

# Assessment of technology adoption in construction safety management: Case study in China

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## Abstract

The current body of literature indicates that the utilization of emerging digital safety technologies has the potential to enhance the efficacy of safety management in construction significantly. Nevertheless, there has been limited uptake of digital safety technologies within the construction industry in developing countries. This study is focused on evaluating the adoption of digital safety technologies in construction specifically from the perspective of developing countries. Questionnaire data were gathered from project management professionals in China and subjected to analysis using mean ratings, factor analysis, and fuzzy composite evaluation. The developed model for assessing safety technology adoption comprises four primary criterion groups about factors influencing adoption, namely organizational, technological, individual, and external categories. The study results indicate that factors within the technology category exert the most significant influence on the adoption assessment model, followed by those in the external and organizational categories, and finally by individual category factors. These findings contribute to advancing the theory of digital technology adoption in construction safety management research within developing countries. Practitioners can utilize this information to effectively evaluate and compare success rates of safety technology adoption, thereby informing management decisions required for projects. The insights provided by this study will equip practitioners with scientific knowledge for more effective and sustainable program management, ultimately enhancing the success of safety technologies.

## Keywords

Construction safety, digital technology, safety management, technology adoption index, adoption of the assessment, developing countries

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## Introduction

The construction industry stands as a crucial pillar of China's economy, playing a significant role in driving economic growth and enhancing the well-being of its citizens. While construction safety remains an essential focus for ensuring the sustainable development of this industry,<sup>1</sup> the unique nature of construction work presents ongoing challenges in safety management. According to data from the National Ministry of Housing and Urban-Rural Development, there were 584 reported safety incidents resulting in 635 fatalities across China's construction sector in 2023, highlighting the continued severity and complexity of construction safety issues.

To increase project construction safety, the industry has attempted to implement various safety management methods such as hazard identification,<sup>2</sup> training methods,<sup>3</sup> job hazard analysis, adopting safety best practices, strengthening organizational leadership, and safety culture.<sup>4</sup> Although these safety approaches are valuable and beneficial, their reliability and effectiveness are still limited. More effective safety measures are required to decrease injuries and fatalities in the construction industry further. In recent years, emerging digital safety technologies have increasingly been integrated into construction site safety management to enhance workplace conditions and lower casualty rates. Digital technology can be defined as advanced information and communication technologies and tools used to increase productivity throughout the building life cycle. This study defines digital security technologies as digital technologies that monitor and improve security management throughout the project lifecycle. There are various digital safety technologies, including virtual reality, building information modeling (BIM), drones, wearable sensing devices, robotics, radio frequency identification, laser scanning, and rapid response codes, have been utilized to monitor safety on construction sites and reduce worker injuries and fatalities.<sup>5</sup> However, the adoption rate of these technologies remains limited, as indicated by surveys. Various obstacles have limited the adoption of safety technologies, including their high costs, employee resistance, uncertainty about their effectiveness, and issues with integrating them into existing systems.<sup>6</sup> Adoption and implementation of new technologies at construction sites can entail significant capital expenditures and recurring costs, which is the main reason for slow technology adoption in construction.<sup>7</sup>

There have been previous studies abroad on the assessment of safety technology adoption,<sup>5</sup> but the factors influencing technology adoption and their extent are slightly different in developing countries than in developed countries.<sup>8</sup> Developing countries may face financial and technological infrastructure constraints, so they may be more cost-effective and usable in the application of new smart technologies. Developed countries, on the other hand, are more likely to prioritize the cutting-edge and innovative nature of technologies and promote their full integration and application. The current decision-making process model used in the domestic construction industry relies heavily on personal experience, which by itself is not sufficient to make informed decisions. In response to the shortcomings of previous studies and the context of China, 22 influencing factors for adopting digital safety equipment and technologies were identified through literature summarization and input from engineering management experts and scholars. Data processing of the 511 valid responses collected resulted in an overall index for safety technology adoption.

Our contributions can be summarized as follows:

The adoption assessment model constructed in this study may assist national practitioners in determining the success of safety technologies.

In addition, the data were categorized into Midwest and East and processed according to the methodology described in this study. Validating the overall assessment model while comparing the differences in the influencing factors of digital safety technology adoption in regions with different economic and building development situations can also provide a reference value for other developing countries.

The remainder of the paper is organized as follows. “Literature review” section outlines the methodology for the application and assessment of construction safety management and construction safety technology. “Data and methodology” section outlines the data collection, sources, and research methodology of the study. “Data analysis and results” section includes data analysis and results, followed by results and discussion in “Discussion of results” section. “Conclusions” section summarizes the main findings. Finally, “Contributions and limitations” section addresses the contributions, limitations, and prospects of this study.

## **Literature review**

There is a wealth of prior research on safety management in construction, and with the continuous advancement of science and technology, there is an increasing focus on the utilization of modern digital technology in safety management. Additionally, scholars have devoted significant efforts to improving assessment methods within this field.

### ***Building construction safety management***

Construction safety is one of the most important issues for the sustainable development of the construction industry.<sup>9</sup> Construction accidents not only lead to casualties but also cause huge property losses. According to the World Health Organization, the construction industry is one of the high-risk areas for accidents and injuries, with a rate much higher than many other industries.<sup>10</sup> Construction safety management involves a series of activities including the collection, transmission, storage, analysis, evaluation, and response to safety-related information. This management can be assessed from two main viewpoints: (1) the managerial aspect, which covers factors such as accident causation, safety climate, risk perception and tendencies, behavioral safety, and hazard management; and (2) the technological aspect, which focuses on the integration of innovative solutions for enhancing safety in construction.<sup>11</sup> Compared to other sectors, the construction industry tends to be slower in adopting new technologies, primarily due to limited investment and a lack of interest in high-tech advancements. This resistance to innovation significantly impacts the effectiveness of safety management in construction.<sup>12</sup>

In this context, the application of safety technology has become an urgent need to solve construction safety problems.<sup>13</sup> Construction safety technologies can be used at different stages throughout the project life cycle to maximize safety performance.<sup>14</sup> Implementing safety technologies can enhance safety controls beyond traditional hazard recognition training for workers. These technologies offer diverse applications,

including the provision of real-time safety data, timely transmission of safety information, and the creation of extensive databases that facilitate risk assessment and accident prediction. By integrating digital safety solutions, construction site safety management can shift from a reactive stance to a more proactive strategy.<sup>11</sup>

### *Application of construction safety technology*

Previous research indicates that technology offers numerous safety and nonsafety benefits in the built environment,<sup>15</sup> although its adoption has been slower compared to industries like manufacturing. In the design and planning stages of construction, professionals have been using virtual reality to train field crews in identifying workplace hazards.<sup>16</sup> Virtual reality enhances the visualization of a project's physical and functional aspects, thereby increasing the chances of identifying potential safety issues.

Beyond virtual reality, construction professionals have also employed BIM to enhance safety design,<sup>17</sup> improve design functionality,<sup>18</sup> aid in construction planning,<sup>19</sup> and facilitate better communication among project teams,<sup>20</sup> all aimed at reducing workplace accidents. Building Information Modeling has been utilized for visualization and management, with 4D-BIM projects demonstrating cost savings and data accuracy improvements.<sup>21</sup> Similarly, drones have been increasingly used to bolster construction safety. Yaacoub et al.<sup>22</sup> evaluated drone usage for safety inspections and found them to be effective and efficient for remote inspections through smart devices. Drones are also used for reality capture in high-risk situations, minimizing worker exposure to hazards.<sup>23</sup> Recently, wearable safety devices, such as smart helmets, have gained popularity in construction due to their effectiveness, user-friendliness, and cost-effectiveness.<sup>24</sup> Other technologies, including robotics, radio frequency identification, sensing devices, laser scanning, and rapid response codes, have also been tested in construction safety management and have proven effective in improving working conditions and reducing injury severity.<sup>25</sup>

### *Assessment methodology*

Adoption assessment of construction safety technologies is typically uncertain and subjective, and fuzzy set theory (FST) allows researchers to deal with imprecise, fuzzy, and subjective judgments.<sup>26</sup> Fuzzy syndrome evaluation (FSE) is an offshoot of FST, developed by Zadeh<sup>27</sup> to represent and manipulate “fuzzy” terms, which uses the degree of affiliation in the set rather than strict true/false affiliation. The degree of affiliation can take any value in a closed interval between 0 and 1 and defines the degree to which an element belongs to a fuzzy set. Artificial neural network technique is also a commonly used evaluation method, but fuzzy synthetic evaluation is superior to artificial neural networks in terms of the accuracy of the results.<sup>28</sup> Fuzzy synthetic evaluation mathematically calculates the operators of the fuzzy domains of these variables,<sup>29</sup> and available data on the linguistic aspects can be quantified. Hu et al.<sup>30</sup> emphasized that FSE was developed to deal with complex problems with multilevel variables. According to Wu and Zhang,<sup>31</sup> it is a well-known technique for multicriteria synthetic evaluation problems, which is effective in capturing diversified and uncertain information from a multitude of sources for decision-makers.

However, the use of safety technology in actual construction projects is not high due to the inability to quantify the potential of safety technology through direct measurement of effectiveness. Moreover, the current decision-making process model used in the construction industry relies heavily on personal experience, which is subjective. Therefore, this study utilizes mean score (MS) ranking, factor analysis (FA), and fuzzy comprehensive evaluation to construct an assessment model for the adoption of construction safety technology. A scientifically informed assessment method is used to evaluate the adoption of construction safety technologies.

### Data and methodology

In this study, we reviewed the literature on technology adoption influencing factors and initially identified the influencing factors affecting safety technology adoption. After that, professionals from the construction industry with many years of management experience as well as experts and scholars from engineering management academia were invited to present the current findings to the experts and scholars and were asked to reassess and refine the initially identified technology adoption influencing factors, and finally we identified all the adoption influencing factors for this study. We distributed and collected questionnaires both on-site and online. Finally, the collected data underwent rigorous scientific screening, and analysis was conducted using data analysis tools (Figure 1). This approach minimized respondent subjectivity and bolstered the robustness of the findings.

#### Identify factors of technology adoption

Factors influencing digital technology adoption were identified and summarized from the existing literature, and the experts on the panel were then invited to assess the importance

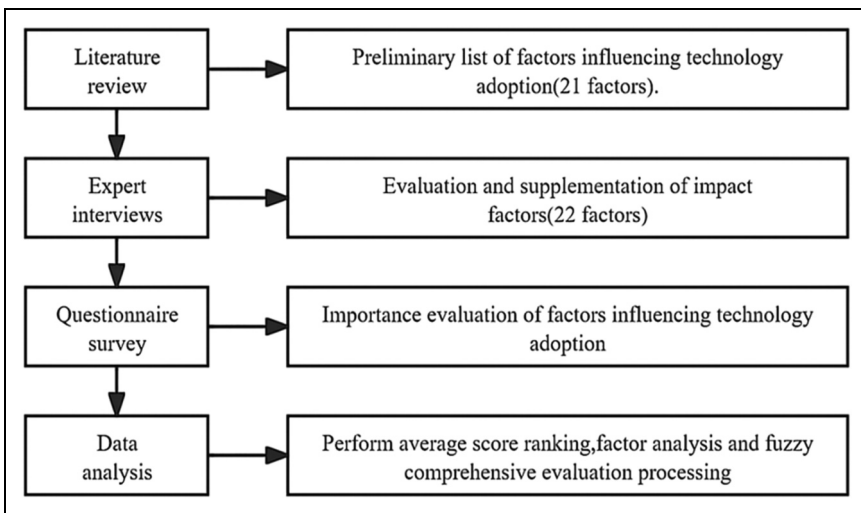


Figure 1. Impact factor selection and data processing.

of each factor. They were given the option of eliminating factors they considered unimportant and were encouraged to add other factors that may have been omitted from the literature review in the context of industry developments. By analyzing the feedback from the participants, a list of factors influencing the adoption of construction safety technologies in this study was finalized.

### *Questionnaires and data collection*

To ensure the quality of the data, practitioners from construction and development units, survey and design units, construction units, consulting organizations, research and educational institutions, and government or industry authorities in the construction industry were selected as respondents. They were asked to have many years of working experience and to be familiar with understanding the current situation of construction project management. To increase the representativeness of the sample, the survey should cover as wide an area as possible. Therefore, the survey was distributed to regions covering North China, South China, East China, Central China, Northeast China, Northwest China, and Southwest China. The survey is divided into three main sections. The first section gathered basic demographic information from the respondents. The second section presented definitions and examples of safety technologies, asking participants to identify which technologies they believe will be promoted in the coming years based on industry trends and their assessments. The third section asked respondents to rate the importance of the identified construction safety technology adoption influences on a 5-point Likert scale to measure the importance of each influence, where 1 = very unimportant; 2 = unimportant; 3 = neutral; 4 = important; and 5 = very important.

### *Data analysis tools*

*Mean score ranking and FA technique.* Several studies in construction management have utilized the MS method to assess the relative significance of various project factors.<sup>29</sup> The MS for each factor was computed using equation (1):

$$MS = \sum (f \times s) / N \quad (1 \ll MS \ll 5) \quad (1)$$

where  $s$  represents the respondents' ratings for each influence, ranging from 1 to 5 (1 = very unimportant, 5 = very important);  $f$  represents the frequency of each rating (1–5) for each influence; and  $N$  represents the total number of responses about the particular influence.

This study employed FA to statistically identify potential clusters of technology adoption factors. Factor analysis is a statistical method designed to reduce a large set of inter-related variables into a smaller number of distinct subgroups. It is mostly used to explain complex phenomena.<sup>32</sup> In addition, the technique is also powerful in identifying and explaining groups of unrelated elements.<sup>33</sup>

*Fuzzy synthetic evaluation.* Fuzzy syndrome evaluation is an application of FST. In recent years, an increasing number of researchers have employed FST (FSE) as a powerful

statistical tool for creating measurement instruments, such as multicriteria decision support frameworks. Fuzzy syndrome evaluation is a versatile modeling technique applicable in management and engineering research, as well as for quantifying multilevel, multiassessment, and multiattribute scenarios.<sup>29,30</sup> This technique has been used in different research areas to evaluate multicriteria decision-making such as health risk assessment, risk assessment and allocation, and program delivery assessment.<sup>6,29</sup>

The FST minimizes the subjectivity of the respondents and the assessment method established in this way is scientific and practical. In this study, FSE was used as the main tool to adopt the index for decision-making measurement of construction safety technologies. This method can objectify and manipulate subjective judgments compared to the common weighting method.<sup>26</sup>

### Data analysis and results

Based on the previous literature study to identify 21 influencing factors for adopting construction safety technologies (as shown in Table 1) and incorporating experts' recommendations, we added an influencing factor: Corporate Social Responsibility. A questionnaire was developed to conduct the survey based on the final 22 influencing factors. A pilot survey was initiated before the distribution of the questionnaire, in which five persons with more than 15 years of experience in engineering management were invited to participate to determine the questionnaire's face and internal validity. Managers of 156

**Table 1.** Factors identified in the literature.

Factors	References
Proven technical effectiveness	Lee et al. <sup>34</sup> ; Chan et al. <sup>35</sup> ; Nnaji et al. <sup>36</sup>
Technically reliable	Algassim et al. <sup>37</sup> , Wimalasena and Gunatilake <sup>38</sup>
Technical durability	Algassim et al. <sup>37</sup> , Chan et al. <sup>35</sup>
Have the required functionality.	Nnaji et al. <sup>36</sup> , Ozumba and Shakantu <sup>39</sup>
Multifunctional	Pan and Pan <sup>7</sup> , Nnaji et al. <sup>36</sup>
Observable	Sepasgozar et al. <sup>40</sup> , Watfa et al. <sup>41</sup>
Trialability	Watfa et al. <sup>41</sup> , Ozorhon and Cinar <sup>42</sup>
Complexity level	Wang et al. <sup>43</sup> , Choi et al. <sup>44</sup>
Level of technical support available	Ozumba and Shakantu <sup>39</sup> , Al Yahya et al. <sup>45</sup>
Level of training required	Antwi-Afari et al. <sup>46</sup> , Ozorhon and Cinar <sup>42</sup>
Colleague Influence	Nnaji et al. <sup>36</sup> , Algassim et al. <sup>37</sup>
The initial cost of technology	Sun et al. <sup>47</sup> , Nnaji et al. <sup>36</sup> , Chan et al. <sup>48</sup>
Company culture	Lee et al. <sup>34</sup> , Al Yahya et al. <sup>45</sup>
Project cost savings	Ozorhon et al. (2017), Antwi-Afari et al. <sup>46</sup>
Compatibility with current technology	Mittal et al. <sup>49</sup> , Welch et al. <sup>50</sup> , Al Yahya et al. <sup>45</sup>
Senior management support	Sun et al. <sup>47</sup> , Lee et al. <sup>34</sup> , Ozorhon and Cinar <sup>42</sup>
Competitive advantages	Rogers et al. <sup>51</sup>
Competitors use similar technology.	Jia et al. <sup>52</sup> , Chan et al. <sup>35</sup>
Stakeholder support	Lau et al. <sup>53</sup>
Client demand	Yigitcanlar et al. <sup>54</sup> , Rogers et al. <sup>51</sup>
Government policies and regulations	Jia et al. <sup>52</sup> , Chan et al. <sup>35</sup>

large civil engineering and construction projects nationwide were contacted. Three to four senior managers from each project were randomly invited to participate in the survey. A total of 673 questionnaires were recovered from the study, excluding 162 questionnaires due to incomplete or unexplained answers, resulting in a valid sample of 511 questionnaires, with a validity rate of 76%.

The survey respondents were geographically distributed across North, South, East, Central, Northeast, Northwest, and Southwest China (Table 2). The Northeast, which had the lowest data, also had approximately 6% of the participants. Approximately 91% of the participants had a bachelor's degree or higher, and 57% had more than 5 years of experience in the construction industry, their feedback provided valuable insights due to their extensive expertise. This survey asked the participants about their workplaces, and over 55% of the participants were from construction organizations, understood the real developments and needs of construction project management, and had extensive field experience. This added to the confidence and reliability of the survey.

### *Selection of critical adoption factors for safety technology*

The questionnaire of this study investigated a total of 22 construction safety technology adoption influencing factors, but not all 22 factors will be included in the adoption assessment model, the adoption influencing factors need to be screened. Ultimately, 19 key adoption factors were left. Table 3 shows the mean ratings and rankings for each influencing variable. Respondents identified compatibility with current technology, technology reliability, validated technological validity, complexity, and level of technical support available as the five most important influencing factors. Although all 22

**Table 2.** Sample characteristics.

Characteristics	Attributes	Number	Percentage (%)
Working experience	5 years and below	220	43.1
	5–10 years	214	41.9
	10–20 years	65	12.7
	20 years and more	12	2.4
Education	Specialized and below	47	9.2
	Undergraduate	343	67.1
	postgraduates	121	23.7
Enterprise Type	State-owned enterprise	436	85.3
	Private enterprise	60	11.7
	The foreign-invested or joint venture	12	2.3
	Other	3	0.6
Area	North China	67	13.1
	South China	57	11.2
	East China	128	25.1
	Central China	123	24.1
	Northwest China	56	11.0
	Southwest China	50	9.8
	Northeast China	30	5.9



**Table 3.** Average rating and significance of factors influencing technology adoption.

Factors	MS	SD	Rank	Normalization
Compatibility with current technology	4.47	0.679	1	1.000
Technically reliable	4.44	0.686	2	0.964
Proven technical effectiveness	4.43	0.804	3	0.952
Complexity level	4.43	0.751	4	0.952
Level of technical support available	4.40	0.655	5	0.916
Senior management support	4.38	0.725	6	0.892
Project cost savings	4.36	0.801	7	0.867
Multifunctional	4.36	0.677	8	0.867
Have the required functionality	4.34	0.642	9	0.843
Competitive advantages	4.33	0.784	10	0.831
Technical durability	4.32	0.803	11	0.819
Client demand	4.32	0.797	12	0.819
Corporate Social Responsibility	4.31	0.755	13	0.807
Stakeholder support	4.29	0.832	14	0.783
Observable	4.29	0.840	15	0.783
Government policies and regulations	4.27	0.922	16	0.759
Level of training required	4.19	0.883	17	0.663
The initial cost of technology	4.16	0.904	18	0.627
Colleague Influence	4.12	0.920	19	0.578
Competitors use similar technology	3.95	1.158	20	0.373
Company Culture	3.89	1.171	21	0.301
Trialability	3.64	1.372	22	0.000

factors average a rating higher than 3, the index should be developed to include only the most important variables. Therefore, only impact variables with relatively high importance should be selected. One way to identify key factors is to standardize the mean values obtained from descriptive analysis.<sup>29</sup> Normalization typically entails evaluating the significance of each impact variable about the other variables being assessed. [normalized value = (actual value – min. value) / (max. value – min. value)].

Consistent with past research,<sup>32</sup> influence variables with normalized values equal to or higher than 0.5 were retained, while influence variables with normalized values lower than 0.5 were deleted. Therefore, the influence variables “trialability,” “company culture,” and “competitors’ adoption of similar technologies” were removed from the catalog. From the initial list of 22 influence variables, only 19 influence variables remain.

### *Identification of critical factors category groupings for safety technology*

In general, two main requirements should be met before conducting FA. First, the adequacy of the variable-to-sample ratio needs to be assessed. Previous research in construction management has recommended a ratio of 1:5 (i.e. 5 samples per variable). In this study, the ratio was approximately 1:26, which exceeds the recommended threshold. Second, it is essential to evaluate the strength of relationships among variables. The results of the analysis showed that KMO value of 0.919, which satisfies the prerequisite requirements for FA; and  $p < 0.001$ , indicating that the research data is suitable for FA.

Fulfillment of both requirements. Principal component extraction with maximum variance rotation was performed using the Statistical Package for the Social Sciences (SPSS). Varimax rotation was chosen because of its ability to simplify interpretation and the lack of a high degree of intercorrelation between components.<sup>35</sup> After seven iterations, four category groups were extracted, which accounted for 53% of the variance of the responses received, and the variance explained (information extracted) for the four categories were 17.654%, 14.669%, 11.742%, and 9.080%, respectively, which is a relatively even distribution of information extracted, which comprehensively indicates that the results of this FA are good. As shown in Table 4, the categories were named organizational variables (category grouping [CG] 1), technology quantities (CG 2), individual variables (CG 3), and external variables (CG 4). Based on the characteristics of the impact variables within each category. The correlations between the variables within the categories (in this case the influence variables) are called factor loadings. For example, the correlation between “level of technical support available” and “CG 1” is 0.536. According to Osei-Kyei and Chan,<sup>29</sup> a factor loading above 0.5 indicates an acceptable correlation. Only two of the 19 impact variables (“initial cost of technology” and “having the required functionality”) had factor loadings below 0.5. Although below the threshold, “initial cost of technology” and “having the required functionality” had factor loadings below 0.5.

**Table 4.** Classification of factors influencing the adoption of safety technologies.

Number	Factors	Factor loadings	Eigenvalue	PVE	CPVE
CG 1: Organizational			6.666	17.654	17.654
1	Level of technical support available	0.536			
2	The initial cost of technology	0.460			
3	Project cost savings	0.557			
4	Compatibility with current technology	0.559			
5	Competitive advantages	0.651			
6	Stakeholder support	0.598			
7	Government policies and regulations	0.688			
CG 2: Technology			1.391	14.669	32.323
1	Have the required functionality	0.470			
2	Technically reliable	0.735			
3	Proven technical effectiveness	0.651			
4	Technical durability	0.714			
5	Multifunctional	0.612			
6	Observable	0.539			
CG 3: Individual			1.102	11.742	44.065
1	Complexity level	0.687			
2	Level of training required	0.752			
3	Colleague Influence	0.526			
CG 4: External			0.940	9.080	53.145
1	Corporate Social Responsibility	0.568			
2	Client demand	0.682			
3	Senior management support	0.500			

PVE: percentage of variance explained; CPVE: cumulative percentage of variance explained.

Although below the threshold, the factor loadings for “initial cost of technology” and “having the required functionality” are relatively high at 0.460 and 0.470, and are therefore retained.<sup>5</sup>

In addition, reliability tests were conducted using Cronbach’s coefficient alpha model to ensure internal consistency among the impact variables. First, data reliability was assessed for the impact variables within each proposal category, and then overall reliability was tested for all 19 impact variables. According to Olatunji et al.,<sup>11</sup> an alpha coefficient greater than 0.6 indicates acceptable internal consistency among the responses received from participants. The alpha coefficient values for the Technology, Organizational, External, and Individual categories were 0.796, 0.784, 0.645, and 0.708, respectively. The overall Cronbach’s alpha for the categories was 0.893, which is in line with the requirements.

*Calculation of weights and affiliation functions for influencing factors and CGs*

Calculate the weights of the adoption influencing factors and category groups (Table 5). Apply equation (2) to calculate the weights for each Adoption Influencer and for each of the four main category groups. To determine the weights of each impact factor, begin by calculating the total MS for each category group. The total MS is obtained by summing the average scores of all impact factors within that category. The weight of each technology adoption impact factor is then found by dividing the average score of the specific impact factor by the total MS:

$$W_i = M_i / \sum_{i=1}^5 M_i \quad 0 < W_i < 1, \quad \sum W_i = 1 \tag{2}$$

where  $W_i$  represents the weight;  $M_i$  represents the MS of the influencing factor; and  $\sum W_i$  represents the 1 is the sum of the mean ratings.

The affiliation function in FST is typically derived at two or three levels, depending on the research goals.<sup>26</sup> This function, which ranges from 0 to 1, measures how strongly elements belong to a fuzzy set.<sup>29</sup> These levels involve creating an affiliation function for a subset (level 2) before developing one for the broader category (level 1).<sup>5</sup> In this study, Level 2 pertains to the affiliation function for the variable measuring the impact of technology adoption, while Level 1 relates to the affiliation function for the overall category. Level 2 affiliation functions were determined based on the distribution of responses from survey participants, who rated the impact variables using the previously described 5-point Likert scale.

Once the membership function for Layer 2 has been established, equation (3) will be utilized to determine the membership function for Layer 1. In this equation,  $W_i$  denotes the weights of all factors within each category, while  $R_i$  represents the fuzzy matrix:

$$D = W_i \circ R_i \tag{3}$$

where  $D$  represents the final FSE evaluation matrix;  $\circ$  represents the fuzzy synthesis operator.

**Table 5.** Average ratings and weights of impact factors and categories for technical adoption.

Number	Factors	MS	Weightings	Total MS for each CG	Weightings of each CG
CG 1: Organizational				30.28	0.368
1	Level of technical support available	4.40	0.145		
2	The initial cost of technology	4.16	0.137		
3	Project cost savings	4.36	0.144		
4	Compatibility with current technology	4.47	0.148		
5	Competitive advantages	4.33	0.143		
6	Stakeholder support	4.29	0.142		
7	Government policies and regulations	4.27	0.141		
CG 2: Technology				26.18	0.318
1	Have the required functionality	4.34	0.166		
2	Technically reliable	4.44	0.170		
3	Proven technical effectiveness	4.43	0.169		
4	Technical durability	4.32	0.165		
5	Multifunctional	4.36	0.167		
6	Observable	4.29	0.164		
CG 3: Individual				12.74	0.155
1	Complexity level	4.43	0.348		
2	Level of training required	4.19	0.329		
3	Colleague Influence	4.12	0.323		
CG 4: External				13.01	0.158
1	Corporate Social Responsibility	4.31	0.331		
2	Client demand	4.32	0.332		
3	Senior management support	4.38	0.337		
Total groups MS				82.21	

Table 6 shows the level 1 and level 2 affiliation functions. Next, the adoption index (AI) for each category is calculated using the equation:

$$AI = \sum_{i=1}^5 D \times L \tag{4}$$

where  $D$  represents the final FSE assessment matrix;  $L$  represents the scale measure for the hierarchical category set.

The AI values for the four category groups (CG1 represents the Organizational, CG2 represents the Technology, CG3 represents the Individual, and CG4 represents the External) were calculated as follows:

$$AI \text{ CG1} = (0.006, 0.032, 0.073, 0.406, 0.484) \times (1, 2, 3, 4, 5) = 4.330$$



$$AI\ CG2 = (0.005, 0.021, 0.086, 0.348, 0.505) \times (1, 2, 3, 4, 5) = 4.363$$

$$AI\ CG3 = (0.005, 0.045, 0.110, 0.371, 0.469) \times (1, 2, 3, 4, 5) = 4.253$$

$$AI\ CG4 = (0.004, 0.026, 0.075, 0.421, 0.474) \times (1, 2, 3, 4, 5) = 4.336$$

**Development of digital technology adoption index for construction safety (CS-DTAI)**

Nonsignificant correlations between variables often indicate the presence of nonlinearity. Previous studies have used a similar approach to create benchmark success indices using FSE.<sup>5</sup> In developing the CS-DTAI, the influence indices for each category of variables were normalized to ensure that they summed to 1. As shown in Table 7, the summary of the weights indicates that the factors in the technology category have the greatest influence on the potential adoption of digital security technologies. That is, the inherent characteristics of the technology are critical to its adoption and subsequent diffusion.

The index to measure the acceptance of digital technology in construction safety management is represented by equation (5):

$$CS-DTAI = (0.251 \times \text{Organizational factors}) + (0.252 \times \text{Technology factors}) + (0.246 \times \text{Individual factors}) + (0.251 \times \text{External factors}) \tag{5}$$

There is a widely recognized consensus that a significant economic development gap exists between the eastern part of China and its central and western regions. The difference in economic development will affect the development of the construction industry. On the one hand, the economy of the eastern region is developed, while the economic base of the central and western regions is relatively weak. As a result, the east part of the country has a high level of urbanization and good infrastructure. In contrast, the central and western parts of the country have a low level of urbanization and insufficient infrastructure. On the other hand, the better economic development of the eastern part of the construction market demand will be more vigorous, promoting the innovative development of construction technology and design. Due to the gap in economic and construction development between the Midwest and the East, are there also differences in the factors considered when selecting construction safety technologies? To conduct a more in-depth study, the researcher again partitioned the data according to the Midwest and

**Table 7.** AI and the coefficient for each CG.

Number	CG	Adoption index (AI)	Coefficient
CG 1	Organizational factors	4.330	0.251
CG 2	Technology factors	4.363	0.252
CG 3	Individual factors	4.253	0.246
CG 4	External factors	4.336	0.251
Total		17.281	1.000

Note: Coefficient = (AI for Category /  $\sum$  AI for all categories).

**Table 8.** Midwest and east adoption index (AI) and coefficients for each CG.

Number	CG	Midwest (AI)	Coefficient	East (AI)	Coefficient
CG 1	Organizational factors	4.347	0.250	4.326	0.251
CG 2	Technology factors	4.381	0.252	4.327	0.251
CG 3	Individual factors	4.348	0.250	4.320	0.251
CG 4	External factors	4.302	0.248	4.245	0.247
Total		17.378	1.000	17.218	1.000

the East, analyzed the data according to the above methodological process (Table 8), and made the CS-DTAI respectively:

$$\begin{aligned}
 \text{CS-DTAI}_{\text{Midwest}} = & (0.250 \times \text{Organizational factors}) + (0.252 \times \text{Technology factors}) \\
 & + (0.250 \times \text{External factors}) + (0.248 \times \text{Individual factors})
 \end{aligned}
 \tag{6}$$

$$\begin{aligned}
 \text{CS-DTAI}_{\text{East}} = & (0.251 \times \text{Organizational factors}) + (0.251 \times \text{Technology factors}) \\
 & + (0.251 \times \text{External factors}) + (0.247 \times \text{Individual factors})
 \end{aligned}
 \tag{7}$$

## Discussion of results

### *National model*

From the results of the national technology adoption assessment model, the highest coefficient is found for the technology category factor (0.252), followed by the organization category (0.251) and the external category (0.251), and lastly, the individual category (0.246). The coefficients were obtained by normalizing the adoption index for each category of influencing variables, which represents the weight of each category in the CS-DTAI.

The highest coefficient for the technology category factor indicates that the technology category factor has the greatest impact on the technology adoption model. This is consistent with the findings of Sepasgozar and Davis<sup>55</sup> that technology attribute factors are critical for technology adoption. In the technology category, “technology reliability” and “validated technology effectiveness” are the two factors with the highest weights, which is consistent with the findings of Nnaji et al.<sup>36</sup> Regardless of the country, the most favorable way to increase the likelihood of technology adoption is to improve the reliability of the technology and demonstrate validity in its dissemination. In the second-ranked organizational category, the factor “Compatibility with current technology” has the highest factor weight. This is similar to the Harris et al.<sup>56</sup> argument that when considering the adoption of a new technology, there is a preference for it to be compatible with the technology currently in use. The highest factor weight was given to “support from top management” in the external category, where support from the top

management of the company would make it more likely for a safety technology to be adopted, and the study by Abbasnejad et al.<sup>18</sup> suggests that communicating with the top management of a company and getting their support is very beneficial for a new technology to be adopted.

### *Regional models*

Because of the imbalance in development between the Midwest and the East, we conducted another subregional study. From the results of the regional technology adoption assessment model, the coefficient of the technology category factor of the Midwest assessment model is the highest (0.252), followed by the organization category (0.250) and the external category (0.250), and lastly, the individual category (0.248). The Eastern assessment model has coefficients for the technology, organizational, and external factors (0.251) and the individual category (0.247). It is more consistent with the national assessment model, which proves the generalization of the national technology assessment model. However, there are some differences in the degree of influence of certain factors.

For the Midwest study, the Midwest data were analyzed in comparison to the East and the overall study results. In terms of organization, the average rating of “competitive advantage” is higher in the Midwest (4.38) than in the East (4.32), and there is more room for the development of the construction industry in the Midwest and firms want to take advantage of the competition. This further validates Lacal-Arántegui<sup>57</sup> research. Research on the competitiveness of the construction industry tends to focus on how to measure and improve competitiveness, and enterprises that continue to grow are more sincere in their desire to take advantage of the competition. The “government policies and regulations” factor had the highest average rating in the Midwest. In a study by Ding et al.,<sup>58</sup> it was noted that the government may initiate demonstration programs to prove the economic benefits and effectiveness of adopting safety technologies. The construction industry in the central and western regions is lagging, and it is more beneficial to receive the government’s attention and support, so construction companies in the central and western regions are more concerned about meeting the government’s requirements. As a result, the rating of “corporate social responsibility” is also higher in the Midwest (4.34) than in the East (4.29) and overall (4.31). Jamali and Karam<sup>59</sup> found that socially responsible companies in China are more likely to be well-liked and supported. The mean rating for “level of training required” was higher in the Midwest (4.21) than in the East (4.17) and overall (4.19), while the mean rating for “level of technical support available” was also higher in the Midwest (4.43) than in the East (4.38) and overall (4.40). The average rating for “level of technical support available” is also higher in the Midwest (4.43) than in the East (4.38) and overall (4.40). This demonstrates that employees in Midwestern organizations want less training and easier access to technology and that technical support is readily available when needed.

Adoption assessment models in the East compared to the Midwest and overall adoption assessment models. The factors “influence of colleagues” and “initial cost of technology” have the lowest average ratings in the East. The East has better economic development and more financial support, so the initial cost of the technology is less



important when choosing a technology. Among the factor mean ratings, “complexity” has a higher mean rating in the East (4.43) than in the Midwest (4.39). Due to the better development of the construction industry in the East, the employees of the companies in the East have more technologies available to them, and they would prefer the technology to be simple and less cumbersome to operate. This is consistent with Walczuch et al.<sup>60</sup> study, which found that when choosing from a wide range of technologies, users preferred those that were easier to use.

### *Practical significance*

From a practical standpoint, this research holds significant implications for the management of safety in construction. Firstly, by quantifying the probability of adopting digital technology in construction safety management, practitioners can accurately evaluate the effectiveness of their technological adoption. To calculate an adoption index, an index must be computed for each construction group (CG). There are two methods available for calculating an index for a subgroup: (1) Practitioners should assess the true score for each factor under each subgroup within a given program using any measurement scale (e.g. 5-point or 7-point scale). The average adoption index for each CG is then determined and substituted into the adoption index (equation (5)), and (2) Practitioners should reimplement the entire fuzzy synthetic evaluation methodology proposed in this study using a new dataset.

Secondly, practitioners can utilize the adoption index to conduct a reliable and objective comparison of various digital safety technologies, to establish benchmarks and enhance control measures. The comparison process may adhere to any of the methodological procedures previously discussed. Furthermore, this study examines the significance of influencing factors on safety technologies and explores variations in these factors between the Midwest and East regions, each with distinct developmental profiles. These findings aim to offer insights for domestic practitioners seeking to enhance the implementation of construction safety technologies.

### **Conclusions**

This study has developed an index for the adoption of digital safety technology to quantitatively assess the likelihood of its implementation in construction safety management. The findings suggest that technical factors exert the greatest influence on the adoption of digital safety technologies, followed by organizational and external factors, with personal factors being the least influential. Within technological factors, “technological reliability” and “proven technological effectiveness” were found to carry the most weight.

Additionally, the results of the partitioning study indicate that the construction safety technology adoption assessment model is generalizable. However, there are variations in the impact of certain factors. Construction companies in less developed regions in central and western China prioritize whether technology adoption facilitates obtaining government support and enhancing their competitive advantage. Conversely, firms in more developed eastern regions show less concern about the initial cost of the technology, while emphasizing employees’ preference for user-friendly technology.

## Contributions and limitations

This study developed an index model for adopting digital technology in construction safety management, investigated the factors influencing the uptake of digital safety technology, and conducted a comparative analysis of regions with varying levels of economic and construction development. The findings may offer valuable insights for enhancing the adoption rate of digital safety technology.

However, it is important to acknowledge the limitations of this study. Firstly, the results were obtained through analysis of data provided by industry professionals, which may introduce bias due to respondents' subjective judgment. Fortunately, applying FST helps mitigate subjectivity and strengthens the robustness of the findings compared to using clear values directly. Secondly, it should be noted that this study was conducted in China, and as such, the influencing factors and their significance may differ in other countries, particularly those that are more developed. Nonetheless, the insights gained from this study can still provide valuable information for researchers in other countries. Future studies could supplement these influencing factors by considering their own country's specific circumstances and current state of development within the construction industry. Additionally, it is recommended that future research incorporate actual project cases to further facilitate the practical application of the technology adoption assessment model.

## Author contribution statement

Jinjing Xu: conceptualization, methodology, resources, software, data curation, writing—original draft, writing—review & editing. Jintao Li: conceptualization, methodology, resources, supervision, writing—review & editing. Xiaohong Chen: supervision, revision of the manuscript, acquisition of funding for the research, manuscript language embellishment. All authors have read and agreed to the published version of the manuscript.

## Declaration of conflicting interests

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