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A Holistic Approach to Exploring the Root Factors of Work Zone Accidents

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Abstract: Work zones are crucial for infrastructure maintenance and improvement. However, ongoing projects within work zones sometimes can place workers and drivers in dangerous situations. Despite safety regulations, work zone accidents persist with notable severity and frequency. Previous research has explored work zone accident causation, but it has not provided a comprehensive understanding of the factors that impact work zone safety. This paper addresses this research gap by following a multistep methodology. First, a systematic literature review (SLR) was conducted to identify a comprehensive list of 37 factors impacting work zone safety. Second, social network analysis (SNA) was employed to analyze the connectivity between these identified factors, based on the theoretical, mathematical, and computational approaches found in the literature. Third, the factors were grouped into clusters using the *k*-means clustering technique, considering the overall discussions present in the literature. Last, association rules were mined from the clustered factors to determine combinations of factors that have not been extensively examined together, thereby identifying gaps and deficiencies in the present body of knowledge. The findings of the SNA indicate that design-related factors have received more extensive attention in the literature, whereas certain driver- and state-related factors have received comparatively less attention. The clustering analysis shows that a significant number of theoretically addressed safety factors in the literature frequently are examined together, which indicates a necessity for additional computational and mathematical investigations to gain a more comprehensive understanding of these factors. Moreover, the association rules highlight the groups of underexamined relationships of factors that affect work zone safety. Ultimately, this research contributes to the body of knowledge by consolidating the studies concerning work zone safety and using them to provide a robust roadmap for future research, thereby enhancing the advancement of this field and ultimately leading to improved work zone safety practices. **DOI: 10.1061/JMENEA.MEENG-5729.**

Introduction

Work zones are essential for the preservation and development of transportation infrastructure, and broadly are characterized as any construction or maintenance activities that occur on or in proximity to roadways and involve the presence of both workers and equipment. However, work zones usually entail traffic control, signage, speed reductions, and other temporary measures, which place drivers and workers in unexpected conditions. Driving through a work zone involves multiple interactions among workers, passing vehicles, and mobile construction equipment, thereby increasing the potential risk of a crash for drivers (Meng et al. 2010; Weng and Meng 2011), and giving rise to hazardous circumstances leading to injuries or fatalities (Jumari et al. 2022). Additionally, collisions that occur within work zones are more serious than those that occur elsewhere and affect both drivers and workers (Ha and Nemeth 1995; Ullman et al. 2006). Consequently, work zone intrusions contribute to 10% of nonfatal injuries and 8% of fatal injuries in traffic incidents (Bryden et al. 2000). In the last decade there has been a persistent trend of over 100 fatalities annually in the US resulting from work zone accidents (NHTSA 2014), of which 76% were caused by work zone intrusions or mobile equipment colliding with workers (FHWA 2017).

In accidents involving the public, rear-end collisions and head-on crashes are the predominant types of vehicular crashes in work zones, followed by collisions with small objects (FHWA 2017; INDOT 2017). It is estimated that 70% of work zone accidents involve motorists outside the construction area, while the remaining 30% extend to include injuries/fatalities among construction workers (Mohan and Gautam 2002). These types of incidents have the potential to cause severe injuries and fatalities to both workers and drivers. According to national estimates, approximately 80% of work zone accident fatalities are attributed to motorist drivers and passengers (INDOT 2017). In 2015, work zone intrusions led to 700 road fatalities and injuries in the US (NHTSA 2016). Within work zones, the most frequent cause of occupational injury not

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related to the public (i.e., intruder vehicles) is workers being impacted by dump trucks in reverse motion, which causes almost half of the occupational work zone fatalities (FHWA 2022).

Previous research on work zone accidents and crashes has concentrated primarily on investigating their causes and implementing preventive safety technologies. Zhang et al. (2022) investigated the factors that affect work zone safety. They analyzed how different characteristics of roadways and work zones influence the likelihood of crashes. To achieve this, they utilized a supervised machine learning (ML) model, known as a random forest network, to analyze work zone crash data collected from the state of Pennsylvania. The developed model enabled the inference of crash probability and revealed that work zones with higher daily traffic volume and longer work zones are more susceptible to accident occurrences. Liang et al. (2014) developed a cellular automata model to simulate freeway work zone traffic flow and found that vehicles changing lanes in critical sections of work zones increased the likelihood of sideswiping and rear-end collisions. Moreover, several studies have been undertaken to improve work zone safety through the development and evaluation of safety technologies. For example, Elghamrawy et al. (2012) examined the effectiveness of temporary work zone rumble strips in enhancing safety by studying their impact on audible warnings when vehicles pass through work zones, and ultimately concluded that temporary strips effectively increase audible warnings during work zone traversal. Hang et al. (2022) studied the significance of in-vehicle warnings, and specifically emphasized the importance of extended warnings beyond the drivers' line of sight, particularly for crash avoidance in foggy conditions.

Despite the existing body of research on work zone safety, the majority of studies have focused on specific combinations of work zone safety factors, resulting in a lack of comprehensive examination of these factors. For example, Ermagun et al. (2021) investigated 14 factors related to driver response to work zone dynamic messages, but their analysis primarily considered driver-related factors, and neglected other work zone or environment-related factors. Similarly, Mokhtarimousavi et al. (2021) examined temporal-related factors that impact work zone injury severity, along with specific driver and environmental factors such as alcohol involvement and rainy conditions, but did not extend their investigation to include worker-related factors. The present paper aims to bridge this research gap and contribute to this important field of study.

The goals of this paper were to offer a comprehensive analysis and synthesis of the current body of knowledge pertaining to work zone safety factors, study the interconnectivity of the safety factors within a system-based analytic context, and analyze the underexplored factors both individually and in combination with other factors. By doing so, the study aimed to identify research gaps and provide a roadmap for future endeavors addressing work zone safety themes. The associated objectives were to (1) develop a comprehensive list of work zone safety factors derived from the existing literature, considering both theoretical and mathematical approaches employed to evaluate these factors; (2) investigate the interconnections among the identified factors and assess the current state of the literature in relation to work zone safety; (3) analyze and identify associations and deficiencies among the factors based on their respective levels of treatment in the literature, using association rule (AR) mining techniques; and (4) propose a roadmap for future research endeavors in the field of work zone safety, highlighting yet-to-be addressed topics, which subsequently should contribute to the overall advancement of knowledge and ultimately the promotion of safer work zones.

Background Information

Previous Research Works Related to Safety in General

Considerable research has been conducted to investigate safety aspects across various industries and domains, such as healthcare activities (Vincent and Amalberti 2015), agriculture (Murphy 1992), manufacturing (Silvestri et al. 2012), school sectors (Gairín and Castro 2011), and the construction industry (Törner and Pousette 2009; Choudhry 2014; Assaad and El-adaway 2021), among other industries. Similarly, the methodologies and modeling approaches vary across safety-related studies. Nabi et al. (2020) constructed a system dynamics model to simulate construction safety behavior, enabling the prediction of on-site injury occurrence and the identification of underlying causal factors. Zhao and Shi (2019) employed density-based clustering and recurrent neural networks to identify maritime anomalies, aiming to enhance the situational awareness of vessel traffic supervisors and reduce maritime accidents. Yuan et al. (2020) utilized case statistics and dynamic Bayesian networks to deduce scenarios related to fire accidents, with the aim of assisting decision-makers in formulating more-precise emergency response measures. Chiang et al. (2018) studied fatal accidents in Hong Kong construction trades and found that a greater number of such accidents occurred in repair, maintenance, alteration, and addition works. Wilson-Donnelly et al. (2005) analyzed the macrolevel perspective of safety in the manufacturing sector by conducting a review that examined the influence of organizational measures on worker safety and putting forth guidelines to promote occupational safety across multiple levels. Fang et al. (2020) conducted a literature review focused on computer vision studies related to construction safety, and explored the integration of deep learning with computer vision techniques to enhance safety practices in the field of construction. Eteifa and El-adaway (2018) investigated the fundamental causes of construction fatalities by employing a graph theory approach, a methodological step which was undertaken in the present study, as detailed in the "Research Methodology" section. Through their analysis, they identified the root causes, modeled their interrelationships, and concluded that the absence of job-specific training is the primary factor contributing to accidents involving struck-by and caught-in-between incidents. Assaad and El-adaway (2021) expanded on the previous study by employing spectral clustering, frequent pattern mining, and the Apriori algorithm, which are methodological steps akin to those undertaken in the present study, as outlined in the "Research Methodology" section, to identify the significant combinations and associations of causes that predominantly contribute to fatal accidents on construction sites.

Previous Research Works Relevant to Work Zone Safety in Particular

Considerable focus has been dedicated in previous studies to determining the significant factors contributing to safety accidents within work zones. Primarily, many studies have concentrated on the theoretical examination and/or empirical testing of specific work zone safety parameters, namely employing driving simulations. Domenichini et al. (2017) conducted driving simulation experiments to examine the influence of work zone crossovers on driver speeding behaviors across various work zone configurations, and found that the average speed significantly decreased only when there were alterations in the geometrical characteristics; based on these findings, they recommended increasing signage, enhancing work zone design, and implementing more-effective speed enforcement measures. Similarly, Naujoks et al. (2017) utilized driving

simulation experiments to evaluate the proficiency of drivers when transitioning from partially automated driving to manual driving in work zones where lane markings are absent or temporary lines are present. The study found that participants were able to handle the vehicles safely in such scenarios, indicating the harmlessness of these situations. Furthermore, Hou and Chen (2020) utilized simulator experiments to investigate the safety of traffic in work zones under inclement weather conditions. Their findings demonstrated that adverse conditions led to increased congestion and a higher frequency of lane changes, which in turn increased the likelihood of collisions.

Alternatively, several studies have employed field or laboratory testing methods to assess specific work zone safety parameters, particularly those associated with work zone design and temporary traffic control measures. Patel et al. (2014) introduced a novel precast concrete barrier wall system designed specifically for bridge deck work zones, incorporating structural, freeze–thaw, and impact testing, and concluded that the system offers notable advantages compared with conventional cast-in-place concrete barriers, including simplified replacement of damaged sections to mitigate the impact of accidents or related concerns. Ravani and Wang (2018) conducted field data collection in work zones and found that the presence of law enforcement and changeable message signs had a statistically significant effect on reducing vehicular speeds. Kersavage et al. (2018) conducted field experiments to evaluate the effectiveness of different warning beacons and flash intensities employed on vehicles for accident prevention, aiming to enhance worker detection and driver reaction time. Park et al. (2017) conducted field testing to assess the effectiveness of a sensing system for enhancing work zone safety that utilizes Bluetooth Low Energy devices to minimize the occurrence of occupational hazards between workers and construction equipment.

Additionally, numerous studies have devised ML models to analyze work zone crash occurrence and severity, the majority of which are parametric in nature. For example, Santos et al. (2021) investigated the risk factors influencing work zone crashes by utilizing probit regression and binary logistic models, considering factors such as weather conditions, speed limits, pavement grip, and other relevant variables. Murthy et al. (2013) assessed the effects of intelligent transportation system operations on reducing traffic congestion and incidents, employing logistic regression models. Sze and Song (2019) developed a multinomial logistic regression approach to analyze the relationship between various factors and work zone crash severity, considering variables such as location, time, vehicle type, objects involved in the crash, lighting and weather conditions, and road surface conditions, among others. Weng et al. (2016a) employed a multinomial logistic regression model to investigate the relationship between factors such as environmental conditions, road characteristics, driver attributes, crash characteristics, and work zone crash severity. Debnath et al. (2014) introduced a Tobit regression model that analyzed the likelihood and extent of speed limit compliance in work zones, incorporating various vehicle and traffic factors. Their findings indicated that vehicles tend to exhibit higher speeds during periods of increased traffic volume and when a larger proportion of vehicles are speeding. Parametric models, such as logistic regression, may encounter limited prediction accuracy due to the predetermined assumptions on which they rely, in addition to the possible nonhomogeneity of the input variables. For example, Weng et al. (2013) demonstrated that a tree-based logistic regression approach outperformed the standalone logistic regression model in assessing work zone casualties by effectively addressing the marginal effects of the risk factors.

For this reason, several studies employed nonparametric models to assess work zone safety. Rahim and Hassan (2021) utilized a deep learning approach to develop a crash severity model, incorporating a wide range of 98 variables including factors such as year, date, time, roadway features, and environmental features. Ghasemzadeh and Ahmed (2019a) introduced a probit-classification tree model that combines nonparametric classification tree techniques with the parametric probit regression model to investigate the influence of environmental factors and drivers' behavior on weather-related work zone crashes. Chang et al. (2020) proposed and evaluated four classification methods for crash event classification and prediction in work zones. Their findings highlighted the significance of factors such as speed, following distance, lane changes, driver distraction, work zone configuration, lane width, and signage in contributing to hazardous events.

Among the nonparametric ML models, association rule mining has been utilized in certain studies. Weng et al. (2016b) applied association rule mining to study factors affecting work zone crash casualties and determine patterns in the crashes. Their findings revealed common occurrences of variables such as exceeding speed limit, involvement of alcohol, presence of four or more lanes, and proximity of the crash to the posted speed limit sign. Pande and Abdel-Aty (2009) adopted a unique approach by analyzing crashes as supermarket transactions, employing association rules aiming to identify interdependencies among crash characteristics. Geurts et al. (2003) employed the frequent item sets association algorithm to investigate patterns in areas with high crash occurrences, although their study was not restricted to work zones.

Currently, the existing work zone safety studies individually have focused on several combinations of parameters, but there is a lack of comprehensive coverage of safety factors in line with the evolving nature of the literature. This study addresses this area of research need.

Previous Research Works Employing Systematic Literature Reviews

Numerous prior research endeavors have contributed to the advancement of knowledge through the execution of systematic literature reviews (SLRs), which serve as the fundamental methodological framework upon which this study is based. These reviews primarily involve the exhaustive analysis of the existing literature to identify and quantify the prevalence of specific factors, topics, or themes. For example, Alaka et al. (2017) employed a SLR to identify significant factors in construction industry insolvency prediction models and quantified the frequency of the literature-addressed factors. Similarly, Rashvand and Zaimi Abd Majid (2014) performed a SLR of client and customer performance satisfaction criteria, and established a ranking for factors that affect customer and client satisfaction.

In addition to assessing the current state of knowledge, the results of SLRs can guide and shape future research endeavors, contributing to the advancement of existing knowledge. For example, Nasirian et al. (2019) performed an extensive review of the literature on labor multiskilling, and highlighted research gaps that should be prioritized for future investigation. Elbashbishy et al. (2022) conducted a SLR of the utilization of blockchain technology in the construction industry, and evaluated the challenges, needs, requirements, and capabilities of blockchain, and identified knowledge gaps for future research focus. Abdul Nabi and El-adaway (2020) performed a SLR highlighting the insufficient analysis of decision factors such as regulatory factors, green practices, and waste management in the existing scholarly works on modular construction, and suggested a need for further scholarly investigation in

these areas. Assaad and El-Adaway (2020) conducted a comprehensive literature review of the applications of construction business failure, and provided a systematic mapping of existing knowledge and identified underexamined failure factors that could be considered in future research endeavors. Li et al. (2019) conducted a SLR to assess the current state of research pertaining to organizational behavior within the context of megaprojects, which involved proposing directions for future scholarly inquiry. Song et al. (2019) engaged in an extensive investigation to determine the intellectual structure and knowledge domains inherent in the domain of public–private partnerships, and provided valuable insights to guide future research endeavors.

According to Webster and Watson (2002), this particular research approach provides significant advantages to the expansion of the body of knowledge. By integrating and synthesizing the outcomes of previous studies, a SLR establishes robust foundations for enhancing knowledge in a particular domain. Therefore this study adopted the widely recognized and extensively employed method of SLR as a fundamental framework to evaluate the existing body of knowledge pertaining to work zone safety. The study comprehensively examined the literature to identify and elucidate the current gaps in knowledge while providing insights that can guide future research.

Research Methodology

This study employed an interdependent and multistep research methodology (Fig. 1). The authors (1) conducted an extensive review and analysis of the literature on work zone safety, (2) identified the factors that impact public and occupational safety in work zones and mapped them with the reviewed articles, (3) conducted a social network analysis (SNA) to measure the significance of the identified factors, (4) applied clustering analysis to the constructed SNA model to group the factors based on their research popularity, and (5) performed association rule analysis (ARA) on the identified clusters to uncover significant associations among safety factors discussed in the literature and establish a roadmap highlighting associations that necessitate additional investigation. Details pertaining to each step are presented in the subsequent subsections.

Systematic Literature Review

The first step was to conduct a SLR to review articles related to work zone safety. To this end, the authors followed three steps for the collection of scholarly articles: search, screening, and selection (Fig. 2).

Search

The authors utilized the Scopus search engine to conduct an all-inclusive search with the article title, abstract, and keywords fields. The search was restricted to papers classified as article type. The SLR for relevant publications utilized various keywords, such as "work zone," "work-zone," and "safety," among others, and focused on articles published within the previous 10 years (2012–2022). This time frame is considered to be appropriate for identifying the relevant literature body (Jin et al. 2018). Notably, this range of years was used in previous research on various topics, including the construction field (Ma et al. 2019; Wang et al. 2020). This search led to the collection of 166 journal articles published.

Although the scope of this study was limited to the 10-year period, the essential aspects of research preceding the data collection period are incorporated into newer literature papers collected. Ultimately, the selected data collection period was deemed to be appropriate for the scope and objectives of this study. Furthermore, to avoid duplication of results or data, the search was restricted to journal articles; theses or conference papers that may have been subsequently published in journals were excluded.

Screening

The authors conducted a two-step screening to assess the relevancy of the collected articles. The screening process involved

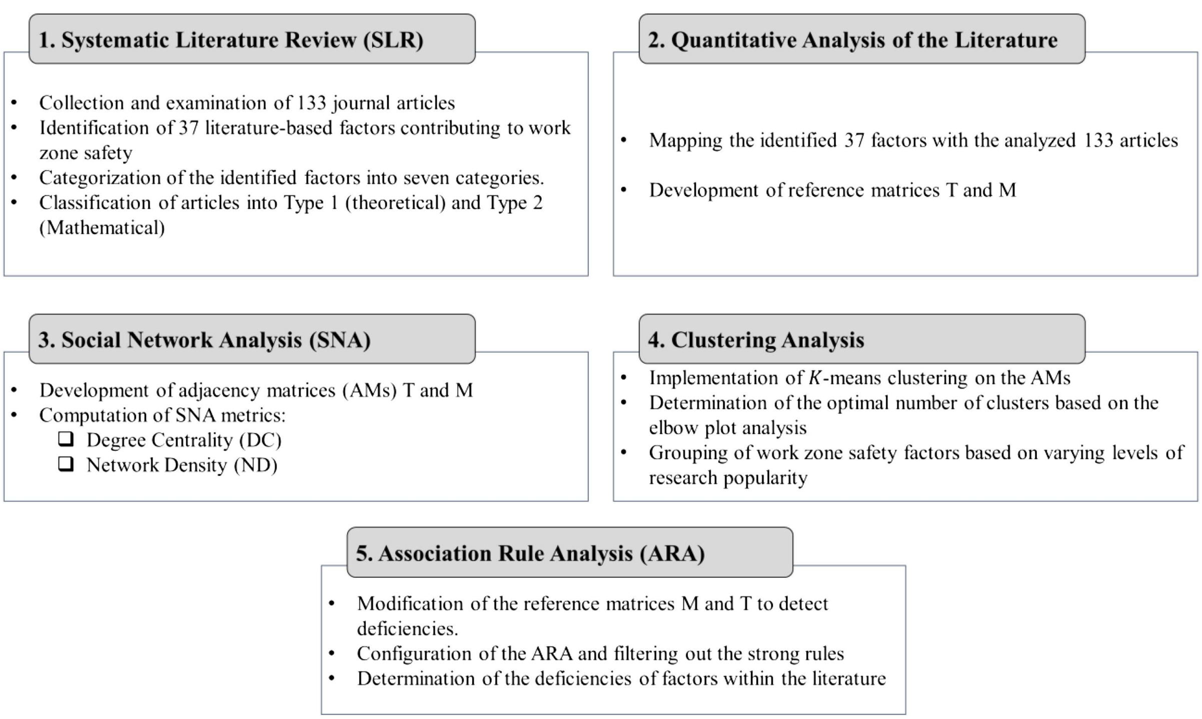

Fig. 1. Research methodology.

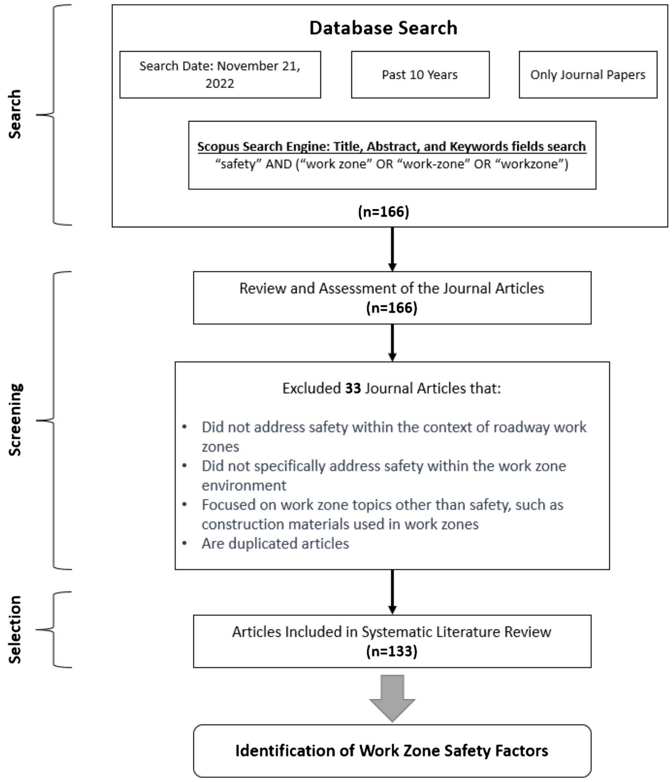

Fig. 2. Steps followed for selection of articles.

two steps to ascertain the relevance of each article to the research field. In the first step, the articles were screened based on their abstracts and titles. In the second step, the articles underwent a comprehensive content review. As a result, 10 articles were excluded in the initial screening step, and an additional 23 articles were excluded during the content review for one of the following reasons:

1. nonrelevance to roadway work zones: these articles did not address safety within the context of roadway work zones;
2. irrelevant safety focus: the research in these articles did not specifically address safety within the work zone environment;
3. different work zone topics: these articles focused on work zone topics other than safety, such as construction materials used in work zones; and
4. duplicate articles: these articles were duplicates of studies already included, and therefore were excluded to avoid redundancy.

As an example of the exclusion of an article, in Türkay and Aydin (2020), "work zone" was mentioned in the article's abstract, and "safety" was mentioned in the article's keywords; therefore the paper was found in the aforementioned database search process. However, this study focused on the development of software for the visualization of tree felling, specifically addressing the safety concerns of loggers in forest work zones rather than roadway work zones. Consequently, based on the initial screening process, this article was deemed irrelevant to the research topic, and was excluded from the data set.

Selection

Following the adopted screening process, the data set for the establishment of literature-studied work zone safety factors included the remaining 133 journal articles (Table 1), which were selected for review and analysis.

The authors conducted a manual content analysis of the 133 selected articles. The manual content analysis was carried out in a manner similar to that established by Neuendorf (2002) and Krippendorff (2004). According to Ahmed and El-adaway (2023), such manual review and analysis should increase the accuracy and specificity of the identification of factors impacting safety in work zones. First, the authors manually and independently read the articles, in detail, without using any content analysis software. Second, the authors independently recorded their identified work zone–related factors using Microsoft Excel. These factors were stated clearly throughout the articles. Moreover, the authors aggregated identical or similar factors during the process of reviewing and analyzing the selected 133 articles. Third, the authors compared the developed lists of factors. In the event of disagreement, another review cycle was carried out until agreement was reached. Overall, a total of three review cycles were conducted. Ultimately, the authors identified a comprehensive list of 37 factors that impact safety in work zones. The identified list of 37 factors is presented in the "Results and Analysis" section. Furthermore, the collected factors were consolidated and classified into seven distinct categories: (1) design-related factors; (2) roadway-related factors; (3) driver-related factors; (4) vehicle-related factors; (5) work-related factors; (6) temporal-related factors; and (7) state-related factors. These categories are elaborated and discussed in the "Results and Analysis" section of this paper.

After performing content analysis of the articles, the journal articles were classified into two categories based on previous similar research (Abdul Nabi and El-adaway 2020; Khalef and El-adaway 2023):

1. The articles included in this class covered theoretical discussions of topics related to work zone safety, which centered on insights into the factors associated with work zone safety without conducting controlled experiments or testing. Additionally, articles focusing on statistical analyses of historical injury data also were included in this category. The articles that contained theoretical discussions were incorporated into Reference matrix T in this study.
2. The articles in this class predominantly described the results of controlled experiments investigating select safety factors, as well as the development of predictive ML models, tools, frameworks, and other computational methods related to work zone safety. These articles were included in Reference matrix M. Notably, articles with substantial theoretical discussions, particularly within their literature review sections, also were included in Reference matrix T.

Quantitative Analysis of the Literature

Following the SLR, the authors performed a quantitative analysis of the collected literature to develop two reference matrices, T and M. The columns in these matrices correspond to the journal articles analyzed, and the rows represent the safety factors. Matrix T comprises factors that were addressed theoretically in the literature, whereas matrix M encompasses factors that were addressed mathematically or empirically. To construct these matrices, the authors assigned a binary value of 1 or 0 to each factor–article combination based on whether the factor was addressed in the article. This process is illustrated in Fig. 3, in which F_i represents an identified factor, and A_i represents an analyzed journal article. In this example, factor F_1 is recorded in article A_1, but not in Article A_2; therefore a value of 1 is added to the cell relating to $[F_1; A_1]$, and a value of 0 is input in the cell corresponding to $[F_1; A_2]$. Consequently, $i \times j$ binary Reference matrices T and M were constructed, where i is the number of factors identified, and j is the number of articles

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Table 1. Articles reviewed

Year	Articles	Number of articles
2012	Elghamrawy et al. (2012) and Weng and Meng (2012)	2
2013	Meng and Weng (2013), Rayaprolu et al. (2013), and Yang et al. (2013)	3
2014	Bham et al. (2014), Choe et al. (2014), Debnath et al. (2014), Fan et al. (2014), Huang and Bai (2014), Liang et al. (2014), Shakouri et al. (2014), Weng and Meng (2014), and Yousif et al. (2014)	9
2015	Bai et al. (2015), Chen and Ahn (2015), Debnath et al. (2015), Jin and Jin (2015), Kaber et al. (2015), Ren and Wu (2015), Ščerba et al. (2015), Weng et al. (2015a, b), and Yang et al. (2015)	10
2016	Ahmed et al. (2016), Cao and Liu (2016), Genders and Razavi (2016), Martin et al. (2016), Melcher and Keller (2016), Nyende-Byakika (2016), Osman et al. (2016), Park et al. (2016), Weng et al. (2016a, b), Wennström et al. (2016), Xu et al. (2016), and Zhu et al. (2016)	13
2017	Domenichini et al. (2017), Ferreira et al. (2017), Hamzeie et al. (2017), La Torre et al. (2017), Lyu et al. (2017), Park et al. (2017), Qiao et al. (2017), Rahman et al. (2017), Yang et al. (2017), and Zhang and Gambatese (2017)	10
2018	Abdelmohsen and El-Rayes (2018), Abdulsattar et al. (2018), Kachroo and Sharma (2018), Kang and Momtaz (2018), Kersavage et al. (2018), Nnaji et al. (2018b), Osman et al. (2018), Park et al. (2018), Ravani and Wang (2018), Rea et al. (2018), Weng et al. (2018), and Zhang et al. (2018)	12
2019	Awolusi and Marks (2019), Banerjee et al. (2019), Du and Razavi (2019), Ge et al. (2019), Ghasemzadeh and Ahmed (2019a, b), Osman et al. (2019), Qing et al. (2019), Steinbakk et al. (2019a, b), Sze and Song (2019), Valdes et al. (2019), Vignali et al. (2019), Xu and Yang (2019), and Zhang and Hassan (2019)	15
2020	Al-Bdairi (2020), Ambros et al. (2020), Barlow et al. (2020), Chang et al. (2020), Cheng and Cheng (2020), Duan et al. (2020), Ge and Yang (2020), Ge et al. (2020), Hou and Chen (2020), Idewu et al. (2020), Koilada et al. (2020), Kummetha et al. (2020), Lee et al. (2020), Lopez-Flores et al. (2020), Nnaji et al. (2020a, b), Raddaoui et al. (2020), Raju et al. (2020), Xu et al. (2020), and Zhang et al. (2020)	20
2021	Ahmed et al. (2021), Almallah et al. (2021), Bakhshi and Ahmed (2021), Cao et al. (2021), Dehman and Farooq (2021), Jing et al. (2021), Du and Razavi (2021), Ermagun et al. (2021), Hubbard and Hubbard (2021), Kim et al. (2021a, b), Lv et al. (2021), Mahasirikul et al. (2021), Mokhtarimousavi et al. (2021), Nasrollahzadeh et al. (2021), Park et al. (2021), Rahim and Hassan (2021), Ren et al. (2021), Saha (2021), Santos et al. (2021), Sayed et al. (2021), Shen et al. (2021), Son et al. (2021), Valdés-Díaz et al. (2021), Wang and Lee (2021), Wang et al. (2021), and Zhao et al. (2021)	27
2022	Duan et al. (2022), Galvis Arce and Zhang (2022), Hang et al. (2022), Islam (2022), Jumari et al. (2022), Kitali et al. (2022), Mathew et al. (2022), Niska et al. (2022), Sakhakarmi and Park (2022), Sakhare et al. (2022), Wang et al. (2022), and Zhang et al. (2022)	12

	A_1	A_2	…	A_j
F_1	1	0	…	0
F_2	0	0	…	1
…	…	…	…	…
F_i	0	1	…	1

Fig. 3. Example of a reference matrix.

analyzed. Ultimately, analyzing each matrix independently, by implementing the subsequent methodological steps as detailed in the following subsections, enabled the identification of research gaps and understudied safety factors in work zones. Furthermore, comparing the two matrices indicated a clear distinction between theoretical and empirical studies on these factors, offering valuable insights for guiding future research endeavors.

Social Network Analysis

The utilization of the SNA approach in this study was driven by its inherent capability to capture and analyze the interconnections among the diverse factors investigated in this research, thereby enhancing the understanding of their interrelationships. SNA is a methodology rooted in graph theory that explores network behavior by taking into account the interconnections among the network components (Otte and Rousseau 2002). SNA is a widely employed technique for creating, visualizing, and exploring network relationships among various topics, factors, and research themes. Furthermore, SNA has practical applicability in evaluating literature-based factors in terms of their interconnectivity, relative importance, and for identifying understudied areas of research that require further investigation (Elbashbishy et al. 2022). Therefore, this study utilized SNA as a methodological approach to assess the interconnections among work zone safety factors as depicted in the literature, quantify the level of literature coverage concerning these factors, and identify work zone safety factors that have been inadequately investigated, from both theoretical and computational or mathematical perspectives.

The SNA method consists of multiple interconnected nodes (vertices) connected by links (edges). In this study, the nodes corresponded to work zone safety factors, and edges were created between the nodes based on the number of articles connecting them. Fig. 4 demonstrates an illustrative example of constructing an SNA model. The approach begins with constructing a reference matrix that cross-references the factors with the analyzed articles (Fig. 4). The quantitative analysis of the literature yielded two reference matrices: the Theoretical matrix T and the Mathematical matrix M. To obtain the adjacency matrix (AM) for each reference matrix, the reference matrix was multiplied by its transpose matrix, and the diagonal values subsequently were set to zero. Thus, the AM is a square matrix that portrays the relationships between the factors, enabling the calculation of the degree centrality (DC) for each of the identified factors. For literature-based work zone safety factors, the degree centrality signifies the factor's popularity in terms of papers connecting it to other factors. The degree centrality for each node of the two networks is determined using Eq. (1), where DC_i denotes the weighted degree centrality of a factor i, and a_{ij} signifies the edge weight between factors i and j present in the AM

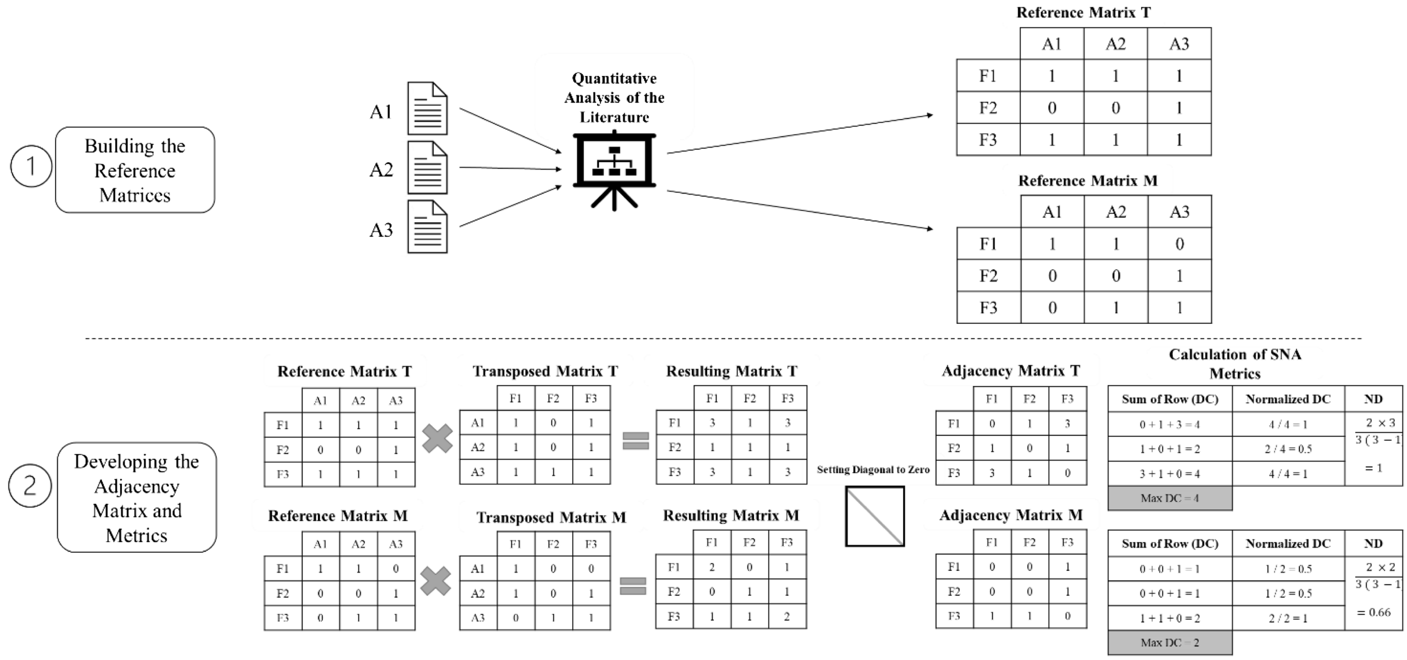


Fig. 4. Overview of the SNA procedure.

$$\mathrm{DC}_i = \sum_{j:j\neq i} a_{ij} \tag{1}$$

Because the number of articles used for Matrices T and M was unequal, a normalized DC_i was computed by dividing the DC_i of each factor by the maximum DC_i obtained in the respective reference matrix [Eq. (2)]. This was done because the degree centrality is influenced by the network's size, resulting in the normalized DC_i for each work zone safety factor ranging from 0 to 1

$$\text{Normalized}\,\mathrm{DC}_i = \frac{\mathrm{DC}_i}{M\text{aximum}\,\mathrm{DC}_i\ \text{in the network}} \tag{2}$$

Furthermore, to quantify the connectivity among the work zone safety factors in each of the two networks, the authors utilized an additional SNA metric, known as network density (ND) (Eteifa and El-adaway 2018; Aljassmi et al. 2014). The ND is a measure of the proportion of links or edges that are established in the network out of all possible links (Giuffre 2015). The ND was employed to evaluate the connectivity of the two networks individually (Park et al. 2011), as well as to serve as a point of comparison for the interconnectivity between Matrices T and M. The calculation of ND is based on Eq. (3), where n denotes the number of vertices, i.e., work zone safety factors, present in the network

$$\mathrm{ND} = \frac{2 \times \text{Actual connections}}{n \times (n-1)} \tag{3}$$

The Python programming language was employed to implement the SNA model discussed in this paper. Python is an object-oriented programming environment that has considerable adoption in the domains of engineering and scientific computing research. The Python version 3.10.6 programming environment was instantiated via Project Jupyter, an open-source software tool that furnishes an array of packages and libraries that were employed in this study, including Pandas, Numpy, Matplotlib, and scikit. Data processing, computations, and clustering were performed within the Python programming language, and the resulting network was visualized and analyzed utilizing Gephi.

Clustering Analysis

For increased insight, this research conducted cluster analysis on the constructed SNA models. Clustering, which is an unsupervised ML technique, was employed to categorize similar entities into distinct groups. The goal of clustering was to cluster work zone safety factors into groups of varying research interests. This allowed for the identification of highly researched factors and underexamined factors that require further investigation. The authors selected k-means clustering, which is an unsupervised ML technique that partitions x observations into k clusters, due to its frequent use in the relevant literature (Yen et al. 2007).

K-means clustering partitions x observations into k clusters with the objective of minimizing the sum of squared distances to the nearest centroid. It allocates data points to clusters based on their proximity, employing the Euclidean distance, and iteratively assigning them to the cluster with the closest mean. The iterative process continues until convergence is achieved, indicating stable assignments of data points to clusters. When convergence is reached, each data point is assigned to a single cluster based on the mean of the cluster with the least squared distance to it. The allocation of data points to clusters is accomplished by minimizing the sum of squared distances between each data point and its corresponding cluster mean. The resulting clusters can be analyzed further to identify patterns or trends in the data.

Alternatively, clustering could be employed using a graph theory approach. Spectral clustering partitions the data by solving a graph partitioning problem, constructing an undirected weighted graph where each data point is a vertex, and the weighted edge connecting any two vertices represents their similarity (Jia et al. 2014). This results in the decomposition of the graph into connected data points, with each agglomeration representing a cluster (Jia et al. 2014). Spectral clustering was utilized to categorize the disputed causes in modular construction and construct interconnected associations (Abdul Nabi and El-adaway 2022). However, for the

purpose of this study, k-means clustering was deemed more appropriate, because it allows for the classification of safety factors that co-occur in the literature, thereby facilitating the identification of clusters with varying levels of research popularity. To establish a consistent reference for comparison between two networks, this study employed k-means clustering analysis of the AMs derived from Matrices T and M. By applying k-means clustering analysis to the AMs of both networks, this study identified patterns of similarity or dissimilarity between the two networks based on their respective research-based clustered work zone safety factors.

The implementation of the k-means clustering model in Python was conducted using the scikit-learn package (Pedregosa et al. 2011). The algorithm comprises three sequential steps: (1) initializing the cluster centroids, (2) assigning each data point to the nearest centroid, and (3) updating the centroids and reclassifying the data points based on the difference between the new and previous centroids. Steps 2 and 3 are iterated until the centroids converge within a predetermined threshold. The optimal number of clusters is obtained by analyzing the elbow plot, which illustrates the distortion score with respect to the number of clusters. The elbow method identifies the point at which additional clusters provide diminishing returns by plotting the sum of squared errors (SSE) for each cluster number k (Syakur et al. 2018; Shi et al. 2021).

Association Rule Analysis

One of the objectives of this study was to identify key associations among the various factors affecting work zone safety. This study aimed to identify the associations that are most understudied in the literature, offering a roadmap for future works. To this end, ARA was employed as a powerful method for detecting indications of deficiencies in AMs (Khalef and El-adaway 2023). The ARA approach frequently is employed to identify correlations among variables within extensive databases. In contrast to conventional methods, association rule mining offers the advantage of adaptable applicability, because it does not necessitate predetermined functions or dependent variables (Weng et al. 2016b). By deriving association rules from the work zone safety factors, research roadmaps can be recommended to address the deficiencies with practical implementations through future works.

The ARA methodology can be applied using various algorithms. For this study, the Apriori algorithm was utilized, which initially was proposed by Agrawal et al. (1993). This technique extracts latent rules from a given data set (Cheng et al. 2010). The Apriori algorithm possesses notable features, including its ability to uncover elusive patterns (Verma et al. 2014), ease of implementation (Rahman et al. 2019), and practicality for data mining (Htet 2019). This algorithm has been used extensively in construction engineering and management research, particularly for exploring the interconnectivity among various elements (Liao and Perng 2008; Xu et al. 2018; Ahmed and El-adaway 2023). Therefore, this study employed the Apriori algorithm to identify the associations among the safety factors of work zones, with a specific focus on determining the factors that have not received sufficient attention in previous research.

Through the development of AMs and the determination of the optimal number of clusters (k), the Apriori algorithm was applied to each cluster submatrix. The reference matrices had a value of 1 when a factor F_i was addressed in article A_i, and a value of 0 otherwise. The AR analysis technique functions by detecting the underlying trends found. In other words, it detects the trends in the values that are 1 in the reference matrix. Because the aim of this study was to identify indications of factors that have not been researched sufficiently, the reference matrices for the ARA were adjusted to indicate a value of 1 when a factor was not found and 0 when it was found. This enabled the ARA to identify deficiencies in the data set, leading to the formulation of recommendations for future studies. Consequently, the Apriori rule was run as follows: Let $F = \{F_1, F_2, \ldots, F_n\}$ be a set of safety factors in a Cluster$_i$, and let $A = \{A_1, A_2, \ldots, A_n\}$ be the set of journal articles, where each journal article contains a set of safety factors addressed therein, so that $A_i \subseteq F$. For example, if a journal article does not include the safety factors F_i and F_j, the article can be expressed as the set of factors $\{F_i, F_j\}$. An association rule was defined as an implication of the factors represented by $F_i \cup F_j$, where $F_i, F_j \subseteq F$, and $F_i \cap F_j = \emptyset$. The same approach was extended to rules that included more than two factors. Consequently, the AR produced all conceivable rules within the clusters. However, this technique presents certain challenges, particularly in generating numerous correlations among variables (Verma et al. 2014). Therefore, the authors utilized four measures of significance and interest to determine the robust associations with the clusters: the number of consequents and antecedents, support value, confidence, and lift. The following steps were undertaken:

- The application of ARA can establish principles of variables that are interrelated through a pattern of correlation. This method reveals a relationship between antecedent and consequent variables, whereby one variable (antecedent) is linked to another (consequent). To concentrate on unambiguous indications of inadequacies between variables, the analysis was limited to a single consequent and antecedent. This technique enabled identification of individual safety factors that have not been previously studied in conjunction.
- The support value $\mathrm{Supp}(F_i \cup F_j)$ is an indicator that determines the frequency of occurrence of a specific rule within the data set analyzed through AR, quantified as a ratio in accordance with Eq. (4). Thus, a minimum support value threshold of 0.85 was implemented to exclude trivial deficiencies and detect the prominent rules of deficiencies between the factors of each cluster derived from Matrices T and M, in line with previous scholarly research (Kaulkar et al. 2018; Kagdi et al. 2007)

$$\mathrm{Supp}(F_i \cup F_j) = \frac{\#\text{ of articles not including factors } F_i \text{ and } F_j \text{ simultaneously}}{\#\text{ of all articles in the cluster}} \tag{4}$$

- The confidence $\mathrm{Conf}(F_i \cup F_j)$ denotes the dependability ratio of a rule, that is, the conditional probability of discovering the rule $F_i \sim F_j$ when factor F_i is found. Because the aim of this study was to identify the deficiencies, the confidence was evaluated as the conditional probability of the absence of the association rule $F_i \sim F_j$ when factor F_i was discussed [Eq. (5)]. To identify the significant indicators of deficiencies, a confidence threshold of 0.9 or higher was utilized

$$\mathrm{Conf}(F_i \cup F_j) = \frac{\mathrm{Supp}(F_i \cup F_j)}{\mathrm{Supp}(F_i)} \tag{5}$$

- Because too many associations still can be generated satisfying the support and confidence thresholds, the lift value is employed to rank and further filter out the associations. The lift value is the frequency of the co-occurrence of the consequent and the antecedent. Accordingly, the lift value $\mathrm{Lift}(F_i \cup F_j)$ is the ratio of the rule's confidence to the rule's expected confidence [Eq. (6)]. A lift value below 1 indicates a negative interdependence between the antecedent and consequent, a value of 1 represents independence, and a value above 1 indicates a positive

interdependence (Montella et al. 2011). Consequently, significant rules are expected to have a lift value exceeding 1 (Verma et al. 2014). Therefore, the authors set a lift threshold of 1, removing all rules with a lift value below 1

$$\mathrm{Lift}(F_i \cup F_j) = \frac{\mathrm{Supp}(F_i \cup F_j)}{\mathrm{Supp}(F_i) \times \mathrm{Supp}(F_j)} \tag{6}$$

Results and Analysis

Work Zone Safety Factors

After conducting a SLR that resulted in the collection of 133 relevant articles (Table 1), the authors performed a content analysis of the literature. This analysis aimed to extract the work zone safety factors investigated in each of the studies, which subsequently were utilized in the quantitative analysis of the literature to construct the reference matrices, as further described in a subsequent subsection of the "Results and Analysis" section. Consequently, a total of 37 factors that pertain to work zone safety considerations were identified and categorized into 7 distinct groups based on their descriptions. The seven categories of work zone safety factors are presented in Table 2, and Table 3 provides a detailed list of the identified factors. Thus, Table 3 presents a comprehensive compilation of the work zone safety factors addressed throughout the literature. Additionally, Fig. 5 highlights the identified factors (x-axis) and their citing sources (y-axis). This comprehensive list of factors incorporates all aspects of work zone safety addressed in the literature (both theoretically and mathematically). Accordingly, Fig. 5 holistically maps the identified factors across the body of literature.

Articles Classification and Constructing the Reference Matrices

After conducting a quantitative analysis of the literature and identifying 37 work zone safety factors, the authors created Reference matrices T and M using the classification criteria previously outlined in the "Research Methodology" section (Table 4); 38 articles focused solely on theoretical discussions about work zone safety, falling into Type 1 and being included in Matrix T. Conversely, 95 articles involved experimentation or mathematical modeling of work zone safety, belonging to Type 2 and contributing to Matrix M. Among these 95 articles, 70 also incorporated extensive theoretical discussions, thereby contributing to both Matrix T and Matrix M. From the classification of the 37 work zone safety factors in this study (Table 3), the dimensions of Matrix T were 37×108, and Matrix M had dimensions of 37×95.

Results of SNA

Overview

Using the identified factors and the developed Matrices T and M, the authors constructed the AMs for each data set, as described in the "Research Methodology" section. Subsequently, the authors conducted SNA on each AM to highlight the literature study of work zone safety factors, and to provide a basis to recommend research into the underaddressed factors. The normalized DC values of AMs T and M are depicted in Fig. 6, which indicates the importance of a work zone safety factor in terms of the articles addressing it. Factors with a normalized DC value greater than 0.8 generally are considered to be significant in a network (Abotaleb and El-adaway 2018). Factors F1 Design of Work Zone Layout, F13 Driver's Compliance with Work Zone Speed Limit, and F15 Driver's Unsafe Behavior emerged as highly studied factors in both theoretical and mathematical/computational literature (Fig. 6). Conversely, certain driver-related factors, such as F19 Driver's Income, F20 Driver's Ethnicity, and F21 Driver's Educational Level, received relatively little attention. Notably, driver-related factors such as F17 Driver Gender and F18 Driver's Age are discussed relatively more extensively in the literature, particularly in computational models (Koilada et al. 2020; Chang et al. 2020; Steinbakk et al. 2019b).

Furthermore, Factor F37 Safety Budget, which belongs to the category of state-related factors, has been addressed inadequately in both theoretical and computational models. This work zone

Table 2. Categories of work zone safety factors

Category	Description	No. of factors
Design-related factors	Refers to the layout and elements of the work zone that are designed to ensure safe and efficient traffic flow, including roadway design, signage, pavement markings, and temporary traffic control devices.	5
Roadway-related factors	Refers to the characteristics of the roadway that may impact traffic flow and safety, including the road type, alignment, and slope, as well as factors such as pavement conditions, traffic volume, and speed limits.	7
Driver-related factors	Refers to the characteristics and behaviors of motor vehicle drivers that can impact safety in work zones, including distraction, impairment, fatigue, and aggressive driving.	9
Vehicle-related factors	Refers to the characteristics and conditions of the motor vehicles traveling through work zones that can affect safety, such as mechanical characteristics, vehicle size, weight, and speed.	4
Work-related factors	Refers to the occupational conditions and tasks that workers are exposed to while working in the zone, including the type of work being performed, duration of work, and proximity to moving traffic.	5
Temporal-related factors	Refers to the impact of time on safety conditions in the work zone. These factors may include the time of day, day of the week, and season of the year, as well as the duration of the project and the schedule of work activities.	4
State-related factors	Refers to the influence of state-level policies and regulations on work zone safety practices. These factors may include the state's work zone safety standards, policies for speed limit reductions, worker protection laws, and funding for safety programs.	3

safety factor has a significant impact on several other factors, especially the design-related factors, because the cost of work zone safety systems can hinder their implementation (Nnaji et al. 2018a). To address this issue, Saha (2021) developed an optimization model using linear integer programming to determine the optimal budget allocation for implementing work zone safety countermeasures. Similarly, Galvis Arce and Zhang (2022) proposed a framework to estimate the benefit-to-cost ratio of improving pavement

Table 3. Identified factors related to work zone safety

Category	Code	Factor	Description
Design-related factors	F1	Design of work zone layout	Refers to the configuration and design of a work zone, which can include a variety of elements such as reduced lane width, altered dimensions, entrance and exit bypasses, number of lanes, and median opening length. Additionally, protective systems may be implemented, such as concrete barriers, intrusion alarm systems, and the presence of spotters or flaggers.
	F2	Design of safety measures	Refers to mistakes or errors in the design of the work zone area, as well as issues with the implementation and location of safety measures. Such errors can include unclear temporary pavement markings and other factors that can contribute to confusion or hazards for drivers and workers within the work zone.
	F3	Additional preventive measures	Refers to the use of supplementary safety tools, equipment, and technologies intended to prevent accidents. These additional measures may include temporary rumble strips situated at the periphery of highway work zones, blue lights affixed to equipment, wearable light systems, animation-based message signs, sensing technologies, variable speed limits, and other similar measures.
	F4	Clarity of signage or pavement markings	Refers to unclear safety signage or pavement markings that impede a driver's comprehension.
	F5	Speed variance regulations	Refers to the presence of abrupt changes in speed within a work zone that may not allow drivers enough time to react and avoid potentially dangerous accidents.
Roadway-related factors	F6	Type of road	Refers to the type of roadway or highway, such as rural, suburban, or urban roads or motorways; arterial roads; local roads; and so on.
	F7	Roadway lighting conditions	Refers to the lighting conditions present on-site during nighttime hours.
	F8	Road surface condition	Refers to the surface conditions (roughness, smoothness, and so forth) of the road on which traffic is passing through the work zone area.
	F9	Road alignment	Refers to the characteristics of the road alignment, such as whether it is straight or curved, and whether there are slopes that are either upgrading or downgrading.
	F10	Median type	Refers to the different types of medians, such as rigid post barriers, grass, flexible post barriers, and semirigid post barriers.
	F11	Sight distance	Refers to the line of sight and the buffer segment of the work zone, located between the upstream transition area and the working area.
	F12	Volume of traffic at the area of work zone	Refers to factors such as the traffic volume, whether the work zone is located in a high or low-traffic area, and the percentage of trucks or commercial vehicles present.
Driver-related factors	F13	Driver's compliance with work zone speed limited	Refers to vehicles moving at high speeds through work zones and disregarding the required speed reductions.
	F14	Driver's level of attention	Refers to drivers who are inattentive while passing through work zones and may become distracted by various factors such as using their smartphones, focusing on GPS, or having their attention diverted elsewhere. This also applies to drivers who may only realize they are entering a work zone area at a late stage.
	F15	Driver's unsafe behavior	Refers to drivers engaging in unsafe behaviors while passing through work zones. Such behaviors include driving under the influence of drugs or alcohol, engaging in aggressive driving maneuvers such as queue jumping, straddling lanes, forcing merges, or riding motorcycles without helmets.
	F16	Driver impairments	Refers to potential reasons for obstructed driver behavior, decision-making, or driving skills, which may include factors associated with advanced age.
	F17	Driver gender	Refers to the gender of the vehicle driver.
	F18	Driver's age	Refers to the age of the vehicle driver.
	F19	Driver's income	Refers to the income of the vehicle driver.
	F20	Driver's ethnicity	Refers to the ethnicity of the vehicle driver.
	F21	Driver's educational level	Refers to the educational level of the vehicle driver.
Vehicle-related factors	F22	Characteristics of driving vehicle	Refers to the characteristics of the vehicle being driven, such as its type, features, workability, age, weight, and so forth.
	F23	Level of technology within driving vehicle	Refers to automated and connected vehicular systems.
	F24	Characteristics of construction equipment	Refers to characteristics of heavy-construction equipment, such as type, maneuverability, and weight.
	F25	Level of technology within construction equipment	Refers to the use of technology controls, such as radars or backup cameras, within construction equipment or vehicles that can help prevent accidents involving pedestrians or workers when backing up.

Table 3. (*Continued.*)

Category	Code	Factor	Description
Work-related factors	F26	Work zone type	Refers to the type of work zone, which may include construction, maintenance, utilities, and others (such as traffic management operations, among others).
	F27	Job training	Refers to the job training provided to workers, drivers, and operators working in work zone areas, such as training on how to deal with associated risks and hazards, and how to avoid becoming accustomed to workplace hazards.
	F28	Worker's behavior	Refers to the behavior exhibited by workers due to their habituation of the risks associated with work zone areas and their judgment of hazardous situations.
	F29	Traffic control inside work zone	Refers to the traffic control plan within the work zone area to regulate the movement of construction equipment and vehicles.
	F30	Level of congestion in the work zone	Refers to the limitations of the work zone area in terms of congestion with workers and equipment.
Temporal-related factors	F31	Weather condition	Refers to the adverse weather conditions that can result in accidents and incidents within work zones due to reduced visibility. Such factors also increase the risk of safety incidents to workers who are working in unfavorable weather conditions.
	F32	Time of the year	Refers to the month or season of the year.
	F33	Day of the week	Refers to the specific day of the week and involves a comparison between weekdays and weekends.
	F34	Time of day	Refers to the time of day, such as morning, evening, and nighttime.
State-related factors	F35	Adequacy of the safety guidelines and procedures	Refers to deficiencies or insufficiencies in the safety policies of the state.
	F36	Law enforcement	Refers to the presence of law enforcement in work zones, which can be either active (ready to pull over drivers) or passive (for warning purposes). It also includes the enforcement of driving laws and the work zone restrictions.
	F37	Limited safety budget	Refers to the budget allocated for the safety countermeasures such as the widening of highway shoulders, augmenting police presence, and so forth.

friction to reduce crashes. However, the factor of safety budget has not been addressed comprehensively in the literature in relation to work zone safety.

Additionally, there were notable disparities in the normalized DC values between the theoretical and computational treatment of work-related factors, specifically F28 (Worker's Behavior), F29 (Traffic Control inside Work Zone), and F30 (Level of Congestion in the Work Zone), as well as state-related factors, namely F35 (Adequacy of the Safety Guidelines and Procedures) and F36 (Law Enforcement). These factors are discussed more extensively in theoretical literature than in computational models. It is anticipated that such discrepancies may arise for various reasons, such as the challenge of modeling theoretical factors (Iyer and Sagheer 2010) and the unavailability of data owing to confidentiality concerns (Krizek et al. 2009). Nonetheless, these gaps highlight potential avenues for future research on factors that do not fall under the aforementioned constraints. Moreover, all these factors have been addressed to some extent in computational models, indicating that they are not entirely excluded from mathematical or computational approaches (Fig. 6).

Network Analysis

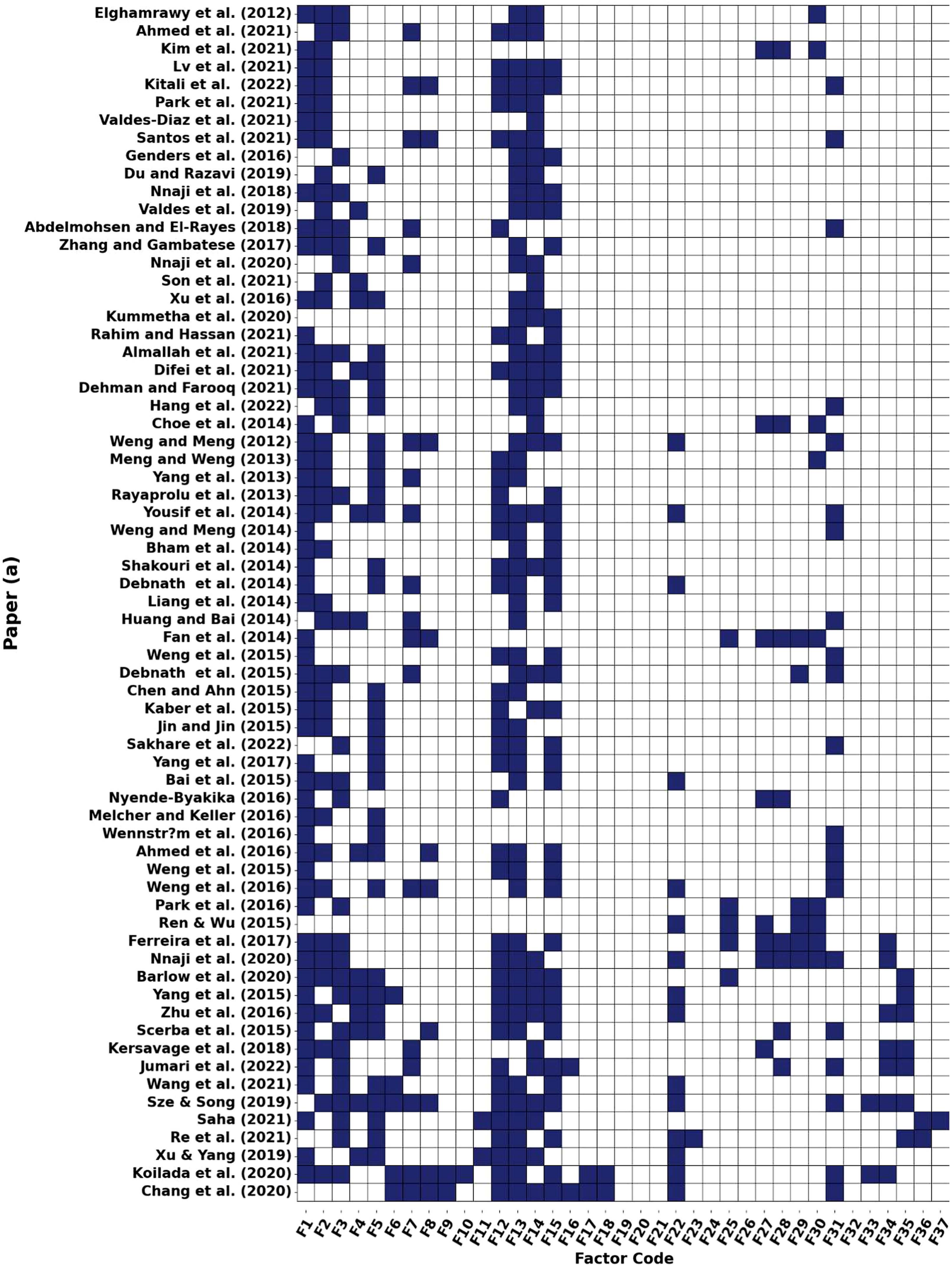
Using the developed AMs and the computed DC weights, the network graphical illustrations were generated using Gephi software (Fig. 7). Additionally, a heatmap was produced for each AM (Fig. 7). The thickness and darkness of the web-shaped network edges, as well as the darkness of the network nodes and heatmap color coding, correspond to the DC values indicated on the scale.

The networks had variations in their node and edge counts, as well as their connectivity weights (Fig. 7). Network T had a density of 77.6%, indicating that 77.6% of the connections within the network were realized. In contrast, Network M had a density of 58.3%, signifying that only 58.3% of its connections were realized. Similarly, Network T had more-pronounced and -robust links, indicative of a densely interconnected system with a greater proportion of realized connections among the work zone safety factors. Conversely, Network M had more-subtle and slenderer links, reflecting a sparser interconnected system with fewer realized connections among the work zone safety factors.

Furthermore, the heatmap of the networks highlights the disparities in the theoretical and mathematical approaches utilized to address the work zone safety factors (Fig. 7). Although both networks' heatmaps suggest that certain factors have received relatively inadequate attention from the literature, Network M's heatmap displays darker hues (greater DC values) for most of the factors than does Network T's heatmap. Moreover, the correlation gap between the mathematically addressed factors is wider than that under theoretical treatment. For example, Network T's heatmap reveals some literature-based correlation between the work-related factors (F26, F27, F28, F29, and F30) and F2 (Design of Safety Measures), whereas such correlation largely was absent in Network M. Similarly, the correlation between the work-related factors and F1 (Design of Work Zone Layout) was more pronounced in Network T than in Network M, as indicated by the darker color (i.e., a higher DC value).

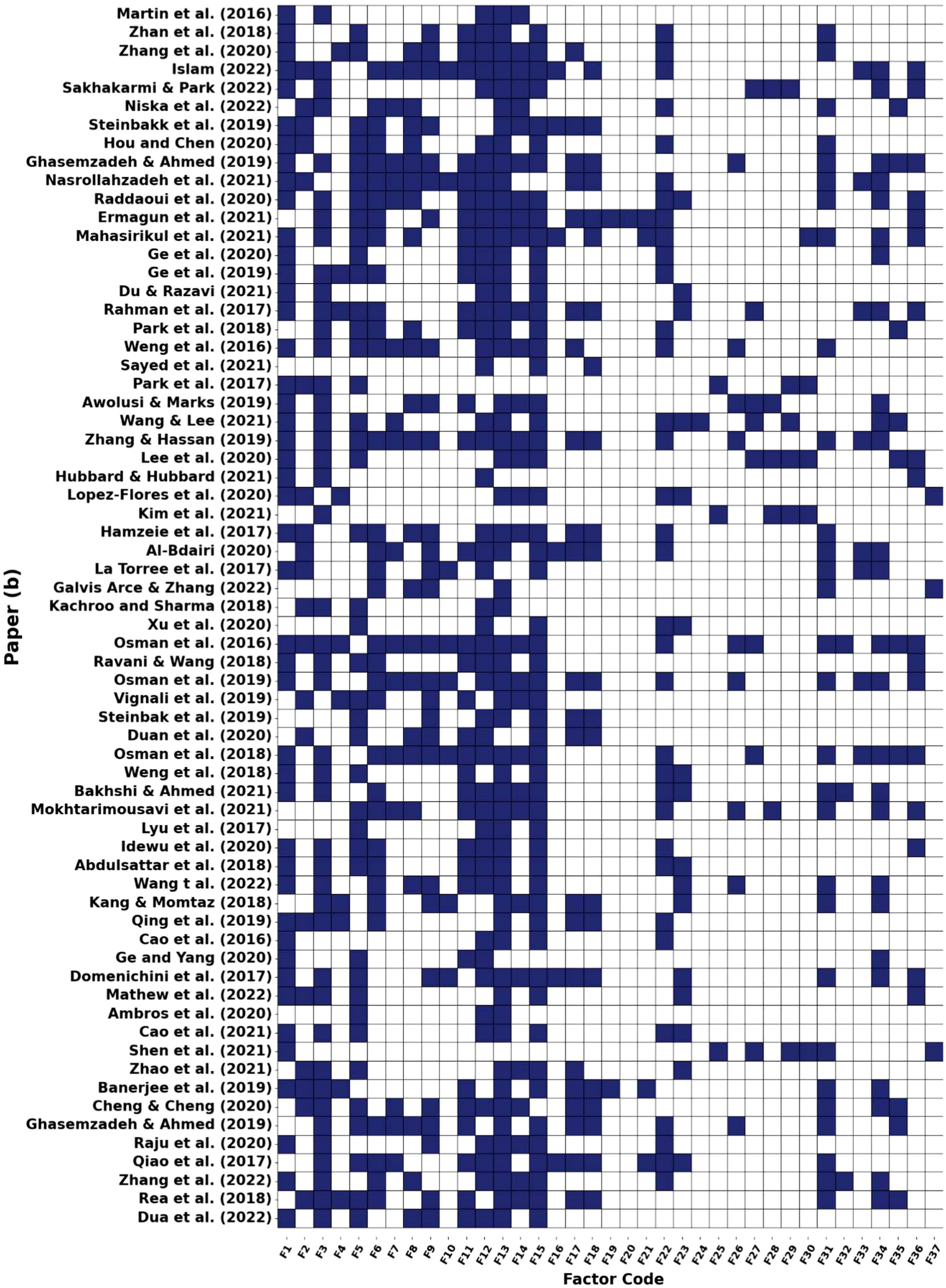
Results of K-Means Clustering

As outlined in the "Research Methodology" section, this study utilized *k*-means clustering to classify the work zone safety factors into groups of co-occurring factors in the literature. This was accomplished by performing the clustering on the matrix of agglomerations of both AMs, and the optimal number of clusters was determined using the elbow method (Fig. 8). Accordingly, the optimal number of clusters was found to be three. Table 5 presents the list of clustered work zone safety factors and with their corresponding categories. The partitioning of the work zone safety factors into three distinct clusters yielded a varying number of factors within each group. Specifically, the clusters comprised 15, 13, and 9 work zone safety factors, respectively. Each clustered group of work zone



(a)

Fig. 5. (a and b) Mapping of the work zone safety factors and the analyzed articles.



(b)

Fig. 5. (*Continued*.)

Table 4. Classification of reviewed articles and their corresponding matrices

Article citation	Type	Corresponding reference matrix: Matrix T	Matrix M
Kitali et al. (2022)	1	X	—
Santos et al. (2021)	1	X	—
Son et al. (2021)	1	X	—
Dehman and Farooq (2021)	1	X	—
Weng and Meng (2012)	1	X	—
Meng and Weng (2013)	1	X	—
Yang et al. (2013)	1	X	—
Rayaprolu et al. (2013)	1	X	—
Yousif et al. (2014)	1	X	—
Weng and Meng (2014)	1	X	—
Debnath et al. (2014)	1	X	—
Liang et al. (2014)	1	X	—
Fan et al. (2014)	1	X	—
Weng et al. (2015b)	1	X	—
Debnath et al. (2015)	1	X	—
Chen and Ahn (2015)	1	X	—
Jin and Jin (2015)	1	X	—
Nyende-Byakika (2016)	1	X	—
Melcher and Keller (2016)	1	X	—
Wennström et al. (2016)	1	X	—
Jumari et al. (2022)	1	X	—
Xu and Yang (2019)	1	X	—
Koilada et al. (2020)	1	X	—
Chang et al. (2020)	1	X	—
Mahasirikul et al. (2021)	1	X	—
Sayed et al. (2021)	1	X	—
Lee et al. (2020)	1	X	—
Hubbard and Hubbard (2021)	1	X	—
Lopez-Flores et al. (2020)	1	X	—
Hamzeie et al. (2017)	1	X	—
Al-Bdairi (2020)	1	X	—
La Torre et al. (2017)	1	X	—
Kachroo and Sharma (2018)	1	X	—
Osman et al. (2016)	1	X	—
Osman et al. (2019)	1	X	—
Steinbak et al. (2019b)	1	X	—
Osman et al. (2018)	1	X	—
Cao and Liu (2016)	1	X	—
Genders and Razavi (2016)	2	—	X
Valdes et al. (2019)	2	—	X
Abdelmohsen and El-Rayes (2018)	2	—	X
Zhang and Gambatese (2017)	2	—	X
Hang et al. (2022)	2	—	X
Yang et al. (2017)	2	—	X
Bai et al. (2015)	2	—	X
Ahmed et al. (2016)	2	—	X
Weng et al. (2015a)	2	—	X
Weng et al. (2016a)	2	—	X
Ren et al. (2021)	2	—	X
Martin et al. (2016)	2	—	X
Steinbakk et al. (2019a)	2	—	X
Hou and Chen (2020)	2	—	X
Ge et al. (2020)	2	—	X
Ge et al. (2019)	2	—	X
Du and Razavi (2021)	2	—	X
Zhang and Hassan (2019)	2	—	X
Kang and Momtaz (2018)	2	—	X
Domenichini et al. (2017)	2	—	X
Ambros et al. (2020)	2	—	X
Cao et al. (2021)	2	—	X
Banerjee et al. (2019)	2	—	X
Ghasemzadeh and Ahmed (2019a)	2	—	X
Rea et al. (2018)	2	—	X

Table 4. (*Continued*.)

Article citation	Type	Corresponding reference matrix: Matrix T	Matrix M
Elghamrawy et al. (2012)	2	X	X
Ahmed et al. (2021)	2	X	X
Kim et al. (2021a)	2	X	X
Lv et al. (2021)	2	X	X
Park et al. (2021)	2	X	X
Valdés-Díaz et al. (2021)	2	X	X
Du and Razavi (2019)	2	X	X
Nnaji et al. (2018b)	2	X	X
Nnaji et al. (2020a)	2	X	X
Xu et al. (2016)	2	X	X
Kummetha et al. (2020)	2	X	X
Rahim and Hassan (2021)	2	X	X
Almallah et al. (2021)	2	X	X
Jing et al. (2021)	2	X	X
Choe et al. (2014)	2	X	X
Bham et al. (2014)	2	X	X
Shakouri et al. (2014)	2	X	X
Huang and Bai (2014)	2	X	X
Kaber et al. (2015)	2	X	X
Sakhare et al. (2022)	2	X	X
Park et al. (2016)	2	X	X
Ren and Wu (2015)	2	X	X
Ferreira et al. (2017)	2	X	X
Nnaji et al. (2020b)	2	X	X
Barlow et al. (2020)	2	X	X
Yang et al. (2015)	2	X	X
Zhu et al. (2016)	2	X	X
Ščerba et al. (2015)	2	X	X
Kersavage et al. (2018)	2	X	X
Wang et al. (2021)	2	X	X
Sze and Song (2019)	2	X	X
Saha (2021)	2	X	X
Zhang et al. (2018)	2	X	X
Zhang et al. (2020)	2	X	X
Islam (2022)	2	X	X
Sakhakarmi and Park (2022)	2	X	X
Niska et al. (2022)	2	X	X
Ghasemzadeh and Ahmed (2019b)	2	X	X
Nasrollahzadeh et al. (2021)	2	X	X
Raddaoui et al. (2020)	2	X	X
Ermagun et al. (2021)	2	X	X
Rahman et al. (2017)	2	X	X
Park et al. (2018)	2	X	X
Weng et al. (2016b)	2	X	X
Park et al. (2017)	2	X	X
Awolusi and Marks (2019)	2	X	X
Wang and Lee (2021)	2	X	X
Kim et al. (2021b)	2	X	X
Galvis Arce and Zhang (2022)	2	X	X
Xu et al. (2020)	2	X	X
Ravani and Wang (2018)	2	X	X
Vignali et al. (2019)	2	X	X
Duan et al. (2020)	2	X	X
Weng et al. (2018)	2	X	X
Bakhshi and Ahmed (2021)	2	X	X
Mokhtarimousavi et al. (2021)	2	X	X
Lyu et al. (2017)	2	X	X
Idewu et al. (2020)	2	X	X
Abdulsattar et al. (2018)	2	X	X
Wang et al. (2022)	2	X	X
Qing et al. (2019)	2	X	X
Ge and Yang (2020)	2	X	X
Mathew et al. (2022)	2	X	X
Shen et al. (2021)	2	X	X
Zhao et al. (2021)	2	X	X

Table 4. (*Continued.*)

Article citation	Type	Corresponding reference matrix	
		Matrix T	Matrix M
Cheng and Cheng (2020)	2	X	X
Raju et al. (2020)	2	X	X
Qiao et al. (2017)	2	X	X
Zhang et al. (2022)	2	X	X
Duan et al. (2022)	2	X	X

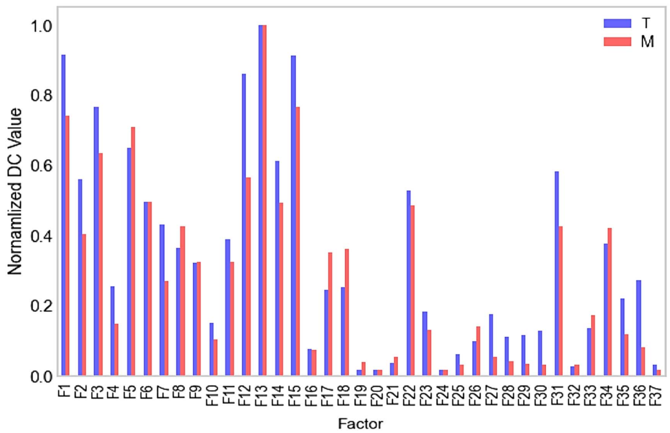


Fig. 6. Normalized degree centrality (DC) values for adjacency matrices (AMs) T and M.

safety factors represents the literature's co-occurring study of this combination of safety factors within the given group. For example, Cluster 3 encompasses 9 of the 37 work zone safety factors. This indicates that there is a tendency in the literature to discuss these nine work zone safety factors as a group, indicating a certain level of interrelatedness and shared attention. Therefore, the clusters categorize the holistic literature trend of collectively discussing specific groups of work zone safety factors among the overall set of factors. Interestingly, a considerable number of the highly addressed work zone safety factors, both theoretically and analytically (i.e., F2, F3, F5, F12, F14, F15, F22, and F31), were categorized within Cluster 1 (Fig. 9). Conversely, the underaddressed factors were dispersed among the three clusters; F16, F27, and F28 were assigned to Cluster 1; F26, F29, and F37 were in Cluster 2; and F4, F10, and F30 were in Cluster 3. This implies that these factors often are addressed marginally in the literature, in the presence of other, more comprehensively addressed factors.

Furthermore, the disparities between the theoretical and mathematical methods employed to address work zone safety factors are accentuated in Fig. 9, which illustrates the discrepancy between the normalized DC values of the factors in Network T and M. A positive discrepancy signifies that the factor received more theoretical attention than analytical study, whereas a negative discrepancy suggests the opposite. Accordingly, the further the factor is to the left, the more it was addressed using a theoretical approach rather than with a mathematical approach. F12 (Volume of Traffic at the Area of Work Zone) and F36 (Law Enforcement), both of which were in Cluster 1, received more study in the theoretical-based literature, as shown by the positive difference in normalized DC values between network T and M in Fig. 9. Moreover, among the 15 factors grouped in Cluster 1, 13 received more study using theoretical approaches than using mathematical approaches, indicating that the factors belonging to Cluster 1 are discussed more often in theoretical approaches than are the other factors.

Conversely, the work zone safety factors of F17 (Driver Gender) and F18 (Driver's Age) were found to receive greater attention through analytical-based literature approaches; these factors belonged to Clusters 3 and 2, respectively. This is supported by the fact that most studies addressing these factors utilized regression analysis to predict work zone crash and injury severity (Islam 2022; Osman et al. 2019). Furthermore, F13 (Driver's Compliance with Work Zone Speed Limit), which had the greatest normalized DC values in both networks (Fig. 6), had a difference of zero between the normalized DC values in the theoretical and mathematical networks, indicating that this factor received nearly equal attention from both approaches. Additionally, other less commonly addressed factors, as indicated by their relatively lower normalized DC values (Fig. 6), also had a difference in normalized DC values of zero (Fig. 9). These factors included F6, F9, F16, F20, F24, and F32. This indicates that fewer literature studies addressed these factors, although they received equal theoretical and mathematical literature studies.

Results of ARA and Apriori Algorithm

To examine further the deficiencies in the literature addressing work zone safety factors, the authors used the Apriori algorithm to conduct ARA on the identified clusters. Fig. 10 illustrates the significant association rules among the clustered factors. Fig. 10 depicts the rules of association of potential deficiencies present in each cluster, based on whether the literature has addressed these factors theoretically or mathematically. Furthermore, the heatmaps for each cluster represent the rules of association between the factors, based on the support value for each rule. A high support value of a rule, depicted in a darker shade in the heatmap, indicates that the interconnectivity of the two factors addressed by the rule has a greater indication of deficiency. Although not necessarily implying a direct need for further studies, the identified rules of association indicate a lack of comprehensive study in the literature of the respective factors, compared with other rules. Future research efforts could focus on addressing these deficiencies to establish a more thorough understanding of work zone safety factors.

The literature on work zone safety factors has a greater emphasis on theoretical approaches than analytical approaches (Fig. 9). This is supported by the Fig. 10, which illustrates the missing associations in literature. Matrix M has more associations, indicating greater deficiencies than Matrix T, namely for Clusters 1 and 3. Additionally, although Cluster 2 has a comparable number of deficiencies in Matrix M and Matrix T, the support of the rules in Matrix M is stronger, suggesting more-significant gaps in the literature in Matrix M.

The greatest deficiency in Matrix T is present in Cluster 1, which relates to F28 (Worker's Behavior) and F25 (Level of Technology within Construction Equipment). Nyende-Byakika (2016) highlighted the importance of workers using personal protective equipment, receiving adequate training, and observing first aid and hygiene practices on site to mitigate preventable occupational work zone injuries. Additionally, risk habituation often is associated with workers' unsafe behavior, specifically workers who repeatedly are exposed to the work zone hazards, because their level of alertness tends to decrease with the frequent exposure to the hazardous environments posed in work zones (Duchon and Laage 1986; Oken et al. 2006). To this end, Kim et al. (2021b) proposed the use of virtual reality environments to elicit work zone workers' risk habituation in order to quantitatively measure

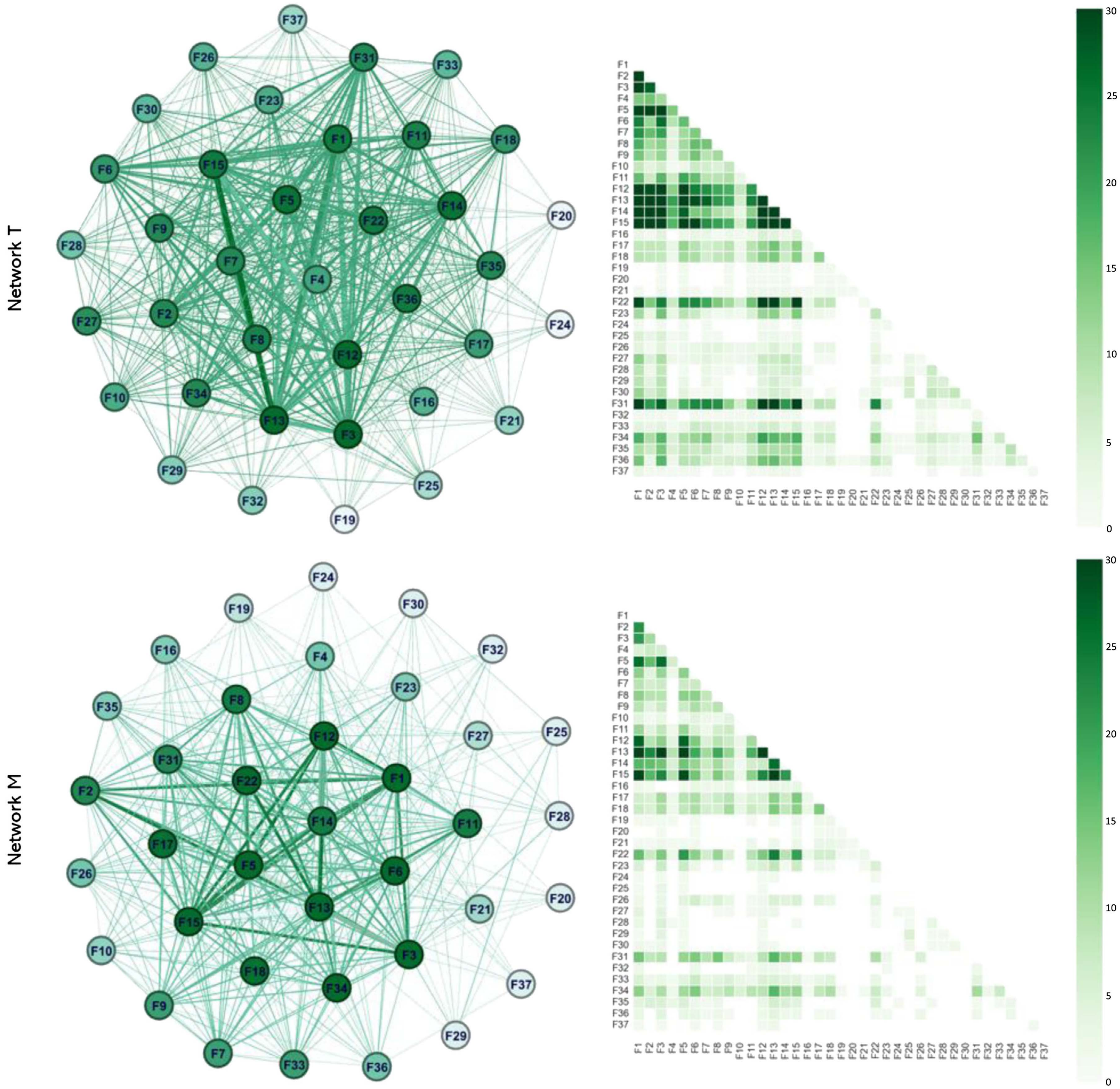


Fig. 7. Visualization of Networks T and M.

workers' attention, thereby contributing to a better understanding of work zone workers' unsafe behaviors. Moreover, Fan et al. (2014) highlighted the importance of adequate training of work zone workers to limit occupational injuries, namely for back-over incidents, which historically have led to over 50% of work zone occupational fatal incidents. Several studies have addressed the level of technology in construction equipment to prevent work injuries from moving construction vehicles. Park et al. (2016) tested the effectiveness of employing Bluetooth devices to alert workers of their proximity to hazardous equipment, and found that such technology has large coverage zones, requires minimal power, and provides functionality to work zone workers. Ferreira et al. (2017) analyzed the use of back-up cameras on dump trucks and their effectiveness in reducing fatalities due to backing equipment, in conjunction with recommendation for the training of workers to avoid being present in blind spots. Ferreira et al. is one of the studies that addressed both factors F25 and F28, focusing on the use of technology in conjunction with workers' behavior. Other studies also have addressed the level of technology in construction equipment when studying work-site collisions, extending beyond the scope of moving vehicles. Ren and Wu (2015) developed and tested an anticollision detection system for cranes to identify static obstacles and slow or stop the movement of the crane, and the system was able to perform emergency stops in most instances. However, this model was unable to detect moving objects, such as workers (Ren and Wu 2015), which again highlights the identified gap in the literature addressing the association between factors F25 and F28. Therefore, future studies can explore the potential impact

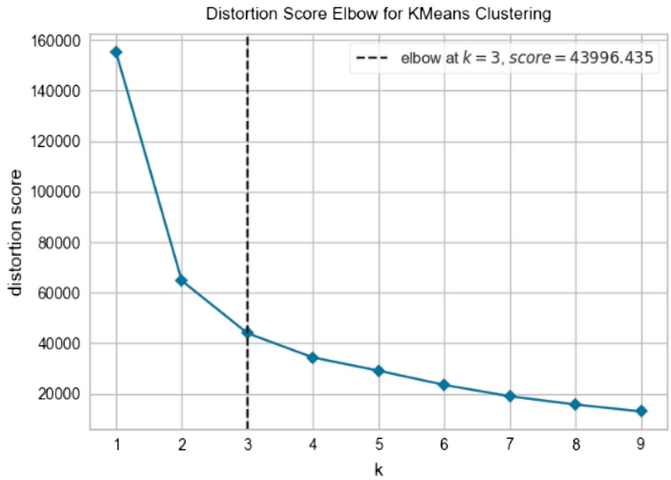


Fig. 8. Elbow plot.

of incorporating technological advancements in work zone construction equipment, in combination with workers' behavior, on improving the overall safety of construction activities in work zones.

The deficiency identified in Matrix T, Cluster 1, which relates to F28 (Worker's Behavior), aligns with the inadequacy found in the same cluster of Matrix M regarding the correlation between F27 (Job Training) and F11 (Sight Distance). Sight distance is particularly crucial for drivers' decision-making because the work zone advance area serves to inform drivers of changing road conditions and provide appropriate guidance (FHWA 2003). Moreover, although most crashes occur in the work-activity area, the crashes in the advance area tend to be more severe (Pigman and Agent 1990). Hang et al. (2022) determined the importance of extending warnings beyond the line of sight in order to improve drivers' crash avoidance in work zones under foggy conditions. Alternatively, several studies focused on the intrusion alarm systems to warn work zone workers about errant vehicles. Martin et al. (2016) emphasized the importance of adequate employee training for effective implementation, but they did not address the factors of variable advance area and driver's sight distance characteristics. Therefore, subsequent studies should aim to investigate various aspects of drivers' sight distance that have received limited attention, along with work zone employee training, specifically focusing on training related to intrusion alarms in adverse weather conditions and varying sight distance conditions.

Cluster 2 in Matrix T reveals a deficiency in the association between Factors F32 (Time of the Year) and F26 (Work Zone Type). This deficiency was expected due to the mathematical nature of F32, compared with the more theoretical nature of other factors. Notably, this deficiency is absent from Matrix M, indicating that this association has been addressed more thoroughly using mathematical approaches than in theoretical discussions. ML models have been developed to investigate the impact of temporal factors along with other factors, including the work zone type, on the work zone safety (Weng et al. 2018; Al-Bdairi 2020; Mokhtarimousavi et al. 2021).

Table 5. Clustered factors and their categories

Category	Cluster 1	Cluster 2	Cluster 3
Design-related factors	F2, F3, and F5	F1	F4
Roadway-related factors	F11 and F12	F6, F8, and F9	F7 and F10
Driver-related factors	F14 and F15	F16, F18, and F21	F13, F17, F19, and F20
Vehicle-related factors	F22, F24, and F25	F23	—
Work-related factors	F27 and F28	F26 and F29	F30
Temporal-related factors	F31	F32 and F33	F34
State-related factors	F36 and F37	F35	—
No. of factors	15	13	9

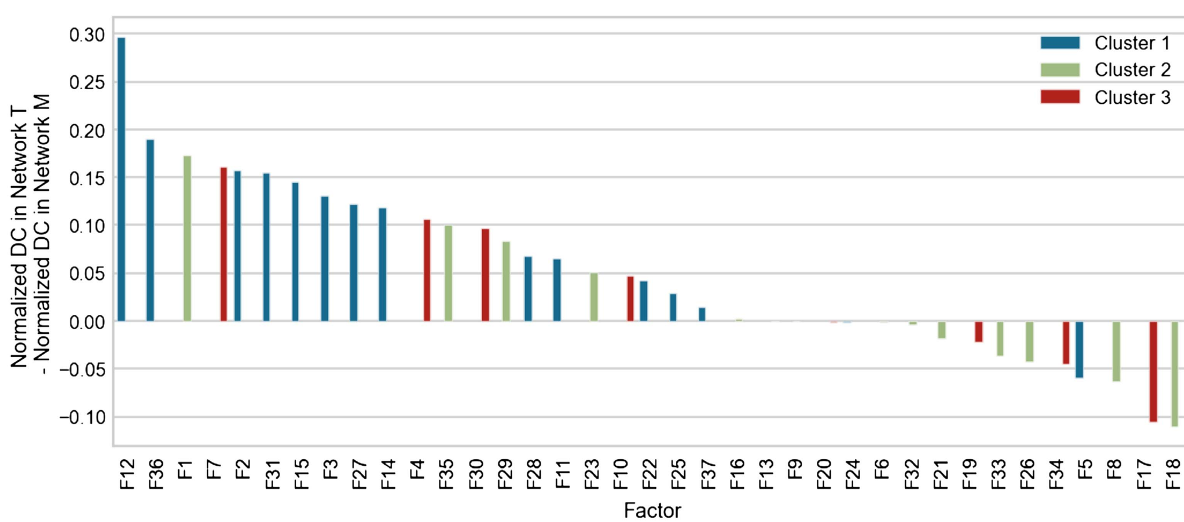


Fig. 9. Difference in normalized degree centrality (DC) values.

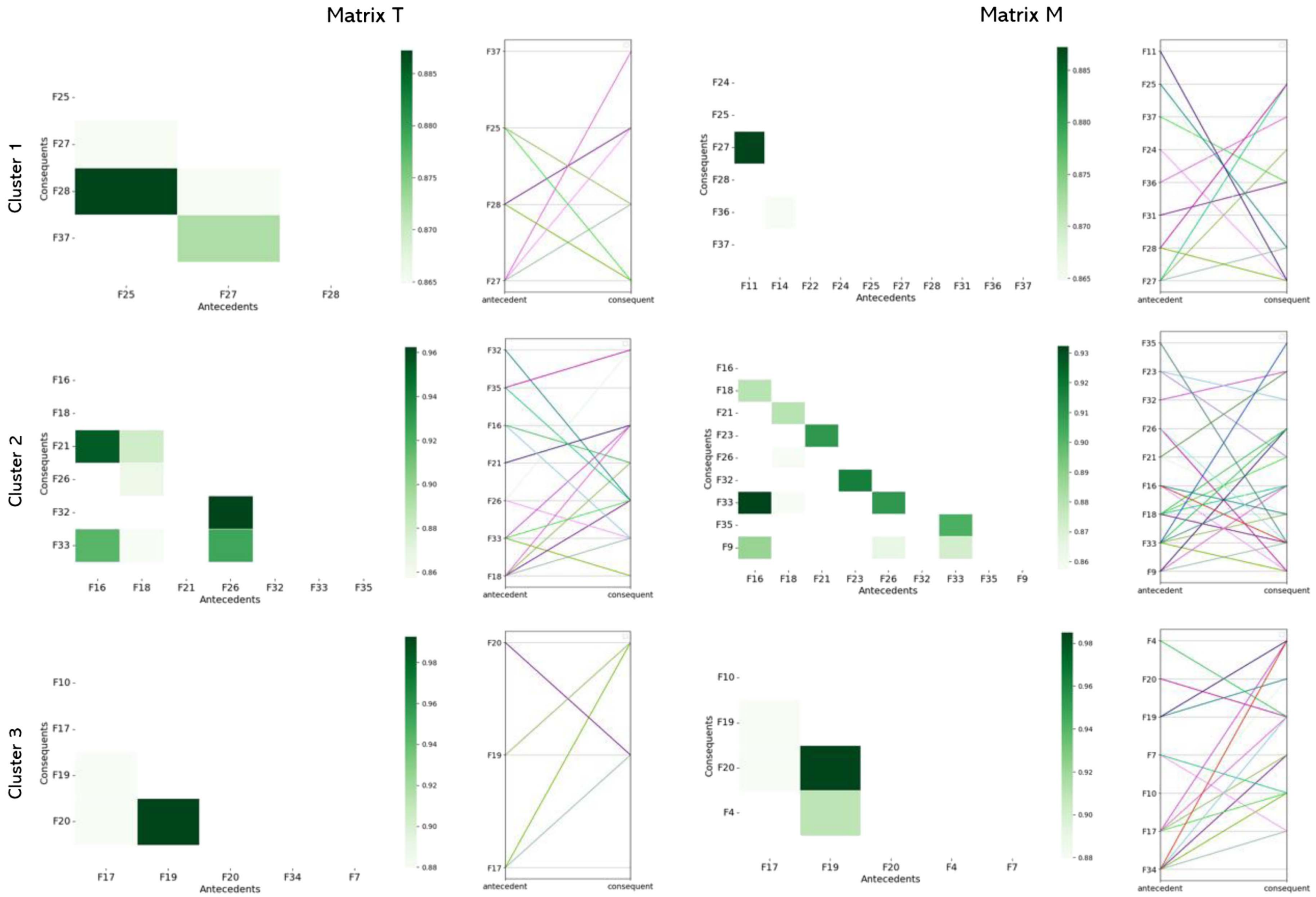


Fig. 10. Significant associations among the clusters of Networks T and M.

In Cluster 2 of Matrix M, the greatest deficiency is the association between F33 (Day of the Week) and F16 (Driver Impairments). Koilada et al. (2020) modeled the odds of different levels of crash severity in various work zone areas, including variables such as weather, speed limit, road alignment, gender, age, and various road characteristics, and found that weekdays had higher rates of crashes than weekends. Similarly, in their study of the factors influencing various levels of injury severity in work zone rear-end crashes, Zhang and Hassan (2019) observed that young male drivers are more prone to experiencing fatal injuries when involved in work zone accidents that occur during the weekends. However, neither studies included driver impairments in the mathematical modeling. Chang et al. (2020) evaluated the risks of crashes using preincident variables, including driver impairments, but excluded the impact of the day-of-the-week variable in classifying and predicting work zone crash events using ML models. Therefore, future computational or mathematical studies potentially could develop models that incorporate the day of the week and driver impairments, among other variables, to improve the modeling of work zone safety, including crash occurrences and severity.

In Cluster 3, the most significant deficiency in both networks was the impact of the association of F19 (Driver's Income) and F20 (Driver's Ethnicity), both of which are driver-related, on work zone safety. Although demographic factors may not necessarily directly affect work zone safety, they could reveal societal-based responses to and reflections of decision-making while crossing work zone areas. For example, Ermagun et al. (2021) studied the response of drivers to hacked message signs when approaching a work zone, considering driver factors such as socioeconomic characteristics and driving habits. They found that certain ethnic backgrounds and household incomes were statistically significant in the decision to change speed. Accordingly, future studies could consider socioeconomic variables, among other preincident variables, in addressing driver responses to certain work zone environments.

Discussion

This paper presents a comprehensive review of the existing literature pertaining to work zone safety. To reflect the validity of the results of this study, this section discusses and interprets the obtained results.

- The SNA DC metricdisplays the normalized DC values for Networks T and M; significant factors had comparatively high normalized DC values, whereas under-addressed factors generally had lower normalized DC values (Fig. 6). Furthermore, the DC values are provided for each of the theoretical and mathematical approaches employed in examining the factors. Notably, certain factors, such as F27 (Job Training), F28 (Worker's Behavior), F30 (Level of Congestion in the Work Zone), and F36 (Law Enforcement), emerge as particularly understudied mathematically. Additionally, the majority of the factors addressed in Cluster 1 received more-extensive

theoretical treatment than mathematical or computational analysis (Fig. 9). Consequently, future studies could focus on investigating these understudied factors or supplementing the mathematical treatment of the underexplored safety factors within this framework.

- The network visualization presented in Fig. 7 effectively highlights the contrasting approaches employed in the examination of work zone safety factors, with a particular emphasis on the theoretical and mathematical perspectives. The visualization demonstrates the varying densities of Networks T (77.6%) and M (58.3%), providing insight into the level of interconnectivity among the factors under investigation. Notably, Network T had a higher density than Network M, indicating a greater degree of interconnections among the theoretically discussed factors in the existing literature than among their mathematical or computational counterparts. Consequently, it can be inferred that the current work zone safety models do not necessarily encompass the comprehensive range of relevant factors, which underscores the significance of focusing on theoretical approaches. Therefore, a thorough analysis encompassing all pertinent work zone safety factors is lacking, highlighting the critical need for such a comprehensive investigation.
- The *k*-means clustering results (Table 5 and Fig. 9) categorized the work zone safety factors based on their comprehensive treatment in the literature. The majority of factors within Cluster 1 have received more-substantial theoretical attention, surpassing the level of consideration given to mathematical and empirical approaches. Furthermore, within Cluster 1, the work zone safety factor F12 (Volume of Traffic at the Area of Work Zone) had the most pronounced disparity between theoretical and mathematical analyses. Notably, despite the acknowledged importance of traffic volume for work zone safety (Shakouri et al. 2014; Zhu et al. 2016), it received more-extensive theoretical investigation than mathematical analysis. Moreover, the underaddressed factors (F6, F9, F16, F20, F24, and F32) were dispersed across the three clusters. This distribution pattern suggests that these particular work zone safety factors are consistently underexplored compared with other extensively examined factors, despite their inherent significance in contributing to a comprehensive understanding of work zone safety. This reinforces the point that there is a notable absence of a comprehensive examination encompassing all relevant work zone safety factors, emphasizing the necessity for such an extensive investigation.
- The ARA results (Fig. 10) depict the interrelationships among deficiencies within the clusters, highlighting the factors that have not received sufficient scrutiny in the existing literature. Cluster 2 had more-pronounced inadequacies than Clusters 1 and 3 in both Networks T and M. Consequently, the associations within Cluster 2 have been relatively understudied in the literature, from both a theoretical and a mathematical standpoint. Specifically, further investigation is warranted regarding the associations involving driver characteristics, such as F16 (Driver Impairments); temporal factors, such as F32 (Time of the Year) and F33 (Day of the Week); and work-related factors, such as F26 (Work Zone Type). Notably, considering the mathematical nature of the temporal factors, ML models could be employed to assess, classify, and potentially predict crash occurrence and severity based on variables encompassing the aforementioned factors.

Based on the analysis presented in this paper, several recommendations can be made to advance the existing knowledge on work zone safety. Scholars are advised to integrate the relatively underaddressed work zone safety factors, specifically those pertaining to drivers and state-related factors, into their future research endeavors. Specifically, researchers can utilize the SNA results presented in Figs. 6 and 7 as a reference to assess the underaddressed factors, considering the adopted theoretical and mathematical approaches, and subsequently incorporate them into future studies. By doing so, the knowledge base pertaining to the impact of these factors on work zone safety will be expanded, thus contributing to a more comprehensive understanding of the subject matter. Moreover, in terms of cross-examination between multiple factors across studies, future researchers can refer to the clustering and ARA results presented in Figs. 9 and 10, respectively, to address the gaps and deficiencies identified within each cluster. These figures provide a visual representation of the areas in which investigation is lacking, enabling researchers to focus on filling these gaps in knowledge. Factors within Cluster 1 had notable deficiencies in terms of mathematical and computational perspectives. Moreover, within Cluster 1, there were cross-examination deficiencies between F25 (Level of Technology within Construction Equipment) and F28 (Worker's Behavior) from a theoretical standpoint, as well as between F11 (Sight Distance) and F27 (Job Training) from a mathematical perspective. Similarly, Cluster 2 highlights deficiencies in the mathematical study of temporal factors in conjunction with F16 (Driver Impairments). Furthermore, Cluster 3 reveals deficiencies in both theoretical and mathematical study of driver-related factors. Future research efforts can focus on addressing these deficiencies and exploring the interrelationships among these factors to advance the understanding of work zone safety.

Conclusion, Contributions, and Limitations

This study provides a thorough and comprehensive review of the existing literature on work zone safety, in order to assess the current state of knowledge and identify future research directions. The authors conducted an extensive review of 133 peer-reviewed articles, resulting in the identification of a comprehensive list of 37 factors that influence work zone safety. To gain further insight into the literature's treatment of these factors, the authors applied SNA to analyze the interconnections among the identified factors. This analysis facilitated the grouping of factors into three clusters based on the literature's treatment and the specific methodologies employed in addressing them. Moreover, the study utilized ARA to mine rules of associations, highlighting gaps in the examination of certain safety factors in conjunction with each other. The findings of this study emphasize the importance of exploring several factors that have received limited attention in previous research, specifically driver-related, work-related, and state-related factors. These understudied factors play crucial roles in work zone safety and warrant further investigation in future research endeavors. Furthermore, it is recommended that future research should focus on the mathematical and computational aspects of highly theoretically addressed topics. By incorporating mathematical and computational approaches, researchers can complement the existing body of knowledge on work zone safety, providing a more comprehensive understanding of these topics. Moreover, high DC values reflect greater focus in the literature rather than work zone safety criticality, and thus, future research could benefit from evaluating the criticality of identified factors on work zone safety and accident severity. This study collectively contributes to the comprehensive understanding of the present body of knowledge and identifies avenues for future research in this field.

The research conducted in this study makes significant theoretical contributions to the body of knowledge pertaining to work zone safety, including (1) identification of an unprecedented comprehensive list work zone safety factors affecting both occupational and

driver safety within work zones, (2) investigation of the interconnectivity among the identified work zone safety factors and identification of understudied factors in the literature related to safety in work zones, and (3) identification of ill-studied work zone safety factors in the theoretical discussions versus mathematical- or computational-based studies. This provides a solid foundation to provide recommendations and directions for researchers in order to avoid redundancies and enhance the benefits of relevant future research efforts. Additionally, this study provides practical contributions to safety practitioners by promoting a comprehensive understanding of potential factors that impact safety in work zones. Specifically, this research identified various factors that are potential determinants of safety in work zone projects, including specific state-related factors, such as F35 (Adequacy of Safety Guidelines and Procedures), F36 (Law Enforcement), and F37 (Safety Budget), along with other factors influenced by the state, such as work zone-related factors. These factors can serve as benchmarks for relevant state safety personnel to evaluate their state's performance and strive to improve work zone safety measures accordingly.

Nevertheless, like any research endeavor, this study is not without limitations. Specifically, the application of the ARA methodology in this study may generate a substantial number of association rules. To address this issue, as detailed in the "Research Methodology" section, the focus was placed on extracting high-lift rules of associations, which helped identify critical gaps that have not received comprehensive examination in the existing work zone safety literature. Furthermore, the body of knowledge in this field is constantly evolving and subject to change. Therefore, the findings presented in this study are based on the available literature up to the time of data collection. To ensure the currency of information, it is recommended that similar analyses be replicated using subsequent data cut-off dates to update the findings over time and capture any emerging trends or development.

Data Availability Statement

All data, models, and code generated or used during the study appear in the published paper.

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