**Enabling the green total factor productivity**

**of the construction industry with the prospect of digital transformation**

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#### *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 to 2017, the CCR model and PCE model evaluation model are used to measure the GTFP of the construction industry in the context of digital trans- formation. 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)

## 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” (Yang & Zhao, 2015), 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 (Cao et al., 2014). Moreover, digital and green development has become an inevitable trend in the development of the construction industry (Feng et al., 2014). 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 (Xiang et al., 2019).

“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 in implications for products, services and business models as a whole (Matt et al., 2015). 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 (Vial, 2019). However, digital transformation in the construction industry is currently still its infancy and while many have advocated the potential benefits (Aghimien, 2020; Berlak et al., 2020; Elghaish et al., 2020; Newman et al., 2020; Succar & Poirier, 2020), 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 (Feroz et al., 2021; Moshood, 2020) 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 to 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 cannot 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, cannot 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 discusses these results. Finally, conclusions are made in Section 6.

## Literature review

### Digital transformation in the construction industry

In recent years, the topic of digital transformation has aroused the attention of the business management community (Westerman et al., 2014). Indeed, industries are actively embracing digital transformation, including the automotive industry (Llopis-Albert et al., 2021), food industry (Savastano et al., 2018), fashion industry (Bertola & Teunissen, 2018), aerospace industry (James & Cervantes, 2019) as well as the construction industry (Klinc & Turk, 2019). In the case of the construction industry, digital transformation can be viewed as building on the use of building information modelling (BIM) that acts as a big data plat- form in the architecture, engineering and construction (AEC) industry and to support the transition to a smart industrial paradigm (Bosdriesz, 2018).

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 (Boton et al., 2021). 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 (Widyatmoko, 2020). 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 (Dahanayake & Sumanarathna, 2021), 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 (Hodorog et al., 2021).

In regard to the technological dimension of digital transformation, there are opportunities to utilize various technologies, such as artificial intelligence (Elhouar et al., 2020), IoT and big data (Daissaoui et al., 2020), augmented and virtual reality (Dallasega et al., 2020), robotics (Boulos et al., 2020) and additive manufacturing (Ghaffar et al., 2020). 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 (Perera et al., 2020). 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) (Prakash & Ambekar, 2020), whereas digital twins have been evaluated as having application to workforce safety in the construction industry (Hou et al., 2021) and explored as providing improved capabilities for construction site logistics (Greif et al., 2020).

From an international perspective and in the case of Nigeria, Ezeokoli et al. (2016) 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. (2014) 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. (2019) 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. (2020) 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 (2020) 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.

### 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 (Ebrahimi & Salehi, 2015). Research on GTFP originated in the middle and late twentieth century and was developed during the first ten years of the twenty-first century (Liu, 2020).

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 (Raa & Shestalova, 2011), stochastic frontier analysis (SFA) method (Zhang et al., 2019) and the nonparametric data envelopment analysis (DEA) (Li et al., 2015) 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 (2015) 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. (2017), based on the Malmquist index of DEA and sequential benchmark technology, proposed an index for evaluating car- bon emission performance in the framework of TFG, whereas Xiang et al. (2019) 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.

## Research methods

### 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.

### CCR model of self‑efficiency evaluation

Assuming that *D* = {DMU1, DMU2, …… 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 *Xik* (*i* = 1, 2,…*m*), and output is defined as *Yrk* (*r* = 1, 2, 3…*s*); see Table 1. The relative efficiency of *DMUk* is defined as follows:

*Ekk* =

*s*

*r*=1

*urk yrk*

*m*

*i*=1

*vikxik*

(1)

**Table 1** Input–output value of DMUs

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| DMUs | DMU1 | DMU2 | …… | DMU*n* |
| Output values | 11 | 12 | …… | 1*n* |
|  | 21  …… | 22  …… | ……  …… | 2*n*  …… |
| Input values | *s*1 11 | *s*2  12 | ……  …… | *sn*  1*n* |
|  | 21  …… | 22  …… | ……  …… | 2*n*  …… |
|  | *m*1 | *m*2 | …… | *mn* |

where *urk* and *vik* 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 *Ekk* =

*s*

*r*=1

*urk yrk*

*m*

*i*=1

*vikxik*

s.t.

*s*

*r*=1

*urk yrj*

*m*

*i*=1

*vikxij* ≤ 1, *j* ∈ *N*

(2)

*urk* , *vik* ≥ 0 *r* ∈ *S i* ∈ *M*

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 *Ekk* = L *urk yrk*

*s*

*r*=1

*s m*

s.t. L *urk yrj* − L *vikxij* ≤ 0, *j* ∈ *N*

*r*=1

*m*

*i*=1

(3)

L *vikxik* = 1

*i*=1

*urk* , *vik* ≥ 0, *r* ∈ *S*, *i* ∈ *M*

where *urk* ∗ and*vik* ∗ are the optimal output and input weights, respectively, and

∗= ∑

*E*kk

s

r=1

urk

∗ yrk

is the CCR efficiency of *DMUk* , which represents the best relative

efficiency of *DMUk* calculated through self-evaluation. If *E*kk ∗=1 and optimal weights

*urk* ∗ and*vik* ∗ are positive, then 6 is valid; otherwise, it is invalid.

### 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, Feroz et al., 2021 proposed a cross- efficiency evaluation CCR model, which evaluates the overall performance of each DMU

by using the total weight of all DMUs. If *urk* ∗ and *vik* ∗ are the optimal weights of the out-

put and input, respectively, of DMU*k* given by Model (3), then the cross-efficiency score of

DMU*d* is as follows:

*Edk* =

*s*

*r*=1

*Urk yrd*

*m*

*i*=1

*Vik Xid* , *d* ∈ *N*, *d* ≠ *k*

(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 ∗.

**Table 2** Cross-efficiency matrix of DMUs

DMU Target DMU Average

cross-effi-

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | DMU1 | DMU2 | …… | DMU*n* | ciency |
| DMU1 | *E*11 | *E*12 | …… | *E*1*n* | ∑k=1 *E*1k/*n* |
| DMU2 | *E*21 | *E*22 | …… | *E*2*n* | ∑k=1 *E*2k/*n* |
| ……  DMU*n* | ……  *En*1 | ……  *En*2 | ……  …… | ……  *En*3 | ……  ∑k=1 *E*nk/*n* |

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:

*n*

*Ed* =

*k*=1

*Edk n*, *d* ∈ *N*

(5)

Cross-efficiency score *Ed* provides a peer-to-peer evaluation of DMU*d* , and accordingly, these *n* DMUs can be completely compared or ranked.

### Prospect theory

In 1979, Kahneman and Tversky proposed the prospect theory (Moshood, 2020). 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 (Westerman et al., 2014). Moreover, prospect theory involves the following important principles (Moshood, 2020).

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:

(Δ*Z*)𝛼, Δ*Z* ≥ 0

*V*(Δ*Z*)=

−𝜃(−Δ*Z*)𝛽 , Δ*Z* < 0

(6)

∆*Z* is used to measure the deviation of Z from reference point *Z*0. If ∆*Z* ≥ 0, then the result is regarded as a gain; otherwise, the result is regarded as a loss (∆*Z* < 0). Parameters 0 < *α* < 1 and 0 < *β* < 1 indicate the convexity of the value function in the gain and loss domains, respectively, *θ* indicates the loss avoidance coefficient, and *θ* > 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.

### 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 and the *r*th output is *V* + = (*x* − − *x* )*a* and *V* + = (*y* − *y* −)*a*, respectively,

*k*

{ } *Iik*

*ik*

*i* { }

*Ork*

*rk r*

among which *xi*− = max

*xik*

and *yr* − = min

*yrk* .

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* − = −*B*(*x* − *x* +)*P* and *V* − = −*B* *y* + − *y* /*P* , respectively,

*Iik*

*ik i*

*Ork*

*r rk*

among which *xi*+ = min{*xik* } and *yr* + = max {*yrk* }.

Suppose that *N* = {1, 2, … , *n*}, *k*∈ *N* , *M* = {1, 2..., *m*}, *I* ∈ *M* , and *S* = {1, 2, … , *s*}, for *r* ∈ *S*, and that there are *n* DMUs to be evaluated; the output and input of DMU*k* (*k N*) are *yrk* (*r S*) and *xik* (*i M*), respectively. Thus, a PCE model is constructed as follows:

max *,1*

*s*

*r*=1

*i*

*urk*

*a*

*yrk* − *y*−

*r*

*m*

+

*i*=1

*vik* (*x*− − *xik* )*a*

( *s m*

*i*

− (1 − *,1*)

*m*

*urk*

*r*=1

+

*yr* − *yrk*

+ *vik*

*i*=1

(*xik*

− *x*+)

s.t.

*s*

*vikxik* = 1

*i*=1

(7)

*r*=1

*s*

*urk yrk* = *Ekk* ∗

*m*

*r*=1

*urk yrj* −

*i*=1

*vikxij* ≤ 0 *j* ∈ *N*

*urk* , *vik* ≥ 0, *r* ∈ *S i* ∈ *M*

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

0.5 < *λ* ≤ 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 trans- formation 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.

### 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 to 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.

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.

## 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.

### 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.

**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 |

**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 | 104 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 |

Therefore, the PCE model was introduced to calculate the cross-efficiency value of each DMU to comprehensively rank all DMUs.

This study followed the research of scholars Llopis-Albert et al., 2021 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 Shan- dong, 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 Figure 1 for the specific division of regions in China.

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, and 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 Figure 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.

### 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.

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.

**Table 5** Input–output of the construction industry in 2016

DMU Input Output Efficiency of

Labours Total assets Total power of construction

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | | machinery and equipment | sumption | emissions |  | | |
| Beijing | 58.14 | 20,263.67 | 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 | 17,835.24 | 3671.8 | 349.66 | 78.57 | 25,791.76 | 992.63 | 1.0000 |
| Zhejiang | 770.28 | 12,087.88 | 2188.4 | 370.69 | 572.96 | 24,989.37 | 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 | 11,135.87 | 2177 | 472.1 | 307 | 10,087.43 | 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 | 11,862.4 | 475.72 | 1.0000 |
| Hunan | 219.96 | 4631.92 | 1009.5 | 377.91 | 597.68 | 7304.22 | 230.3 | 0.9643 |
| Guangdong | 228.57 | 12,200.09 | 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 |

Energy con-

Carbon dioxide

Total output value Gross profit

the CCR model

**Table 5** (continued)

DMU Input Output Efficiency of

Labours Total assets Total power of construction

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  | machinery and equipment | sumption | emissions |  |  |  |
| 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 |

Energy con-

Carbon dioxide

Total output value Gross profit

the CCR model



**Fig. 1** Division of the six regions

**Table 6** CCR efficiency values of the regional construction industry during 2011–2017

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Area | Year |  | | | | | | |
|  | 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 |

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).

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

1

0.912

0.837

0.902

0.961

0.95

0.918

0.929

0.75 0.8 0.85 0.9 0.95 1

All Northwest China Southwest China Northeast China North China South-Central China East China

**Fig. 2** CCR average efficiency value of the regional construction industry

Figure 3). According to Figure 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.

### 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 is 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 Figure 4. It is clearly shown from Figure 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 South- west China, where related countermeasures and suggestions should be proposed to enable suitable improvements in the future.

**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 | 1.445E−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 |

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 7** (continued) |  |  |  |  |  |  |  |  |
| 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 |
| 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 |

**Table 8** Regional efficiency value of the construction industry during 2011–2017

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Area | Year |  | | | | | | |
|  | 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 |

8

0.6

0.61

0.70

0.647

0.703

0.

0.667

1

712

0.54 0.56 0.58 0.6 0.62 0.64 0.66 0.68 0.7 0.72 0.74

All Northwest China Southwest China Northeast China North China South-Central China East China

**Fig. 3** Regional average efficiency value of the construction industry

### 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 10 for the detailed results).

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

**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 |

1

0.9

0.8

0.7

0.6

0.5

0.4

East China South-Central North China Northeast

Southwest

Northwest

China

China

China

China

Efficiency of the CCR model Efficiency of the PCE model

**Fig. 4** Comparison of the CCR and PCE models

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, Figures 3, 4, and 5 show the impact of changed parameters *α*, *β* and *θ* on the efficiency value, respectively.

Figure 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. Figure 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.

Figure 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 Figure 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. Figure 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.

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. Figure 7 shows the change in the regional efficiency value when parameter *θ* is changed, with *θ* set between 1 and 6. As shown in Figure 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

**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 |

0.820

0.800

0.780

0.760

0.740

0.720

0.700

0.680

0.660

0.640

0.620

0.1 0.2 0.3 0.4 0.5 0.6

North China Northeast China East China South-Central China Southwest China Northwest China

**Fig. 5** Influence of *α* on the efficiency values of the regional construction industry

0.820

0.800

0.780

0.760

0.740

0.720

0.700

0.680

0.660

0.640

0.620

0.600

0.1 0.2 0.3 0.4 0.5 0.6

North China Northeast China East China South-Central China southwest The northwest

**Fig. 6** Influence of *β* on the efficiency values of the regional construction industry

0.78

0.76

0.74

0.72

0.7

0.68

0.66

0.64

0.62

0.6

1 2 3 4 5 6

North China Northeast China East China South-Central China Southwest China Northwest China

**Fig. 7** Influence of *θ* on the efficiency values of the regional construction industry

continuous increase in *θ*, the overall efficiency rises steadily. In other words, Figure 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 shows 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.

The above results may indicate that holding a positive attitude towards the transformation of the construction industry will increase the investment in various elements of the construction industry and overestimate the possible output. However, the digital transformation has a lag in improving the production efficiency of the construction industry, so the more optimistic the digital transformation of the construction industry is in the early stage, the GTFP will decline.

## 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, and 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 et al. 2019.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, and the difference of digital transformation degree between different regions is verified; Yahong & Shu, 2022 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 North- eastern 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, and 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 eco- nomic gap and promoted the digital transformation of the construction industry, increased green total factor productivity in regional construction; Zhou & Liu, 2021 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 north-eastern regions, showing an imbalance in the region, and Fan & Yu, 2012 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 conform 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, and the proposal of the regional development strategy of the Yangtze River Economic Belt makes the central region grow rap- idly, 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, and 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 favoured by policy makers, and the GTFP of the construction industry has been improved to a certain extent. This is not in line with the expectation of prospect theory. A powerful explanation for this phenomenon is that at present, it is the early stage of digital transformation in the construction industry, and there is a phenomenon of high investment cost and slow effect. Generally speaking, the advantages are not obvious enough to effectively reduce investment and increase output. This means that in the early stage of digital transformation, the more optimistic the policy makers are about the prospect of digitalization, the more radical policies they adopt, and the higher GTFP they can’t get. However, in the long run, digital transformation, as a means to change the green development of the construction industry, will improve the green total factor productivity of the construction industry to a certain extent. The digital transformation of China’s construction industry should pay attention to the development quality and improve the input–output ratio of digital transformation of construction industry.

## 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. 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. Particularly 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.

1. Chinese managers should fully understand and accept the fact that the digital transformation of construction industry is in its infancy. At the initial stage of transformation, based on the possible negative spillover effects, we should be more cautious in formulating industrial policies and more comprehensive in evaluating industrial policies. At the same time, with the deepening of the digital transformation of the construction industry, we should adjust the governance measures and development countermeasures of the construction industry in time according to the stage and reality of the digital transformation of China’s construction industry, so as to provide a long-term development policy basis for the digital transformation of the construction industry.

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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**Data availability**

The datasets generated or analysed during this study are not publicly available but are available from the first author on reasonable request.

## Declarations

**Conflict of interest**

The authors declare no conflict of interest.

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