International Journal of Disaster Risk Reduction 111 (2024) 104653

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

Characteristics of crowd disaster: Database construction and pattern identification

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ARTICLE INFO

Keywords:
Crowd disaster
Incident database
Cluster analysis
Crowd management

ABSTRACT

Crowd disasters pose a serious societal threat with frequent occurrence and high fatality. Despite thorough research having been conducted on the basic mechanisms behind crowd disasters, further qualitative study is required to explain patterns of crowd movement under different environmental conditions. This paper describes the methodology behind the creation of a novel crowd disaster database, incorporating unprecedentedly strict inclusion criteria and well-defined characteristics in order to facilitate better qualitative understanding. The data characteristics are retrieved from previous literature reviews and a 2014 Shanghai crowd disaster case study. Online news database Factiva is used as the main data source, combining with supplemental Internet sources. The completed database contains 293 crowd disasters from 1989 to 2021 and is subject to a data quality assessment procedure. Through the cluster analysis algorithm K-Modes, the entire database has been categorized into nine clusters and distinct features within each cluster are discussed. Each cluster is thus considered as a unique type of crowd disaster, enabling event organizers to link combination of characteristics with likelihood of crowd disaster. Consequently, a more explicit crowd management strategy can be developed to target most common causal factors.

1. Introduction

Rapid urbanization and globalization, coupled with major developments in transportation, has seen a major increase in the number of large gatherings around the world. Unfortunately, this has been accompanied by a considerable rise in the number of crowd disasters[1], i.e., incidents occurring during crowded situations that can result in fatalities or serious injuries. The reported cause, and the number of recorded fatalities and injuries of certain prominent crowd disasters are illustrated in Table 1. Some of these disasters have occurred during major annual set pieces e.g., Hajj religious gathering, the UEFA Champions League Final in football. It is also notable that certain events have been cancelled permanently due to crowd disasters e.g., the Shanghai New Year Light Show and the

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[1] Such a tragedy has often been referred as crowd disaster, stampede, or human crush. To avoid ambiguity and imprecision the term “crowd disaster” is used in this in this paper.

https://doi.org/10.1016/j.ijdrr.2024.104653
Received 25 December 2023; Received in revised form 19 April 2024; Accepted 1 July 2024
Available online 6 July 2024

Table 1
Crowd disasters in the past.

Incident	Cause	Fatality	Injury
1989 Hillsborough disaster	Influx of football fans into standing terrace	97	766
2010 Love parade disaster	Crowd turbulence	21	652
2014 Shanghai crowd disaster	Counterflow at staircase	36	49
2015 Hajj crowd disaster	Timetables were ignored	2000+	Unknown
2017 Turin crowd disaster	Rumor of bomb attack	3	1672

Love Parade in Duisberg, Germany. The severity of these disasters has resulted in the critical need for research in understanding the relevant risks of large events and their mitigation.

In recent years, there have been considerable efforts to obtain a better understanding of the quantitative aspects of crowd movement. State-of-the-art crowd modelling approaches can be broadly categorized according to their modelling scales [1]: macro-scale models [2], micro-scale (agent-based) models [3] and meso-scale models [4]. While macro-scale models focus on local average quantities such as the density of the crowds, micro-scale models further investigate deterministic individual behaviour [5]. The meso-scale models can be viewed as an extension of micro-scale models with a probability distribution.

A typical example of a micro-scale model is the Social Force Model proposed by Ref. [3]. In this model, an individual's obstacle avoidance is described as a virtual repulsive force (as opposed to the real physical forces), while a virtual attractive force exists between people and their targets of interest. Due to complex interactions between the crowd and the external environment, both the repulsive and attractive forces can originate from almost every physical entity in the scene. Furthermore, these forces are sometimes interchangeable e.g., a sculpture in the middle of the road can have repulsive force against daily pedestrians but exert attractive forces on certain tourists. Consequently, a complementary qualitative understanding of crowds is needed to address the focal points of crowds and the fluctuations in crowd behaviour caused by complex interactions.

Based on prior research [6], Force, Information, Space and Time (FIST), which are identified as four primary elements involved in crowd disasters, are selected as qualitative characteristics of crowd disasters in this paper. Incident scenario (e.g., sports event) and the environment (e.g., stadium) are also incorporated as two additional characteristics based on a case study of the 2014 Shanghai crowd disaster given the wealth of information about this incident. A total of 293 crowd disasters ranging from 1989 to 2021 have been identified from news articles and coded based on these characteristics.

The main novelties of this research are as follows:

i) We propose an extension of the FIST model by incorporating qualitative characteristics of crowd disasters based upon our analysis of the Shanghai crowd disaster (2014);
ii) Furthermore, we develop a code book (i.e. a form of data dictionary) of crowd disasters based upon the analysis conducted in the paper. While code books have been developed in other domains, to the best of the authors' knowledge, this is the first such book for crowd disaster.

A major outcome of this research is the identification of nine types of crowd disasters and their underlying factors, thereby enabling targeted, rather than generic, crowd management measures. The data is strictly verified based on its quality and analysed through a cluster analysis algorithm (K-Mode).

The paper is structured as follows: section 2 reviews the relevant literature and identifies current research gaps, section 3 provides the definition of each characteristic of crowd disasters, sections 4 and 5 introduce the methodologies for database construction and data analysis respectively, section 6 discusses the database and section 7 concludes the paper.

2. Literature review

As highlighted by [7, p. 217] an "improved collective understanding of human stampedes has crucial planning implications and is indispensable in mitigation of this unique form of crowd disaster." Two perspectives are often taken to seek patterns among different crowd disasters. One perspective considers crowd management. For instance Ref. [7], noted common problems faced by Hajj in Mecca such as the failure to follow the schedule [8]. identified common threads leading to major crowd disasters in the U.K. from 1863 to 1994, including inadequate planning and flaws within infrastructures. Likewise [9], analysed 68 crowd safety projects that the lead author had experienced in order to recognize potential place of crowd safety issues from the perspective of design, information and management.

For the other perspective, considerable research has studied the common characteristics of crowd disasters, including venues [6], causal factors (mechanism) [10–12], fatalities [13,11], and other epidemiological characteristics [13].

Based on this latter perspective, we propose to incorporate the "FIST" model, proposed by Ref. [6], in this research in order to identify the characteristics of crowd disasters. Within this model, "F" stands for crowd forces, "I" stands for the information that crowds act upon, "S" stands for the physical space where the disasters take place and "T" denotes the time duration. This model has been widely used, ranging from understanding the causal factors of one specific incident [14] to forming a panic growth model suitable for 68 previous incidents [15]. In addition, this model has proved effective in improving crowd management in confined spaces [16] and public venues [17].

Furthermore, a case study of the 2014 Shanghai crowd disaster has conducted, based on the first perspective (i.e. crowd management), to further identify key crowd disaster characteristics. This disaster took place on December 31, 2014 near Chenyi Square on the Waitan area in Shanghai city. Nearly 300,000 people had gathered there for the New Year celebrations in order to view a fireworks display. A disaster ensued at a staircase providing access to the viewing platform, when people going down the stairs collided with those who were going up to get a better view from the platform. This resulted in 36 reported deaths and 49 injured.

After the incident, an official report [18] was published giving the results of an investigation by Shanghai City Government that identified several causes. The report contains valuable information about the crowd disaster; similar details are often hard to retrieve for such incidents [19]. Consequently, the 2014 Shanghai crowd disaster has been widely used as a case study in order to gain valuable insights into a crowd disaster for either the event preparedness stage [20] or in-event crowd aggregation detection [21].

Once key characteristics are identified, developing a database is invaluable for collective pattern identification [13]. To the best of our knowledge, databases in the literature, mostly categorize incidents based on either the severity of their consequences in order to identify the types of crowd disaster with the highest fatality rates [11,12] or the distribution of underlying mechanisms with respect to a particular time period [13]. Such databases suffer from several drawbacks, notably the failure to introduce a specific inclusion criteria, i.e., the criteria (e.g., time, information source) for an incident to be included in the database, and the lack of precise definitions, both for a crowd disaster itself and each of its characteristics. This has resulted in discrepancies in the databases, i.e., not all collected incidents describe the same disaster, and this provides challenges for research reproduction. This research aims to address this gap by adopting a codebook (attached in Appendix A) which states the inclusion criteria of the database (section 4) and provides an exact definition for each characteristic (section 3).

The main contribution of this research includes:

- Propose the combination of causal factors from the FIST model, with scenario and environment settings as qualitative characteristics for understanding crowd disasters.
- Propose precise definitions for qualitative characteristics enabling future reproduction and subsequently construct a crowd disaster database with clear inclusion criteria ensuring consistency, accuracy and completeness.
- Identify nine types of crowd disasters through cluster analysis and thereby enabling event organizers to develop a more explicit crowd management strategy, as they are able to locate most common causal factors of crowd disasters based on the event scenario and environment.

3. Characteristics of crowd disaster

In this research, we employ the FIST model to systematically capture causal factors of crowd disasters. Meanwhile, scenario and environment characteristics are also incorporated, given their ability to comprehend both the environmental settings and the crowd behaviour. Finally, a case study of the 2014 Shanghai Crowd disaster is used to validate the significance of this inclusion.

3.1. FIST model

3.1.1. Crowd force (F)

The main source of fatalities from any crowd disaster is the crowd force [6]. According to Ref. [2], when the density of people reaches approximately seven persons per square meter, a transition from laminar to longitudinally unstable flows will occur “inside” crowds. Such a phenomenon, known as crowd turbulence, is defined as an unanticipated and unintended irregular motion of individuals in different directions due to strong and rapidly changing forces in crowds of extreme density [22].

At extreme density (typically taken to be seven persons per square meter), a crowd acts more like a fluid mass than a solid mass, so that individuals lose control of themselves, and everyone becomes a part of the fluid mass involuntarily. Shock waves can thus be propagated through the crowd sufficiently in order to lift people off of their feet and propel them distances of three or more meters [23]. The lungs of individuals in the crowd may be compressed by the forces accumulating in the crowd due to crowd turbulence, such that individuals are unable to breathe sufficiently in order to acquire the required amount of oxygen [22]. Consequently, compressive asphyxia has been identified as the main cause of death for crowd disasters [6].

Considerable research [24–27] has suggested that the local average speed of crowds will drop sharply when the local density reaches seven persons per square meter, which indicates that people are forced into a restricted “shuffling” gait at this point.

Another form of crowd force is pushing. People will unintentionally push each other during a queuing effect and, as the distance between them is so small, there will be inadvertent body contact [22]. During a rush situation, people will start to intentionally push each other so as to overtake those in front of them [28,29]. The interactions among people will become physical and people will be injured, becoming non-moving obstacles for others [30]. Such pushing, followed by a “domino effect”, can exert a force as high as 4500 N which is able to bend steel [6].

As summarized by the [16], the key indications of crowd force contain the following: breathing difficulties, crowd pushing, movement difficulty, crowd pressure (from high density), uncontrollable pushing, and suffocation.

3.1.2. Physical space (S)

The degree of crowding is sometimes restricted by the physical space (“S” element) of assembly facilities. For instance, the safe static crowd density has been identified to be below five persons per square meter [31], while the safe density for walking downstairs and upstairs is defined to be 3.5 and 3.2 persons per square meter, respectively [32]. Some physical facilities may have a lower safe density.

Meanwhile, the safe density will be affected by the desired velocity of pedestrian. When people try to pass through a bottleneck with a high desired velocity (i.e., in a rush), an irregular succession of arch-like blockings will be formed at the entrance of the bottleneck. Friction between people will be amplified due to impatient resulting in pushing, and avalanche-like bunches of leaving pedestrians will be found when the arch-like blocking break [33].

In conclusion, the key indicators of physical space are the: existence of staircase, escalators and lifts; density at entrances and exits; densities at other physical facilities [16].

3.1.3. Information (I)

[6] identified the information ("I" element) that crowds act upon to be a major cause of crowd disasters. Perceived information has numerous forms ranging from any visual information received by an individual's retina and their brain [34] to real time communication (e.g., announcement) from the event organizer. Previous research [16] has opted to focus on any information given by the event organizer, such as all types of instruction signs and warning signs. However, such information is hard to achieve without knowledge of the venue configuration or access to the official incident report.

In this research, we are interested in the high desired velocity scenario stated above. The term "panic" is commonly used by the media report to describe such situation. The panic situation, as defined by Ref. [35], is when people "are suddenly confronted with an imminent danger and provided with a means of escape that is limited and for which they do not possess any prior organized mode of use." People tend to show herding behavior (i.e., to follow others' actions) under panic situation [36] and thus alternative exits are often inefficiently used [23,37,38]. Such inefficient usage of emergency exits will lead to both overcrowding and intentional pushing as people try to move faster than normal during panic situation [30].

However, the term panic only accounts for a small proportion of the incidents [39]. Additional indicators are therefore required to present other types of information that might lead to a high desired velocity. After reviewing numerous incidents, we further identified information that will lead to a rushing situation including an unexpected incident (e.g., sudden rain) and limited desirables (e.g., charity distribution, discounted product). Combined with imminent danger, these are the key indicators of the information element.

3.1.4. Time (T)

Time is another important factor identified in the FIST model. This relates mainly to the control of the pedestrian demand rate so that any traffic flow does not exceed the capacity of any element of the physical environment (especially the queuing area).

A long waiting time could eventually prove to be fatal, as the formation of a high crowd density may not only originate from a limited physical space, but also from the so-called queuing effect identified by Ref. [5]. When a queue has been static or moving slower than expected, some of the waiting individuals will begin to move forward a little thereby creating an illusion of progression, causing their successor to perform the same behaviour. Such behaviour will unconsciously increase people density and has been demonstrated as one of the contributing factors for crowd disasters, such as the 2010 Love parade [22].

As summarized by Ref. [16], the key indicators of time are crowd flows control and waiting time.

3.2. Case study: 2014 Shanghai Crowd disaster

The framework for crowd disaster analysis proposed by Ref. [40] is introduced here, and each cause identified in the report [18] of the 2014 Shanghai crowd disaster has been categorized into one of the components of the FIST model. The result of case study is summarized below.

Culture: "Reluctance to make a decision" has long been a feature of China's local bureaucratic culture, since the responsibility of making an incorrect judgement often falls on individuals who can subsequently be punished. Huangpu district government made an application on November 13, 2014 to Shanghai City Government to change the venue of New Year countdown event. The latter then clarified that the district government was responsible for its own decision, thus it took until December 9, 2014 for the district government to decide on the new venue of the event which only received official approval on December 26, 2014. Consequently, the new venue was officially announced to the public on the morning of 30 December 2014, just a day prior to the event.

People: Most attendees were tourists from other cities, unfamiliar with the local area. In addition, the name of the new venue, Waitanyuan, is very similar to the name of the original, Waitan.

Goal: The main goal of attendees was to watch the lightshow scheduled to commence at 23:30. Hence increasing numbers of people were trying to reach the viewing platform in order to get a good viewing spot, rather than leave, around that time.

Process: Failure to predict the location of gatherings. The late announcement, coupled with the tourists' lack of familiarity with the local area, meant that most attendees gathered in Waitan, in contrast to the main police force which had gathered at Waitanyuan. Furthermore, because the goal of attendees was not taken into account, the gathering at the viewing platform was not foreseen by the authorities. Indeed, only seven police personnel had been allocated to the viewing platform prior to the event.

Technology: Due to the reasons outlined above, inadequate technology was used. The viewing platform is supposed to be unidirectional, with one staircase going up and the other down. However, only warning tape had been used to enforce this unidirectional system. Due to the unequal inflow and outflow, people started to rush to the exit staircase. The warning tape was easily torn down by this strong pedestrian flow and the unidirectional system started to fail. At 23:23, the inflow and outflow clashed and formed a stalemate. Soon afterwards, one person in the stalemate fell and caused a massive domino effect in the crowd (Crowd pressure identified).

Infrastructure: The Waitan area is located near the Huangpu River, which naturally makes this a restricted area i.e., only three directions are accessible for pedestrians and there are fewer escape options during emergencies (Insufficient physical space identified).

Based on [32], the pedestrian flow on a staircase is more unstable than that on a flat surface. There're several staircases in Chenyi square, and the local authority failed to consider this when performing their safety checks. At 21:14, they reported 50 % of the maximum capacity, which based on their experience, was approximately 160,000 people. However, subsequent video footage analysis estimates that the maximum capacity should have been approximately 240,000.

As demonstrated in Fig. 1, three components contributed to failure in the process, which also led to insufficient usage of crowd management measures. Within the three contributing components, only infrastructure can be partially captured by FIST model (staircase), while goal and people need to be further comprehended by other characteristics.

Consequently, the scenario of the event is incorporated as a characteristic of a crowd disaster due to its ability to capture the common features of participants and their goals. Another characteristic, environment, is also introduced to comprehend the nature of the spacious settings in the infrastructure (allowed degree of freedom in the movement direction), apart from the local physical space studied in FIST model. Additionally, casualty is added as the last characteristic to reflect the severity of the consequences.

The Shanghai disaster case study shows that in addition to the causal factors derived from the FIST model, it is essential to consider the characteristics of the crowd disaster in particular the social scenario and the physical environment. Consideration of such characteristics does not imply any causality, in contrast to the factors derived from the FIST model.

4. Methodology – database construction

4.1. Source identification

The ideal primary source of any crowd disaster data is the published official report and the accompanying video footage. However, due to difficulties in accessing the relevant data from organizations [19], news articles (in print or online) and solely online sources are often used as alternatives. Consequently, an online news database, Factiva [41], has been selected as the main source of data in this research.

Since crowd force is the main cause of fatality and injury [6] during crowd disasters, the term crowd disaster in this research is defined as:

"An incident in which people are injured or die caused by a high density of surrounding people."

The inclusion criteria of the database are then developed based on the following definition:

I. The Incident must occur between the 1st January of 1989 and 31st December of 2021.
II. The incident has been reported either in Chinese or English by a well-known news publisher.
III. People must have been either injured or died in the incident due to crowd force originating from the high density of surrounding people.

Based on the above inclusion criteria, "(crowd and (stampede or crush) and (die or injured) and (tragedy or disaster)) or 踩踏事件"is entered in the search form box of Factiva, and a date range from 01/01/1989 to 31/12/2021 is selected. The term "踩踏事件" means stampede in Mandarin and is entered to explore Chinese news articles in order to increase the inclusiveness of the database. Correspondingly, English, Chinese – Simplified and Chinese – Traditional are selected in the Language section. A screen shot is provided in Fig. 2 for reproduction purpose.

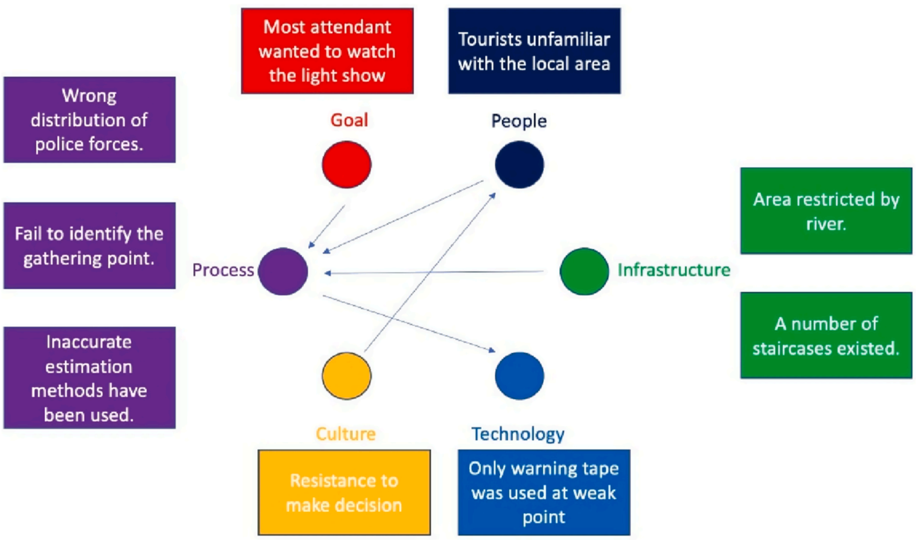

Fig. 1. Shanghai 2014 Crowd disaster from a system perspective.

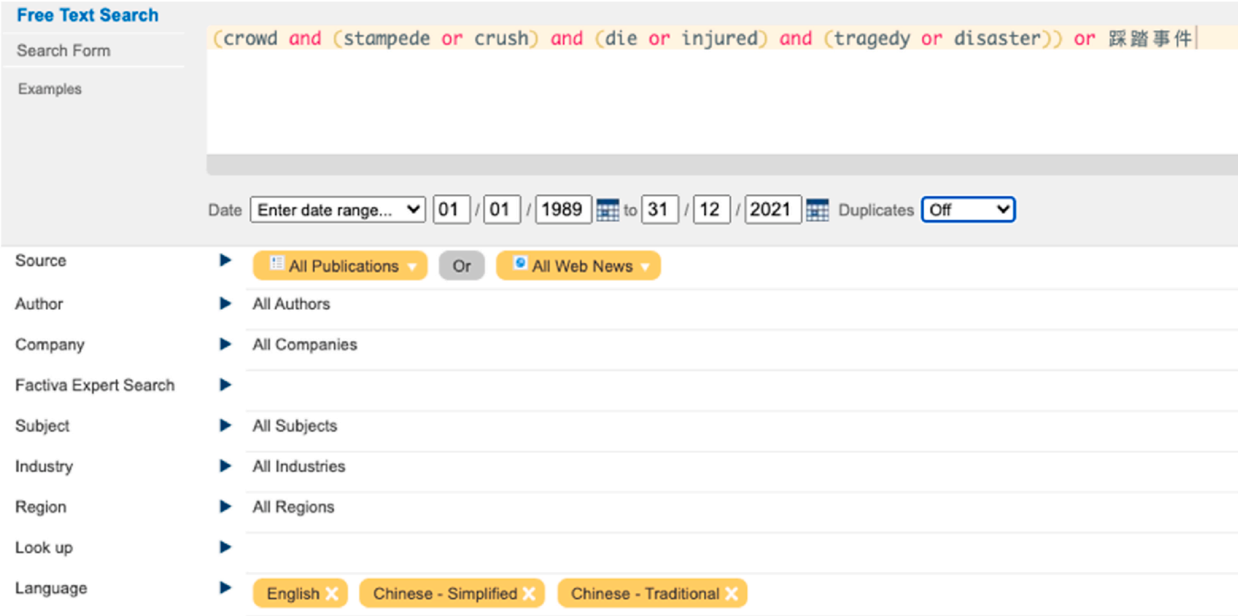

Fig. 2. Input in the Factiva search box.

Two supplemental Internet sources are also used in this research, Wikipedia and a website named 'working with crowds' [42] that focuses on crowd safety management. Although Wikipedia has been criticized for its creditability [43] alongside with other Internet sources, it is nonetheless capable of retrieving useful information about commonly recognized crowd disasters after strict source verification.

Incidents retrieved from above sources are further filtered following the inclusion criteria stated above and subsequently added to a list of crowd disasters. Depending on availability, a maximum of three news articles were downloaded for each crowd disaster to serve as the data source.

To maximize the reliability of news obtained from the Internet, the principle of maximum variation sampling is adopted. This approach involves maximizing the number of news publishers and the variety of written languages based on availability. Optimally, an incident should be reported by at least three different news publishers in traditional Chinese, simplified Chinese, and English. When more than three news publishers are available, priority is given to the most recent publications and those from local news sources or with later publication date are prioritized.

The process of adopting the principle removes the biases that might exit within a single new publisher, and ensures a more complete view as different publishers tend to report the incident from different angles. Finally, it facilitates the reliability of the data as the existence of each characteristic is reported by different data sources. The data collection procedure is illustrated in Fig. 3.

Based on the above procedure, the first two authors collected a total of 293 crowd disasters. Out of the 246 incidents identified through Factiva keyword search, 47 are identified solely from Chinese news sources. Additional 47 incidents are identified through supplemental Internet sources.

4.2. *Data coding*

In order to systematically collect and compare characteristics of crowd disasters, data coding is utilized to extract data for the database. Data coding is a method of recording observations in a data format in which a defined taxonomy is used by researchers to denote specific characteristics as they are witnessed. The process is explained below.

To construct the database, the content of the news articles for each incident is analysed by data coding, and its relevant characteristics data field are denoted by predefined subcategories. As stated above, the characteristics of crowd disaster entail social scenario, physical environment as well as the causal factors derived from the FIST model.

A code book (attached in Appendix A), composed of a comprehensive definition and taxonomy for the characteristics, has been constructed for the guidance of data coding. The subcategory of each characteristic is developed based on indicators summarized in Table 2, literature review of relevant crowd management papers [13,10,11] and the researchers' own observations during source identification. Due to the complexity of real-life situations and limitations related to news articles, in those cases where the certain characteristics of an incident fails to fit into any existing subcategory, a subcategory "other" is introduced. When certain characteristics of an incident cannot be identified, a 'No' subcategory is added into the causal factor characteristics and an "Unknown" subcategory is added into scenario characteristics.

Seven common types of social scenarios have been identified:

1) Sports event.

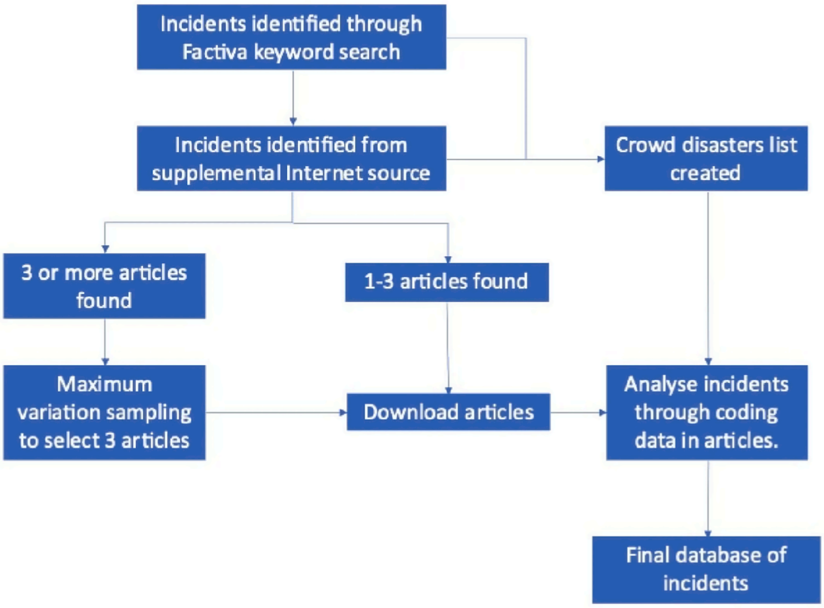

Fig. 3. Database data collection flowchart.

Table 2
Indicators for FIST model.

Cause	Indicator
F (Crowd Force)	Breathing difficulties
	Crowd pushing
	Movement difficulty
	Uncontrollable pushing
	Suffocation
	Crowd pressure
I (Information)	Imminent danger
	Unexpected incident
	limited desirables
S (Physical Space)	Staircase, escalators and lifts
	Density at entrances and exits
	Densities at other physical facilities
T (Time)	Crowd flows control and Waiting time

2) Performance.
3) Religion.
4) Jostle;
5) Organized event.
6) Nightclub.
7) School.

Due to numerous physical environments present in crowd disaster, the criteria for the taxonomy adopted here is based on the level of free movement available for the crowds. Four common types of physical environment have then been identified.

1) Stadium.
2) Building.
3) Open area.
4) Restricted area.

Six types of information have been identified:

1) Fire.
2) Imminent danger.
3) Unexpected incident.
4) Desirable 1, mainly describing a situation that things or items desirable for most participants are limited in amount or has to be done in a timely manner.

5) Desirable 2, mainly describing a situation that quality of things or items desirable for most participants is decreased with distance.
6) Official announcement.

There is a wide range of desirable things or items to reflect what most of participants in a crowd want, e.g. a discounted consumer good or an ideal vantage or participation location,

As stated above, all the subcategories of information must lead to a higher desired velocity, otherwise no information element is recorded.

Three types of physical space have been identified:

1) Staircase and escalators.
2) Entrance and exit.
3) Bridge and Tunnel.

Furthermore, due to the effect of desired velocity upon the critical density of physical space, each subcategory will be divided into two situations: low desired velocity and high desired velocity.

As bidirectional pedestrian flow in a confined space has been a point of interest in this field [44], a further categorization is applied to represent both unidirectional and bidirectional flow. Consequently, a total of 17 subcategories are entailed under this characteristic (including “other” under 4 situations and “no”).

Two types of time have been identified:

1) Ingress.
2) Egress.

These two subcategories are based on the researchers’ observation during source identification and different space availability during ingress and egress and indicate long waiting times.

Four levels of casualty have been identified:

1) 0.
2) 1–10.
3) 11–50.
4) Over 50.

Detailed definitions for each subcategory are outlined in Appendix A.

5. Methodology – data analysis

5.1. Data quality

The three data quality dimensions utilized in Ref. [45] for database assessment used in this paper are outlined in turn below.

5.1.1. Consistency

This data quality dimension accesses the consistency and compatibility between the taxonomy schemes used for each characteristic and the raw data. Any characteristic data field that cannot be put into existing subcategories (i.e., that data field contains “other”) is marked as ‘inconsistent’, and the overall consistency is calculated as:

$$consistency = \left(0.2N_{inconsistent} + N_{consistent}\right) / N$$

Where N is the number of relevant data fields. The result evaluates the ability of taxonomy schemes employed in the code book to capture characteristics, i.e., the percentage of data fields can be categorized under the taxonomy scheme.

5.1.2. Completeness

This data quality dimension accesses the proportion of missing data within the database. Each data field contains “Unknown” will be treated as missing data as there's always a scenario for each incident. The completeness is calculated as:

$$completeness = 1 - 1/N * \sum_{i=1}^{M} R_{missing}/R$$

Where N is the number of data fields, M is the number of characteristics and R is the number of relevant data fields inside each characteristic.

5.1.3. Accuracy

This data quality dimension accesses the accuracy of data extraction process. As two researchers have been involved in the data coding process, an inter-rater reliability test [46] is used to evaluate the agreement rate between the two coders. A high agreement rate ensures a sufficiently accurate standard has been applied in the data extraction process.

To perform the inter-rater reliability test, 15 incidents are randomly sampled by each coder out of the incidents coded by the other coder (representing approximately 10 %) and coded again. The results are compared with the original data and the statistic Cohen's Kappa κ [46] is calculated as:

$$\kappa = (p - p_e) / (1 - p_e)$$

Where p is the proportion of data fields both coders agree upon, and p_e is the probability that agreement arose by chance, calculated as [47]:

$$p_e = \sum\nolimits_{j=1}^{n} p_{ij} p_{i'j}$$

Where p_{ij} is the proportion of data fields that rater i assigned to category j.

A value of κ bigger than 0.8 can be viewed as almost perfect agreement and a value between 0.6 and 0.8 can be viewed as substantial agreement [48].

5.2. Cluster analysis

To address the objective of pattern identification, cluster analysis is used in this paper to identify different types of crowd disasters. Cluster analysis is a technique that “divides a supposedly heterogeneous set of data into homogeneous clusters” [49, p. 143]. In this research, the k-Modes algorithm is utilized because all the data inside the database is categorical.

The k-Modes algorithm assigns each object to a cluster through minimizing the cost function between the object and cluster centroid, which serves as centres of each cluster [50]. The cost function is developed based on a matching dissimilarity measure, which calculates the ‘distance’ between categorical objects [51].

Let X be a categorical object denoted by $[x_1, x_2, \ldots, x_m]$, where $x_j \in DOM(A_j)$, for $1 < j < m$ and A_j stands for jth attribute of object. For instance, a typical categorical object in this research is denoted as (sports events, stadium, no information, entrance and exit, ingress, 11–50).

The k-Modes algorithm looks for a way of dividing n categorical objects X_n (denoted by a $k \times n$ $\{0, 1\}$ matrix W) into k clusters (with centroids Z_k) that minimize the cost function F_n:

$$F_n(W, Z) = \sum_{l=1}^{k} \sum_{i=1}^{n} w_{il} d_n(Z_l, X_i)$$

Where w_{il} is entries of W and d_n is the dissimilarity measure.

In this research, the dissimilarity measure between two objects used in Ref. [52] is utilized and it is defined as:

$$d_n(Z_l, X_i) = \sum_{j=1}^{m} \varphi(z_{l,j}, x_{i,j})$$

where

$$\varphi(z_{l,j}, x_{i,j}) = \begin{cases} 1, if\ z_{l,j} \neq x_{i,j} \\ 1 - |c_{l,j}| / |c_l|, otherwise \end{cases}$$

Where $|c_l|$ is the number of objects in l th cluster and $|c_{l,j}|$ is the number of objects in l th cluster contains same attribute A_j as centroid z_l.

6. Discussion

6.1. Data quality

A total of 1758 datafields were tested based on the three data quality dimensions discussed above. For consistency and completeness [53], suggested a minimum score of 60 %.

6.1.1. Consistency

Three out of six characteristics required the addition of an “Other” subcategory during the data coding process, including: social scenario, physical environment and physical space. A total of 112 datafields are labelled with “other” and hence the consistency of this crowd disaster database is calculated as 94.90 %.

6.1.2. Completeness

Only five data fields within physical environment characteristics are labelled as “Unknown” since relevant information is missing in the identified data sources. Consequently, the completeness of this crowd disaster dataset is calculated as 99 %.

6.1.3. Accuracy

There is perfect 100 % agreement within "social scenario" and "casualty" characteristics between two researchers. The agreement rates and corresponding κ values are presented in Table 3 for the remaining four characteristics. All the characteristics besides "Physical space" have demonstrated a near perfect agreement between two researchers.

The slightly lower agreement rate in the 'Physical Space' category stems from the subjective nature of assessing desired velocity and the challenges in judging bidirectionality in pedestrian flow. Specifically, our analysis found that 2 out of 6 instances of disagreement within this subcategory were due to differing assessments of desired velocity, while 3 instances were related to disagreements on pedestrian flow directionality. However, this still indicates a reasonably high level of accuracy of this crowd disaster database, and the effect of disagreement for directionality upon accuracy is further moderated as it is omitted in the data analysis process.

6.2. Data analysis

The optimal number of clusters k is determined to be nine through a silhouette analysis, which assesses the quality of cluster by comparing level of separation among clusters [54] based on the same dissimilarity measure d_n.

Table 4 demonstrates the outcome of the cluster analysis indicating the number of incidents in each cluster. The distribution of subcategories within each characteristic and cluster are discussed below.

6.2.1. Social scenario

Across the entire database, the most frequent social scenario identified for crowd disasters is that associated with religion, followed by performance, other and sports (See detailed distribution in Fig. 4). The incidents classified as "other" under this characterization primarily refer to daily scenarios, including waiting for public transportation and walking on the street.

Within each cluster, religion is also the most frequent scenario within clusters 3 and 7, accounting for 37.5 % and 56 % respectively. The most frequent scenario within cluster 9 is "jostle", but it only accounts for 33.90 %. It is the lowest occupancy rate for the most frequent scenario within a single cluster, however, it has overwhelmingly high occupancy rates for the rest of most frequent characteristics, indicating a weak correlation with social scenario for this type of crowd disaster.

It is also noticeable that although school scenario is the least frequent scenario across the entire database (only 7 %), it has the highest occupancy rate within a single cluster, e.g. as high as 70.83 % of cluster 4. This is mainly because most crowd disasters that occur in schools share unique and identical features which are discussed in the following section.

Table 3
Accuracy of four characteristics.

	Physical Environment	Information	Physical Space	Time
Agreement rate	96.67 %	90 %	80 %	96.67 %
κ value	0.951	0.876	0.758	0.870
Performance	Near perfect	Near perfect	Substantial	Near Perfect

Table 4
Number of incidents within each cluster.

Cluster	1	2	3	4	5	6	7	8	9
Number of incidents	25	24	24	24	50	43	25	19	59

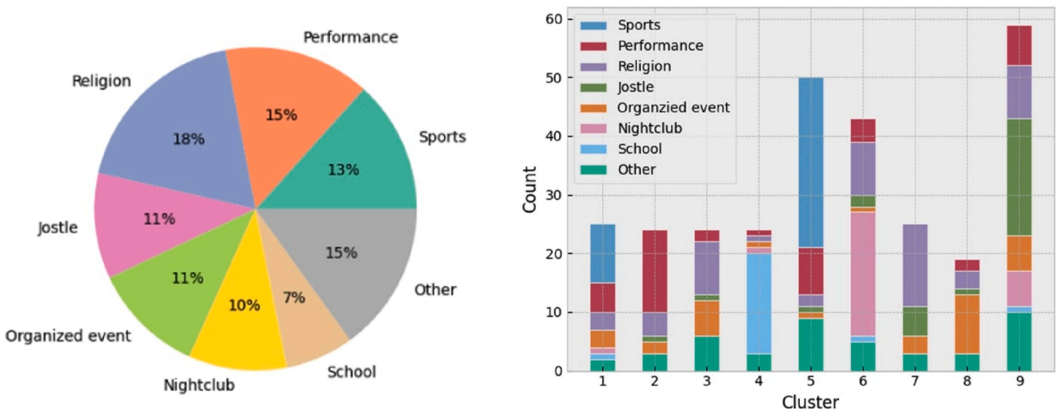

Fig. 4. Social scenario distribution.

6.2.2. Physical environment

Fig. 5 demonstrates that approximately 66 % of crowd disasters occur in indoor spaces (stadium and building), while only 30 % occur in outdoor space (open space and restricted space). The incidents classified as "other" under this characteristic primarily refer to complex environments that cannot be easily categorized as a single category which only accounts for lower than 5 %.

Building is the most frequent environment within clusters 4, 6 and 9, demonstrating overwhelming occupancy rates of 95.83 %, 97.67 %, 76.27 % respectively. Unsurprisingly, there is a strong correlation between stadium and scenario sports, as both are the most frequent scenario and environment within clusters 1 and 5. Although there is a low proportion of open area across the database, it is still the most frequent environment within cluster 2, accounting for 54.17 %. This is mainly because both the information and physical space that lead to crowd disasters in cluster 2 can barely be found in other clusters.

6.2.3. Information

A total of 69 % of crowd disasters have been identified, entailing information causal factors. Very few of them are caused by an unexpected incident and official announcement (accounting for 4 % and 3 % respectively), while desirables and dangers are approximately equal in proportion.

On the other hand, three clusters have overwhelming occupancy rates of "no information" causal factor, with two 100 % (cluster 7 and 8) and one 96 % (cluster 1). The other cluster that has no information causal factor as its highest occupancy rate subcategory is cluster 4, which accounts for 41.67 % (See Fig. 6). This is in contrast with the most frequent physical space for this type of crowd disaster (high desired velocity at staircase and escalator according to Fig. 7), indicating that a large number of people hold a high desired velocity without any external information given. The reason is primarily due to the most frequent scenario within the same cluster "school" refers mostly to primary school, while most victims are students.

Primary school children are viewed as being easily impatient due to their mental and physical developmental stage, and thus a high desired velocity. This poses a significant risk on staircases, especially since they often walk in groups during school time. It is also noticeable that "official announcement" has the second highest occupancy rate within this cluster (20.83 %), and this typically refers to teachers' guidance in asking students to move quickly to reach destinations more promptly.

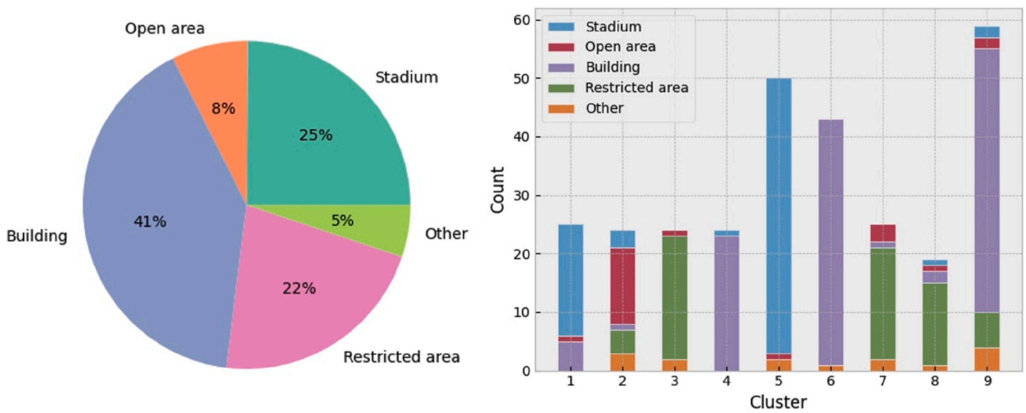

Fig. 5. Physical environment distribution.

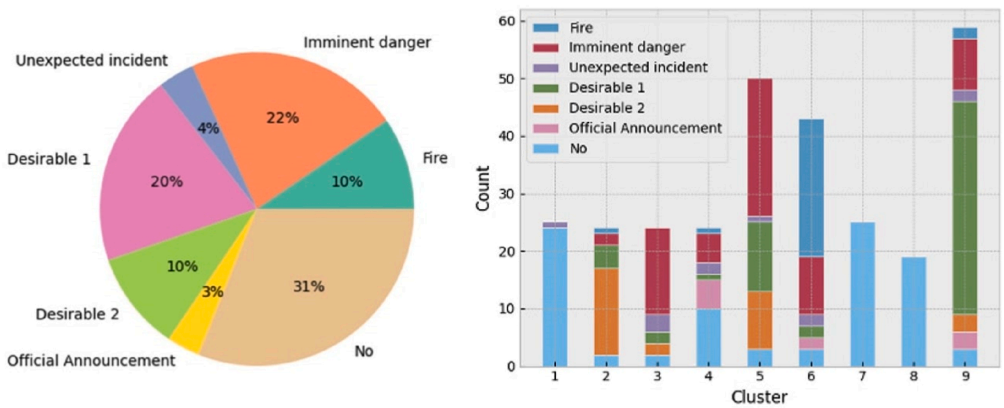

Fig. 6. Information distribution.

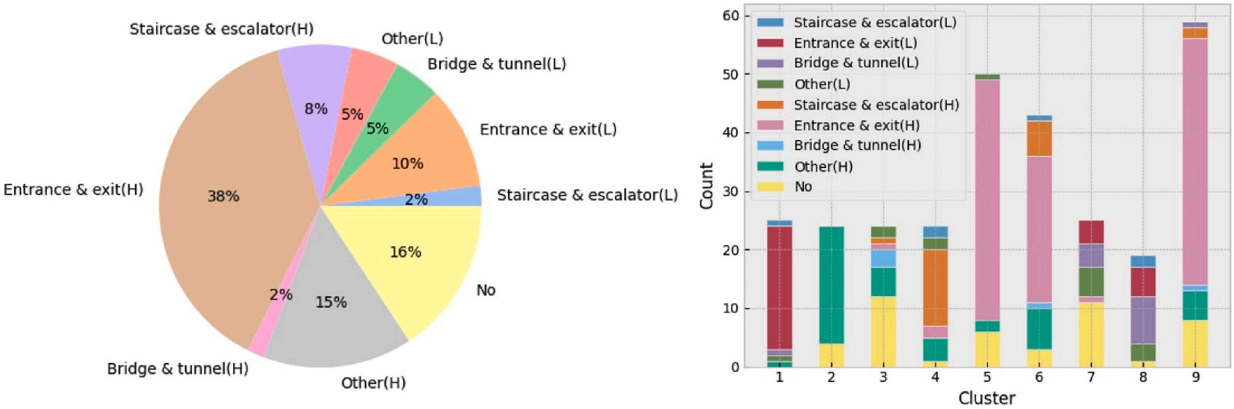

Fig. 7. Physical Space Distribution[2].

6.2.4. Physical space

In total, 16 % of crowd disasters have been identified as entailing no physical space causal factors. Among the remaining crowd disasters, only 13.41 % contain bidirectional pedestrian flow. Due to its unbalanced proportion compared to unidirectional flow, as well as the significantly increased data dimensionality when accounting for it, the directionality of pedestrian flow is omitted in the cluster analysis and following discussion.

Fig. 7 shows that 63 % of crowd disasters are caused by physical space under high desired velocity, while low desired velocity only accounts for 22 %. Entrance and exit have been identified as the most common locations for crowd disasters both within high and low desired velocity.

Other physical space under high desired velocity is the most common place for crowd disaster within cluster 2, accounting for 83.33 %. This typically refers to fences around a stage or the stage itself, as most crowd disasters within this cluster occur during a performance, and the appearance of the performer(s) serves as information that incentivises participants to get as close as possible. This aligns with the definition of desirable 2, which holds the highest occupancy rate within this cluster (62.5 %).

Further correlations between information and physical space are discovered. When presented with fire or other imminent danger within a stadium or other enclosed building (cluster 5 and cluster 6 respectively), people tend to flee as fast as they could, and such high desired velocity often leads to severe congestion at the exit, which are the most frequent physical spaces, accounting for 82 % and 58.14 % respectively. Cluster 9 also has entrance and exit as its most common physical space, and is also driven by the external information that some desired items will be offered with limited quantity (desirable 1) inside an enclosed building. People tend to get into the building as fast as possible to secure their possession of the item, thus leading to congestion at the entrance.

Cluster 7 is the only cluster that has no physical space causal factor as its highest occupancy rate subcategory, accounting for 44 %. This indicates the already dense nature of the participants that require no deterioration from the physical space, and it is sourced from its most frequent scenario, religion, that normally no measures can be taken to limit the number of arrivals.

6.2.5. Time

Unlike other causal factors, time, i.e. whether there is long waiting time at the time of the incident, has not been explicitly identified within many crowd disasters, accounting for only 21 % of the entire database. Nevertheless, it still contributes significantly towards clusters 1, 7 and 8 (See Fig. 8). Ingress has been identified in 70 % crowd disasters within cluster 1 and 80 % within cluster 7, while egress accounts for 73.68 % of cluster 8. This indicates a distinct difference in the underlying causes among these three clusters in contrast to the others, as the incidents originated from mismanagement of flow rate, and could potentially take place at any physical space inside a building during organized event, as revealed by cluster 8.

The high occupancy rate of ingress within cluster 1 is mainly caused by low admission rates at stadium entrances, which leads to the impatience of crowds and queuing effects. A similar situation also takes place within cluster 8, where the slower than expected flow rate is caused by physical space constraints (e.g., bridge and tunnel) during egress. As will be discussed later, such findings relating to ingress and egress enable targeted crowd management measures.

6.2.6. Casualty

Fortunately, casualties during most crowd disasters are below 10 persons. However, 14 % of crowd disasters still result in fatalities exceeding 50 persons, a significant concern for society (See Fig. 9).

The crowd disaster with highest fatality is found in cluster 6, where 58.13 % of the incidents lead to fatalities exceeding 50 persons. It is also noteworthy that many victims die from fire rather than crowd force within this cluster, and it is challenging to achieve a precise statistic to differentiate them.

Crowd disasters within cluster 4 share the highest non-fatal rate among all the nine types, reaching as high as 50 %. This is assumed to originate from most victims, as they are still primary school students and have much less body mass than adults, thus less

[2] L stands for low desired velocity and H stands for high desired velocity

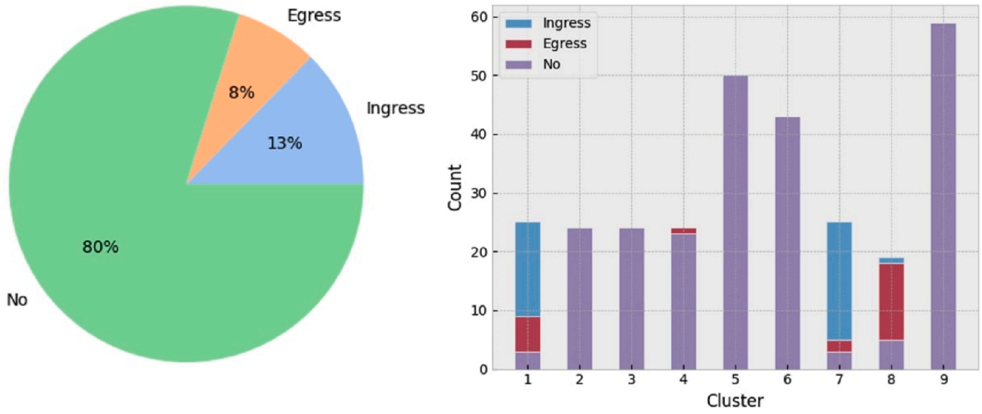

Fig. 8. Time distribution.

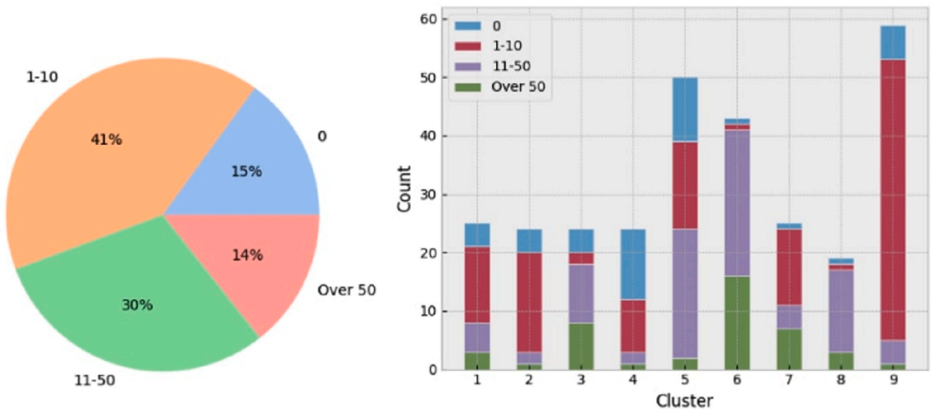

Fig. 9. Casualty distribution.

crowd forces are exerted. Future research should investigate further this type of crowd disaster in order to facilitate crowd management and building architecture design within schools.

In summary, the centroid of each cluster is presented in Table 5 (L and H denote low and high desired velocity as above). Crowd disasters within same cluster are considered as the same type, given that they are more similar with each other with respect to their characteristics based on the cluster analysis. For instance, type 2 crowd disaster tends to take place at a performance event, e.g., concert, music festival ('Social Scenario') hosted in an open area ('Physical Environment'), and it is mainly caused by crowds rushing towards other physical space (e.g., the stage) due to the presence of desirable 2 (e.g., the appearance of performer). The 'Time' element is not presented in this type of crowd disaster, and once it occurs, there's a high likelihood of resulting in 'Casualty'.

Based on the results, event organizers can develop a more explicit crowd management strategy, as they are able to locate most common causal factors of crowd disaster based on the event scenario and the environment. For example, for a sports event that is hosted in a stadium, which shares same social scenario and physical environment with type 1 and type 5 crowd disaster, 'Guide to Safety at Sports Grounds' [55] is commonly used to access the safe capacity and conduct safety planning for sports event in U.K. The safety capacity is calculated for every single part of the stadium, and extra work is encouraged for the entrance and exit capacities.

Table 5
Types of crowd disaster.

	Social Scenario	Physical Environment	Information	Physical Space	Time	Casualty
Type 1	Sports	Stadium	No	Entrance and exit(L)	Ingress	1–10
Type 2	Performance	Open area	Desirable 2	Other (H)	No	1–10
Type 3	Religion	Restricted area	Imminent danger	No	No	11–50
Type 4	School	Building	No	Staircase and escalator(H)	No	0
Type 5	Sports	Stadium	Imminent danger	Entrance and exit(H)	No	11–50
Type 6	Nightclub	Building	Fire	Entrance and exit(H)	No	11–50
Type 7	Religion	Restricted area	No	No	Ingress	1–10
Type 8	Organized event	Restricted area	No	Bridge and Tunnel (L)	Egress	11–50
Type 9	Jostle	Building	Desirable 1	Entrance and exit(H)	No	1–10

This is due to type 1 crowd disasters usually being caused by a long waiting time during ingress at the entrance, and type 5 usually takes place because of rushing towards the exits during an emergency evacuation when imminent danger presents itself.

For other events that share similar scenario and environment settings with any type of crowd disaster, the organisers are encouraged to allocate more resources around such physical spaces, pay attention to the critical moment when certain information might emerge, and/or control the flow of ingress/egress.

7. Conclusion

This paper has introduced the methodology behind the creation of a crowd disaster characteristics database, containing 293 crowd disasters worldwide between 1989 and 2021. The main data source is from online news database Factiva [41], combined with supplemental Internet sources. The characteristics included in the database are retrieved from the FIST model proposed by Ref. [6], combining with social scenario, physical environment and causality whose importance is shown by the analysis of the Shanghai crowd disaster. To the best of our knowledge, this database is the most well-defined database for such incidents as it presents a structured taxonomy of crowd disasters.

The principle of maximum variation sampling is adopted during the data collection process. Data quality dimensions consistency, completeness and accuracy have also been utilized to validate the consistency of proposed characteristics taxonomy, the completeness of data and the accuracy of data coding. Such data quality assurance procedure is not usually seen in the literature. A further data analytic has also been conducted using cluster analysis, and the K-Modes algorithm, which specifically focuses on categorical data, has identified nine clusters.

Based on the cluster analysis result, the distribution for each characteristic across the entire database and within each cluster has been discussed, and distinct features have been identified so that each cluster forms a unique type of crowd disasters. This classification enables a more specific measure to be taken during crowd management when event settings are similar to any type of crowd disaster. A more promising research direction could be investigated further within each type to gain a clearer picture of the underlying mechanism.

CRediT authorship contribution statement

Xiangmin Yang: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Yuelin Liu:** Writing – original draft, Visualization, Methodology, Data curation. **Arnab Majumdar:** Writing – review & editing, Validation, Supervision, Methodology. **Emilia Grass:** Writing – review & editing, Methodology. **Washington Ochieng:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2024.104653.

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