Enabling the Green Total Factor Productivity of the Construction Industry with the Prospect of Digital Transformation

Abstract: This research study adopts 30 provinces, municipalities and autonomous regions in China as the research object in order to explore the green total factor productivity (GTFP) of the construction industry with the prospect of digital transformation. Based on construction industry panel data from 2011-2017, the CCR model and PCE model evaluation model are used to measure the GTFP of the construction industry in the context of digital transformation. The results of the research study identify the following: (A) The PCE model was able to differentiate all decision units and complete ranking. (B) The GTFP of the construction industry in East, North, South-Central, and Southwest China is relatively high, while that in Northeast and Northwest China is low. Thus, there is room for improvement in Northeast and Northwest China to a certain extent. (C) The higher the optimism of decision makers about the digital transformation of the construction industry is, the higher the GTFP of the construction industry; additionally, when decision makers become increasingly more optimistic about the digital transformation of the construction industry, the GTFP of the construction industry decreases to a certain extent, while when decision makers become increasingly less optimistic about the digital transformation of the construction industry, the GTFP of the construction industry increases to a certain extent.

Keywords: Digital transformation; Prospect theory; Construction industry; Green total factor productivity (GTFP).

1 Introduction

Since the reform and opening up more than 40 years ago, China’s economy has developed rapidly, leading to the emergence of the ‘Chinese economic miracle’[1], which has attracted worldwide attention. However, this rapid growth of China’s economy has come at the expense of the environment. The development path of high investment, high consumption and high pollution has become a "bottleneck" for sustainable economic development. As an important sector of the national economy, the construction industry is no exception[2]. Moreover, digital and green development has become an inevitable trend in the development of the construction industry[3]. With the innovative breakthrough and integrated development of the new generation of information and communication technology (ICT), digital technologies that build on building information modelling (BIM) are becoming the driving force behind the transformation, upgrading and sustainable development of the construction industry[4].

'Digital transformation' is a concept based on harnessing the latest digital technologies (such as cloud computing, big data, artificial intelligence, Internet-of-Things, robotics, and blockchain) and related capabilities to drive organizational business model innovation and business ecosystem reconstruction. Indeed, digital transformation can be viewed as moving beyond more traditional information technology (IT) implementations focused on process automation and optimization through enabling changes and resulting implications for products, services, and business models as a whole[5]. With the development of a new generation of IT and the increase in the availability of innovative technologies, such as big data, artificial intelligence and cloud computing, digital transformation is enabling the creation of new value creation paths in order to facilitate organizational change and concomitantly drive disruptions, such as driving consumer behaviours and creating new competitive landscapes[6].However, digital transformation in the construction industry is currently still its infancy and while many have advocated the potential benefits[7-11] there is now a pressing need to investigate the prospect of digital technologies in the construction industry. Furthermore, digital transformation has also been viewed as an important emerging enabler to improve the sustainability of the construction sector[12, 13] and thereby generate improved performance for the industry across economic, environmental and social outcomes. Therefore, this research study has adopted the Chinese construction industry as the object of an empirical investigation of industry panel data from 2011-2017 in order to utilize the prospect cross-efficiency evaluation model is used to measure the green total factor productivity of the construction industry with the prospect of digital transformation.

First,the existing articles seldom pay attention to the influence of digitalization on total factor productivity, so this paper expands the existing research. Second,this paper adopts the PCE model based on prospect theory, which not only overcomes the disadvantage that some evaluation units can not be further distinguished because the traditional DEA model always evaluates the efficiency value from its own perspective, but also solves the problem that the traditional cross-efficiency model does not fully consider the subjective preference of decision makers in the process of efficiency evaluation, can not reflect the different risk attitudes of decision makers when they face the benefits and losses, and is difficult to meet the actual decision-making needs of decision makers. Third,this study systematically combs the existing research,and concludes that the input index and output index of total factor productivity improve the reliability of the research as much as possible. Finally, the results of this study are helpful for the government to evaluate the prospect of GTFP digital transformation in construction industry.

The paper is organized as follows. Section 2 presents the literature review. Then, methodology is presented in Section 3. Section 4 shows the empirical results, with Section 5 discussing these results. Finally, conclusions are made in Section 6.

2 Literature review

2.1 Digital transformation in the construction industry

In recent years, the topic of digital transformation has aroused the attention of the business management community [14]. Indeed, industries are actively embracing digital transformation, including the automotive industry [15], food industry [16], fashion industry[17], aerospace industry[18] as well as the construction industry [19]. In the case of the construction industry, digital transformation can be viewed as building on the use of building information modeling (BIM) that acts as a big data platform in the architecture, engineering, and construction (AEC) industry and to support the transition to a smart industrial paradigm [20].

Extending the functionality of BIM usage in the construction sector offers the capability to provide improved efficiencies across different aspects of the industry and this has also been articulated in terms of the paradigm of Construction 4.0 [21]. For instance, BIM systems can be extended through incorporating material databases along with corresponding use of big data, smart sensors and increasing levels of automation in order to improve the efficiency and safety of the construction of roads incorporating recycled materials [22]. This extension can also be considered in terms of moving beyond purely the construction stage, since it has been identified that IoT (internet-of-things)-BIM systems can be deployed to whole life benefits for FM (facilities management) and the built environment applications, namely energy management, operations and maintenance management, space management, FM project management, emergency management and quality management [23], While yet other options also exist in regard to utilizing BIM to secure sustainability related benefits, such as improved energy efficiency in the built environment [24].

In regard to the technological dimension of digital transformation, there are opportunities to utilize various technologies, such as artificial intelligence [25], IoT and big data [26], augmented and virtual reality [27], robotics [28] as well as additive manufacturing [29]. There are also a number of more emerging technologies that can be considered as part of digital transformation in the construction sector. In this regard, blockchain systems based on distributed ledger technology have been identified as having a number of potential applications in the construction industry[30]. This includes enabling higher levels of productivity through adopting situational instances of Payments in Project Management (PPM) and Procurements in Supply Chain Management (PSCM) as well as harnessing BIM to underpin using Smart Asset Management (SAM) [31]. Whereas digital twins have been evaluated as having application to workforce safety in the construction industry [32] and explored as providing improved capabilities for construction site logistics [33].

From an international perspective and in the case of Nigeria, Ezeokoli et al. [34] investigated the opinions of construction sector professionals on the digital transformation of the construction industry; the study showed that 69% and 12% of professionals believe that digital transformation is an opportunity and a threat, respectively, while 19% of professionals believe that it is both. Whereas, Kraatz et al.[35] have described the productivity benefits in the Australian transport infrastructure sector through the construction industry adopting BIM, virtual design and construction (VDC) and integrated project delivery (IPD) systems. Koseoglu et al. [36] carried out research on the BIM-Enabled Digital Transformation of a new airport project in Istanbul, Turkey, finding that the major challenges involve sustaining continuous monitoring and controlling the project execution phase as well as managing engineering complexity while remaining aligned with the BIM learning curves of key stakeholders. The researchers also identified that more strategic level control measures, incentivized virtual systems to enable collaborative working and ongoing digital delivery mechanisms can be viewed as enablers of digital transformation on infrastructure projects. Hwang et al. [37] investigated the implementation status and project performance in the Singapore construction industry through integrated digital delivery (IDD) and found that IDD implementation resulted in a number of benefits for the sector, including improved overall project, project cost, project quality and project schedule performance. In other work, Pfnür and Wagner[38] identified three impact mechanisms of the digital transformation in the real estate industry in Germany, which is based on the perspectives of occupiers (concerned with access to more flexible space), service providers (concerned with increasing the efficiency of traditional processes) and investors (acknowledging the needs of the occupiers but not necessarily pursuing resulting strategies.

2.2 Green total factor productivity

In the construction industry, green total factor productivity (GTFP) is an intuitive manifestation of economic growth through considering energy consumption and carbon emissions. Indeed, it can be argued that GTFP reflects the real green growth performance indicators of the economic system during a certain period of time. In this regard, a systematic analysis of the GTFP of the construction industry enables the evaluation of the development status of the construction industry[39]. Research on GTFP originated in the middle and late 20th century and was developed during the first ten years of the 21st century[40].

The current research on this topic focuses on the measurement of GTFP in the construction industry. The parameter estimation method using the Solow residual value[41], stochastic frontier analysis (SFA) method[42] and the nonparametric data envelopment analysis (DEA)[43] have all been widely used. DEA is more popular among scholars due to its advantages in dealing with multiple inputs and outputs. In 1983, Pittman used DEA for the first time to study GTFP considering poor output. Ebrahimi and Salehi[39] used DEA to calculate technical efficiency, pure technical efficiency, scale efficiency, and cross-efficiency to discuss carbon dioxide emission reduction and improve energy efficiency. Hu et al.[44], based on the Malmquist index of DEA and sequential benchmark technology, proposed an index for evaluating carbon emission performance in the framework of TFG. Whereas Xiang et al.[4] used the global Malmquist-Luenberger model to measure the GTFP of the construction industry. Although scholars have conducted extensive research on the GTFP of the construction industry, there is a lack of research on the prospect of digital transformation in this sector. Therefore, empirical research is required on whether digital transformation can engender greater benefits to the construction industry. Such research also needs to identify the role that digital transformation can play in resource conservation and whether it can improve the GTFP of the construction industry.

3 Research methods

3.1 Research strategy

In order to address the gap in the knowledge base identified in the literature review, this research study uses the prospect cross-efficiency (PCE) model to measure the GTFP of the construction industry with the prospect of digital transformation. The model deploys a self-evaluation system to alleviate the drawbacks of the traditional method of relying solely on the self-evaluation system for the evaluation of decision-making units (DMUs). This approach determines that the globally optimal DMU has achieved the goal of fully ranking all DMUs. The model has been used to describe the degree of optimism of decision makers regarding the prospect of the digital transformation of the construction industry in a cross-efficiency evaluation and analyses the six major regions of China for the construction industry from 2011 to 2017. This is achieved by changing the parameter value representing the degree of optimism of decision makers about the prospect of the digital transformation of the construction industry (excluding the GTFP of Tibet, Hong Kong, Macao and Taiwan regions) to compare the ranking of the GTFP of the construction industry in various regions under different parameter values. This study uses a systematic GTFP measurement model to comprehensively and accurately measure the GTFP of the construction industry. The study thereby enhances the application of GTFP in the construction industry and provides a reference for research on GTFP in other industries. Furthermore, the study explores the impact of the prospect of digital transformation on GTFP in the construction industry.

3.2 CCR model of self-efficiency evaluation

Assuming that D={DMU_1，DMU_2， ......DMU_n} is a set of n evaluated DMUs, each DMU generates s outputs by consuming m inputs. Let N={1,2,3...n}, k∈N; M={1,2,3…m}, i∈M; and S={1,2,3…s}, r∈S. For DMU_k, k=1, 2, 3…n, input is defined as X_{ik} (i=1, 2,…m), and output is defined as Y_{rk} (r=1, 2, 3…s); see Table 1. The relative efficiency of DMU_k is defined as follows:

$$\mathrm{E_{kk}} = \sum_{r=1}^{s} u_{rk}\, y_{rk} / \sum_{i=1}^{m} v_{ik}\, x_{ik} \qquad (1)$$

where u_{rk} and v_{ik} are the nonnegative weights of s outputs and m inputs, respectively. In the self-efficiency evaluation, the relative efficiency of 3 compared to other DMUs can be measured with the following Charnes–Cooper–Rhodes (CCR) model:

$$\max \mathrm{E_{kk}} = \sum_{r=1}^{s} u_{rk}\, y_{rk} / \sum_{i=1}^{m} v_{ik}\, x_{ik}$$

$$\text{s.t.} \sum_{r=1}^{s} u_{rk}\, y_{rj} / \sum_{i=1}^{m} v_{ik}\, x_{ij} \le 1,\ \ j \in N$$

$$u_{rk},\ v_{ik} \ge 0 \ \ r \in S,\ i \in M \qquad (2)$$

Model (2) is a nonlinear programming model. To facilitate the solution, this section uses the CCR model to transform Model (2) into the following linear programming model:

$$\max E_{kk} = \sum_{r=1}^{s} u_{rk}\, y_{rk}$$

$$\text{s.t. } \sum_{r=1}^{s} u_{rk}\, y_{rj} - \sum_{i=1}^{m} v_{ik}\, x_{ij} \le 0,\ \ j \in N$$

$$\sum_{i=1}^{m} v_{ik}\, x_{ik} = 1$$

$$u_{rk},\ \ v_{ik} \ge 0\ \ r \in S,\ \ i \in M \qquad (3)$$

where $u_{rk}*$ and $v_{ik}*$ are the optimal output and input weights, respectively, and $E_{kk}* = \sum_{r=1}^{s} u_{rk} * y_{rk}$ is the CCR efficiency of DMU_k, which represents the best relative efficiency of DMU_k calculated through self-evaluation. If $E_{kk}*=1$ and optimal weights $u_{rk}*$ and $v_{ik}*$ are positive, then 6 is valid; otherwise, it is invalid.

Table 1 Input-output value of DMUs

DMU_s	DMU_1	DMU_2	…….	DMU_n
Output values	y_{11}	y_{12}	…….	y_{1n}
	y_{21}	y_{22}	…….	y_{2n}
	…….	……	…….	…….
	y_{s1}	y_{s2}	…….	y_{sn}
Input values	x_{11}	x_{12}	…….	x_{1n}
	x_{21}	x_{22}	…….	x_{2n}
	…….	…….	…….	…….
	x_{m1}	x_{m2}	…….	x_{mn}

3.3 CCR model of cross-efficiency evaluation

In Model (3), each DMU is evaluated with the optimal weight, which may lead to a CCR efficiency value of 1 for many DMU self-efficiency evaluations, which cannot be further distinguished. To compensate for this shortcoming, Sexton et al. [12] proposed a cross-efficiency evaluation CCR model, which evaluates the overall performance of each DMU by using the total weight of all DMUs. If $u_{rk}*$ and $v_{ik}*$ are the optimal weights of the output and input, respectively, of DMU_k given by Model (3), then the cross-efficiency score of DMU_d is as follows:

$$E_{dk}=\sum_{r=1}^{s} U_{rk}\, y_{rd} / \sum_{i=1}^{m} V_{ik}\, X_{id},\ \ d \in N,\ \ d \ne k \qquad (4)$$

For each DMU_k, Model (3) is calculated n times each time, and each DMU obtains n-1 crossover efficiency and optimal self-efficiency. Moreover, n DMUs can obtain n groups of input-output weights using n*n crossover. In terms of the efficiency matrix, the diagonal elements in Table 2 present the CCR efficiency score of self-efficiency evaluation, $E_{kk}*$.

To evaluate the overall performance of each DMU and calculate the average cross-efficiency of each row (see Table 2), the cross-efficiency of DMU_d is defined as follows:

$$E_d=\sum_{k=1}^{n} E_{dk}/n, \quad d\in N \tag{5}$$

Cross-efficiency score E_d provides a peer-to-peer evaluation of DMU_d, and accordingly, these n DMUs can be completely compared or ranked.

Table 2 Cross-efficiency matrix of DMUs

DMU	Target DMU				Average cross-efficiency
	DMU_1	DMU_2	……	DMU_n	
DMU_1	E_{11}	E_{12}	……	E_{1n}	$\sum_{k=1}^{n} E_{1k}/n$
DMU_2	E_{21}	E_{22}	……	E_{2n}	$\sum_{k=1}^{n} E_{2k}/n$
……	……	……	……	……	……
DMU_n	E_{n1}	E_{n2}	……	E_{n3}	$\sum_{k=1}^{n} E_{nk}/n$

3.4 Prospect theory

In 1979, Kahneman and Tversky proposed the prospect theory [13]. As a descriptive theory about the decision-making behaviour of risky individuals, prospect theory has been regarded as one of the most influential behavioural decision-making theories [14]. Moreover, prospect theory involves the following important principles [13].

(1) Reference dependence, where a decision maker usually perceives a gain or loss according to a reference point; therefore, the decision maker's foreground value curve is divided into a gain domain and a loss domain on the basis of this reference point.

(2) Loss aversion, where a decision maker is more sensitive to loss than to gain. For this reason, the loss domain of the foreground value curve is steeper than the gain domain.

(3) Sensitivity reduction, where a decision maker shows a profit trend of avoiding risk and a loss trend of seeking risk. Correspondingly, the foreground value curve is concave in the gain domain and convex in the loss domain.

The functional aspect of prospect theory is described as follows:

$$V(\Delta Z)=\begin{cases} (\Delta Z)^{\alpha}, & (\Delta Z \geq 0) \\ -\theta(-\Delta Z)^{\beta}, & (\Delta Z < 0) \end{cases} \tag{6}$$

ΔZ is used to measure the deviation of Z from reference point Z_0. If $\Delta Z\geq 0$, then the result is regarded as a gain; otherwise, the result is regarded as a loss ($\Delta Z<0$). Parameters $0<\alpha<1$ and $0<\beta<1$ indicate the convexity of the value function in the gain and loss domains, respectively, θ indicates the loss avoidance coefficient, and $\theta>1$ indicates that the loss area value function is steeper than the gain area value function.

Existing cross-efficiency evaluation methods assume that a decision maker is completely rational and usually belongs to the theoretical framework of expected utility. Noting that prospect theory is very consistent with the actual decision-making behaviour of human beings, the following section proposes a new cross-efficiency evaluation model based on prospect theory.

3.5 PCE model

Prospect theory reveals that a decision maker usually reflects the quality of results according to a reference point. The selection method for the reference point considers the following points: zero value, average value, median value, worst value and best value. This study is based on prospect theory and chooses the best and worst values. The worst DMU usually consumes the most input and produces the least output, and the best DMU usually consumes the least input and produces the most output. In prospect theory, if the value of a DMU is higher than that of the worst DMU, then it is viewed as a return. Relative loss can be regarded as a lower value than the optimal DMU, in which case, the DMU is regarded as a loss.

If the reference point is the worst DMU, then the foreground gain of the i-th input of DMU_k and the r-th output is ${V_{I_{ik}}}^+ = ({x_i}^- - x_{ik})^\alpha$ and ${V_{O_{rk}}}^+ = (y_{rk} - {y_r}^-)^\alpha$, respectively, among which ${x_i}^- = \max\{x_{ik}\}$ and ${y_r}^- = \min\{y_{rk}\}$.

If the reference point is the best DMU, then the prospect loss of the i-th input of DMU_k and the r-th output is ${V_{I_{ik}}}^- = -\theta(x_{ik} - {x_i}^+)^\beta$ and ${V_{O_{rk}}}^- = -\theta({y_r}^+ - y_{rk})^\beta$, respectively, among which ${x_i}^+ = \min\{x_{ik}\}$ and ${y_r}^+ = \max\{y_{rk}\}$.

Suppose that $N = \{1, 2, \dots, n\}$, $k \in N$, $M = \{1, 2 \dots, m\}$, $i \in M$, and $S = \{1, 2, \dots, s\}$, for $r \in S$, and that there are n DMUs to be evaluated; the output and input of DMU_k（k∈N）are y_{rk}（r∈S）and x_{ik}（i∈M）, respectively. Thus, a PCE model is constructed as follows:

$$\max \lambda\left(\sum_{r=1}^{s} u_{rk}\,(y_{rk} - {y_r}^-)^\alpha + \sum_{i=1}^{m} v_{ik}\,({x_i}^- - x_{ik})^\alpha\right)$$

$$-(1-\lambda)\left(\sum_{r=1}^{s} u_{rk}\,\theta(({y_r}^+ - y_{rk})^\beta + \sum_{i=1}^{m} v_{ik}\,\theta(x_{ik} - {x_i}^+)^\beta\right)$$

$$\text{s.t. } \sum_{i=1}^{m} v_{ik}\,x_{ik} = 1$$

$$\sum_{r=1}^{s} u_{rk}\,y_{rk} = E_{kk}{}^*$$

$$\sum_{r=1}^{s} u_{rk}\,y_{rj} - \sum_{i=1}^{m} v_{ik}\,x_{ij} \le 0 \quad j \in N$$

$$u_{rk},\ v_{ik} \ge 0,\ \ r \in S\ \ i \in M \qquad (7)$$

Parameter λ represents the relative importance of the gain that satisfies $0 \leq \lambda \leq 1$. In the PCE model, different λ values represent different attitudes of decision makers. If $0 \leq \lambda < 0.5$, then the decision maker will pay more attention to a loss rather than a gain; if $\lambda = 0.5$, then the decision maker will consider the factors of gain and loss equally important; and if $0.5 < \lambda \leq 1$, then the decision maker will pay great attention to the gain preference.

Parameter α represents the concavity of the value function in the gain area, which indicates the degree of optimism of the decision maker about the digital transformation of the construction industry. A larger α value means that the decision maker is very optimistic about the digital transformation of the construction industry. At this time, the decision maker is looking for risks. When α tends towards 0, the decision maker avoids risks in the evaluation process, and the evaluation results of the corresponding PCE model are quite conservative. Parameter β represents the convexity of the internal value function of the loss area, which represents the degree of the decision maker's disapproval of the digital transformation of the construction industry. A larger β value means that the decision maker is very dissatisfied with the digital transformation of the construction industry. At this time, the decision maker is sensitive to losses. When β tends towards 0, the decision maker seeks risks in the evaluation process, and the evaluation results of the corresponding PCE model are quite risky.

3.6 Data and evaluation index system

The DMUs in the model are the provinces, municipalities and autonomous regions examined in this study, which selects the construction industry panel data of 30 provinces, municipalities, and autonomous regions from 2011-2017 in China. The data used in this study mainly come from the "China Statistical Yearbook", "China Energy Statistical Yearbook", "China Construction Statistical Yearbook" and the relevant statistical yearbooks of various provinces and regions in China. Other data come from the following website; http://cyfd.cnki.com.cn/. Due to lack of data availability and completeness, relevant data for the Tibet Autonomous Region were excluded.

In order to select appropriate indicators, this study refers to the selection of input-output variables in the existing research on GTFP in the construction industry, as shown in Table 3.

Table 3 Existing GTFP evaluation index system for the construction industry

Author	Years	Investment index	Output indicators
Li and Liu	2010	(1) Labour (2) Capital	(1) Total value added
Wang et al.	2011	(1) Labour (2) Capital	(1) Total value added
Liu et al.	2013	(1) Labour (2) Capital	(1) Value added
He	2013	(1) Labour (2) Capital (3) Mechanical value of labour per capita	(1) Total value added (2) Total profit and taxes (3) Overall labour productivity

Li et al.	2014	(1) Labour (2) Capital (3) Number of enterprises (4) Mechanical value of labour per capita	(1) Total income of the enterprise (2) Completed construction area
Shi et al.	2016	(1) Capital (2) Operational investment	(1) Total profit (2) Project settlement profit
Hu and Liu	2016	(1) Labour (2) Completed construction (3) Energy	(1) Total value added
Hu and Liu	2017	(1) Labour (2) Completed construction	(1) Total value added (2) Carbon dioxide emissions
Chen et al.	2018	(1) Labour (2) Equipment	(1) Value added (2) Total value added (3) Total profit and tax
Hu and Liu	2018	(1) Labour (2) Capital (3) Equipment	(1) Total value added
Huo et al.	2018	(1) Labour (2) Capital (3) Equipment (4) Energy	(1) Total added value (2) Completed construction area

This study examined the existing evaluation indicators of GTFP in the construction industry. Subsequently, four input variables as well as two output variables and one undesired output variable were selected and digital transformation was established. Table 4 presents the prospective evaluation index system for the GTFP of the construction industry.

Table 4 GTFP Evaluation Index System of the Construction Industry

Index	Type	Unit
Number of employees in construction enterprises	Input	Millions
Total assets of construction enterprises	Input	Billions
Total power of construction machinery	Input	10^4 kw
Building energy consumption	Input	Ten thousand tons
Total output value of the construction industry	Expected output	Billions
Total profit of the construction industry	Expected output	Billions
Carbon dioxide emissions	Undesired output	Ten thousand tons

4 Results and Analysis

This empirical study takes the construction industry of 30 provinces, municipalities and autonomous regions in China from 2011 to 2017 as the research object. Taking the digital transformation of the construction industry as the prospect, the CCR model and the PCE model are used to measure the GTFP of the construction industry, and the GTFP of the construction industry with the prospect of digital transformation is measured. The two models are compared and subjected to sensitivity analysis, and the following conclusions are drawn.

4.1 Evaluation Results of the CCR Model

It is useful to present an illustrative example of the evaluation results from 2016. The evaluation results for the other years could be obtained in the same way. Based on the input-output data of the construction industry in 2016, the efficiency values of 30 DMUs were calculated by the CCR model (self-efficiency evaluation). The results are provided in last column of Table 5. According to Table

5, the efficiency value of most DMUs is 1, signifying that they are effective and that each DMU cannot be further distinguished. Therefore, the PCE model was introduced to calculate the cross-efficiency value of each DMU to comprehensively rank all DMUs.

Table 5 Input-Output of the Construction Industry in 2016

DMU	Input					Output		Efficiency of the CCR model
	Labours	Total assets	Total power of construction machinery and equipment	Energy consumption	Carbon dioxide emissions	Total output value	Gross profit	
Beijing	58.14	20263.67	366.8	119.47	115.86	8841.19	675.32	1.0000
Tianjin	73.64	6016.72	521.6	237.24	428.63	4891.81	97.58	1.0000
Hebei	130.88	4972.68	1028.8	312	234.03	5517.69	154.65	0.9312
Shanxi	75.43	4845.39	697	163.28	208.91	3318.47	97.21	0.7853
Inner Mongolia	29.7	1975.86	198.8	367.7	362.22	1220.81	60.63	0.7553
Liaoning	126.14	5984.5	1011.2	282.81	78.12	3926.71	121.14	0.6984
Jilin	57.02	2418.51	255.8	144.72	211.28	2283.56	91.15	0.8709
Heilongjiang	37.36	1957.63	324.1	56.9	28.63	1716.61	51.24	0.9772
Shanghai	104.02	9049.64	270	236.64	186.3	6046.19	217.74	1.0000
Jiangsu	763.75	17835.24	3671.8	349.66	78.57	25791.76	992.63	1.0000
Zhejiang	770.28	12087.88	2188.4	370.69	572.96	24989.37	573.78	1.0000
Anhui	168	5496.33	753.7	220.69	307.92	6047.29	203.62	0.8583
Fujian	325.27	4758.45	1047.6	258.58	245.27	8531.45	279.45	1.0000
Jiangxi	152.57	3447.48	531.6	114.34	64.77	5179.03	186.8	1.0000
Shandong	293.19	11135.87	2177	472.1	307	10087.43	415.28	0.7864
Henan	260.9	7043.58	2263.3	263.44	333.61	8807.99	438.53	1.0000
Hubei	269.64	9853.31	1233.7	367	318.05	11862.4	475.72	1.0000
Hunan	219.96	4631.92	1009.5	377.91	597.68	7304.22	230.3	0.9643
Guangdong	228.57	12200.09	1666.9	740.18	233.95	9652.31	418.28	0.8664
Guangxi	120.02	1898.15	291.8	62.06	6.92	3449.19	67.75	1.0000
Hainan	7.42	251.5	30.9	47.8	44.78	307.76	12.12	0.9870
Chongqing	209.08	5325.94	456.3	115.09	191.33	7035.81	326.57	1.0000
Sichuan	282.87	9858.72	1014.8	548.5	311.99	9959.68	266.44	0.8549
Guizhou	67.53	3544	341.5	161.07	187.99	2362.95	60.11	0.6807
Yunnan	115.63	4590.56	508.7	232.01	265.06	3867.22	147.02	0.7439
Shaanxi	118.32	5344.17	716.5	192.27	116.17	5329.23	163.42	0.9837
Gansu	56.58	1863.44	372.2	110.68	123.56	1947.24	64.37	0.8158
Qinghai	11.44	568.09	109	45.63	58.47	410.62	15.51	0.7167
Ningxia	9.93	747.63	53	89.74	66.67	511.25	19.95	0.8525
Xinjiang	38.41	2319.34	233.1	202.35	138.61	2258.24	50.15	1.0000

This study followed the research of scholars Zhang et al. [15] through aiming to further reveal the differences in the spatial distribution of GTFP in the construction industry. Therefore, the 30 provinces and cities were divided into six regions based on their geographical location and economic development level, namely, East, South-Central, North, Northeast, Southwest, and Northwest China. Specifically, East China includes Shandong, Jiangsu, Anhui, Jiangxi, Zhejiang, Fujian, and Shanghai; South-Central China refers to Henan, Hubei, Hunan, Guangxi, Guangdong, and Hainan; North China includes Inner Mongolia, Beijing, Tianjin, Hebei, and Shanxi; Northeast China contains Heilongjiang, Jilin, and Liaoning; Southwest China includes Sichuan, Chongqing, Yunnan, and Guizhou; and Northwest China contains Xinjiang, Qinghai, Gansu, Ningxia, and Shaanxi China. See Fig. 1 for the specific division of regions in China.

Fig. 1 Division of the Six Regions

Table 6 CCR Efficiency Values of the Regional Construction Industry during 2011-2017

Year / Area	2011	2012	2013	2014	2015	2016	2017	Average
East China	0.907	0.918	0.929	0.924	0.905	0.949	0.894	0.918
South-Central China	0.919	0.944	0.948	0.956	0.958	0.970	0.956	0.950
North China	0.951	0.990	0.990	0.971	0.965	0.894	0.968	0.961
Northeast China	0.931	0.933	0.940	0.920	0.876	0.849	0.866	0.902
Southwest China	1.000	0.973	0.992	0.998	0.873	0.820	0.848	0.929
Northwest China	0.786	0.824	0.865	0.852	0.844	0.874	0.817	0.837
All	0.907	0.918	0.929	0.924	0.905	0.904	0.894	0.912

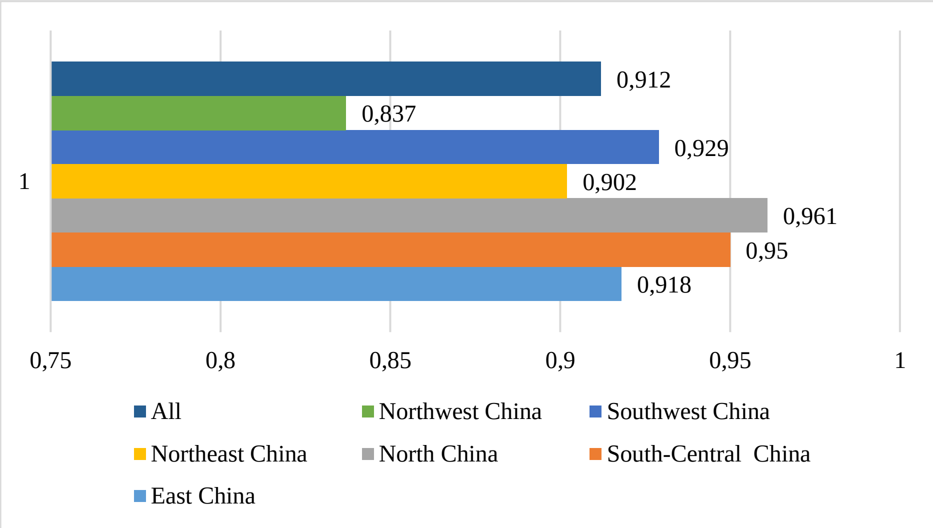

Fig. 2 CCR Average Efficiency Value of the Regional Construction Industry

Table 5 shows the CCR efficiency value of the construction industry in 2016, and similarly such data can also be obtained for the period 2011-2017， the results are shown in Table 6. In fact, the CCR efficiency values of the construction industry were analysed for the years 2011-2017 from the regional perspective (as shown in Fig. 2), which clearly highlights that the average CCR efficiency during the study period was 0.912. In particular, the average CCR efficiency of East, North, South-Central, and Southwest China was higher than that of the whole country and investment in the construction industry in these regions is lower than that in other regions. This indicates that during the study period, the GTFP value of the construction industry in East, North, South-Central and Southwest China were higher, while those of the construction industry in Northeast and Northwest China were lower. Thus, there is room for improvement in Northeast and Northwest China to a certain extent.

4.2.Evaluation results of the PCE model

It was believed that the digital transformation of the construction industry would arrive as expected (λ=0.5). Other parameters, α, β and θ, in the model were 0.89, 0.92 and 2.25, respectively. The input-output weight of the construction industry was calculated in accordance with the CCR efficiency of self-evaluation in the first step and the PCE model, as shown in Table 7.

Table 7 Input-Output Weights of the Construction Industry

DMU	Weight of Input					Weight of Output	
	Labour	Total assets	Total power of construction machinery and equipment	Energy consumption	Carbon dioxide emissions	Total output value	Gross profit
Beijing	1.720E-02	0	0	0	0	0	1.481E-03
Tianjin	8.219E-03	6.561E-05	0	0	0	2.044E-04	0
Hebei	3.950E-03	9.060E-05	0	2.646E-08	1.390E-04	1.688E-04	0
Shanxi	6.824E-03	8.076E-05	0	2.410E-04	2.615E-04	2.367E-04	0
Inner Mongolia	1.689E-02	2.522E-04	0	0	0	4.878E-04	2.634E-03
Liaoning	4.527E-03	5.909E-05	0	0	9.648E-04	1.778E-04	0
Jilin	7.400E-03	1.420E-04	9.168E-04	0	0	3.476E-04	8.468E-04
Heilongjiang	1.449E-02	1.891E-04	0	0	3.088E-03	5.693E-04	0
Shanghai	0	1.302E-05	3.267E-03	0	0	1.654E-04	0
Jiangsu	0	0	0	0	1.273E-02	0	1.007E-03
Zhejiang	0	1.38E-05	0	2.25E-03	0	4.00E-05	0
Anhui	3.385E-03	7.536E-05	0	7.782E-05	0	1.419E-04	0
Fujian	0	2.102E-04	0	0	0	6.518E-05	1.588E-03
Jiangxi	3.815E-03	6.467E-05	2.127E-04	1.822E-04	9.427E-04	1.896E-04	9.600E-05
Shandong	1.984E-03	2.590E-05	0	0	4.229E-04	7.795E-05	0
Henan	1.598E-03	6.929E-05	0	3.604E-04	0	0	2.280E-03
Hubei	1.747E-03	2.908E-05	1.742E-04	7.496E-05	0	8.425E-05	1.151E-06
Hunan	2.226E-03	1.102E-04	0	0	0	9.486E-05	1.178E-03
Guangdong	2.285E-03	2.982E-05	0	0	4.870E-04	8.976E-05	0
Guangxi	0	0	0	0	1.445 E-01	2.899E-04	0
Hainan	5.985E-02	1.302E-03	7.397E-03	0	0	3.003E-03	5.172E-03
Chongqing	0	1.915E-05	5.953E-04	5.442E-03	0	1.421E-04	0
Sichuan	1.707E-03	2.982E-05	1.837E-04	0	1.173E-04	8.583E-05	0
Guizhou	5.974E-03	9.931E-05	5.940E-04	2.567E-04	2.280E-06	2.881E-04	0
Yunnan	3.749E-03	7.195E-05	4.644E-04	4.128E-08	0	1.761E-04	4.289E-04
Shaanxi	4.698E-03	6.133E-05	0	0	1.001E-03	1.846E-04	0
Gansu	9.629E-03	2.443E-04	0	-2.456E-09	0	4.058E-04	3.974E-04
Qinghai	5.020E-02	7.493E-04	0	0	0	1.450E-03	7.827E-03
Ningxia	3.242E-02	6.223E-04	4.016E-03	0	0	1.523E-03	3.709E-03
Xinjiang	1.683E-02	1.441E-04	0	0	1.394E-04	4.428E-04	0

According to Table 7 (input-output weights) and Table 5 (construction industry input-output), the cross-efficiency matrix of the construction industry can be obtained. The average cross-efficiency of each row of the matrix is calculated, reflecting the overall efficiency of the construction industry.

Moreover, this study explored the cross-efficiency value in six regions and obtained their ranking order.

Table 8 Regional Efficiency Value of the Construction Industry during 2011-2017

Year / Area	2011	2012	2013	2014	2015	2016	2017	Average
East China	0.609	0.636	0.667	0.673	0.696	0.690	0.697	0.667
South-Central China	0.652	0.681	0.680	0.700	0.751	0.751	0.772	0.712
North China	0.624	0.670	0.703	0.701	0.729	0.728	0.762	0.703
Northeast China	0.575	0.615	0.672	0.659	0.673	0.670	0.662	0.647
Southwest China	0.792	0.756	0.762	0.757	0.641	0.626	0.625	0.708
Northwest China	0.513	0.553	0.617	0.625	0.665	0.650	0.648	0.610
All	0.609	0.636	0.667	0.673	0.696	0.690	0.697	0.600

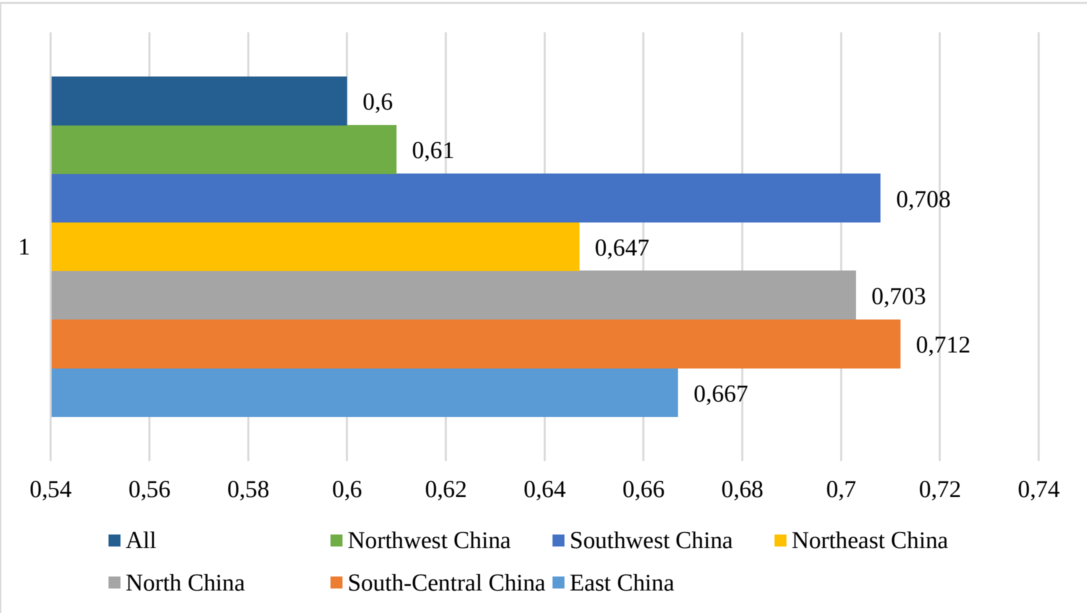

Fig. 3 Regional Average Efficiency Value of the Construction Industry

The PCE model was applied to measure the efficiency values of China's construction industry during 2011-2017, which are provided in Table 5. First and foremost, this study analysed the efficiency value during the period 2011-2017 from the regional perspective (as shown in Fig. 3). According to the Fig. 3, the average efficiency is 0.600 across the entire nation. However, in South-Central, Southwest and North China, the efficiency value is the highest because these regions are the most developed and actively promote the construction industry. In contrast, the value is the lowest in Northeast and Northwest China, and consequently there is scope for these regions to encourage greater levels of capital investment and thereby enhance the construction industry. As indicated by the analysis, the results calculated by the PCE model are consistent with those calculated by the CCR model.

4.3. Comparison of the CCR and PCE models

In this part of the study, the construction industry in 2016 is taken as an illustrative example, and the impact of the CCR and PCE models on the efficiency value of the construction industry in the six regions studied are compared and analysed. Additionally, the sensitivity of the evaluation results is analysed. Table 9 provides the efficiency values of the 30 provinces and cities in these six regions in 2016. In order to more intuitively display the efficiency values calculated by the CCR and PCE models, this study adopted a line graph to show the changes in these values, as shown in Fig. 4. It is clearly shown from Fig. 4 that the efficiency value calculated by the PCE model is lower than that calculated by the CCR model because the PCE model evaluates the efficiency value in two stages and performs self-evaluation with a set of the best weighting coefficients. At the same time, the weighting coefficients of other DMUs are used for peer evaluation. Furthermore, the efficiency values of East, South-Central, and North China are higher, signifying that the economic growth of the construction industry in these regions has changed from traditional extensive economic growth to intensive, more efficient economic growth. However, lower efficiency values are found in Northeast and Southwest China, where related countermeasures and suggestions should be proposed to enable suitable improvements in the future.

Table 9 Regional CCR and PCE Efficiency Values of the Construction Industry in 2016

Number	Area	Province	Efficiency of the CCR model	Rank	Efficiency of the PCE model	Rank
1	East China	Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong	0.949	2	0.751	1
2	South-Central China	Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan	0.970	1	0.728	2
3	North China	Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia	0.894	3	0.670	3
4	Northeast China	Liaoning, Jilin, Heilongjiang	0.849	5	0.626	6
5	Southwest China	Sichuan, Chongqing, Yunnan, Guizhou	0.820	6	0.650	4
6	Northwest China	Xinjiang, Qinghai, Gansu, Ningxia, Shaanxi	0.874	4	0.648	5

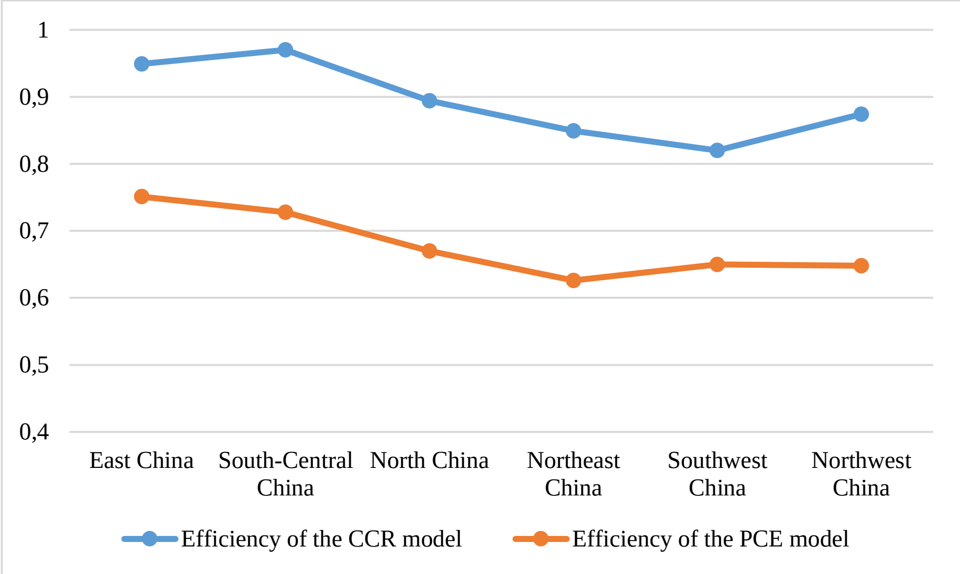

Fig. 4 Comparison of the CCR and PCE Models

4.4 Sensitivity Analysis

Sensitivity analysis is to evaluate the influence of one parameter (independent variable) on the value of another parameter (dependent variable) from the perspective of quantitative analysis. In this part, a discussion is provided on how the GTFP of the construction industry was affected by the decision maker's optimism about the digital transformation prospect of the construction industry (that is, parameters α, β, θ, and λ).

The efficiency values of the regional construction industry when parameter λ is set with different values, such as 0, 0.2, 0.4, 0.6, 0.8, and 1, are calculated (see Table 9 for the detailed results).

Table 10 Efficiency Value of the Regional Construction Industry with Different λ Values

Area	λ= 0		λ= 0.2		λ= 0.4		λ= 0.6		λ= 0.8		λ= 1	
	Result	Rank	Result	Rank	Result	Rank	Result	Rank	Result	Rank	Result	Rank
East China	0.789	1	0.753	1	0.753	1	0.751	1	0.747	1	0.749	1
South-Central China	0.774	2	0.738	2	0.736	2	0.728	2	0.727	2	0.732	2
North China	0.672	5	0.666	3	0.666	3	0.671	3	0.670	3	0.677	3
Northeast China	0.647	6	0.627	6	0.625	6	0.626	6	0.623	6	0.313	6
Southwest China	0.680	3	0.649	5	0.650	5	0.650	4	0.647	4	0.504	5
Northwest China	0.673	4	0.653	4	0.652	4	0.648	5	0.645	5	0.652	4

When λ is assigned values of 0, 0.2, and 0.4, the decision maker is optimistic about the prospect of digital transformation in the construction industry. However, when the values are 0.6, 0.8 and 1, the decision maker is pessimistic about this prospect. According to Table 9, when λ is set with different values, the efficiency value in each region also changes accordingly, but there are no significant changes as a whole. Regardless of the value assigned to λ, East China and South-Central China are always the regions with the most effective efficiency values. The region with the lowest value is Northeast China, and slight changes are also found in North, Southwest and Northwest China.

This study, by changing the values representing optimistic and pessimistic attitudes (that is, parameters α, β, and θ) towards the prospect of the digital transformation of the construction industry, explored how the different attitudes of the decision maker affected the efficiency value of the regional construction industry. Here, the original values of α, β and θ were assumed to be 0.5, 0.3, and 3, respectively. Consequently, Figs. 3, 4, and 5 show the impact of changed parameters α, β and θ on the efficiency value, respectively.

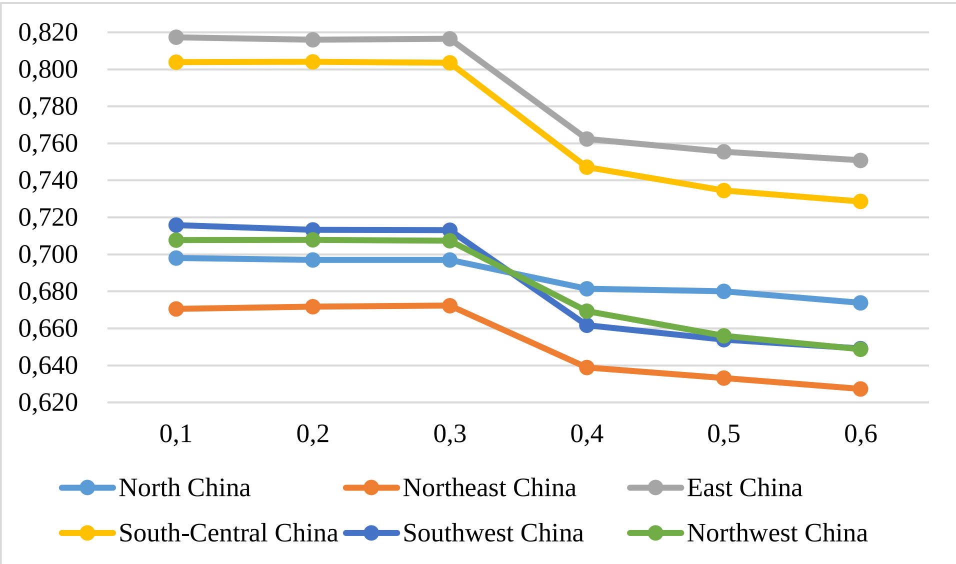

Fig. 5 Influence of α on the Efficiency Values of the Regional Construction Industry

Fig. 5 shows the change in efficiency value when the degree of the decision maker's optimism about digital transformation of the construction industry (parameter α) is changed. The value of parameter α is set to 0.1-0.6. As shown in the figure, the higher the value of α is, the more optimistic the decision maker is about the digital transformation of the construction industry. However, analysis indicates that with the continuous increase in α, the overall efficiency of the construction industry in various regions changes steadily first and then declines. Fig. 5 identifies that although the decision maker is more optimistic about digital transformation, this optimism fails to improve the GTFP of the entire construction industry.

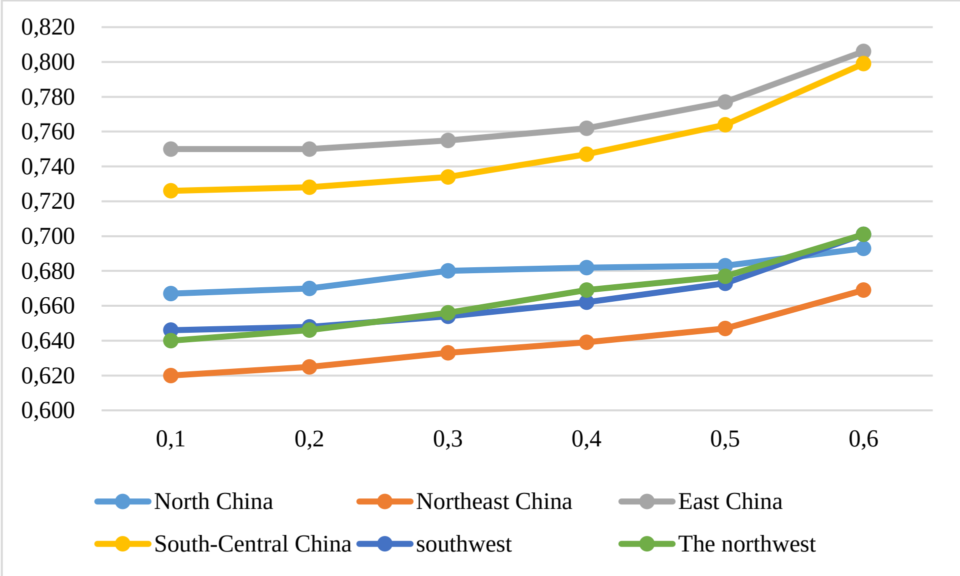

Fig. 6 Influence of β on the Efficiency Values of the Regional Construction Industry

Fig. 6 shows the change in efficiency value when the degree of the decision maker's pessimism about digital transformation of the construction industry (parameter β) is changed. The value of parameter β is set to 0.1-0.6. As shown in Fig. 6, the higher the value of β is, the more pessimistic the decision maker is about the digital transformation of the construction industry.However, analysis indicates that with the continuous increase in β, the overall efficiency of the construction industry in various regions changes steadily first and then rises. Fig. 6 shows that although the decision maker is more pessimistic about digital transformation, this pessimism improves the GTFP of the entire construction industry to some extent.

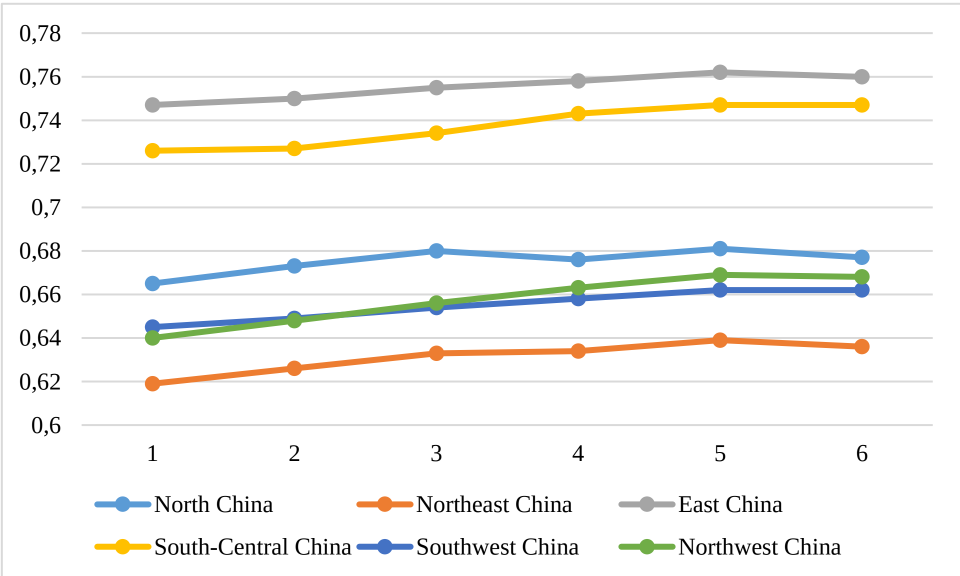

Fig. 7 Influence of θ on the Efficiency Values of the Regional Construction Industry

Parameter θ indicates the degree of the decision maker's pessimism about digital transformation. Specifically, a larger value signifies that the construction industry suffers from greater loss during digital transformation. Fig. 7 shows the change in the regional efficiency value when parameter θ is changed, with θ set between 1 and 6. As shown in Fig. 7, the higher the value of θ is, the more optimistic the decision maker is about digital transformation of the construction industry. However, analysis indicates that with the continuous increase in θ, the overall efficiency rises steadily. In other words, Fig. 7 shows that although the decision maker is more pessimistic about digital transformation, this pessimism improves the GTFP of the entire construction industry to some extent.

The appeal showes that the decision maker is increasingly optimistic about the digital transformation of the construction industry (parameter α), but the GTFP of the construction industry has not improved. Further, the decision maker is increasingly less optimistic about the digital transformation of the construction industry (parameters β and θ), and the GTFP of the construction industry has been improved to some extent.

5 Discussion

The research and analysis in this paper provides a new perspective on the relationship between regional differences in the construction industry, the preference of decision makers for digital transformation and Total factor productivity in the context of digital transformation, this paper fills the blank of the research on the digital transformation prospect of the construction industry, and makes an empirical study on whether the digital transformation can bring more benefits to the construction industry.

According to the results of PCE model and CCR model, there are obvious differences between regions in the green Total factor productivity of construction industry. The results are consistent with those of Xiang Pengcheng et al [45].The regional differences of China's construction industry show that the GTFP values are higher in the east, north, south-central and south-west, while the GTFP values are lower in the northeast and northwest, the difference of digital transformation degree between different regions is verified; Feng Yahong et al [46] believe that there are also regional differences in the transformation rate of green economy in the construction industry. The green economy output benefit of the construction industry in Eastern and central China is far higher than that in Western and northeastern China, showing a trend of polarization, behind the trend of polarization, there is a tendency for the inter-regional output benefit to shrink, which may be due to the implementation of our overall regional development strategy, the "Belt and Road", the coordinated development of Beijing, Tianjin and Hebei, the Yangtze River Economic Belt and other new national-level regional development strategies have narrowed the regional economic gap and promoted the digital transformation of the construction industry, increased Green Total factor productivity in regional construction; Zhou Yong et al [47] believe that the GTFP in various regions of China is on the rise, and that the growth rate in the Eastern Region is obviously higher than that in the western and northeastern regions, showing an imbalance in the region, fan Jianshuang et al [48] think there are some differences in the growth of TFP in the regional construction industry. Generally speaking, the growth of TFP in the construction industry is slow, the growth of Midwestern Sectional Figure Skating Championships is low, and the growth of TFP in the eastern region is high, the coupling degree distribution of TFP growth and regional economic growth basically conforms to the law of spatial differentiation in the East, middle and West, which is closely related to the economic situation at that time, but in recent years, with the implementation of the strategy of national rejuvenation of Central Plain, the proposal of the regional development strategy of the Yangtze River Economic Belt makes the central region grow rapidly, which also drives the development of the construction industry and makes the central region’s TFP grow rapidly.

In the context of digital transformation, the change of GTFP in the construction industry is also closely related to the attitude of decision makers towards digital transformation, the study is a ground breaking analysis of how decision makers’ expectations of the digital transformation of the construction industry affect Total factor productivity. The results show that policymakers are increasingly optimistic about the digital transformation of the construction industry, but the construction industry’s GTFP has not improved. In addition, the digital transformation of the construction industry is becoming less and less favored by policy makers, and the GTFP of the construction industry has been improved to a certain extent.

6 Conclusions

At present, it is the initial stage of construction industry digital transformation. Due to the phenomenon of high investment cost in digital transformation, the input-output ratio of China's construction industry digital transformation is not high in the short term, and the impact of digital transformation on green total factor productivity of construction industry is not obvious, so it fails to improve the growth of green total factor productivity of construction industry in the short term. This study provides some practical implications for managers and policy makers to better understand the impact of digitization on the construction industry. Based on the above analysis, the following policy suggestions are proposed:

(1) Chinese manufacturing managers should fully understand and accept the positive impact of digital transformation on the construction industry. Digital transformation, as a means to transform the green development of the construction industry, will improve the green total factor productivity of the construction industry to a certain extent. Through the use of digital technology and application, managers should constantly improve the level of building product planning and design, create green building construction standards, so as to improve the quality of building products.

(2) On the one hand, Chinese policy makers should formulate differentiated policies based on the actual regional development situation to stimulate the growth of GTFP in construction industry.

Especially in the northeast and northwest regions, the government should guide the industry to improve the GTFP by means of economic stimulus or financial support. On the other hand, Chinese policymakers should pay attention to high-quality development in the digital transformation of the construction industry. They should focus on the digital technological innovation of construction industry, formulate and issue relevant fiscal policies, laws, standards and evaluation systems, so as to form a good environment for digital innovation of construction industry in the whole society, and improve the input-output ratio of digital transformation of construction industry in this way.

This study has some limitations. First, the research on green total factor productivity under the prospect of digital transformation is limited to the construction industry and has not been extended to other industries. Second, sample data of construction industry in different countries or regions should be included and compared with China's data, so as to fully understand the development of green total factor productivity under the prospect of digital transformation.

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