Evaluating Construction 4.0 technologies in enhancing safety and health: case study of a national strategic plan

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Abstract
Purpose – Policymakers are developing national strategic plans to encourage organizations to adopt Construction 4.0 technologies. However, organizations often adopt the recommended technologies without aligning with organizational vision. Furthermore, there is no prioritization on which Construction 4.0 technology should be adopted, including the impact of the technologies on different criteria such as safety and health. Therefore, this study aims to evaluate Construction 4.0 technologies listed in a national strategic plan that targets the enhancement of safety and health.

Design/methodology/approach – A list of Construction 4.0 technologies from a national strategic plan is evaluated using the fuzzy technique for order preference by similarity to ideal solution (TOPSIS) method. Then, the data are analyzed using reliability, fuzzy TOPSIS, normalization, Pareto, sensitivity, ranking, and correlation analyses.

Findings – The analyses identified six Construction 4.0 technologies that are critical in enhancing safety and health: Internet of Things, autonomous construction, big data and predictive analytics, artificial Intelligence, building information modeling and augmented reality and virtualization. In addition, six pairs of Construction 4.0 technologies illustrate strong relationships.

Originality/value – This study contributes to the existing body of knowledge by ranking a list of Construction 4.0 technologies in a national strategic plan that targets the enhancement of safety and health. Decision-makers can use the study findings to prioritize the technologies during the adoption process. Also, to the best of the authors’ knowledge, this study is the first to evaluate the impact of Construction 4.0 technologies listed in a national strategic plan on a specific criterion.

Keywords Construction 4.0, Emerging technologies, Fuzzy TOPSIS, Safety and health

Paper type Research paper

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1. Introduction

Adopting Construction 4.0 technologies has immense potential in enhancing safety and health (Musarat et al., 2023). The advancement of Construction 4.0 technologies has efficiently optimized safety procedures and enhanced accident response, significantly enhancing overall safety and health (Yap et al., 2022). Selecting the most effective Construction 4.0 technologies in enhancing safety and health poses significant organizational responsibilities (Nnaji et al., 2018). Inaccurate decisions to adopt these technologies can leave safety risks unaddressed, resulting in dangerous construction sites (Shafei et al., 2022). Similarly, ineffective choices may fail to eliminate construction hazards, leading to increased accidents and injuries (Nnaji and Karakhan, 2020). Consequently, this increased accident rate contributes to considerable productivity loss in the construction industry, equivalent to over 4% of the global gross domestic product (Barbosa et al., 2017). Therefore, making effective decisions to adopt Construction 4.0 technologies is crucial in enhancing safety and health.

Informed decision-making is crucial for guiding organizations to adopt Construction 4.0 technologies in enhancing safety and health (CIDB, 2021). Organizations are aware of the benefits of Construction 4.0 technologies in enhancing safety and health (Nagy et al., 2021). However, top management of organizations is not adopting the technologies because of concerns about wasting resources and misjudging the technologies (Nagy et al., 2021). Furthermore, a lack of prioritization and standardized guidelines for selecting these technologies leaves organizations uncertain (Shafei et al., 2022). This results in difficulty in identifying critical technologies that align with safety and health requirements (Olatunde et al., 2023). In addition, limited awareness of available technologies and potential impact may lead organizations to invest in solutions that do not address the specific safety and health needs (Dobrucali et al., 2022). Therefore, providing insights that allow informed decision-making when adopting Construction 4.0 technologies is essential.

Construction 4.0 technologies have a high potential in enhancing safety and health at construction sites (Yap et al., 2021). Informed decision-making regarding critical Construction 4.0 technologies is vital for organizations to achieve these enhancements (Shafei et al., 2022). Such understanding enables organizations to effectively manage resources, including time, cost and personnel, during the adoption process (Nagy et al., 2021). By optimizing resource allocation, organizations can invest in multiple Construction 4.0 technologies simultaneously, further enhancing safety and health (El Jazzar et al., 2021). The strategic adoption of different technologies can eliminate safety and health risks, reduce accidents and significantly enhance overall productivity (Dobrucali et al., 2022). Therefore, informed decisions empower organizations in enhancing safety and health in construction and overall productivity.

This study aims to evaluate Construction 4.0 technologies listed in a national strategic plan that targets the enhancement of safety and health. Three objectives are established to achieve the following study aims:

(1) to identify the critical Construction 4.0 technologies listed in a national strategic plan that targets the enhancement of safety and health;

(2) to investigate the ranking performance of the Construction 4.0 technologies; and

(3) to analyze the interrelationship between the Construction 4.0 technologies.

This study makes a significant academic and practical contribution by offering an informed ranking of Construction 4.0 technologies listed in a national strategic plan that targets the enhancement of safety and health. Decision-makers can benefit from this ranking, as it highlights the criticality of these technologies and helps prioritization during the adoption
process. Moreover, the study suggests the potential integration of Construction 4.0 technologies to increase the effectiveness in enhancing safety and health. Notably, this study is the first that evaluates Construction 4.0 technologies listed in a national strategic plan that targets the enhancement of safety and health. Future works can use the framework to analyze lists of Construction 4.0 technologies in other national strategic plans.

2. Literature review

2.1 Safety and health in construction

The construction industry poses significant risks, with high fatality rates globally, as reported by the Bureau of Labor Statistics (BLS, 2021). According to the Health and Safety Authority (has, 2022), the construction industry ranks among the top five industries for nonfatal accidents and illnesses, as well as accounting for up to 29% of overall fatal workplace accidents. The fatal accidents, primarily attributed to falls, slips and trips, led to 370 fatalities in 2021, marking a 7.2% increase from the previous year (BLS, 2021). In addition, the demanding and stressful nature of construction projects exposes industry personnel to significant mental health challenges (Langdon and Sawang, 2018). Unfortunately, prioritizing productivity over safety and health in construction projects often leads to decreased adherence to safety measures (Neale and Gurmu, 2022), resulting in poor safety and health performance (Yap et al., 2021). Thus, innovative efforts are indispensable in enhancing safety and health in construction.

2.2 Construction 4.0 technologies and safety and health

Construction 4.0 refers to adopting principles and technologies from Industry 4.0 within the construction industry (García de Soto et al., 2022). There are extensive discussions surrounding adopting Construction 4.0 technologies, which hold great promise in enhancing safety and health (Okpala et al., 2020). Several works have extensively examined Construction 4.0 technologies in enhancing safety and health. Musarat et al. (2023) ranked Construction 4.0 technologies to address safety and health issues (in descending order): building information modeling (BIM), wireless monitoring and sensors, augmented reality (AR) and robotics and automation (R&A). Nnaji and Karakhan (2020) identified the top three technologies used by construction industry professionals in enhancing safety and health: BIM, wearable sensing devices (WSDs) and onsite mobile devices. Dobrucali et al. (2022) ranked a list of Construction 4.0 technologies based on the potential impact in enhancing safety and health (in descending order): BIM, R&A, artificial intelligence (AI), virtual reality (VR), AR, machine learning, WSDs, eye tracking, radio frequency identification (RFID), laser scanning and Internet of Things (IoT). Yap et al. (2021) explored the effectiveness of ten technologies in enhancing safety and health, with the following ranking: BIM, WSDs, R&A, unmanned aerial vehicles, 3D laser scanning, network cameras, digital signage, VR, AR and RFID. These works collectively demonstrate that differences exist in the ranking of the Construction 4.0 technologies in enhancing safety and health.

2.3 Knowledge gap

This subsection outlines the knowledge gaps in the existing literature, justifying the rationale for this study. In summary, previous works have explored Construction 4.0 technologies in enhancing safety and health. However, there is a lack of investigation into the effectiveness of Construction 4.0 technologies listed in national strategic plans that target the enhancement of safety and health. Furthermore, previous works have not examined the potential interrelationships between these technologies. Having insights into
the potential interrelationships could increase the effectiveness in enhancing safety and health in construction. Therefore, this study aims to fill these gaps by evaluating a list of Construction 4.0 technologies listed in a national strategic plan that targets the enhancement of safety and health as a case study.

3. Research methodology
To achieve the study aim and objectives, the multicriteria decision-making (MCDM) method was adopted, as it provides a robust approach for evaluating and ranking alternatives based on predefined criteria. Common MCDM methods include the analytic hierarchy process (AHP), preference ranking organization method for enrichment (PROMETHEE), analytic network process (ANP), Višekriterijumsko Kompromisno Rangiranje (VIKOR) and technique for order preference by similarity to ideal solution (TOPSIS) (Basilio et al., 2022). In addition, previous works also adopted fuzzy MCDM methods such as fuzzy TOPSIS (Singh et al., 2022), fuzzy AHP (Lazar and Chithra 2021a, 2021b), fuzzy ANP (Wang et al., 2023), fuzzy VIKOR (Papathanasiou, 2021) and fuzzy PROMETHEE (Akram et al., 2023).

In detail, AHP uses pairwise comparisons for solving complex decision-making but faces challenges with large numbers of criteria and alternatives (Lazar and Chithra, 2021b; Mousavi-Nasab and Sotoudeh-Anvari, 2018; Ren et al., 2022). PROMETHEE also uses pairwise comparison for transparent decision-making but faces challenges in handling large numbers of criteria and alternatives (Serrai et al., 2017) and the absence of criteria weighing (Ren et al., 2022). Meanwhile, ANP offers comprehensive decision-making processes considering feedback relations, but it is computationally complex (Chou, 2018; Sen et al., 2015). VIKOR can solve complex problems but suffers from rank reversal issues that lead to potential inaccuracies (Papathanasiou, 2021; Ren et al., 2022; Zimonjić et al., 2018). In contrast, TOPSIS offers flexible and straightforward decision-making processes and can handle a large number of criteria and alternatives (Uzun et al., 2021). However, TOPSIS introduces data vagueness, as it lacks a built-in inconsistency checker (Panda and Jagadev, 2018; Uzun et al., 2021). To address that limitation, Chen (2000) extended TOPSIS using a fuzzy set theory that addresses vague data and captures information from linguistic inputs. These efficiencies and deficiencies of MCDM methods are summarized in Table 1.

In summary, compared to other MCDM methods, fuzzy TOPSIS exhibits a lower susceptibility to rank reversal problems (Chou, 2018; Oubahman and Duleba, 2021; Ren et al., 2022; Mousavi-Nasab and Sotoudeh-Anvari, 2018). Moreover, sensitivity analysis can be conducted in fuzzy TOPSIS to identify inconsistencies in judgments (Singh et al., 2022). Because of these considerations, the fuzzy TOPSIS was adopted to achieve the study aim and objectives (i.e. evaluating criteria and ranking 12 alternatives). Figure 1 shows the overall research methodology framework of this study, which includes the fuzzy TOPSIS instrument development, data collection and data analysis. The following subsections detail the research methodology.

3.1 Instrument development
Based on a national strategic plan, safety and health criteria, along with 12 Construction 4.0 technologies, were identified as alternatives for the fuzzy TOPSIS instrument. The decision-making model is based on the safety and health criteria and 12 technologies, as shown in the Appendix (Figure A1). Subsequently, the instrument was developed into three sections: Section 1 for demographic information, Section 2 provides rating guidelines to experts and Section 3 for expert rating. A pilot study involving four doctoral students and two construction management professors was conducted to validate and refine the instrument.
<table>
<thead>
<tr>
<th>Abilities required for the MCDM method</th>
<th>AHP</th>
<th>TOPSIS</th>
<th>VIKOR</th>
<th>PROMETHEE</th>
<th>ANP</th>
<th>Fuzzy AHP</th>
<th>Fuzzy TOPSIS</th>
<th>Fuzzy VIKOR</th>
<th>Fuzzy PROMETHEE</th>
<th>Fuzzy ANP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Suitable for weighing criteria</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>importance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Deal with data vagueness</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Handle a large number of criteria and alternatives</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Check for inconsistencies</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Flexible and simple decision process</td>
<td>✓</td>
<td></td>
<td>✓</td>
<td></td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Evaluate complex decision problem</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Less rank reversal problem</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Notes: “✓” denotes efficiencies of MCDM method for assessing its suitability for this study; and “–” signifies deficiencies of MCDM method.

Sources: Abdullah et al. (2023), Alsalem et al. (2018); Gul et al. (2016); Lazar and Chithra (2021a, 2021b); Mousavi-Nasab and Sotoudeh-Anvari (2018); Oubahman and Duleba (2021); Papathanasiou (2021); Ren et al. (2022); Sen et al. (2015) and Zimonjić et al. (2018); Authors' own creation.
Feedback from the draft resulted in minor grammatical changes and clarifications in the instrument’s instructions.

### 3.2 Data collection

The data collection involves using the purposive sampling method. The method was used to ensure that the collected data was directly related to the study (Aghababayi and Nikabadi, 2021). The sampling method results in 14 experts completing the data collection instrument. Prior works suggest that ten respondents are sufficient for using the fuzzy TOPSIS method in construction management research (Karimiazari et al., 2011; Mahpour, 2018; Turoff and Linstone, 2002). Furthermore, considering that previous works collected data from fewer
experts (between three and six), the number of respondents is deemed sufficient for further analyses (Karimiazari et al., 2011; Mahpour, 2018; Turoff and Linstone, 2002).

3.3 Data analysis
This subsection discusses the data analysis methods to achieve study objectives. Each analysis method is detailed in subsequent sections. Furthermore, an overview of the capabilities and incapabilities of the used methods, accompanied by justifications for their selection, is presented in Appendix (Table A1).

3.3.1 Reliability analysis
3.3.1.1 Cronbach’s alpha. Before analyzing the collected data, Cronbach’s alpha values were computed to assess the internal consistency of the data. The Cronbach’s alpha reliability coefficient ranges from 0 to 1, and values above 0.70 are acceptable (Hair et al., 2016).

3.3.1.2 Kendall’s coefficient of concordance. Furthermore, this study computes Kendall’s coefficient of concordance (KCC) (denoted as “W”) to measure the level of agreement between the rankings (Kendall and Gibbons, 1990). The range of “W” is from 0 to 1, with higher values indicating stronger agreement (Cruz and Cruz, 2022). The interpretation of “W” is as follows: 0.00–0.09 as no agreement, 0.10–0.29 as weak agreement, 0.30–0.59 as moderate agreement, 0.60–0.99 as strong agreement and 1.00 as perfect agreement (Lazar and Chithra 2021a, 2021b).

3.3.2 Criticality analysis
3.3.2.1 Fuzzy technique for order preference by similarity to ideal solution. Fuzzy TOPSIS involves several steps to derive the priority weight for each criterion. The detailed steps involved in deriving the priority weights are shown in Appendix (Table A2). The steps involved using expert ratings of criteria and alternatives that are expressed using linguistic terms as fuzzy numbers. The linguistic terms used to express the expert ratings and criteria are presented in Appendix (Tables A3 and A4).

3.3.2.2 Pareto analysis. Pareto analysis, often called the “80/20” rule, identifies that 20% of the causes lead to 80% of the outcomes. In this context, the analysis identifies the critical Construction 4.0 technologies (20%) that hold 80% of the significance in enhancing safety and health. By synthesizing the experts’ ratings, this analysis effectively differentiates critical and noncritical technologies (Nasir et al., 2022).

3.3.2.3 Normalization value analysis. The normalization value (NV) was also used to identify critical variables (in this case, critical Construction 4.0 technologies). In this analysis, NVs greater than 0.50 indicate critical variables (Al-Mohammad et al., 2023). Numerous scholars use this technique to identify critical variables within the construction management area (Dahalan et al., 2023; Farouk et al., 2023; Omer et al., 2022; Tan and Rahman, 2023; Zamani et al., 2022). The NV was calculated using the formula $NV = \frac{\text{mean}}{\text{minimum mean}}/\frac{\text{maximum mean} - \text{minimum mean}}{\text{minimum mean}}$ (King et al., 2022).

3.3.3 Ranking performance analysis
3.3.3.1 Sensitivity analysis. Sensitivity analysis is valuable in illustrating changes in criteria weight that impact the evaluation of alternatives. It determined the implications of criteria weights on decision-making, ensuring robust and well-informed alternatives. Widely used in analytics, sensitivity analysis determines the degree to which an alternative’s ranking stability relies on slight variations in input weights of the criteria (Zubayer et al., 2019).

3.3.3.2 Spearman rank correlation coefficients. Spearman rank correlation coefficients, denoted by the Greek letter “rho” ($\rho$), was used to establish the descriptive comparison of rankings and assess any statistical significance (Mahamadu et al., 2020). This coefficient calculates the correlation between ranks derived from two different algorithms applied to the same set of observations (Singh et al., 2022).
The formula for $\rho$ is given as equation (13):

$$
\rho = \frac{6 \sum \sigma_i^2}{n^3 - n}
$$

(13)

3.3.3.3 Kendall’s tau coefficient. Kendall’s tau coefficient ($\tau$) quantitatively describes the ranking of alternatives by measuring the number of pairs of ranks that are larger or smaller in magnitude than the reference rank. The pairs of ranks larger in magnitude are called concordant pairs, and the smaller ones are termed discordant pairs (Velencia et al., 2013).

3.3.3.4 Root mean square error. Root mean square error (RMSE) is a crucial metric for evaluating the ranking quality of Construction 4.0 technologies. By comparing predicted and actual ranks, RMSE estimates the overall ranking performance (Fletcher et al., 2000). A lower RMSE value signifies a more accurate ranking performance.

The formula for RMSE is as given in equation (14):

$$
RMSE = \sqrt{\sum_{i=1}^{n} \frac{(R_{obs,i} - R_{act,i})^2}{n}}
$$

(14)

where $R_{obs,i}$ is predicted rank, and $R_{act,i}$ is actual rank.

3.3.3.5 Average absolute distance. The average absolute distance (AAD) is used to assess the accuracy of ranking performance by measuring the relative distance between predicted and actual ranks (Nguyen and Bui, 2019). A lower AAD value indicates a better ranking performance (Ferrari and Castro, 2015).

The formula for AAD is as given in equation (15):

$$
AAD = \frac{\sum_{i=1}^{n} |R_i - A_i|}{n}
$$

(15)

where $R_i$ is the predicted rank, and $A_i$ is the actual rank for the $i$th observation.

3.3.4 Correlation analysis. Finally, this study uses Spearman rank correlation coefficients ($\rho$) to examine the relationship between Construction 4.0 technologies. This analysis measures the strength and direction of association between two variables (King et al., 2022). Correlation values can be interpreted as follows: 0.00–0.19 as a very weak correlation, 0.20–0.39 as a weak correlation, 0.40–0.59 as a moderate correlation, 0.60–0.79 as a strong correlation and 0.80–1.00 as a very strong correlation (Musarat et al., 2022).

4. Results

4.1 Results for reliability analysis

4.1.1 Cronbach’s alpha. The Cronbach’s alpha value obtained in this study is 0.971, exceeding the minimum threshold of 0.70. This result signifies high reliability and strong internal consistency of the data collected using the fuzzy TOPSIS instrument. Consequently, the data is deemed valid for further analysis.

4.1.2 Kendall’s coefficient of concordance. The Kendall’s coefficient of concordance ($W$) value for the collected data is 0.126, indicating 12.6% agreement among experts in the ranking of the Construction 4.0 technologies in enhancing safety and health. Furthermore, the obtained $F$-value demonstrates that the ranked constraints were statistically significant at the 1% level. The results suggest a weak agreement among experts in the ranking of the
4.2 Results for criticality analysis

4.2.1 Fuzzy technique for order preference by similarity to ideal solution. Table 2 shows normalized alternatives, weighted normalized alternatives, FPIS, FNIS, $CC_i$, NV and final ranking. The $CC_i$ values of all Construction 4.0 technologies close to each other (ranges from $CC_i = 0.486$ to $CC_i = 0.528$). Among the Construction 4.0 technologies, IoT secured the top rank with the highest $CC_i$ of 0.528, followed by autonomous construction ($CC_i = 0.523$) and big data and predictive analytics ($CC_i = 0.520$). In contrast, blockchain placed last with $CC_i$ of 0.486.

4.2.2 Pareto analysis. Following the fuzzy TOPSIS analysis, the Pareto analysis was used. The “80/20” principle revealed that all Construction 4.0 technologies are critical in enhancing safety and health, as demonstrated in the Appendix (Figure A2).

4.2.3 Normalization value analysis. Unlike fuzzy TOPSIS and Pareto, this NV analysis identifies six Construction 4.0 technologies that are critical in enhancing safety and health with NV values greater than 0.50. Notably, the six critical technologies include IoT, autonomous construction, big data and predictive analytics, AI, BIM and AR and virtualization as shown in Table 2.

4.3 Results for ranking performance analysis

The sensitivity analysis and ranking performance validation results are displayed in Appendix (Table A5). Notably, the ranking remains unchanged across all tested scenarios. Also, the ranking from all scenarios exhibits high positive correlations with the actual ranking, evident from Spearman rank correlation coefficients ($\rho = 1.00$). Kendall’s Tau

<table>
<thead>
<tr>
<th>Construction 4.0 technologies</th>
<th>Normalized alternatives</th>
<th>Weight-normalized alternatives</th>
<th>FPIS</th>
<th>FNIS</th>
<th>$CC_i$</th>
<th>NV</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>IoT</td>
<td>(0.111, 0.746, 1.000)</td>
<td>(0.111, 5.435, 9.000)</td>
<td>5.529</td>
<td>5.982</td>
<td>0.528</td>
<td>1.00*</td>
<td>1</td>
</tr>
<tr>
<td>Autonomous construction</td>
<td>(0.111, 0.635, 1.000)</td>
<td>(0.111, 4.626, 9.000)</td>
<td>5.720</td>
<td>5.756</td>
<td>0.523</td>
<td>0.875*</td>
<td>2</td>
</tr>
<tr>
<td>Big data and predictive analytics</td>
<td>(0.111, 0.667, 1.000)</td>
<td>(0.111, 4.857, 9.000)</td>
<td>5.662</td>
<td>5.818</td>
<td>0.520</td>
<td>0.807*</td>
<td>3</td>
</tr>
<tr>
<td>AI</td>
<td>(0.333, 0.762, 1.000)</td>
<td>(0.333, 5.551, 9.000)</td>
<td>5.385</td>
<td>6.018</td>
<td>0.512</td>
<td>0.622*</td>
<td>4</td>
</tr>
<tr>
<td>BIM</td>
<td>(0.111, 0.635, 1.000)</td>
<td>(0.111, 4.626, 9.000)</td>
<td>5.720</td>
<td>5.756</td>
<td>0.512</td>
<td>0.622*</td>
<td>4</td>
</tr>
<tr>
<td>AR and virtualization</td>
<td>(0.111, 0.698, 1.000)</td>
<td>(0.111, 5.088, 9.000)</td>
<td>5.607</td>
<td>5.882</td>
<td>0.509</td>
<td>0.560*</td>
<td>6</td>
</tr>
<tr>
<td>Advanced building materials</td>
<td>(0.111, 0.651, 1.000)</td>
<td>(0.111, 4.741, 9.000)</td>
<td>5.691</td>
<td>5.787</td>
<td>0.507</td>
<td>0.498</td>
<td>7</td>
</tr>
<tr>
<td>Prefabrication and modular construction</td>
<td>(0.333, 0.730, 1.000)</td>
<td>(0.333, 5.320, 9.000)</td>
<td>5.436</td>
<td>5.950</td>
<td>0.507</td>
<td>0.498</td>
<td>7</td>
</tr>
<tr>
<td>Cloud and real-time collaboration</td>
<td>(0.111, 0.683, 1.000)</td>
<td>(0.111, 4.973, 9.000)</td>
<td>5.634</td>
<td>5.849</td>
<td>0.504</td>
<td>0.435</td>
<td>9</td>
</tr>
<tr>
<td>3D scanning and photogrammetry</td>
<td>(0.111, 0.540, 1.000)</td>
<td>(0.111, 3.932, 9.000)</td>
<td>5.908</td>
<td>5.586</td>
<td>0.502</td>
<td>0.373</td>
<td>10</td>
</tr>
<tr>
<td>3D printing and AM</td>
<td>(0.111, 0.667, 1.000)</td>
<td>(0.111, 4.857, 9.000)</td>
<td>5.662</td>
<td>5.818</td>
<td>0.502</td>
<td>0.373</td>
<td>10</td>
</tr>
<tr>
<td>Blockchain</td>
<td>(0.111, 0.698, 1.000)</td>
<td>(0.111, 5.088, 9.000)</td>
<td>5.607</td>
<td>5.882</td>
<td>0.486</td>
<td>0.000</td>
<td>12</td>
</tr>
</tbody>
</table>

Notes: FPIS = fuzzy positive ideal solution; FNIS = fuzzy negative ideal solution; $CC_i$ = closeness coefficient; NV = normalized value; NV = ($CC_i$ - minimum $CC_j$)/(maximum $CC_i$ - minimum $CC_j$); * represents technologies with NV > 0.50

Source: Authors’ own creation
coefficients further confirm these results ($\tau = 1.00$). In addition, RMSE and AAD demonstrate no distance between the scenarios and actual ranks. These results support the robustness and accuracy of the study findings in the ranking of the Construction 4.0 technologies in enhancing safety and health in construction.

4.4 Results for correlation analysis
Spearman correlation coefficients ($\rho$) between the Construction 4.0 technologies are presented in Appendix (Table A6). The results reveal that most technologies exhibit very weak to moderate correlations with each other. However, six pairs of technologies show strong correlations. These results indicate associations between Construction 4.0 technologies. An overview of the correlations between Construction 4.0 technologies can be seen in Figure 2.

5. Discussion
The study findings revealed that six Construction 4.0 technologies are critical in enhancing safety and health. The following subsections discuss the potential relationships between the
technologies and safety and health enhancement in construction. Furthermore, these potential relationships are illustrated in Figure 3.

5.1 Internet of Things
IoT is a global network of smart devices that interact wirelessly and self-organize to achieve specific goals (Singh et al., 2019). IoT offers real-time connectivity with different devices and systems, positioning it as a leading Construction 4.0 technology in enhancing safety and health (Arshad et al., 2023; Dobrucali et al., 2023). This technology is critical in safety and health monitoring to provide accurate real-time data through various sensors, including barcode, radio frequency, infrared and QR codes (Xu et al., 2022; Yang et al., 2020). These sensors facilitate the collection of health metrics, safety behaviors, workers’ positions, trajectories, personal protective equipment conditions, structural health and environmental conditions (Xu et al., 2022). Moreover, IoT’s virtual fence system prevents occupational accidents onsite by warning workers when approaching hazardous areas and providing alerts to supervisors in case of potential safety violations (Rey-Merchan et al., 2021). IoT-based technologies such as RFID technology, thermal infrared sensors, bluetooth modules, smartphones, Web and cloud computing help detect, locate and alarm unauthorized intrusions in hazardous areas in real time, reducing safety hazards at construction sites (Jin et al., 2020). Considering these, IoT proves to be critical in enhancing safety and health in construction.

5.2 Autonomous construction
Autonomous construction involves using autonomous robots to do repetitive tasks and enables construction processes in hazardous environments with minimal or no human

![The relationship between Construction 4.0 technologies and safety and health enhancement in construction](image)

**Source:** Authors’ own creation
supervision (Melenbrink et al., 2020). Through this ability, this technology reduces human errors that are responsible for 82% of accidents in construction (Winge et al., 2019). Moreover, autonomous construction excels in handling numerical data and can replace human tasks for inspecting confined and hazardous areas as well as detecting construction defects, thereby reducing human errors (Yap et al., 2021). Prior work also suggests that using autonomous climbing platforms as formwork systems reduces fall risks in high-rise construction by providing stable and secure platforms (Cai et al., 2020). In addition, adopting autonomous construction, including floor cleaning robot, wall and ceiling grinding robots, wall spraying robot and wall tile paving robot, significantly reduce health risks associated with dust and noise exposure (Chen et al., 2022). As such, autonomous construction is a critical technology in enhancing safety and health in construction.

5.3 Big data and predictive analytics

Another critical technology in enhancing safety and health in construction is big data and predictive analytics. Big data refers to large and complex data sets that conventional software cannot effectively handle. At the same time, predictive analytics uses these data to forecast trends and behavior patterns (Ongsulee et al., 2018). This technology enables the control of dangerous behavior at construction sites through data collection and analysis (Meng et al., 2022). For instance, Ajayi et al. (2019) proposed a system named Big Data Accident Prediction Platform with functions to minimize occupational hazards in construction. Similarly, Zhou et al. (2021) established a subway construction accident database for in-depth analysis of accident trends, providing valuable information for safety planning and decision-making to prevent accidents. These accidents are analyzed using data mining through mathematical models for safety management onsite (Lu and Zhang, 2021). Despite the compelling effectiveness of this technology in enhancing safety and health in construction, limited research has been conducted in this area (Meng et al., 2022). Therefore, adopting big data and predictive analytics is critical in enhancing safety and health in construction, and it requires further exploration.

5.4 Artificial intelligence

According to Mckinsey & Company (2023), AI refers to machines' capability to do tasks that involve cognitive ability. This study identifies AI as a critical technology in enhancing safety and health. AI has emerged as a trending technology in enhancing safety and health in construction through visual algorithms to provide onsite safety personnel with better risk monitoring and intercepting capabilities (DobrucaI et al., 2022). This technology offers unbiased risk assessment by automatically detecting safety and health hazards and ranking the criticality of risks onsite using photo and project data (Jallow et al., 2022). In addition, AI reduces accident risks when operating cranes for material placement on construction sites through mathematical algorithms (Mansoor et al., 2020). Furthermore, hazards are measured at construction sites using a remote AI eye-tracking tool, and heat maps are generated to visualize risks for safety responses (Zhu et al., 2022). Moreover, the effectiveness of the AI-based prediction model developed by Ayhan and Tokdemir (2019) to predict accidents at construction sites is proven to have 84% accuracy with 10% error at most. As evidenced by previous works, AI is critical in enhancing safety and health in construction.

5.5 Building information modeling

This study identifies that both BIM and AI are equally critical in enhancing safety and health in construction. However, both technologies have a weak correlation with one another. In other words, both technologies have independent strengths and distinct
functionalities in enhancing safety and health in construction (Statsenko et al., 2022). Unlike AI, BIM enhances safety and health in construction through the digital representation of projects using 3D models and object-oriented techniques (Yap et al., 2021). The visualization capabilities of BIM enhance safety and health in construction, as it constructs a virtual building model, enabling the early identification of potential hazards and unsafe conditions throughout the project life cycle (Othman et al., 2021; Yap et al., 2022). BIM also allows project stakeholders to generate safety schedules, coordinate projects, provide hazard prevention measures and establish safety training trackers (Singh et al., 2023). Moreover, BIM can automatically detect fall risks and assess hazards using plug-ins (Rodrigues et al., 2021). Plug-ins that function as model checkers in BIM can also visualize building components, spaces and environments to develop control measures for reducing accidents (Meem et al., 2022). Considering these potential applications, the criticality of BIM in enhancing safety and health in construction is undeniable.

5.6 Augmented reality and virtualization

Finally, AR and virtualization is another critical technology in enhancing safety and health in construction. AR and virtualization focuses on human–computer interaction to distinguish between virtual and real-world objects (CIDB, 2021). By integrating digital models into real-world settings, AR and virtualization enable cost-effective safety and health training through virtual exercises and instructional headsets (Alaloul et al., 2021). Parallel with Alaloul et al. (2021), Dobrucali et al. (2022) also emphasize the high impact of AR and virtualization in enhancing safety and health in construction through safety education and training. Furthermore, AR and virtualization is critical in recognizing and preventing hazards through the virtual environment, conducting safety training, education, inspections and providing safety instructions (Li et al., 2018). Therefore, adopting AR and virtualization is critical in enhancing safety and health in construction, especially when the organizations emphasize better experience for safety training and education.

5.7 Comparison with prior works

This section compares the findings from this study and those of prior works to identify similarities and differences. This comparison offers insights for decision-makers, especially top management and company owners, for making strategic decisions to adopt Construction 4.0 technologies in enhancing safety and health.

Table 3 presents the comparison results. There are varying perspectives on IoT, autonomous construction, AI and AR and virtualization technologies. These discrepancies reflect the dynamic landscape of Construction 4.0, where interpretations of criticality vary. Notably, the absence of exploration into big data and predictive analytics in prior works signifies an area open for future investigation (Meng et al., 2022). Remarkably, the unanimous recognition of BIM as critical Construction 4.0 technology emphasizes its crucial role in enhancing safety and health. BIM demonstrates significant potential in various areas, such as proactive hazard identification through 4D BIM integration with accident case analysis, reducing potential risks of spatial-temporal and overlapping activities (Rashidi Nasab et al., 2023; Tran et al., 2021). In addition, identifying potential hazards enables properly planning suitable control measures in construction (Møller et al., 2021). BIM also becomes a critical technology in enhancing safety and health, as it allows the mitigation of fall-related accidents (i.e. the leading cause of fatalities in construction) during the design stage (BLS, 2021; Rafindadi et al., 2022). Finally, different plug-ins in BIM are available to enable the automatic calculation of construction safety risks, facilitating design consultants in selecting design alternatives that optimize safety (Ying Lu et al., 2021). Collectively, prior
works underscore BIM’s versatility and effectiveness in addressing safety and health concerns, aligning with the broader consensus in Construction 4.0 literature.

In contrast to prior works, this study proposes six Construction 4.0 technologies with significant criticality in enhancing safety and health. This expands the current knowledge base, providing a more comprehensive list of critical Construction 4.0 technologies for top management in the organizations to consider for adoption. In addition, this study identifies IoT as the foremost critical technology, deviating from the prevalent emphasis on BIM. This emphasis reflects the dynamic nature of Construction 4.0, acknowledging its continual evolution and the emergence of new technologies for improving safety and health outcomes in construction.

5.8 Study implications

5.8.1 Theoretical implications. This study overcomes the limitation on the existing body of knowledge by providing a critical evaluation and ranking of Construction 4.0 technologies listed in a national strategic plan. The findings provide researchers with structured and evidence-based insights into the critical role of technologies in enhancing safety and health. Apart from ranking the Construction 4.0 technologies, this study also uncovers correlations between these technologies. This knowledge helps researchers explore which technologies are recommended to be adopted together in enhancing safety and health. This study used the fuzzy TOPSIS method to evaluate the Construction 4.0 technologies listed in a national strategic plan. Its robust methodology can serve as a solid foundation for future research, enabling similar analyses of Construction 4.0 technology lists from other national strategic plans. This consistency promotes comprehensive understanding and advancements in the field. Moreover, this study sets a precedent for evaluating the lists of Construction 4.0 technologies in other national strategic plans, facilitating comparisons and benchmarking across different countries in enhancing safety and health in construction.

5.8.2 Practical implications. This study provides valuable guidance for top management in organizations, including small and medium-sized enterprises (SMEs), in adopting Construction 4.0 technologies for enhancing safety and health. Construction 4.0 technologies are often associated with substantial additional costs. However, improving safety and health in construction is a long-term investment. Over time, organizations fostering a strong safety and health culture can lower related costs, including medical bills, worker compensation claims, penalties and legal liabilities. Moreover, improving safety and health in construction

<table>
<thead>
<tr>
<th>Construction 4.0 technologies</th>
<th>This study</th>
<th>Agyekum et al. (2022)</th>
<th>Dobrucali et al. (2022)</th>
<th>Musarat et al. (2023)</th>
<th>Nnaji and Karakhan (2020)</th>
<th>Yap et al. (2021)</th>
<th>Yap et al. (2022)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IoT</td>
<td>√</td>
<td>√</td>
<td>0</td>
<td>√</td>
<td>0</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Autonomous construction</td>
<td>√</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Big data and predictive analytics</td>
<td>√</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>AI</td>
<td>√</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>BIM</td>
<td>√</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>AR and virtualization</td>
<td>√</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 3. Critical Construction 4.0 technologies comparison between this study and existing literature

Notes: “√” indicates critical technology; “0” indicates noncritical technology; and “–” indicates technology that was not investigated in each work
may lead to insurance premium reductions. Furthermore, enhanced safety and health bolster an organization's reputation and market competitiveness. This reputation for good safety and health not only attracts clients, partners and skilled workers but also provides a competitive advantage when bidding for contracts or projects. Reducing accident-related expenses and improving operational performance are especially compelling for capital-constrained SMEs. Therefore, the study findings aid top management in selecting cost-effective technologies that organizations, including SMEs, can leverage for long-term benefits. Furthermore, policymakers can leverage the study findings to incentivize organizations, especially SMEs, to embrace the identified critical technologies through several initiatives, including tax breaks, subsidies and financial incentives. In summary, the study findings equip top management and policymakers with the necessary information to make informed decisions to adopt Construction 4.0 technologies in enhancing safety and health.

5.9 Limitations and future works
Although this study successfully achieved its aim, several limitations exist that could limit the applicability of the study findings. First, the study focused on a specific list of Construction 4.0 technologies in a national strategic plan. As a result, technologies that are not listed in the plan are not evaluated. Any national strategic plans that list additional Construction 4.0 technologies should consider evaluating the technologies for a comprehensive comparison. Second, the findings are based on subjective judgment and may not represent the actual performance of the technologies. Thus, future works can opt to conduct parallel experiments to provide a more objective assessment of the actual performance of the technologies in enhancing safety and health in construction. Finally, the data collection involved respondents from a single country. As workplace environment and cultural differences may affect the applicability of the findings elsewhere, the study findings should be used cautiously in different countries. Despite these limitations, the study findings still offer valuable insights for informed decision-making to adopt Construction 4.0 technologies in enhancing safety and health.

6. Conclusion
Making informed decisions to adopt Construction 4.0 technologies listed in a national plan is paramount in enhancing safety and health at construction sites. This study aims to evaluate Construction 4.0 technologies listed in a national strategic plan that targets the enhancement of safety and health in construction. Three objectives were established to achieve the following study aims: to identify the critical Construction 4.0 technologies listed in a national strategic plan that targets the enhancement of safety and health; to investigate the ranking performance of the listed Construction 4.0 technologies; and to analyze the interrelationship between the listed Construction 4.0 technologies. This study used the fuzzy TOPSIS method and used different data analyses, including reliability, criticality, ranking performance and correlation analyses, to achieve the study aim and objectives. The results revealed six Construction 4.0 technologies that are critical in enhancing safety and health. Notably, all technologies exhibit excellent ranking performance, and weak to moderate relationships exist among most technologies. As a result, this study significantly contributes to the body of knowledge and industry practices concerning informed decision-making to adopt Construction 4.0 technologies in enhancing safety and health.
References


**Further reading**


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Figure A1. The decision-making model for selecting Construction 4.0 technologies that target the enhancement of safety and health

Source: Authors’ own creation

Figure A2. Results for Pareto analysis

Source: Authors’ own creation
<table>
<thead>
<tr>
<th>Data analysis</th>
<th>Reliability analysis</th>
<th>Criticality analysis</th>
<th>Ranking performance analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Metric</strong></td>
<td><strong>Cronbach’s alpha</strong></td>
<td><strong>Kendall’s coefficient of concordance</strong></td>
<td><strong>Fuzzy TOPSIS</strong></td>
</tr>
<tr>
<td><strong>Capabilities</strong></td>
<td>Widely used to measure the reliability and internal consistency of a test or scale</td>
<td>Widely used to measure agreement among multiple raters in rankings of a set of subjects</td>
<td>Widely used MCDM method across various backgrounds</td>
</tr>
<tr>
<td></td>
<td>Produce single values (0–1) for easy interpretation, with an acceptable value for alpha (&gt;0.70)</td>
<td>Suitable for small sample sizes (nonparametric statistics)</td>
<td>Capable of handling complex multicriteria decision processes</td>
</tr>
<tr>
<td></td>
<td>Assesses agreement among multiple raters in rankings of a set of subjects</td>
<td>Capable of handling complex multicriteria decision processes</td>
<td>Of  straightforward and simple decision processes</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Incapabilities</strong></td>
<td>Assumes the instrument is unidimensional</td>
<td>The significance of W values is too dependent on the number of raters and variables</td>
<td>Incapable of checking inconsistency during decision procedures</td>
</tr>
<tr>
<td></td>
<td>This can be affected by the length of the scale and the number of items</td>
<td>Insensitive to positive and negative interpretation</td>
<td>Subject to subjective judgment in decision-making</td>
</tr>
<tr>
<td></td>
<td>Assumes the instrument is unidimensional</td>
<td>The significance of W values is too dependent on the number of raters and variables</td>
<td>May not consider interactions between factors</td>
</tr>
<tr>
<td></td>
<td>This can be affected by the length of the scale and the number of items</td>
<td>Insensitive to positive and negative interpretation</td>
<td>May subject to subjective judgment in decision-making</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Justification for method selection in this study</strong></td>
<td>To measure internal consistent and reliability of data collected</td>
<td>To measure agreement between experts in giving technologies</td>
<td>To rank the Construction 4.0 technologies</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(continued)
<table>
<thead>
<tr>
<th>Data analysis</th>
<th>Metric</th>
<th>Ranking performance analysis</th>
<th>Correlation analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spearman rank correlation coefficients&lt;sup&gt;16,17,18&lt;/sup&gt;</td>
<td>• Widely used to measure nonparametric rank-based correlation</td>
<td>• Widely used to measure the strength of the relationship between two ordinal variables</td>
<td>• Assesses nonparametric correlation between variables</td>
</tr>
<tr>
<td></td>
<td>• A robust method to measure the strength and direction of the monotonic relationship between two variables</td>
<td>• Measure nonparametric correlation based on ranks of the data values</td>
<td>• A robust method to determine the monotonic relationship between two variables</td>
</tr>
<tr>
<td></td>
<td>• Usually used for ordinal data, and it is robust to outliers</td>
<td>• A simpler method than that of the Spearman rank correlation coefficients</td>
<td>• Usually used for ordinal data, and it is robust to outliers</td>
</tr>
<tr>
<td>Kendall’s tau coefficient&lt;sup&gt;19,20&lt;/sup&gt;</td>
<td>• Widely used to measure the strength of the relationship between two ordinal variables</td>
<td>• Widely used to quantify the accuracy of model performance</td>
<td>• Potential unreliable of its threshold values</td>
</tr>
<tr>
<td></td>
<td>• Measure nonparametric correlation based on ranks of the data values</td>
<td>• Measures the difference between predicted and actual values</td>
<td>• Sensitive to outlier</td>
</tr>
<tr>
<td></td>
<td>• A simpler method than that of the Spearman rank correlation coefficients</td>
<td>• Satisfies the triangle inequality requirement for a distance metric</td>
<td>• Does not provide information about the direction of the error</td>
</tr>
<tr>
<td>RMSE&lt;sup&gt;21,22&lt;/sup&gt;</td>
<td>• Widely used to measure the strength of the relationship between two ordinal variables</td>
<td>• Measures average differences between predicted and observed values</td>
<td>• Sensitive to single large outliers</td>
</tr>
<tr>
<td></td>
<td>• Measure nonparametric correlation based on ranks of the data values</td>
<td>• Less sensitive to outliers than RMSE</td>
<td>• Does not satisfy the triangle inequality requirement for a distance metric</td>
</tr>
<tr>
<td></td>
<td>• A simpler method than that of the Spearman rank correlation coefficients</td>
<td>• It is simpler than RMSE and easy to interpret</td>
<td>• Does not imply a cause-and-effect relationship</td>
</tr>
<tr>
<td>AAD&lt;sup&gt;21,22,23,24&lt;/sup&gt;</td>
<td>• Widely used to measure the strength of the relationship between two ordinal variables</td>
<td>• Measures average differences between predicted and observed values</td>
<td>• Not suitable for analyses of agreement between variables</td>
</tr>
<tr>
<td></td>
<td>• Measure nonparametric correlation based on ranks of the data values</td>
<td>• Less sensitive to outliers than RMSE</td>
<td>• Does not imply a cause-and-effect relationship</td>
</tr>
<tr>
<td></td>
<td>• A simpler method than that of the Spearman rank correlation coefficients</td>
<td>• It is simpler than RMSE and easy to interpret</td>
<td>• Does not provide information about the direction of the error</td>
</tr>
</tbody>
</table>

Justification for method selection in this study:
- To check the strength of relationships between ranked Construction 4.0 technologies
- To evaluate the quality of ranking performance by measuring the distance between predicted and actual ranks
- To assess the interrelationships between Construction 4.0 technologies for finding potential adoption in pair
References


### Table A2

The steps for analyzing the collected data using the fuzzy TOPSIS method.

<table>
<thead>
<tr>
<th>Step no.</th>
<th>Description</th>
<th>Equation (Eq)</th>
<th>Eq no.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Step 1</strong></td>
<td>Introduce the linguistic assessment scale and membership functions.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>A membership function was defined to convert linguistic assessments of criteria and alternatives to fuzzy numbers. The linguistic terms for criteria and membership functions are shown in Appendix (Table A3).</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Step 2</strong></td>
<td>Construct a decision matrix and assign linguistic ratings to criteria and alternatives</td>
<td>$D = \begin{pmatrix} \frac{X_{11}}{C_1} &amp; \frac{X_{12}}{C_2} &amp; \frac{X_{1n}}{C_n} \ \frac{X_{21}}{C_1} &amp; \frac{X_{22}}{C_2} &amp; \frac{X_{2n}}{C_n} \ \vdots &amp; \vdots &amp; \vdots \ \frac{X_{m1}}{C_1} &amp; \frac{X_{m2}}{C_2} &amp; \frac{X_{mn}}{C_n} \end{pmatrix}$</td>
<td>Equation (1)</td>
</tr>
<tr>
<td></td>
<td>Selection criteria are referred to $n$ where $C_j (j = 1, 2, \ldots n)$ and alternative $m$, where $(A_i, i = 1, 2, \ldots m)$ are ranked by the experts. In this step, the subjective assessment was executed by the experts to measure the weighting vector $W = (w_1, w_2, \ldots, w_n)$. The decision matrix $(X_{ij}, i = 1, 2, \ldots m; j = 1, 2, \ldots n)$ denotes the rating of alternatives $A_i$ against selection criteria $C_j$. The experts' ratings for criteria and alternatives were converted into fuzzy triangular numbers via equation (1), as presented in Appendix (Tables A3 and A4).</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Step 3</strong></td>
<td>Compute criteria aggregated fuzzy weights for subjective weight and objective weight</td>
<td>$\tilde{W}<em>j = \frac{1}{n} \left( \sum</em>{i=0}^{n} W'_j \right)$</td>
<td>Equation (2)</td>
</tr>
<tr>
<td></td>
<td>Subjective assessments were made to determine experts' weights for criteria, as shown in Appendix Table A3 via equation (2).</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Objective weight was measured using entropy measure. The decision matrix must be normalized for each criterion using the entropy method to obtain the projection value via equation (3)</td>
<td>$P_j = \frac{x_j}{\sum_{j=1}^{m} x_j}$</td>
<td>Equation (3)</td>
</tr>
<tr>
<td></td>
<td>After the decision matrix has been normalized, entropy values $e_j$ were calculated via equation (4)</td>
<td>$e_j = -k \sum_{j=1}^{n} p_j \ln p_j$</td>
<td>Equation (4)</td>
</tr>
<tr>
<td></td>
<td>$k$ is constant where $k = \frac{1}{\ln(m)}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Then, the degree of divergence $d_j$ for each criterion was calculated via equation (5)</td>
<td>$d_j = 1 - e_j$</td>
<td>Equation (5)</td>
</tr>
</tbody>
</table>

(continued)
The greater the divergent value, the more significant the criteria. Then the objective weight was measured via equation (6)

\[ W_j = \frac{d_j}{\sum_{k=1}^{n} d_k} \]  

Equation (6)

Step 4 Calculate the aggregate weight for each criterion \( W_q \).
The aggregate weight for each criterion \( W_q \) was calculated as shown in Appendix (Table A3) via equation (7)

\[ \tilde{X}_{ij} = \frac{1}{n} \left( \sum_{i=1}^{n} \tilde{x}_{ij} \right) \]  

Equation (7)

Step 5 Normalize the fuzzy decision matrix for alternatives
The normalized value for the decision matrix referred to benefit- and cost-related criteria, as shown in Table 2 via equation (8)

\[ \tilde{r}_{ij} = \begin{cases} \left( \frac{a_{ij}}{c_{ij}^+}, \frac{b_{ij}}{c_{ij}^-} \right), & j \in B \\ \left( \frac{a_{ij}}{c_{ij}^+}, \frac{b_{ij}}{c_{ij}^-} \right), & j \in C \end{cases} \]  

Equation (8)

\[ c_j^+ = \text{Max} c_{ij} \text{ if } j \in B \]  
\[ a_j^- = \text{Min} a_{ij} \text{ if } j \in C \]

Step 6 Compute weight normalized matrix and fuzzy positive and negative ideal solution.
The weight-normalized matrix was calculated in Table 2 via equation (9)

\[ \tilde{V} = [\tilde{r}_q]_{mx}, i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \]  
\[ \tilde{v}_q = \tilde{r}_q \otimes \tilde{W}_q \]  

Equation (9)
Next, the fuzzy ideal solution (FPIS) and fuzzy negative solution (FNIS) were computed via equation (10)

$$FPIS = (\tilde{v}_1^+, \tilde{v}_2^+ , \cdots \tilde{v}_k^+ )$$

$$FNIS = (\tilde{v}_1^-, \tilde{v}_2^- , \cdots \tilde{v}_k^- )$$

Step 7 Calculate the distance from FPIS and FNIS for each of the alternatives
The distance of each alternative from FPIS and FNIS is presented in Table 2 via equation (11)

$$d(A_1, A_2) = \sqrt{\frac{1}{3} \sum_{h=1}^{m} (x_h - y_h)^2}$$

$$A_1 = a_1b_1c_1, A_2 = a_2b_2c_2$$

Step 8 Calculate the closeness coefficient ($CC_i$) and rank the best alternatives from high to low $CC_i$ value
Calculated $CC_i$ values are presented in Table 2 via equation (12)

$$CC_i = \frac{d_+}{d_+ + d_-}$$

$$i = 1, 2, \cdots, m$$

Step 9 Selection of critical Construction 4.0 technologies
The most critical Construction 4.0 technologies in enhancing safety and health are farthest from FNIS and closest to FPIS. Thus, the critical Construction 4.0 technologies ranked using $CC_i$ are in descending order as shown in Table 2.

Source: Authors’ own creation
<table>
<thead>
<tr>
<th>Experts</th>
<th>Designation</th>
<th>Years of work experience</th>
<th>Stakeholder background</th>
<th>Educational background</th>
<th>Educational discipline</th>
<th>Fuzzy weight</th>
<th>Aggregated fuzzy weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Civil engineer</td>
<td>5 years</td>
<td>Contractor</td>
<td>Master</td>
<td>Building and construction</td>
<td>VH</td>
<td>(7,9,9)</td>
</tr>
<tr>
<td>2</td>
<td>Civil engineer</td>
<td>21 years</td>
<td>Client</td>
<td>Bachelor</td>
<td>Civil engineering</td>
<td>VH</td>
<td>(7,9,9)</td>
</tr>
<tr>
<td>3</td>
<td>BIM coordinator</td>
<td>7 years</td>
<td>Consultant</td>
<td>Master</td>
<td>Mechanical</td>
<td>H</td>
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</tr>
<tr>
<td>4</td>
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<td>9 years</td>
<td>Contractor</td>
<td>Master</td>
<td>Interior designer</td>
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</tr>
<tr>
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<td>Consultant</td>
<td>PhD</td>
<td>Civil engineering</td>
<td>H</td>
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</tr>
<tr>
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<td>7 years</td>
<td>Academic</td>
<td>PhD</td>
<td>Civil engineering</td>
<td>VH</td>
<td>(7,9,9)</td>
</tr>
<tr>
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<td>Bachelor</td>
<td>Architecture</td>
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<td>(5,7,9)</td>
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<tr>
<td>8</td>
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<td>Client</td>
<td>Diploma</td>
<td>Architecture</td>
<td>H</td>
<td>(5,7,9)</td>
</tr>
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<td>Master</td>
<td>Architecture</td>
<td>VH</td>
<td>(7,9,9)</td>
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<td>Bachelor</td>
<td>Architecture</td>
<td>H</td>
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<tr>
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<td>11 years</td>
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<td>Diploma</td>
<td>Building and construction</td>
<td>M</td>
<td>(3,5,7)</td>
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<tr>
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<td>Architecture</td>
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<td>Bachelor</td>
<td>Land surveying</td>
<td>VH</td>
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</table>

Notes: VH = very high importance; H = high importance; M = medium importance; L = low importance; VL = very low importance
Source: Authors' own creation
### Table A4. Fuzzy weight, aggregated fuzzy weight for alternatives and the combined decision matrix for safety and health

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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>Combined decision</th>
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<td>FI (3,5,7)</td>
<td>I (5,7,9)</td>
<td>VI (7,9,9)</td>
<td>I (5,7,9)</td>
<td>VI (7,9,9)</td>
<td>FI (3,5,7)</td>
<td>FI (3,5,7)</td>
<td>I (5,7,9)</td>
<td>I (5,7,9)</td>
<td>VI (7,9,9)</td>
<td>(1,6,714,9)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>3D scanning and photogrammetry</td>
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<td>FI (3,5,7)</td>
<td>I (5,7,9)</td>
<td>I (5,7,9)</td>
<td>I (5,7,9)</td>
<td>FI (3,5,7)</td>
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<td>I (5,7,9)</td>
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<td>FI (3,5,7)</td>
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<tr>
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<td>I (5,7,9)</td>
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<tr>
<td>AI</td>
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<td>I (5,7,9)</td>
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<tr>
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<td>FI (3,5,7)</td>
<td>FI (3,5,7)</td>
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<td>FI (3,5,7)</td>
<td>FI (3,5,7)</td>
<td>FI (3,5,7)</td>
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<td>(1,5,857,9)</td>
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<tr>
<td>Autonomous construction</td>
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<td>I (5,7,9)</td>
<td>I (5,7,9)</td>
<td>FI (3,5,7)</td>
<td>FI (3,5,7)</td>
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<td>FI (3,5,7)</td>
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<tr>
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<td>I (5,7,9)</td>
<td>I (5,7,9)</td>
<td>FI (3,5,7)</td>
<td>FI (3,5,7)</td>
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<td>FI (3,5,7)</td>
<td>FI (3,5,7)</td>
<td>VI (7,9,9)</td>
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<tr>
<td>Blockchain</td>
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<td>FI (3,5,7)</td>
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<td>VI (7,9,9)</td>
<td>I (5,7,9)</td>
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<td>FI (3,5,7)</td>
<td>FI (3,5,7)</td>
<td>FI (3,5,7)</td>
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<tr>
<td>Prefabrication and modular construction</td>
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<td>FI (3,5,7)</td>
<td>FI (3,5,7)</td>
<td>FI (3,5,7)</td>
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<td>FI (3,5,7)</td>
<td>FI (3,5,7)</td>
</tr>
</tbody>
</table>

**Notes:** VI = very important; I = important; FI = fairly important; LI = less important; NI = not important

**Source:** Authors’ own creation
<table>
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<th>Phase no.</th>
<th>Criteria weight</th>
<th>Ranking for sensitivity analysis</th>
<th>Spearman rank correlation coefficients ($\rho$)</th>
<th>Kendall’s tau coefficient ($\tau$)</th>
<th>RMSE</th>
<th>AAD</th>
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<td></td>
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</tr>
<tr>
<td>S1</td>
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<td>1.00</td>
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<tr>
<td>S5</td>
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<td>IoT</td>
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<td>1.00</td>
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</tr>
</tbody>
</table>

**Note:** RMSE = root mean square error; AAD = average absolute distance

**Source:** Authors’ own creation

---

**Table A5.** Sensitivity analysis and ranking performance validation for Construction 4.0 technologies
### Table A6: Results for correlation analysis

<table>
<thead>
<tr>
<th>Construction 4.0 technologies</th>
<th>Big data and predictive analytics</th>
<th>3D scanning and photogrammetry</th>
<th>Advanced building materials</th>
<th>IoT</th>
<th>3D printing and AM</th>
<th>Cloud and real-time collaboration</th>
<th>Autonomous construction</th>
<th>AR and virtualization</th>
<th>Blockchain</th>
<th>Prefabrication and modular construction</th>
<th>BIM</th>
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</thead>
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</tr>
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</tr>
<tr>
<td>3D printing and AM</td>
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<td>0.411</td>
<td>0.625*</td>
<td>0.400</td>
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<td></td>
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</tr>
<tr>
<td>AI</td>
<td>0.151</td>
<td>0.089</td>
<td>0.745**</td>
<td>0.185</td>
<td>0.548*</td>
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<tr>
<td>Cloud and real-time collaboration</td>
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<td>0.327</td>
<td>0.578*</td>
<td>0.232</td>
<td>0.362</td>
<td>0.527</td>
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<td>Autonomous construction</td>
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<td>0.230</td>
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<td>−0.079</td>
<td>0.650*</td>
<td>0.564*</td>
<td>0.550*</td>
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<td>0.423</td>
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<td>0.305</td>
<td>0.721**</td>
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<td>0.617*</td>
<td>0.387</td>
<td>0.232</td>
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</table>

**Notes:** *Construction 4.0 with a correlation significant at the 0.05 level (two-tailed); **Construction 4.0 with a correlation significant at the 0.01 level (two-tailed)  
Values in italics with asterisks indicate a “strong correlation” between Construction 4.0 technologies

**Source:** Authors’ own creation