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Evaluation of Driver-Induced Human Errors in Smart Construction Tower Crane Operations Based on DEMATEL-ISM-MICMAC

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Abstract

With the advent of Industry 4.0, smart construction sites have seen significant development in China. However, accidents involving digitized tower cranes continue to be a persistent issue. Among the contributing factors, human unsafe behavior stands out as a primary cause for these incidents. This study aims to assess the human reliability of tower crane operations on smart construction sites. To proactively enhance safety measures, the research employs text mining techniques (TF-IDF-Truncated SVD-Complement NB) to identify patterns of human errors among tower crane operators. Building upon the SHEL model, the study categorizes behavioral factors affecting human reliability in the man-machine interface, leading to the establishment of the Performance Shaping Factors (PSFs) system. Furthermore, the research constructs an error impact indicator system for the intelligent construction site tower crane operator interface. Using the DEMATEL method, it analyzes the significance of various factors influencing human errors in tower crane operations. Additionally, the ISM-MICMAC method is applied to unveil the hierarchical relationships and driving-dependent connections among these influencing factors. The findings indicate that personal state, operating procedures, and physical environment directly impact human errors, while personal capability, technological environment, and one fundamental organizational management factor contribute indirectly.

Keywords

Text Mining, DEMATEL-ISM-MICMAC, Performance Shaping Factors, Smart Construction Tower Crane Operator

1. Introduction

The integration of modern information technology in smart construction sites has facilitated a high level of interconnectivity among people, objects, and machinery, incorporating safety principles into the production process. Chen *et al*. [1] emphasize the comprehensive integration of safety concepts, enhancing both safety and productivity goals. Notably, the installation of visual devices on crane hooks in many tower cranes has significantly reduced the probability of accidents such as mis-hooking and collisions [2]. However, the widespread adoption of visual devices in smart construction sites poses challenges, as it demands heightened situational awareness from crane operators [3]. Statistics reveal that between 2016 and 2020, China experienced 605 tower crane accidents, averaging approximately 121 incidents annually [4]. Distracted behavior contributes to 19% of tower crane accidents [5], and the introduction of visual devices on crane hooks may increase the likelihood of operator distraction [6]. Despite advancements in tower crane information and automation, human unsafe behavior emerges as a primary cause of accidents [7]. Unsafe actions by construction personnel not only directly lead to accidents, but can also indirectly trigger incidents by altering the state of objects [8]. The introduction of additional interface management tasks for crane operators increases cognitive and operational loads, elevating the potential for human errors such as mode confusion and loss of situational awareness [9]. As a result, the reliability and safety of human-machine interaction systems for cranes with visual hooks increasingly depend on human factors [10]. Analyzing the causes of accidents in smart tower cranes in a timely manner is crucial for improving safety management and has been a focal point in the construction industry.

Currently, scholarly research on traditional tower cranes has explored human errors, primarily focusing on factors influencing safety incidents. Researchers, using Rasmussen's risk management theory, identified 56 factors related to tower crane safety, illustrating causal paths between system levels and influencing factors [11]. Other scholars employed a framework approach to systematically analyze the causes and influencing factors of crane safety incidents in the Australian construction industry [12]. A fuzzy-set-based risk analysis framework (ERAFF) was developed to provide an overview of key causal factors, key risks, and control measures within the overall framework, enhancing tower crane operation safety [13]. Additionally, some studies treated all causes of tower crane accidents as a system, using network analysis to identify seven key factors and three key paths by calculating statistical indicators such as degree, strength, and shortest paths in the network model [14].

Initially, text mining was employed on 229 accident reports from 2018 to 2023 to categorize human factors affecting crane operators into 28 aspects, including physical fitness, fatigue level, attention level, emotional state, knowledge skills, and operational capabilities, using the SHEL model commonly used in aviation safety. A factor questionnaire survey was conducted, excluding factor S10. Subsequently, for the first time, the Decision-Making Trial and Evaluation Laboratory Interpretive Structural Modeling (DEMATEL-ISM) method was utilized to assess human errors in smart building construction tower cranes. The comprehensive impact matrix of indicators was calculated using the decomposition method through expert surveys, establishing the ISM model and constructing a topological network. The MICMAC model was then employed to reflect relationships between various reasons. This study aims to address gaps in previous research on the causes of accidents involving tower cranes.

2. Tower Crane Human-Machine Interface (HMI) and PSF System Construction

2.1. Text Mining for Tower Crane Accidents

To ensure the credibility, accuracy, and timeliness of data, 229 accident reports from traditional and smart tower cranes between 2018 and 2023 were collected from the website of the State Administration of Work Safety and the Crane Engineer website. Due to issues such as the lack of standardization and consistency in recording tower crane accident reports, data cleaning and processing were necessary. Information unrelated to unsafe behaviors and their causes, such as details about the accident unit, improvement suggestions, and the accident investigation process, were excluded. Only the accident process, causes, and responsibility division were retained, and these were integrated for subsequent text mining.

Firstly, using Python, the tower crane accident text corpus was preprocessed by removing non-Chinese characters, tokenizing, and eliminating stop words to construct a tower crane safety feature dictionary. Given the length and semantic complexity of text, the choice for feature vector extraction is the Term Frequency-Inverse Document Frequency (TF-IDF) mode [15]. The TF-IDF algorithm was then applied to extract keywords from all the tower crane safety texts obtained. Lastly, based on the constructed tower crane safety feature dictionary, feature matching was performed on keywords to obtain the feature attributes of each tower crane safety accident text. Due to the large number of features obtained through TF-IDF (around 600,000 words), according Chandrasekaran *et al.*'s research [16], SVM establishes a boundary to separate categories, minimizing the distance between each category and the boundary. Truncated SVD was employed to reduce the dimensionality of the features to 127. A Complement NB class was used to train a Naive Bayes classifier with the obtained features and target variables for fitting [17]. The model parameters were obtained, and predictions were made, resulting in an accuracy output of 1. This preliminary result suggests that the model exhibits accuracy and generalization on the training set. As there were numerous feature words, a representative subset of 97 feature values with top-weighted ranks was selected. After manually removing irrelevant terms such as "construction" and "safety management", 97 feature values were retained, encoded, and the encoding results are shown in **Table 1**.

2.2. Identification and Survey on Behavior Formation Factors

Based on the SHEL model frequently used in the field of aviation safety [18], the

Table 1. Dimension reduction results of the feature items of the intelligent site tower crane accident investigation report.

Impact factors	Frequency	Impact factors	Frequency	Impact factors	Frequency
Feel unwell	0.1273	Teamwork	0.0202	Cockpit temperature	0.0015
Physical state	0.0079	Teamwork	0.0015	Cockpit humidity	0.0014
Illness	0.0318	Operating specification	0.0099	Illumination	0.0028
Health	0.0015	Operating system	0.0128	Hue	0.0014
Fatigued	0.0012	Rules and regulations	0.0124	Noise	0.0014
Dispersion of attention	0.0012	Reward and punishment system	0.0028	Vibration	0.0012
Distract	0.0020	Management system	0.0076	Crossing condition	0.0014
Inattention	0.0021	Job training	0.0318	Construction site	0.0049
Emotional stability	0.0014	Safety education	0.0341	Site obstacle	0.0330
Testiness	0.0021	Job management	0.0012	Weather	0.0034
Safety awareness	0.0069	Operating procedure	0.0180	Digital interface display	0.0049
Professional skill	0.0861	Technical specification	0.0036	Digital interface information delivery	0.0055
Operational skill	0.0359	Regulation	0.0031	Information transmission	0.0082
Defense	0.0038	Long working hours	0.1220	Safety sign	0.0440
Safety belt	0.0029	The work schedule is not reasonable	0.0012	Display and control page layout	0.0070
Safety helmet hat	0.0015	Cable worker communication	0.0021	Display and control operation mode	0.0015
Safety measure	0.0018	Signalman	0.0096	Display and control device density	0.0073
Protective device	0.0015	Untimely signal	0.0055	Drive-by-wire reliability	0.0144
Working hours	0.0021	Improper command	0.0250	Space comfort	0.0063
Staffing	0.0023	Emergency drill	0.0507	Cockpit seat comfort	0.0011
Distribution of responsibilities	0.0423	Emergency plan	0.0032	Communication equipment	0.0064
Time pressure	0.0091	Preventive measures	0.0061	System intelligence	0.0076
Time shortage	0.0334	Working atmosphere	0.0954	System reliability	0.0070

elements covering the human-machine interface of the intelligent construction site tower crane are divided into four aspects: System Personnel (L), System Software Operating Specifications (S), System Hardware (H), and System Environment (E). The focus of the assessment is to determine the relationships between L-L, L-S, L-H, and L-E. Through text mining, we obtained indicators and expert interviews, resulting in a total of 28 PSFs. These indicators provide valuable information about various aspects of the human-machine interface of the intelligent construction site tower crane and can be utilized for further research and analysis.

1) L-L Relationship: Study on the information exchange and collaborative capacity between the crane operator and the team members.

2) L-H Relationship: Research on the interaction between the crane operator and the hardware operating equipment.

3) L-S Relationship: Investigation of the human-machine relationship between the crane operator and the team management, technical training, and operational standards.

4) L-E Relationship: Examination of the relationship between the crane operator and the operating environment of the driver's cabin.

To establish a human reliability Performance Shaping Factors (PSFs) system for the human-machine interface of smart construction tower cranes, a survey questionnaire was used to investigate the 28 identified behavior formation factors [19]. The questionnaire was distributed to male participants, the participants had an average age of around 40 years. Through the analysis of questionnaire data, the survey provided strong support for constructing the PSFs system. The questionnaire included basic information and an investigation of the PSFs that influence human reliability, using a Likert 5-point scale where 1 represented "minimal impact" and 5 represented "significant impact". A pilot survey was conducted before distributing the formal questionnaire to ensure its validity. A total of 137 questionnaires were collected, with 132 of them considered as valid. A reliability test was conducted to ensure the data's validity. The questionnaire was assessed for its reliability and validity:

a) Using SPSS software, the overall reliability of the questionnaire was found to be 0.982, with reliability coefficients of 0.941 (L-L), 0.895 (L-H), 0.940 (L-S), and 0.937 (L-E) for the four dimensions, indicating good consistency across all dimensions.

b) Content validity, correlation calibration validity, and structural validity of the questionnaire were examined. The KMO (Kaiser-Meyer-Olkin) test value for the questionnaire data was 0.974, and Bartlett's spherical test's approximate chi-square value was 3779.906. The communalities for all research items were above 0.4, indicating that the information from the research items could be effectively extracted. Additionally, the KMO value was 0.963, which is higher than 0.6, indicating effective information extraction from the data. The variance interpretation rates of the four factors were 25.172%, 21.044%, 18.427%, and 11.352%, respectively, with cumulative variance interpretation rates of 68.388%, 70.481%, 72.498%, and 74.265% after rotation, suggesting that the information from the research items could be effectively extracted. Items with scores lower than 0.5 were filtered out through principal component analysis. In this study, S10 (operational standard completeness) did not meet the research conditions and was therefore excluded (**Figure 1**).

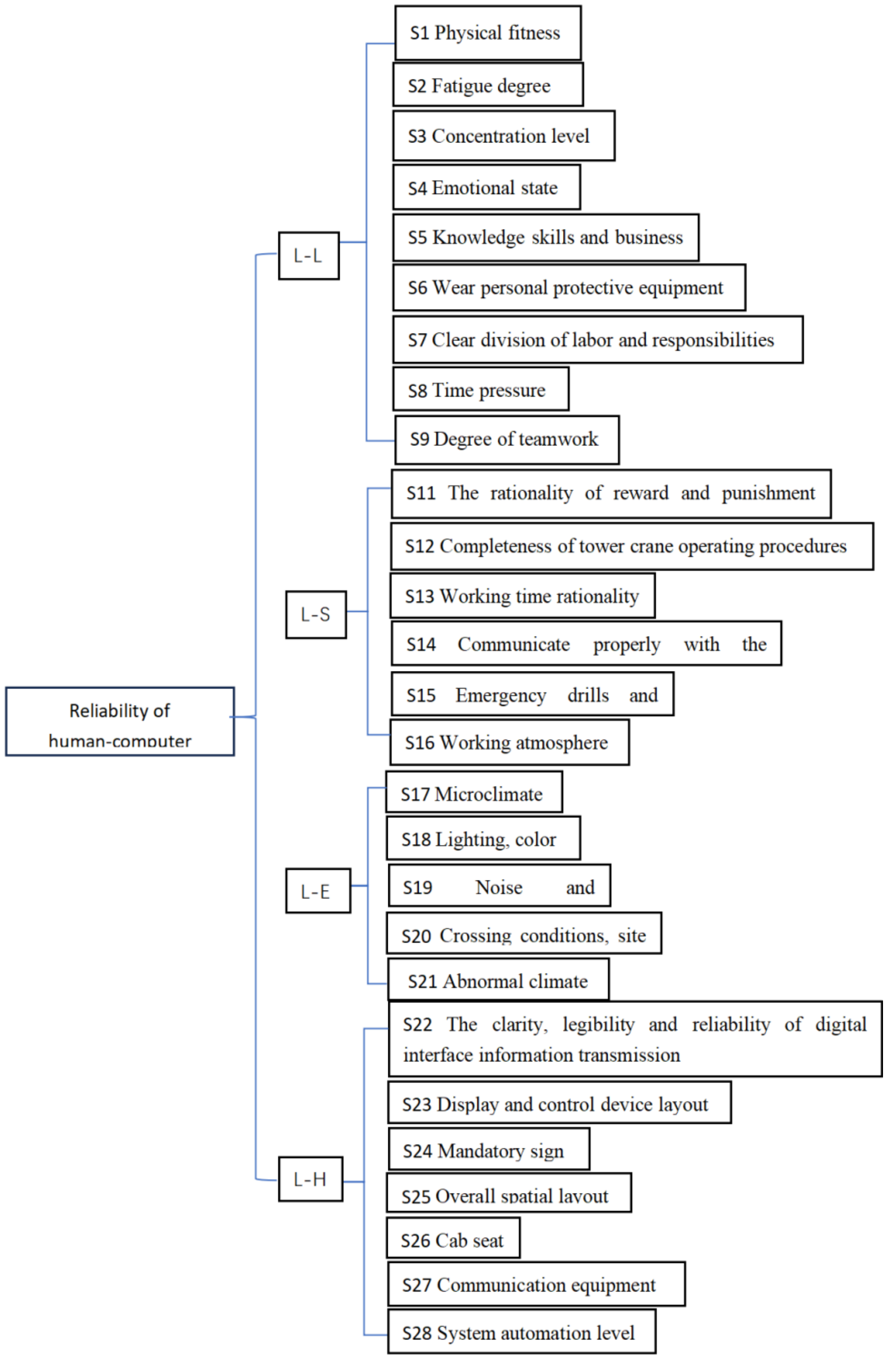


Figure 1. Behavior Formation Factor (PSF) system.

3. DEMATEL-ISM-MICMAC Model

3.1. The DEMATEL-ISM Model

The DEMATEL-ISM model combines expert knowledge and utilizes graph theory and matrix theory to describe the strength of interrelationships between various influencing factors. It calculates indicators such as influence degree, being influenced degree, cause degree, and centrality to identify key elements in complex systems. ISM reflects the intrinsic relationships between influencing factors in a complex system through reachable matrices and constructs a multi-level hierarchical structure model [20].

The specific steps are as follows:

1) Determine the set of influencing factors. Through literature review and analysis of actual accident cases, similar or duplicate factors are merged to ultimately determine the set of influencing factors, $S = \{s_1, s_2, \ldots, s_n\}$.

2) Calculate the initial direct influence matrix, D. Based on expert knowledge and experience, the interrelationships between factors are obtained, resulting in the influence relationship matrix $D = [d_{ij}]_{n\times n}$. The matrix coefficient d_{ij} represents the direct influence of factor a_i on factor a_j.

$$d_{ij} = \begin{cases} 0 \;\; \textit{Factor i has no effect on } j \\ 1 \;\; \textit{Factor i has weak influence on } j \\ 2 \;\; \textit{Factor i has a strong influence on } j \\ 3 \;\; \textit{Factor i has the strongest influence on } j \end{cases} \tag{1}$$

When $i = j$, $d_{ij} = 0$.

3) Normalize the direct influence matrix. Normalization is performed on the direct influence matrix D to obtain the normalized direct influence matrix C, as shown in Equation (2).

$$C = \left[c_{ij}\right]_{n\times n} = \frac{1}{\max\limits_{1\le p\le n} \sum\limits_{q=1}^{n} D_{ij}} D \tag{2}$$

4) Solve the comprehensive influence matrix T to identify the most critical factors, as shown in Equation (3). Here, I represents the identity matrix, indicating the influence of factors on themselves.

$$T = C + C^2 + C^3 + C^4 \cdots C^n = C\left(I - C^{n-1}\right) / I - C = \left[t_{ij}\right]_{n\times n} \tag{3}$$

5) Based on the comprehensive influence matrix T, calculate the impact degree f_i, being influenced degree e_i, centrality z_i, and cause degree y_i of each influencing factor, as shown in Equations (4)-(7).

$$f_i = \sum_{j=1} t_{ij} \left(i = 1, 2, \cdots, n\right) \tag{4}$$

$$e_i = \sum_{j=1}^{n} t_{ji} \left(i = 1, 2, \cdots, n\right) \tag{5}$$

$$z_i = f_i + e_i \left(i = 1, 2, \cdots, n\right) \tag{6}$$

$$y_i = f_i - e_i \left(i = 1, 2, \cdots, n\right) \tag{7}$$

6) Calculate the reachable matrix. By calculating $I + T$, the overall influence matrix is obtained. The reachable matrix in the ISM model is determined, where k_{ij} is calculated as shown in Equation (8). Here, the threshold $\lambda = \alpha + \beta$ (α and β are the mean and standard deviation of elements in matrix T).

$$k_{ij} = \begin{cases} 1 \quad h_{ij} > \lambda \\ 0 \quad h_{ij} \le \lambda \end{cases} \tag{8}$$

7) Hierarchical structure analysis. Based on the reachable matrix K, the reachable set $R(S_i)$ and the antecedent set $A(S_i)$ can be obtained. $R(S_i)$ represents the set of columns in the reachable matrix K where the i-th row factor contains the element 1, while $A(S_i)$ represents the set of rows in the reachable matrix K where the i-th column factor contains the element 1. The hierarchical division of the system is performed according to Equation (9).

$$R(S_i) = R(S_i) \cap A(S_i),\ i = 1, 2, \cdots, n \tag{9}$$

If the discriminant formula holds true, it indicates that the corresponding factor "a" is a bottom-level factor, and the row and column containing this factor are deleted from the reachable matrix K. The remaining factors repeat step 7) until all factors are deleted.

In a given system, factors along with their reachable sets and antecedent sets are outlined in **Table 2**. If the discriminant formula holds true, it indicates that the corresponding factor "a" is a foundational element. In the reachable matrix K, the row and column containing this factor are removed. The remaining factors undergo a repetition of Step 7 until all factors are eliminated. Considering the excessive number of initial indicators, not only does it pose challenges for evaluators, but it also introduces distortions in questionnaire responses, potentially leading to significant issues in subsequent calculations. To mitigate this, a categorization is implemented to reduce errors. L-L relationships can be classified into personal states and personal capabilities. Personal states encompass aspects such as physical fitness, fatigue level, concentration, and emotional state. Personal capabilities include knowledge skills and business acumen, adherence to personal protective equipment, clarity of personnel assignments and responsibilities, and time pressures. L-S relationships are divided into organizational management and safety culture. Organizational management covers team collaboration, completeness of operational procedures, reasonableness of reward and penalty systems, and completeness of tower crane operating procedures. Safety culture encompasses the reasonableness of working hours, effective communication with supervisors, emergency drills and plans, and the overall work atmosphere. L-E relationships and L-H relationships can be respectively categorized as physical environment and technical environment (**Table 3**).

Invitations have been extended to 10 researchers specializing in the field of construction engineering to participate in a questionnaire survey. These researchers, drawing on their own experiences and professional insights, are providing bidirectional ratings for seven influencing factors. Based on the survey results and

Table 2. Reachable set and antecedent set of a certain factor.

Factors	$R(S_i)$	$A(S_i)$	$R(S_i) \cap A(S_i)$	Distinguish
a	{a}	{a,b,c}	{a}	$R(S_i) = R(S_i) \cap A(S_i)$
b	{a,b,c}	{b,c}	{b,c}	$R(S_i) \neq R(S_i) \cap A(S_i)$
c	{a,c}	{b,c}	{c}	$R(S_i) \neq R(S_i) \cap A(S_i)$

expert opinions, a direct impact matrix D is computed. The comprehensive impact matrix is then calculated using Formulas (1) and (2), with detailed data provided in **Table 4** and **Table 5**.

Through Python programming, the impact, affectedness, causality, and centrality of each factor were calculated, and the results are presented in **Table 6**. A causality factor is considered when causality is greater than 0, while a result factor is considered when causality is less than or equal to 0. All causal attributes in this study belong to causality attributes, indicating direct impacts on other

Table 3. System of human error factors in driver interface.

Target layer	Criteria layer	Indicator layer
	L-L	T11 Personal status
		T12 Personal ability
Human error	L-S	T21 Organization and management
		T22 Safety culture
		T23 Operating procedures
	L-E	T3 Physical environment
	L-H	T4 Technical environment

Table 4. Direct influence matrix.

	T11	T12	T21	T22	T23	T3	T4
T11	0	1.5	1.9	2.2	2.4	2.6	1.7
T12	2.3	0	1.9	2.1	2.4	1.6	2
T21	2.4	2.5	0	2.3	1.8	2.1	2.3
T22	2	1.6	2.2	0	1.5	2.3	1.8
T23	2.3	2.2	1.4	1.7	0	2.1	2.4
T3	1.1	1.4	1.9	2.1	2.2	0	1.7
T4	2	1.8	1.7	1.6	2.5	2	0

Table 5. Modified comprehensive influence matrix.

	T11	T12	T21	T22	T23	T3	T4
T11	1.055663	1.075533	1.100771	1.194473	1.268384	1.276701	1.159853
T12	1.215277	0.983644	1.108619	1.197282	1.279076	1.229425	1.186417
T21	1.299244	1.214147	1.059597	1.288935	1.330228	1.340742	1.281043
T22	1.122567	1.022812	1.060257	0.99109	1.150961	1.1927	1.101973
T23	1.19073	1.102499	1.05971	1.152246	1.105842	1.233553	1.185946
T3	0.995949	0.94213	0.970772	1.048161	1.107962	0.963953	1.02199
T4	1.139729	1.049454	1.043702	1.111785	1.225564	1.191473	1.000376

attributes in the original causal relationship matrix. Strong chain reaction effects may exist among the interactions of these attributes, necessitating a comprehensive consideration of their effects to deepen the understanding of the problem's essence and complexity.

Table 7 reveals that the causality factors for human errors, ranked in descending order of causality, are T21 organizational management, T12 personal capability, T11 personal status, T23 operating procedures, T4 technical environment, T22 safety culture, and T3 physical environment. This suggests that organizational management has a higher degree of influence on other factors, implying it may be a crucial factor with significant impact on the overall system or issue. Organizational management likely plays a pivotal role in causing changes in other factors and leading to corresponding changes in the system. Moreover, compared to other factors, inadequate organizational management is more likely to result in human errors. The centrality rankings from **Table 7** indicate that T11 personal status, T4 technical environment, T21 organizational management, T12 personal capability, T3 physical environment, T23 operating procedures, and T22 safety culture have higher centrality, signifying greater importance. Therefore, T11 personal status, T4 technical environment, and T21 organizational management emerge as the primary factors contributing to the occurrence of human errors.

On the basis of the comprehensive impact matrix, the consideration of self-factor influences (added to the identity matrix) is used to establish the overall impact matrix. During the transformation process from the overall impact matrix to the reachable matrix, it is essential to set an appropriate threshold to streamline relationships with lower impact between factors, ensuring a moderate degree of node connectivity. Traditional methods for setting the threshold primarily rely on empirical values obtained through multiple iterations to achieve satisfactory results. Through extensive analysis of multiple threshold values, it is observed that a threshold value (λ) of 0.18 results in a more suitable node connectivity, facilitating the delineation of the hierarchical structure of factors. Therefore, in this study, a threshold value of 0.18 is selected based on the results of the overall impact matrix and Equation (8), yielding the reachable matrix for forming factors, as shown in

Table 6. DEMATEL analysis results for driver interface human error factors.

Influence factor	Influence degree	Affected degree	Causality degree	Factor attribute	Centrality	Centrality ranking
T11	12.1	12.3	21.61286	Cause factor	33.71	5
T12	11	12.3	21.61286	Cause factor	32.61	4
T21	11	13.4	25.65143	Cause factor	36.65	7
T22	12	11.4	18.56571	Cause factor	30.57	2
T23	12.8	12.1	20.91571	Cause factor	33.72	6
T3	12.7	10.4	15.45143	Cause factor	28.15	1
T4	11.9	11.6	19.22286	Cause factor	31.12	3

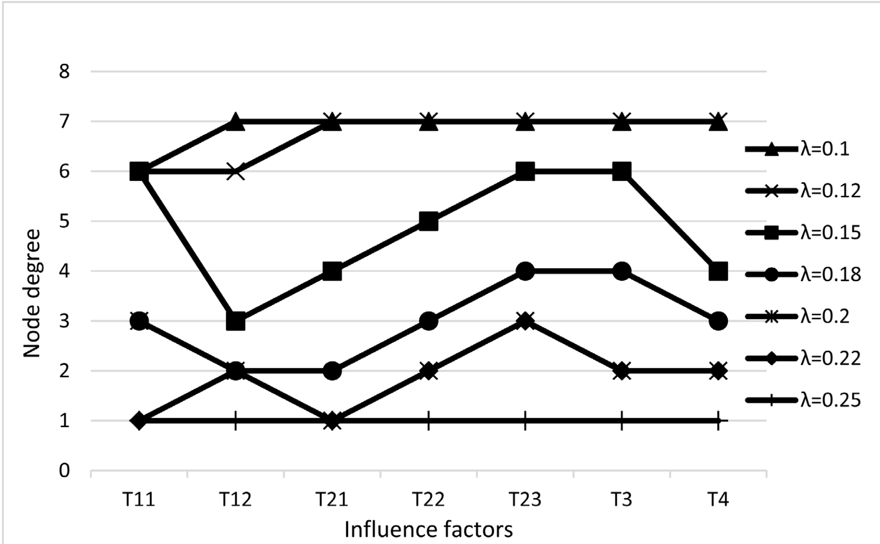


Figure 2. Node degree-influencing factor diagram for driver interface-related human errors at different thresholds.

Table 7. Reachable matrix K of the influencing factors for driver interface-related human errors.

Factors	T11	T12	T21	T22	T23	T3	T4
T11	1	0	0	0	1	1	0
T12	1	1	0	1	1	0	0
T21	1	1	1	1	0	1	1
T22	0	0	1	1	0	1	0
T23	0	0	0	0	1	0	1
T3	0	0	0	0	0	1	0
T4	0	0	0	0	1	0	1

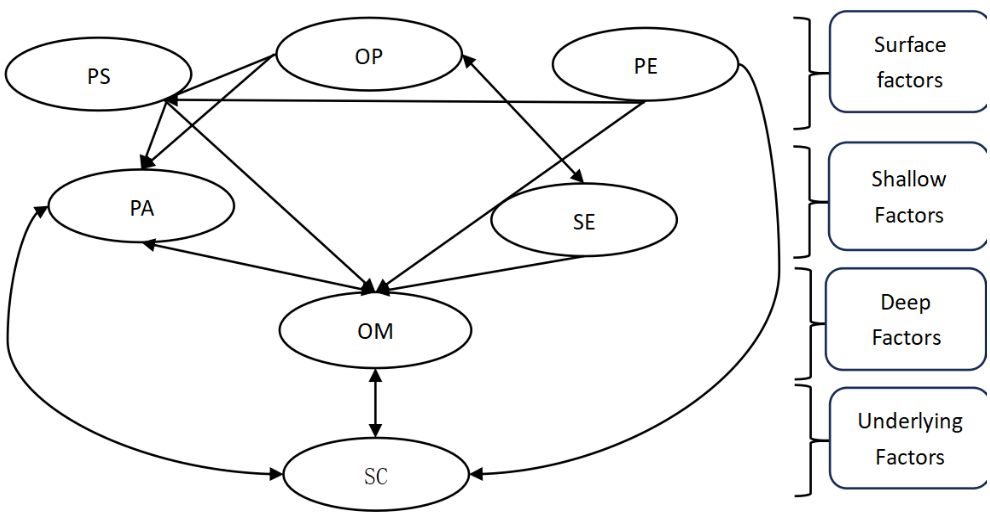
Table 7.

Due to the presence of cycles in the reachable matrix, a Depth-First Search (DFS) algorithm is chosen to traverse the graph. DFS efficiently explores each connected component of the graph [21]. While this method is an approximate approach and does not guarantee optimal layering results, it proves effective in approximating layers in graphs with cycles. The hierarchical structure of factors influencing human errors among intelligent construction site tower crane operators can be divided into four levels, revealing a complex network of interrelated factors. Surface-level factors, such as individual state, operating procedures, and physical environment, directly impact the occurrence of human errors in tower crane operators. It is crucial to ensure the safety and stability of these surface-level factors by addressing potential hazards and ultimately safeguarding the well-being of crane operators. Key nodes in the occurrence of human errors in intelligent construction site tower crane operators include two shallow-level factors, personal capabilities, technical environment, and one deep-level factor, organizational management. These factors play a vital role in the transmission of interactions between various elements, necessitating close attention and reasonable control to create a positive influence on surface-level factors and gradually improve issues related to human errors among crane operators. Deep-level factor organizational management possesses both sudden and widespread characteristics, capable of rapidly exerting profound impacts on tower crane operators at intelligent construction sites. Consequently, preventive and emergency measures are essential to mitigate uncontrollable situations. Safety culture, as a foundational factor, fundamentally influences human errors among intelligent construction site tower crane operators. Strengthening the development of this factor plays a decisive role in ensuring the safety of crane operators.

3.2. Analysis of Causal Attribute Features Based on MICMAC

MICMAC is a quantitative method that uses matrix multiplication principles to reflect the interaction relationships among causal factors. Its core idea is to calculate the driving force values and dependency values between various factors through the reachable matrix Z [22]. Based on the driving force and dependency values, risk factors are categorized into four types: autonomous, dependent, associated, and independent elements, to clarify the attribute characteristics of different hierarchical causes, as shown in **Figure 2**.

From **Figure 3**, it can be observed that the seven factors mentioned above are all associated factors. From **Figure 4**, these factors, including personal status, personal abilities, organizational management, safety culture, operating procedures, physical environment, and technical environment, possess relatively high driving force values and dependency values, belonging to indirect factors. These



Note: PS represents Personal Status, OP represents Operating Procedures, PE represents Physical Environment, PA represents Personal Ability, SE represents Skill Environment, OM represents Organizational Management, and SC represents Safety Culture.

Figure 3. Multi-level and hierarchical model of influencing factors of human error related to driver interface.

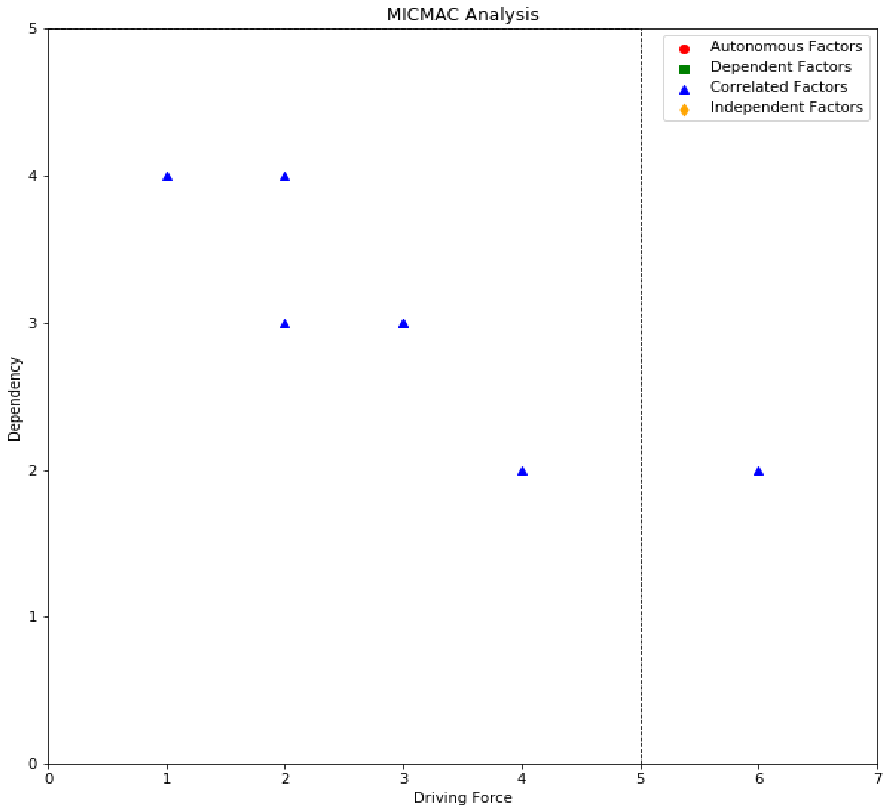


Figure 4. Analysis of causal attribute features based on MICMAC.

factors' states are highly susceptible to change, exhibiting poor stability and being difficult to control. As all factors are associated factors, this implies that each factor is to some extent related to others. In this scenario, there exist interactions and dependency relationships among risk factors. Therefore, compared to other situations, this condition signifies comprehensive risk, whereby the alteration or occurrence of problems in a single factor may trigger a chain reaction affecting the entire system. Complexity adds to the challenge of understanding and managing risks, as changes or risks in the system may propagate through multiple pathways and influences. Interdependence indicates that the dependency relationship between correlated factors may suggest that some factors require support or interaction from other factors to exert their impact. Systemic risk implies that if all factors are interrelated, it may reflect the risk level of the entire system or domain. In such cases, comprehensive risk management methods are needed, considering the system as a whole rather than just the risk of individual factors. In summary, when all factors are associated factors, it indicates that the risk exists not only in the individual factors themselves but also involves interactions and dependency relationships within the entire system or domain. Based on the above analysis, controlling human unsafe behaviors is relatively complex. Human unsafe behavior is a high-incidence factor leading to human errors in tower crane drivers on smart construction sites, consistent with previous research results and preliminary case statistics.

4. Research Conclusions

The factors influencing human error behaviors in tower crane operations at smart construction sites are affected by various factors such as personal status, personal abilities, organizational management, safety culture, operating procedures, physical environment, and technical environment. It is a complex system involving multiple factors such as human-machine-environment. The main research conclusions are as follows:

Organizational management has a relatively high degree of influence on other factors. This indicates that this factor may be a key factor, exerting significant influence on the overall system or issues. This factor may play a crucial role in causing changes in other factors, leading to corresponding changes in the system. Compared to other factors, inadequate organizational management is more likely to lead to human errors. Physical environment has the smallest degree of causality and is the most sensitive, also most susceptible to the influence of other factors, and should be emphasized in the management of tower cranes at smart construction sites.

The ISM multilayer hierarchical structure model divides the influencing factor system of human error behaviors in tower crane operations at smart construction sites into four levels, demonstrating inherent relationships. In the surface factors, personal status, operating procedures, and physical environment directly affect the probability of human errors in tower crane operators. Efforts must be made to maintain the safety stability of these factors to ensure driver safety, addressing potential hazards in surface factors first to safeguard driver safety. In critical nodes, personal abilities, technical environment, and organizational management, two surface factors and one deep factor play a crucial role in the transmission process of various factors' interactions. Close attention and reasonable control of these factors form a benign effect on surface factors, gradually improving the problem of human error in tower crane operators at smart construction sites. Organizational management in deep factors has the characteristics of suddenness and universality, and can rapidly generate profound impacts. Therefore, it is necessary to take preventive and emergency measures to reduce its uncontrollable conditions. All seven factors are interconnected and have relatively high driving force values and dependency values, belonging to indirect factors. The states of these factors change frequently, exhibiting poor stability and being difficult to control. Because all factors are interrelated, this means that each factor is to some extent correlated with other factors. In this case, there are interactions and dependency relationships among various risk factors, increasing the comprehensive risk of the entire system being affected.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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