Asian Journal of Water, Environment and Pollution, Vol. 21, No. 6 (2024), pp. 213-219.
DOI 10.3233/AJW240089

Role of Artificial Intelligence in Modernisation of Fire Risk Management

Rajesh Kumar, Amarjeet Kaur and Hamendra Dangi[1]*
Centre of Excellence in Disaster Management, GGS IP University, Delhi, India
[1]Department of Commerce, University of Delhi, Delhi, India
✉ hkdangi@commerce.du.ac.in

Received June 25, 2024; revised and accepted July 5, 2024

Abstract: Fire in the form of wildfire, indoor fire, and bombardment, regardless of their natural or manmade origin, impacts substantially the economic as well as environmental hazards such as Air Pollution. This research aims to identify the role of artificial intelligence (AI) in modernising fire risk management. Using interpretive structural modeling (ISM) techniques, we can understand the interdependencies and hierarchical relationships within this context. AI enables the analysis of vast amounts of data from various sources, including historical fire incidents, weather patterns, building structures, and human behaviour, to assess and predict fire risks more accurately. ISM is a computational technique that uses a qualitative and interpretive approach to address intricate issues by mapping the relationships between variables and converting them into a multilevel structural model. Interpretive Structural Modeling (ISM) is a mathematical and qualitative tool used to identify key variables and create a hierarchical model that illustrates their interrelationships. Seven variables have been identified based on literature and expert input. Variables have been classified based on their influence and reliance.

Key words: Air pollution, environmental hazard, artificial intelligence, modernisation, fire safety, fire risk management, ISM, AI in disaster management, AI in fire and safety and AI-enabled safety procedures.

Introduction

The modernisation of fire safety management is undergoing a transformative paradigm shift with the integration of artificial intelligence (AI). In the realm of fire safety, AI is not merely a technological advancement but a revolutionary force that leverages computational capabilities to enhance prevention, detection, response, and recovery from fire incidents. AI brings forth a spectrum of intelligent solutions that redefine traditional approaches to fire safety, offering a more proactive, efficient, and adaptive framework.

Fire and safety refer to the practices, procedures, and equipment used to prevent, detect, and respond to fire-related emergencies and other safety hazards. Fire safety involves the design, installation, and maintenance of fire protection systems and equipment, such as fire alarms, sprinkler systems, and fire extinguishers, to minimise the risk of fires and mitigate their impact if they occur. Safety measures may also include practices to prevent slips, trips, and falls, electrical safety, chemical safety, and other forms of workplace safety. Fire and safety procedures are essential to ensuring the safety of people and property, and local and federal government organisations frequently regulate them.

Artificial intelligence (Bazargan, S. et al., 2022) has the potential to revolutionise the field of fire and safety by offering new ways to prevent, detect, and respond to fire-related emergencies and safety hazards. AI systems can process extensive data from sensors, cameras, and gadgets to detect fire threats or

*Corresponding Author

safety issues, like malfunctioning electrical equipment, obstructed emergency exits, or dangerous substances. AI algorithms can also be used to detect fires in their early stages and trigger an immediate response, such as sounding an alarm or activating a sprinkler system. Additionally, AI can help manage and optimise building management systems, such as heating and cooling, lighting, and security systems, to ensure optimal fire safety and energy efficiency. Firefighters and emergency responders can learn how to respond to complex situations and practice making decisions under pressure using training simulations powered by AI.

Moreover, drones equipped with AI-powered sensors and cameras can be used to conduct inspections of buildings, infrastructure, and other areas to detect fire hazards or safety risks in hard-to-reach areas. The integration of AI in fire and safety can help improve safety and prevent accidents by enabling faster and more accurate detection of potential hazards, improving emergency response times, and facilitating more effective training for emergency responders and reducing air pollution (Al-Taai et al., 2022). AI is also essential to the creation of sophisticated fire detection systems. These systems can distinguish between real threats and false alerts thanks to machine learning algorithms, which speed up response times and minimise unneeded disturbances. With the use of AI-powered sensors, real-time monitoring guarantees the prompt and precise detection of fire outbreaks, enabling more focussed and efficient emergency responses. By optimising escape routes based on real-time data, including the location and intensity of the fire as well as the building's current occupancy, artificial intelligence (AI) helps in evacuation management in the case of a fire. This improves occupant safety while also making it easier for emergency responders to learn about the property.

In this paper, to capture real-world scenarios, the ISM technique is used to structure complex issues systematically and comprehensively. ISM is used to identify and summarise relationships among specific variables and in this study, all the variables are captured in real-world fire scenarios with the help of Fire Safety Experts. The rest of the paper is structured as follows: sections Literature review provides the in-depth description of the literature review of AI-based Fire Risk Management and Detection, which is followed by section Methodology and Finding and analysis including methodology and results. Finally, Conclusion section concludes the work.

Literature Review

Qian et al. (2023) said that the multi-level structural model is built using practical experience and knowledge, breaking down complex systems into subsystems. Variables are identified and evaluated using fuzzy Delphi and taxonomy models.

Siraj et al. (2023) discovered that the textile manufacturing sector is confronted with a substantial fire hazard, leading to property damage, loss of life, and business interruption. This study suggests a comprehensive framework for making decisions based on several factors to recognise and address these dangers.

Xu et al. (2023) aim to analyse the role and effectiveness of artificial intelligence technology in managing fire-fighting facilities. It focuses on the current situation and existing problems in fire-fighting facilities maintenance.

Hodges et al. (2022) say that artificial intelligence (AI) is a field that enables computer systems to interpret data, making decisions that traditionally require human insight. In fire suppression operations, AI can help identify hazards, determine effective methods, and determine if interior rescue operations are necessary.

Sun et al. (2022) found that AI is increasingly being used in disaster management to enhance efficiency and decision-making. It is being applied in the mitigation, preparedness, response, and recovery phases.

Guan et al. (2022) identifies safety risks in coastal towns transitioning from rural to urban areas using ISM methods. The Triangular Framework for Safety Risk in New Towns identifies 16 disaster-causing factors, with typhoons, public risk perception, and population migration as key influencing factors. High-rise buildings, port facilities, and transportation have the most direct impact, while environmental degradation is the most conducive.

Zhang et al. (2022) introduced a new framework called Artificial Intelligence Digital Fire (AID-Fire) that is capable of identifying intricate building fire data instantly. The intelligent system comprises the Internet of Things sensor network for data collection and transfer, a cloud server for data storage and administration, an AI engine for data processing, and a user interface for information display. The results indicate that the AI engine successfully recognised fire-related information by analysing the spatial and temporal characteristics of the temperature data with an error rate below 15% and a latency time under one second. Furthermore, the digital twin interface can precisely illustrate the progression and dissemination of a fire.

Maraveas et al. (2021) said that artificial intelligence (AI) has the potential to revolutionise fire safety in agricultural structures, offering economic and technological benefits. AI can improve smoke movement analysis, risk assessment, and postfire analysis and can be combined with next-generation fire-retardant materials.

Wang & Wang et al. (2021) found the transformative impact of AI-enabled technology in revolutionising fire risk management. By harnessing the power of AI to analyse data, predict fire behaviour, and optimise response strategies, we can enhance our ability to prevent, detect, and mitigate wildfires, ultimately saving lives, protecting property, and preserving natural ecosystems.

According to Wu et al. (2021), artificial intelligence is utilised to forecast fire progression in tunnels, allowing for instantaneous forecasts within 1 second. The model utilises a Long Short-term Memory (LSTM) model and a Transpose Convolution Neural Network (TCNN) to detect crucial temperature areas for safe evacuation and direct emergency actions.

Bullock et al. (2019) studied that artificial intelligence (AI) plays a crucial role in shaping human discretion and decision-making within bureaucracies. Its advancements can enhance the quality of administration. However, the role of AI in bureaucracy is complex and uncertain, with task distribution and characteristics playing a significant role.

Krzemień et al. (2019) state that the temperature of syngas is very responsive to variations in the composition and quantity of the gasifying agent. This allows for adjusting the temperature to lower levels when necessary while maintaining it as high as feasible within safe limits, given that underground coal gasification (UCG) is an extremely exothermic process.

Park et al. (2019) developed a fire detection system that uses a versatile artificial intelligence framework and a technique to minimise data transfer delays in smart cities. The system utilises various machine-learning techniques along with an adaptive fuzzy algorithm. Additionally, it incorporates Direct-MQTT based on SDN to address issues related to traffic concentration.

Kim & Sohn et al. (2018) investigate the application of ISM to enhance fire safety management. ISM is a computational technique that employs structural mapping to address intricate issues. The study introduces a seven-level hierarchy for different prequalification criteria, categorised into four clusters according to their influence and reliance strengths.

ISM is being used in the analysis of various practical solutions in fire management. Feng et al. (2022) conducted an Analysis of Bus Fires Using Interpretative Structural Modeling where they identified 17 risk factors associated with bus fires through an analysis of accident records from China using the Delphi approach. Renganath et al. (2016) conducted an analysis of the drivers for safety practices using interpretive structural modeling. The authors make use of interpretive structural modeling whose output elucidates two important components namely, driving power and dependence power. In this paper, ISM is used for Fire Risk Management analysis and previously also it was being used to analyse the environmental impacts of a coal Field by Vijyakumar et al. (1989).

Methodology

The ISM methodology relies on graph theory. ISM has been utilised for variable or factor analysis across multiple disciplines. ISM aims to create a hierarchical relational structure model that relies on intricate elemental connections. Analysing the relational structure model with experts' professional expertise to explain contextual relationships between items results in the creation of a directed graph. ISM examines the connections between particular factors related to an issue, subject, system, or field of research in a meticulously crafted layout that incorporates graphs and text. A structural self-interaction matrix (SSIM) is generated from a pairwise comparison of the variables and then converted into a reachability matrix to verify its transitivity. Upon completion of the transitivity embedding, a matrix model is generated. In this study, temporal data is considered which will be further upgraded to other types of data such as Longitudinal data. The study conducted in this paper helps in understanding the impact of AI in Fire Risk Management which is applicable to the broader context of all types of Fires such as City Fire, Forest Fire, Tunnel Fire, House Fire, etc.

Below are the steps of the ISM approach.

1. Identifying components, elements, barriers, or variables
2. Establishing pairwise correlations among obstacles or variables.
3. Creating a structural self-interactional matrix (SSIM) to

4. Creating a reachability matrix from SSIM involves transforming relationship symbols into binary values of 1 and 0.
5. Partitioning the reachability matrix into several tiers.
6. Creating a relationship graph or directed graph using information from SSIM and reachability matrices.
7. Converting the digraph into an ISM-based hierarchical model.
8. Reviewing the ISM-based model to identify and address any conceptual inconsistencies, if necessary.

Finding and Analysis

Structural Self-Interaction Matrix (SSIM)

A group of Fire Safety experts and academics were consulted in identifying the nature of contextual relationships among the variables. Once the variables have been identified, they should be input into the structural self-interaction matrix (SSIM). This matrix displays the variables with their dimensions, listed in the first row and column, respectively. The pairwise relationships between the variables are defined using symbols. The structural self-interaction matrix is created by comparing the dimensions and indices of the study using four forms of conceptual relations. Process-oriented experts and specialists fill this matrix, and the resulting information is summarised using the interpretive structural modelling method. The states and symbols employed in this conceptual relationship are as shown in Table 1.

V: The column factor (j) can be reached using the row factor (i) as a starting point (a one-way connection from i to j). A: The row factor (i) can be reached using the column factor (j) as a starting point (a one-way connection from j to i). X: The row factor (i) and the column factor (j) are related in both directions. Stated differently, both can serve as a means of communication (a two-way connection from i to j and vice versa). O: Two variables (i, j) don’t relate to each other.

Interpretive structural modeling (ISM) relies on modes in frequencies and non-parametric approaches for its logic. First, a 7 × 7 matrix was created with carefully chosen factors arranged in its rows and columns. The respondent was then asked to identify the kind of two-by-two relationships between the factors based on the introduced symbols (V, A, X, and O). As stated otherwise, the experts evaluate the criteria in pairs using this matrix and then adjust their responses to the pairwise comparisons accordingly.

Reachability Matrix (RM)

The SSIM is transformed into a reachability matrix by substituting the symbols V, A, X, and O with binary values 1 and 0. This conversion to 1s and 0s is based on the following criteria as shown in Table 2:

- When the cell (i,j) in SSIM is assigned the value “V,” the corresponding item in the reachability matrix at (i,j) changes to “1” and the entry at (j,i) changes to “0”.
- When “A” is assigned to cell (i,j) in SSIM, the entry in the reachability matrix at (i,j) changes to “0” and the entry at (j,i) changes to “1”.
- When “X” is assigned to cell (i,j) in SSIM, the corresponding entry in the reachability matrix at (i,j) changes to “1” and the entry at (j,i) likewise becomes “1”.
- When the cell (i,j) in SSIM is assigned the value “O,” the corresponding entries in the reachability matrix at (i,j) and (j,i) are both changed to “0”.

Final Reachability Matrix (FRM)

The final access matrix is derived by assessing the transferability of relationships between the variables after obtaining the initial access matrix. The matrix is square, with entries of one indicating access between elements of any length and zero otherwise. To obtain the access matrix, use Euler’s theory by adding the adjacency matrix to the unit matrix as shown in Table 4.

Level Partitioning (LP)

A reachability matrix partition is produced by iteratively assessing each variable’s reachability and previous sets. Included in the reachability set are the reachable variables. Together with the other elements that would help them be fulfilled, the variable is part of the antecedent set. All the variables are used to build the intersection of these sets. If the variable has the same gravitational pull toward the intersection set and the reachability set, it might be classified at the top of the ISM hierarchy. The others above their level cannot be ascertained using the variable. Using the same procedure, the next-level variable was found.

Micmac Chart

Process-oriented indices can be constructed using the penetration power of each index on other indices, and there are four levels of reliance that can be distinguished between: autonomous, dependent, linked (interface), and independent. Autonomous: The degree of dependence and direction power of autonomous variables is low. Because of their shaky relationships with the system, these criteria are typically kept apart from it. Changes to these factors have no significant systemic impact. Dependent: Dependent variables exhibit weak direction dependency and strong reliance. In general, these variables have a low effect on the system and high affectability. Independent: independent variables are high-affecting and have low affectability, or they have low dependence and high direction. Linked: Link or interface variables are highly dependent on one another and have strong directional power. This means that they have a high degree of affectivity and affectability, and even a slight variation in them can have a significant impact on the system.

It is observed that variable 2 has a driving power of 6 and a dependence power of 2 (Table 3) and therefore, it is positioned at a place that corresponds to a driving power of 6 and a dependence power of 2 as shown in Figure 1. The intention behind the classification of variable is to analyse the driving power and dependence power of the variable. In this classification of barriers, the first cluster is of autonomous variable that has a weak driving power and weak dependence power. Autonomous variables are relatively disconnected from the system. In the present case, there are no autonomous variables. The second cluster consists of dependent variables that have weak driving power and strong

Table 1: Structural self-interaction matrix (SSIM)

Structural Self-Interaction Matrix (SSIM)								
No.	*Variables*	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1	Perceived ease of use		V	O	O	O	O	O
2	Usefullness of AI enabled technology			V	V	V	V	V
3	User acceptance				V	V	V	V
4	Human efficiency					O	O	O
5	Safety procedures						O	O
6	Reducing effects of fire based calamities							O
7	Reducing risks from human avoidance							

Table 2: Reachability Matrix (RM)

Reachability Matrix (RM)									
No.	*Variables*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Driving Power*
1	Perceived ease of use	1	1	0	0	0	0	0	2
2	Usefullness of AI enabled technology	0	1	1	1	1	1	1	6
3	User acceptance	0	0	1	1	1	1	1	5
4	Human efficiency	0	0	0	1	0	0	0	1
5	Safety procedures	0	0	0	0	1	0	0	1
6	Reducing effects of fire based calamities	0	0	0	0	0	1	0	1
7	Reducing risks from human avoidance	0	0	0	0	0	0	1	1
	Dependence Power	1	2	2	3	3	3	3	

Table 3: Final Reachability Matrix (FRM)

Final Reachability Matrix (FRM)									
No.	*Variables*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Driving Power*
1	Perceived ease of use	1	1	1*	1*	1*	1*	1*	7
2	Usefullness of AI enabled technology	0	1	1	1	1	1	1	6
3	User acceptance	0	0	1	1	1	1	1	5
4	Human efficiency	0	0	0	1	0	0	0	1
5	Safety procedures	0	0	0	0	1	0	0	1
6	Reducing effects of fire based calamities	0	0	0	0	0	1	0	1
7	Reducing risks from human avoidance	0	0	0	0	0	0	1	1
	Dependence Power	1	2	3	4	4	4	4	

Table 4: Displays the variables, their levels, intersection set, antecedent set, and reachability set

Level Partitioning (LP)				
Variables	*Reachability Set R(Mi)*	*Antecedent Set A(Ni)*	*Intersection Set R(Mi)∩A(Ni)*	*Level*
1	1,	1,	1,	4
2	2,	1, 2,	2,	3
3	3,	1, 2, 3,	3,	2
4	4,	1, 2, 3, 4,	4,	1
5	5,	1, 2, 3, 5,	5,	1
6	6,	1, 2, 3, 6,	6,	1
7	7,	1, 2, 3, 7,	7,	1

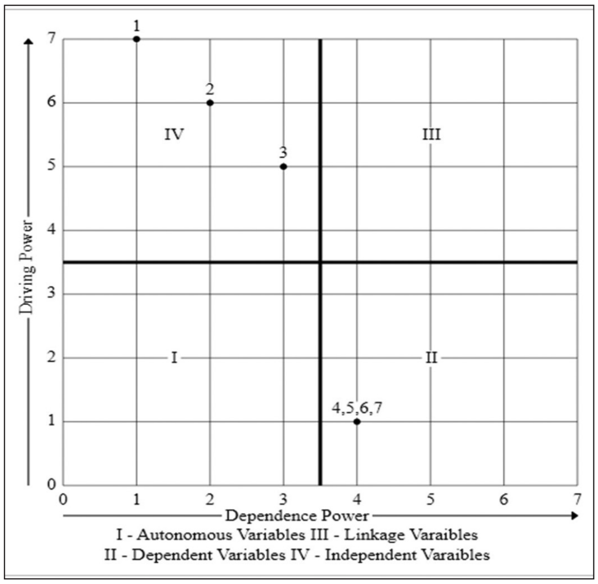

Figure 1: Micmac Chart.

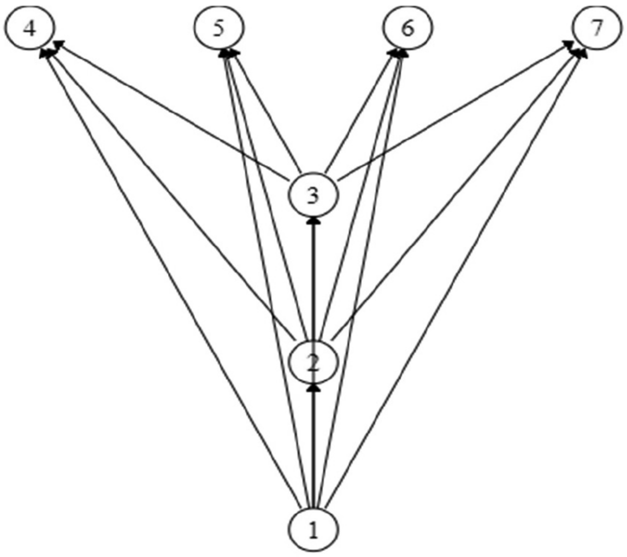

Figure 2: ISM digraph.

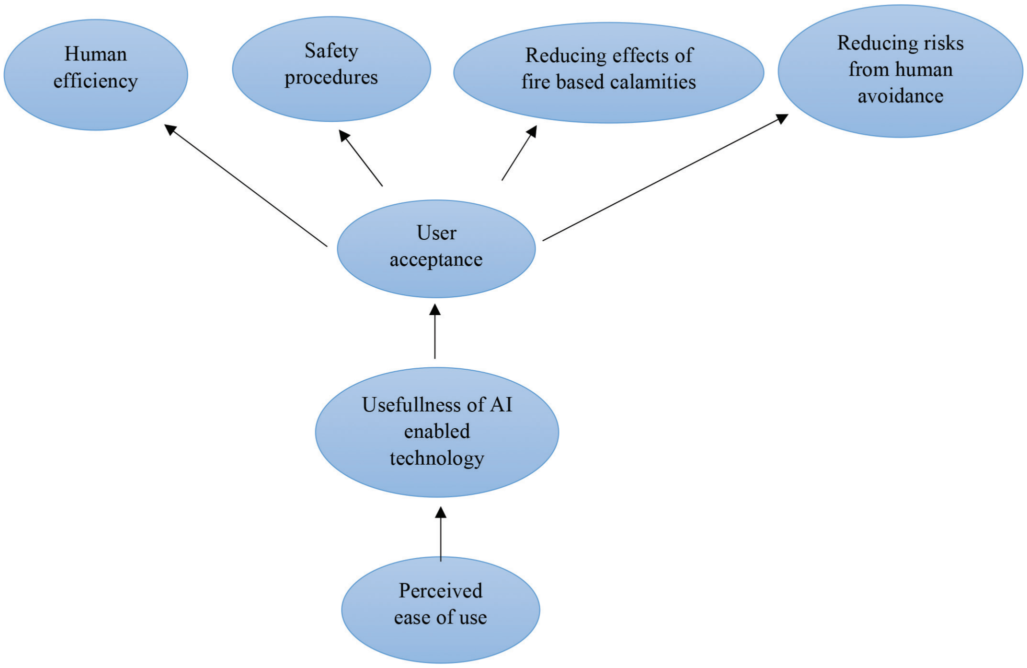

Figure 3: ISM (Interpretive Structural Modelling) Model.

dependence power. In the present case, variables 4,5,6,7 are in the category of dependent variable. The third cluster consists of linkage variables that have strong driving and dependence power. Any action on these variables will influence the other variables and also have a feedback effect on themselves. In this case, there are no linkage variables. The fourth cluster includes independent variables that have strong driving power and weak dependence power. In this case, barriers 1, 2, 3, and 4 are in the category of independent variables.

Digraph

The structural model is generated from the initial reachability matrix and if there is a relationship between the variables i and j, this is presented by an arrow that points from i to j. This graph is called an initial directed graph, or initial digraph as shown in Figure 2. The outcome of the research has been presented in the form of Figure 3.

Conclusion

Interpretive Structural Modeling (ISM) research suggests that artificial intelligence (AI) plays a critical role in updating fire risk management. AI tools that predict, analyse, and manage fire risks more successfully include real-time monitoring, cost-effectiveness of AI implementation, regulatory compliance, and timeliness. It is observed from the results that variables 1 (Perceived ease of use), 2 (Usefullness of AI enabled technology), and 3 (User acceptance) have high driving power and less dependence power. Therefore, these variables can be treated as key variables in Fire Risk Management. As demonstrated by ISM, AI facilitates real-time data analysis, early hazard detection, and optimal resource allocation, all of which enhance fire risk management. In addition, AI-powered systems can improve emergency response plans, enhance general safety precautions, and lessen the effects of fire events. So, utilising AI in fire risk management is a big step toward improving safety procedures and shielding people and property from the destructive impacts of flames.

References

Al-Taai, S.H.H. and W.A.M. al-Dulaimi (2022). Air pollution: A study of its concept, causes, sources and effects. *Asian Journal of Water, Environment and Pollution*, **19:** 17-22.

Bazargan, S. et al. (2022). Analysis of the performance of cutting tools of tunnel boring machine (TBM) in silty-sand soils using artificial neural network (ANN) – Case Study: Tabriz Metro Line 2 Project. *Asian Journal of Water, Environment and Pollution*, **19:** 71-78.

Bullock, J.B. (2019). Artificial intelligence, discretion, and bureaucracy. *The American Review of Public Administration*, **49:** 751-761.

Feng, S., Zhenning Li, Z. and X. Sun (2016). Analysis of bus fires using interpretative structural modelling. *Journal of Public Transportation*, **19:** 1-18.

Guan, C. et al. (2022). Hierarchical structure model of safety risk factors in new coastal towns: a systematic analysis using the DEMATEL-ISM-SNA method. *International Journal of Environmental Research and Public Health*, **19:** 10496.

Hodges, J.L., Lattimer, B.Y. and V.L. Champlin (2022). The Role of Artificial Intelligence in Firefighting. *In:* Handbook of Cognitive and Autonomous Systems for Fire Resilient Infrastructures. Cham: Springer International Publishing, pp. 177-203.

Kim, Y.-K. et al. (2018). Disaster theory. *In:* Disaster risk management in the Republic of Korea, pp: 23-76.

Knyziak, P., Kowalski, R. and J.R. Krentowski (2019). Fire damage of RC slab structure of a shopping center. *Engineering Failure Analysis*, **97:** 53-60.

Maraveas, Chrysanthos et al. (2021). Applications of artificial intelligence in fire safety of agricultural structures. *Applied Sciences*, **11:** 7716.

Park, J.H. et al. (2019). Dependable fire detection system with multifunctional artificial intelligence framework. *Sensors*, **19:** 2025.

Qian, Y. and H. Wang (2023). Vulnerability assessment for port logistics system based on DEMATEL-ISM-BWM. *Systems*, **11:** 567

Renganath, K. and M. Suresh (2016). Analyzing the drivers for safety practices using interpretive structural modeling: A case of Indian manufacturing firms. *In:* 2016 IEEE international conference on computational intelligence and computing research (ICCIC). IEEE.

Siraj, Md Tanvir, et al. (2023). Analysis of the fire risks and mitigation approaches in the apparel manufacturing industry: Implications toward operational safety and sustainability. *Heliyon*, **9: 9.**

Sun, W., Bocchini, P. and B.D. Davison (2020). Applications of artificial intelligence for disaster management. *Natural Hazards*, **103:** 2631-2689.

Wang, B. and Y. Wang (2021). Big data in safety management: An overview. *Safety Science*, **143:** 105414.

Wu, Xiqiang et al. (2022). A real-time forecast of tunnel fire based on numerical database and artificial intelligence. *Building Simulation*, **15:** 511-524.

Xu, W., Chan, S.C. and W.Y. Leong (2023). Effectiveness study of artificial intelligent facility system in maintaining building fire safety (case study: typical public building cases of fire-fighting facilities management in China). *Discrete Dynamics in Nature and Society*, **2023:** 2592322.

Zhang, Shuo et al. (2022). Design of intelligent fire-fighting robot based on multi-sensor fusion and experimental study on fire scene patrol. *Robotics and Autonomous Systems*, **154:** 104122.