104	0.852395

4.2.3. Configuration Results

After completing the data calibration and necessary condition analysis using fsQCA software, this study analyzed the configuration of the causal factors for the digital transformation of construction enterprises. Different combinations of causal factors for the digital transformation of construction enterprises were obtained after constructing a truth table. The frequency threshold was set to exclude combinations that rarely occurred or did not exist, in order to reduce the initial number of combinations and ensure obtaining a certain number of actual case influence factor combinations, but at the same time, it would reduce the percentage of case combination explanations (coverage) [82].

Although Ragin et al. [75] suggested that the case frequency value could be set to 1.5% of the original case number, the truth table case frequency threshold setting still needs to be based on specific research context and actual conditions and is not fixed. Pappas et al. [82] believed that for large samples (cases greater than 150), the frequency threshold could be set to 3 or higher. To ensure the reliability and interpretability of the combinations, this

study initially set the case frequency threshold to 5 and the consistency threshold to 0.8 [76]. Next, standard analysis was selected, and after simplifying the quality implications, the default program setting was selected in the counterfactual analysis of the intermediate solution. Pappas et al. [82] suggested that unless there is sufficient theoretical and literature support, the existence or non-existence option should be selected to ensure obtaining all possible solutions.

Using an intermediate solution and a concise solution [82], this study identified three configuration schemes that can result in high-level digital transformation of construction companies, as shown in Table 7. The overall consistency of the combined scheme is 0.985, and each scheme's consistency exceeds 0.9, indicating strong explanatory power. Furthermore, the overall coverage of the combined scheme is 0.565, demonstrating that the three schemes encompass more than half of the results. Core enabling factors include use of digital technology, digital employees, organizational readiness, digital transformation strategy, and top management support and policy support. Additionally, the study identified one configuration scheme that can result in low-level digital transformation of construction companies. The combined scheme's overall consistency is 0.991, and its coverage is 0.468, encompassing nearly half of the results. Core missing factors include external competitive pressure, partner pressure, and insufficient support from senior leaders and policies.

Antecedent Condition	High Levels of Digital Transformation			Low Levels of Digita Transformation	
	hdt1	hdt2	hdt3	ldt1	
UDT	•	•	٠	×	
CA		0	0	×	
DC	×	0	0		
DE	•	•	•	×	
OR	•	•	•	×	
DTS	•	•	•	×	
TMS	•	•	•	\otimes	
СР	0	0		\otimes	
PP	0		0	\otimes	
PS	•	٠	٠	\otimes	
Raw coverage	0.386	0.470	0.475	0.468	
Unique coverage	0.069	0.021	0.025	0.468	
Consistency	0.994	0.987	0.986	0.991	
Overall solution coverage		0.565		0.468	
Overall solution consistency		0.985		0.991	

Table 7. Digital transformation configuration results.

Note: • = core condition present. \bigcirc = peripheral condition present. \otimes = core condition absent. × = peripheral condition absent. Blank spaces = condition may be either present or absent.

Robustness testing is a crucial step in configuration analysis, and various methods are available, such as adjusting calibration thresholds, changing case frequency or consistency thresholds, adding other conditions, and adding or deleting cases [83]. To test the stability, we adjusted the consistency threshold from the original 0.8 to 0.85. By comparing the research results before and after the adjustment, the three configuration schemes for high-level digital transformation of construction companies and one configuration scheme for low-level digital transformation of construction companies were still supported.

5. Discussion

This study employed the TOE framework to identify the technological, organizational, and environmental factors that affect digital transformation in construction companies and constructed a research model that examines the dual effects of digital transformation. Combining PLS-SEM with fsQCA methods helps to better understand the mechanism of

the multiple antecedents of digital transformation in construction companies. Based on the dual effect perspective, the research results are further discussed.

5.1. Discussion of the Net Effect

In the context of technology, the results show that the use of digital technology (H1) has a positive impact on the digital transformation of construction enterprises. This is consistent with previous research conclusions on the impact of digital technology on enterprise digital transformation [18,31]. Construction companies need to adjust their degree of digital technology use based on their own situation, strengthen the deep integration with enterprise operation and management, and exert the value of digital technology. Relative advantage (H2a/H2b) not only has a significant positive impact on top-level leadership support and the digital transformation of construction enterprises but also promotes the digital transformation of construction enterprises through the positive influence on toplevel leadership support. This indicates that the relative advantage brought about by promoting the digital transformation of construction enterprises through the use of digital technology can effectively enhance top-level leadership support for enterprise digital transformation and is an important driving force for promoting digital transformation. For example, Wong et al. [63] found that the relative advantage of digital technologies such as blockchain in operations and supply chain management plays an important role in promoting the support of senior management in Malaysian small and medium-sized enterprises for digital transformation. In addition, although previous research has suggested that employees' digital skills have a positive effect on digital transformation [31], the results of this study show that digital employees (H3) have no significant impact on the digital transformation of construction enterprises. We consider that there may be the following reasons. On the one hand, digital technology has not been deeply integrated into the production and operation of construction enterprises, and mostly limited to application at the traditional business level. Employees' digital skills may only be limited to the use and demonstration of some digital construction technologies in projects, lacking substantial impact on construction projects. Li et al. [1] also confirmed this view, believing that the use of digital technology in China's construction industry is mostly aimed at winning bids, and it is difficult to fundamentally solve the problems existing in engineering construction projects. On the other hand, compared with other enterprises, construction enterprises face more severe employee turnover problems, and digital employees are no exception. Due to the lack of stability, digital employees may lack a sense of identification and work persistence in their enterprises, thereby limiting their role in the digital transformation of construction enterprises.

In the organizational context, the results show that digital cost (H4) is negatively correlated with the digital transformation of construction enterprises. High digital costs increase the financial burden of adopting digital technologies, which hinders the digital transformation of enterprises. This is especially difficult for small and medium-sized enterprises under the cash flow constraints caused by the pandemic, who cannot afford the high costs of digital technology and digital transformation [31]. Construction enterprises are no exception, as they often face issues such as having to pay for construction costs in advance and delayed payments by the project owner in the current competitive market environment in China, thus needing to bear significant financial risks during the project construction process. In this case, digital cost becomes an important factor for construction enterprises to consider whether to adopt digital technologies and promote digital transformation. This study hypothesizes that organizational readiness (H5) has a positive impact on the digital transformation of construction enterprises. However, empirical results do not support this view. Although previous studies have found no significant relationship between cognitive readiness and digital transformation [65], considering that the current level of digital transformation in construction enterprises is relatively low and their understanding of digital transformation is somewhat vague, they may only use digital technology at the level of usage without making organizational preparations and changes for digital transformation. Furthermore, it may be difficult for organizational members who have already formed fixed work thinking and behavior patterns to adapt to the disruptive innovation that digital transformation will bring [12]. Therefore, it may reduce the positive impact of organizational readiness on digital transformation. Vial [18] also believes that resistance from existing employees in organizations to the introduction of disruptive technologies (such as digital technologies) is one of the obstacles to digital transformation. Digital transformation strategy has the greatest impact on all kinds of independent variables in the digital transformation of enterprises and plays a critical driving role. This result is consistent with the research findings of Kane et al. [59] and Ghobakhloo et al. [60]. Developing a digital transformation strategy is the primary step for successful digital transformation in enterprises [31]. However, it should be noted that the digital transformation strategy of successful enterprises is usually matched with the enterprise's business strategy to ensure that digital technology can add value to the enterprise [65]. Top management support (H7) plays a key role in promoting the digital transformation of construction enterprises. It ranks third among all path coefficient values that affect the digital transformation of construction enterprises. Previous literature has also emphasized the important role of leadership in digital transformation [18,57]. In addition, the relative advantage of technology (H2a), competitive pressure from the environmental context (H8a), and policy support (H10a) have a positive impact on top management support for the digital transformation of construction enterprises. In terms of the relative advantage and competitive pressure on the digital transformation of construction enterprises, top management support plays a partial mediating role. However, it was found that partner pressure (H9a) has no significant effect on top management support for digital transformation. These findings indicate that, except for partner pressure, relative advantage, competitive pressure, and policy support are likely to be the focus of attention for the senior leadership of construction enterprises in adopting new technologies or methods.

In the environmental context, the results indicate that competitive pressure (H8a/H8b) has a positive impact on top management support and digital transformation of construction enterprises, and top management support partially mediates the effect of competitive pressure on digital transformation. The increasingly fierce competitive pressure in the construction industry will force top management to seek changes, such as adopting new technologies and reforming business strategies, to seek enterprise development. In the face of partner pressure (H9a/H9b), top management support and digital transformation of construction enterprises were not significantly affected. There may be two reasons. Firstly, the construction enterprise exists around project construction and is a core enterprise in the construction supply chain. It may be less affected by the digital transformation pressure of partners. Secondly, during the entire construction project cycle, except for technology-intensive enterprises such as design and engineering consulting units, most partners are small and medium-sized enterprises, and the current level of digitalization of Chinese small and medium-sized enterprises is generally low, and more than 70% of small and medium-sized enterprises have not undergone large-scale digital transformation [31], which lack the necessary motivation and resources for digital transformation. Among the external environmental factors, policy support (H10b) has a significant positive impact on the digital transformation of Chinese construction enterprises, and policy support (H10a) also has a positive effect on top management support. In the Chinese market environment, the government's policy guidance and administrative orders may be important factors that influence enterprise direction. In the questionnaire information in Table 1, the proportion of respondents in state-owned units exceeds 60%. Compared with ordinary enterprises, these state-owned units will further strengthen this attribute. This also explains the results well. However, policy support seems to have no impact on the digital transformation of construction enterprises through top management support. The possible reason is that although the government supports the digital transformation of enterprises, to know whether top management has enough motivation to promote digital transformation we may need to

consider more factors, such as whether digital transformation can bring benefits to the enterprise in the short term.

5.2. Discussion of the Configuration Effect

By analyzing the configurational effects of multiple antecedents from technological, organizational, and environmental backgrounds on the digital transformation of construction enterprises, it was found that, firstly, in the three paths of high-level digital transformation antecedent configuration in construction enterprises, the technological usage and digital employees in the technological context, all factors in the organizational context, and policy support in the external environment are the core existing conditions, while competitive pressure and partners belong to marginal or non-existent conditions. This reveals that, in the current context of government support for digital transformation, the level of digital transformation in enterprises is actually determined by the internal organization of the enterprise, rather than external factors' driving role. To achieve a high level of digital transformation, construction enterprises must make efforts from within the organization. Organizations must implement organizational structure and cultural mindset reforms to adapt to digitalization and overcome obstacles in the process of digital transformation [18]. For example, if a construction contractor wants to carry out BIM collaborative work in a project, it must first improve the organization's digital collaboration planning capabilities and have rich experience and capabilities in BIM 3D modeling [16]. Secondly, in the one path of low-level digital transformation antecedent configuration in construction enterprises, environmental factors and top management support are at the core of missing conditions. This indicates that if there is no external environmental pressure, the motivation for construction enterprises to carry out high-level digital transformation may be insufficient because enterprises usually become stuck in and rely on the inherent relationships with other stakeholders, which are difficult to change easily [18]. In other words, for construction enterprises, especially senior leaders, without the necessary external environmental incentives, the internal construction enterprises often do not actively carry out digital transformation, or the effect of digital transformation is not good. Finally, in all combinations of factors, top management support and policy support play important roles, which is basically consistent with the previous analysis conclusion from a "net effect" perspective. Top management support and policy support are the key factors that affect the organizational and environmental contexts of the digital transformation of construction enterprises.

6. Conclusions

In the digital era, traditional construction enterprises urgently need to undergo digital transformation to cope with increasingly severe industry crises and achieve sustainable construction and high-quality development. This study explores the multiple antecedents of digital transformation in Chinese construction enterprises through the TOE framework and establishes a research model of the factors influencing digital transformation in construction enterprises based on the dual effect perspective. Secondly, a mixed method of PLS-SEM and fsQCA is used to investigate the dual effects of the factors influencing digital transformation in construction enterprises. From a net effect perspective, digital transformation in Chinese construction enterprises is significantly influenced by seven factors, including the use of digital technology and relative advantage in the technical context, digital cost and top management support in the organizational context, digital transformation strategy, competition pressure, and policy support in the environmental context. However, three factors-digital employees, organizational readiness, and pressure from partners—were statistically proven to have no significant impact. Furthermore, relative advantage, competition pressure, and policy support have a positive impact on the support of senior leaders for enterprise digital transformation, while partner pressure has no significant impact. Top management support plays a partial mediating role in the relative advantage and competition pressure during the process of digital transformation in construction enterprises, but no mediating role is found in partner pressure and policy

pressure. From the configuration effect perspective, there are three paths for construction enterprises to achieve a high level of digital transformation, mainly driven by internal organizational factors. One path that leads to low-level digital transformation reveals that external environmental incentives are often necessary for enterprises to achieve good results in digital transformation. Finally, through the dual effect perspective, it is found that top management support and policy support are key factors in the current digital transformation of Chinese construction enterprises, which are important for achieving sustainable construction and high-quality development.

The contribution of this study has mainly two aspects. First, the empirical study provides a useful exploration of the impact mechanisms of the current digital transformation of construction enterprises, which helps construction enterprises and stakeholders in many developing countries, including China, to better understand the digital transformation of enterprises and provides a reference basis for successful implementation of digital transformation. Second, the research results enrich the knowledge system in the field of digital transformation of construction enterprises. The validated research model of digital transformation of construction enterprises can provide research inspiration for other research designs.

Despite some research results, the study has several limitations. First, this study is based on the TOE framework to explore the influencing factors of digital transformation in construction firms. In the future, other domain theories can be introduced to expand the digital transformation of construction enterprises, such as PPM theory [84] to assess the factors with a system framework. Second, digital transformation is currently a relatively new field in traditional construction enterprises, and fewer respondents are familiar with digital transformation in construction enterprises and have rich digital experience, which may affect the empirical investigation of this study to some extent. Again, the fsQCA approach to study the digital transformation of construction enterprises is somewhat novel. However, it can be extended by introducing deep learning algorithms in the future [85] to further predict the identification of future digital transformation factors of construction enterprises. Finally, this study does not count data such as firm size, and the digital transformation paths of small and medium-sized construction firms may differ from those of large construction firms. Therefore, future research can further explore the relationship between small and medium-sized construction firms and digital transformation.

Author Contributions: Methodology, G.Z. and T.W.; software, G.Z. and Y.W.; validation, Z.D. and H.D.; formal analysis, G.Z., T.W. and W.L.; resources, S.Z.; writing—original draft preparation, G.Z. and T.W.; editing, G.Z. and Y.W.; supervision, T.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Special Fund for Science and Technology Innovation Strategy of Guangdong Province under grant number pdjh2021b0405. The authors thank the editor and anonymous reviewers for their numerous constructive comments and encouragement that have improved our paper greatly.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The dataset generated and analyzed in this study is not publicly available. Dataset is available from the corresponding author on reasonable request.

Acknowledgments: The authors thank the editor and anonymous reviewers for their numerous constructive comments and encouragement that have improved our paper greatly.

Conflicts of Interest: The authors declare no conflict of interest.

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