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Real-Time Detection, Evaluation, and Mapping of Crowd Panic Emergencies Based on Geo-Biometrical Data and Machine Learning †

Ilias Lazarou *, Anastasios L. Kesidis and Andreas Tsatsaris

Department of Surveying and Geoinformatics Engineering, University of West Attica, 12243 Athens, Greece; akesidis@uniwa.gr (A.L.K.); atsats@uniwa.gr (A.T.)

* Correspondence: ilazarou@uniwa.gr

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Abstract: Crowd panic emergencies can pose serious risks to public safety, and effective detection and mapping of such events are crucial for rapid response and mitigation. In this paper, we propose a real-time system for detecting and mapping crowd panic emergencies based on machine learning and georeferenced biometric data from wearable devices and smartphones. The system uses a Gaussian SVM machine learning classifier to predict whether a person is stressed or not and then performs real-time spatial analysis to monitor the movement of stressed individuals. To further enhance emergency detection and response, we introduce the concept of CLOT (Classifier Confidence Level Over Time) as a parameter that influences the system's noise filtering and detection speed. Concurrently, we introduce a newly developed metric called DEI (Domino Effect Index). The DEI is designed to assess the severity of panic-induced crowd behavior by considering factors such as the rate of panic transmission, density of panicked people, and alignment with the road network. This metric offers immeasurable benefits by assessing the magnitude of the cascading impact, enabling emergency responders to quickly determine the severity of the event and take necessary actions to prevent its escalation. Based on individuals' trajectories and adjacency, the system produces dynamic areas that represent the development of the phenomenon's spatial extent in real time. The results show that the proposed system is effective in detecting and mapping crowd panic emergencies in real time. The system generates three types of dynamic areas: a dynamic Crowd Panic Area based on the initial stressed locations of the persons, a dynamic Crowd Panic Area based on the current stressed locations of the persons, and the dynamic geometric difference between these two. These areas provide emergency responders with a real-time understanding of the extent and development of the crowd panic emergency, allowing for a more targeted and effective response. By incorporating the CLOT and the DEI, emergency responders can better understand crowd behavior and develop more effective response strategies to mitigate the risks associated with panic-induced crowd movements. In conclusion, our proposed system, enhanced by the incorporation of these two new metrics, proves to be a dependable and efficient tool for detecting, mapping, and assessing the severity of crowd panic emergencies, leading to a more efficient response and ultimately safeguarding public safety.

Keywords: panic detection; biometrics; machine learning; classification; real-time data; emergency response systems; geospatial data; domino-effect; noise-filtering; spread

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1. Introduction

Crowd panic emergencies are a major concern for public safety, particularly in densely populated areas such as cities, sports events, concerts, and festivals. These emergencies can result in injuries, fatalities, and property damage and can be triggered by a variety of factors such as perceived threats, rumors, and stampedes. Detecting and mapping crowd panic emergencies in real-time is crucial for rapid response and mitigation, as it allows emergency responders to quickly deploy resources and evacuate affected areas.

In recent years, advances in machine learning and wearable technology have opened up new possibilities for detecting and mapping crowd panic emergencies in real time. The proposed system uses georeferenced biometric data from wearable devices and smartphones, which provides a more accurate representation of the individual's stress levels and movement patterns than solely video or audio data. Specifically, the system uses a Gaussian SVM machine learning classifier to predict whether a person is stressed or not based on its biometric data.

The importance of real-time data analysis for public safety was underscored during the COVID-19 pandemic, where digital platforms such as COVID-19 dashboards played a pivotal role in monitoring and managing public health trends. As described in studies by Dong et al. (2020) in [1] and Malkani et al. (2023) in [2], these dashboards provided critical real-time information that guided government policies and healthcare interventions. They offered comprehensive visualizations and updates on infection rates, enabling authorities to allocate resources efficiently and enact timely public health measures.

In particular, the case studies regarding the areas of Hong Kong [3] and Taiwan [4] highlighted how the smart use of technologies facilitated spatial displays of pandemic informatics. In Hong Kong, interactive dashboards integrated real-time geographic information with case tracking to identify high-risk areas, aiding in targeted interventions. Similarly, Taiwan employed spatial visualization to effectively map outbreaks and allocate healthcare resources, showcasing how such tools could combine real-time data with spatial analytics to enhance situational awareness. These examples illustrate the power of integrating temporal and spatial data to improve decision-making during crises.

Drawing from these examples, our system similarly aims to deliver real-time situational awareness, but in the context of crowd management and safety. By providing emergency responders with continuous updates on crowd behavior, augmented by spatial visualizations of critical metrics like density, flow patterns, and panic spread, the system ensures a proactive approach to managing crises. Much like the COVID dashboards did for public health, our platform is designed to equip authorities with the tools needed to make timely informed decisions, ensuring safety and minimizing risks in high-stakes environments.

In this stage, a novel feature is proposed called the Classifier Level of Trust (CLOT). The CLOT, a numerical parameter from 0 to 10, serves as a measure of confidence in the classifier's output. A lower CLOT value emphasizes swift detection over noise reduction, while a higher value filters noise for fewer false positives at a slower speed. Thus, adjusting CLOT balances detection speed and noise filtering.

Once a person is identified as stressed, the system performs real-time spatial analysis to monitor their movement and identify other stressed individuals in their vicinity. Based on their trajectories and adjacency, the system produces dynamic areas that represent the development of the phenomenon's spatial extent in real time. For this purpose, a newly developed index called DEI (Domino Effect Index) is introduced, which further enhances the system's ability to not only detect but also classify crowd panic emergencies. The term domino effect refers to the situation in which one event causes a series of related events, one following another. The DEI is designed to identify the severity of the detected emergency by taking into account various factors that contribute to the domino effect, such as the rate of panic transmission, the density of panicked people, and alignment with the road network.

By incorporating the DEI, our proposed system takes emergency detection and response to the next level, ensuring public safety in densely populated areas. This information can be used by emergency responders to quickly deploy resources and evacuate affected areas, as well as to better understand the severity of the event and take necessary actions to prevent a potential escalation of the situation.

In the following sections, we will describe the components of the system in detail, including the machine learning classifier, the georeferencing of biometric data from wearable devices and smartphones, the real-time spatial analysis, and the calculation of the DEI. We will evaluate the effectiveness of the system in detecting and mapping crowd panic emergencies in real time and discuss its potential applications and limitations. Finally, we will suggest directions for future research in this area.

2. Related Work

Panic is a phenomenon that has been widely studied in psychology and human sciences due to its consequences. It is characterized by intense fear triggered by the occurrence of real or imaginary danger, simultaneously experienced by individuals in a group, crowd, or population. Panic is accompanied by regressive mentalities and primitive reactions, such as violence, jumps, or collective suicide. Mass panic is a type of anomaly that occurs when a group of people moves faster than usual, triggered by fearsome activities such as stampedes, fires, fights, robberies, or riots.

The detection and management of crowd panic emergencies involve various technologies, each with unique strengths and limitations. Surveillance systems, such as CCTV cameras, offer real-time monitoring of large crowds and utilize techniques like optical flow analysis to detect density and abnormal movement patterns. However, these systems are constrained by environmental factors like lighting and obstructions, require extensive computational resources, and often depend on human oversight. IoT-enabled devices and wearable sensors provide granular real-time biometric data, such as heart rate, enabling more personalized and accurate panic detection. Despite their portability and ability to transmit data seamlessly through IoT networks, their effectiveness hinges on widespread adoption and raises concerns over privacy, data security, and signal interference in dense environments. According to [5], machine learning algorithms, like Gaussian SVM, excel in identifying patterns and adapting to different scenarios, enhancing detection accuracy with features such as HRMAD (Heart Rate Moving Average Deviation). However, these models demand extensive labeled data for training, may face generalization challenges, and risk overfitting to training datasets. Hybrid approaches, combining methodologies like IoT data integration with machine learning or augmenting surveillance systems with biometric sensors, leverage the strengths of each technology for improved detection accuracy and a holistic understanding of crowd behavior. Nevertheless, these systems require significant infrastructure investment and face challenges in data harmonization and real-time processing. In balancing these approaches, our study employs a real-time hybrid system that integrates geo-referenced biometric data with machine learning, aiming to create a nuanced, scalable, and efficient framework for detecting and mapping crowd panic emergencies.

The recent literature includes numerous studies and systems that focus on panic detection using Closed Circuit Television (CCTV) technology. These surveillance techniques analyze human behavior in still images and/or video sequences of individuals or groups of people. For example, Hao et al. in [6] propose an approach based on optical flow features to detect crowd panic behavior, and in [7], Ammar et al. describe a continuous surveillance system for a specific public place using a fixed camera and a methodology for real-time analysis of captured images.

Other advancements in Geographic Information System (GIS) technology have significantly expanded the capacity to analyze and interpret large-scale spatial data. GIS has been widely adopted to study human trajectories, urban transportation networks, and building morphology, offering critical insights for urban planning, disaster response, and public safety management. For instance, in [8], Lu et al. (2023) discussed the integration of GIS with trajectory analysis to model and predict crowd movement patterns in urban spaces, providing valuable data for mitigating congestion and ensuring efficient evacuation routes during emergencies.

Additionally, GIS technology has been employed to understand the impact of urban morphology on pedestrian behavior, as highlighted by Bhowmick et al. (2019) in [9]. Their study demonstrated how spatial analytics, when combined with building morphology data, can reveal critical information about crowd density and movement patterns in public spaces. This approach enables more informed decisions about infrastructure design and the allocation of resources to manage crowd flow effectively.

In our system, the integration of GIS technology allows for real-time monitoring and mapping of stressed individuals' trajectories, helping emergency responders visualize the spread of panic and take appropriate action. By leveraging GIS capabilities, we aim to offer a robust tool for managing emergencies in complex urban environments, similar to how these referenced studies have utilized spatial data for urban analysis.

Another category of panic detection systems is based on user intervention or community engagement in reporting emergency events. Disaster preparedness plans are essential in disrupting entire communities in the occurrence of unpleasant events that may happen inevitably. However, conventional approaches for data acquisition and distribution are insufficient to provide experts with on-site and real-time data, which can pose potential safety hazards, particularly in time-sensitive crises.

Internet of Things (IoT) technology offers a solution to acquire real-time data about objects and transmit it promptly to experts for decision-making. Wearable devices and IoT are used to collect biometric data and analyze them for stress detection. The wearables and IoT sector is exponentially gaining interest due to the technological evolution and progress of related technologies, such as sensors and chips. Thus, real-time sensor data can be paired with 5G smartphone capabilities to provide essential information for decision-making.

Recent studies indicate that research on systems, quantitative analysis, and visualization studies on crowd evacuation is still a developing field. Wearable data are used by Tsai in [10] to predict panic attack disorders based on time series, providing a panic attack prediction model that relates a panic attack to various features, such as physiological factors and air quality. In [11], Kutsarova and Matskin combine mobile crowdsensing and wearables to produce alarms based on the CrowdS platform, with smartwatch sensors detecting abnormal events. In [12], Alsalat uses machine learning to detect human panic based on wearables and classify them as stressed and calm. In [13], Sun et al. focus on the study of crowd behavior in emergencies, specifically during earthquake evacuations. The paper aims to address the gap in knowledge on how to scientifically organize and improve the effectiveness of mass evacuation drills. To achieve this, the researchers conducted an evacuation drill experiment to analyze people's actual evacuation processes, their participation ratio, and evacuation behavior characteristics. The study further developed a computer-aided quantitative simulation by establishing a response rule equation for crowds in emergencies, describing panic behavior and exit familiarity, and quantifying the relationship between exit familiarity and drill training time. The researchers used cellular automation to simulate different exercise strategies by setting various exit familiarity ratios, ultimately aiming to optimize the evacuation process's efficiency through the self-organization of individuals and prevent unnecessary congestion and stampede accidents. The paper also presents a case study of a community in Zhuhai City, China, and proposes the best disaster prevention drill strategy based on the findings.

In [14], Zhang et al. aim to address the challenges in urban security and management related to crowd gathering, which can lead to fights and stampedes in large public spaces such as shopping malls, stations, and entertainment venues. To tackle this issue, the paper proposes a Crowd Density Estimation Model (CDEM-M) based on deep learning and Geographic Information System (GIS) technology. This model overcomes the limitations of traditional crowd density estimation methods, which typically focus on human head features and might struggle in high-altitude scenes or when head information is not visible. The CDEM-M provides a more comprehensive solution by using GIS to offer a unified map visualization interface, enabling accurate crowd area extraction through semantic segmentation and making use of the overall features of the crowd for better monitoring. The model includes four aspects: crowd information extraction, geographic mapping, number estimation, and map visualization.

In [15], Albarakt et al. examine the role of public spaces in cities, focusing on their political, social, economic, and sustainability aspects. It investigates the varying roles of streets, commercial centers, squares, and cafes in supporting or restricting public engagement. The study also delves into the evolving political use of public spaces, the contestation over space, and the competition among various actors for dominance. Using examples from the Middle East and ArcGIS mapping, the research explores the visual and verbal narratives of protest events in contested public spaces. The findings can inform urban planning and management strategies for public spaces.

Overall, these works demonstrate the potential of using machine learning and sensor data to detect and map crowd panic emergencies in real time. Each paper proposes a different approach to the problem, using different types of data and machine learning algorithms. Our proposed system builds on these previous works by using georeferenced biometric data from wearable devices and smartphones and a Gaussian SVM machine learning classifier to detect and map crowd panic emergencies in real time.

While the works mentioned in the literature review have proposed a variety of approaches for the detection and tracking of crowd panic emergencies, our current research takes the approach to a new level by utilizing georeferenced biometric data from wearable devices and smartphones. This type of data provides a more accurate and precise measure of stress levels and panic behavior compared to other types of data such as GPS or video. Additionally, our system uses a Gaussian SVM machine learning classifier, which has been shown to have high accuracy in predicting stress levels. As Lazarou et al. (2022) state in [5], the Gaussian SVM classifier was chosen for this study due to its ability to handle non-linear relationships effectively. The panic detection problem involves complex and non-linear patterns in biometric and spatiotemporal data, making Gaussian SVM a suitable choice. By applying a Gaussian (RBF) kernel, the SVM maps the input data into a higher-dimensional space where the separation between classes (stressed and calm) becomes more apparent, enabling more accurate classification.

Furthermore, our system performs real-time spatial analysis to monitor the movement of stressed individuals and produces dynamic areas that represent the development of the phenomenon extent in real-time. This allows emergency responders to quickly identify the areas that require immediate attention and respond accordingly. Moreover, the dynamic Crowd Panic Areas based on the initial and current stressed locations of the persons and their geometric differences provide emergency responders with an accurate and up-to-date representation of the phenomenon extent.

Overall, our research takes a more comprehensive and precise approach to detecting and mapping crowd panic emergencies in real-time, which can help emergency responders make faster and more informed decisions to mitigate the risks and ensure public safety.

3. Methodology

3.1. Workflow Process

The objective of the proposed system for crowd panic detection is to extract valuable information from collected biometric and spatiotemporal data, in order to identify patterns that may indicate panic behavior in crowds. Figure 1 illustrates the main modules of the proposed scheme. The workflow starts at the user's wrist, where a wearable device running an application monitors real-time biometric data such as heart rate and heart rate variability. Meanwhile, an Android smartphone running a paired application collects GPS location coordinates (longitude, latitude), time data, user activity, speed, and steps. Every second, this information is compiled into a single encrypted UDP packet and sent over the GSM network to a server. On the server side, a Java code receives and decrypts the UDP packets and constructs data points with the aforementioned attributes, allowing for the collection of real-time biometric and spatiotemporal data. The real-time server is designed to receive and analyze a significant amount of live data to identify potential patterns of crowd panic.

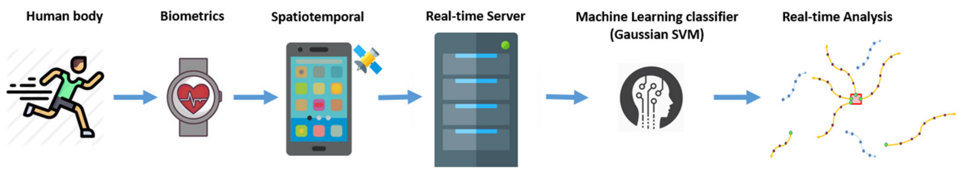

Figure 1. System workflow.

3.2. Stress Profile Index (SPI) Classification

The proposed methodology involves characterizing a subject as being in a calm or panic state using a classifier that takes various biometric and geospatial data collected by wearable devices as input and outputs the subject's panic state as in [5]. To choose the most appropriate machine learning classifier, the efficiency of various classifiers was tested using a dataset consisting of 27 different subjects. The dataset includes biometric data such as heart rate and heart rate variability, spatiotemporal data such as location coordinates, type of activity, subject speed, and the number of steps performed, as well as descriptive data such as gender, age, and weight. A unique identification code for each subject is also included.

The dataset's biometric and spatiotemporal attributes are classified into four groupings, with values informed by pertinent studies. These divisions comprise (i) biometric information (from wearables) encompassing heart rate and heart rate variability. Their values are based on studies providing relevant information; (ii) spatiotemporal information (captured by smartphones) offering location coordinates, activity type, subject velocity, and step count; (iii) descriptive data (from wearables) concerning subject gender, age, and weight; and iv) the secure ID (from smartphones) assigning a distinct identification code to each subject. Additionally, a feature named heart rate moving average deviation (HRMAD) is derived to indicate sudden panic conditions based on heart rate values. The dataset is used to train machine learning models to distinguish panic states from normal behavior. Decision trees, logistic regression, Gaussian and kernel naïve Bayes, Gaussian SVM, and SVM kernel, and boosted trees were examined in [5], with the Gaussian SVM classifier achieving the highest accuracy using the HRMAD60 feature. As a result, the SPI (Stress Profile Index) is introduced as a Boolean-valued index that indicates a Calm (value 0) or Stressed (value 1) state, as shown in Figure 2.

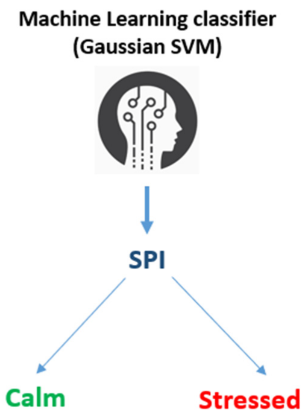

Figure 2. Stress Profile Index (SPI).

3.3. Real-Time Analysis of Spatial Patterns

The purpose of real-time spatial analysis in monitoring panic conditions is supported by a data model as in [16], represented in Figure 3. This model processes streaming data containing spatiotemporal and biometric information collected from wearable devices and smartphones. As stated in the previous section, a Gaussian SVM machine learning classifier is utilized to distinguish between normal behavior and panic conditions, assigning the SPI values of 0 and 1, respectively. The resulting categorization labels the data as either Points of No Interest or Panic Points.

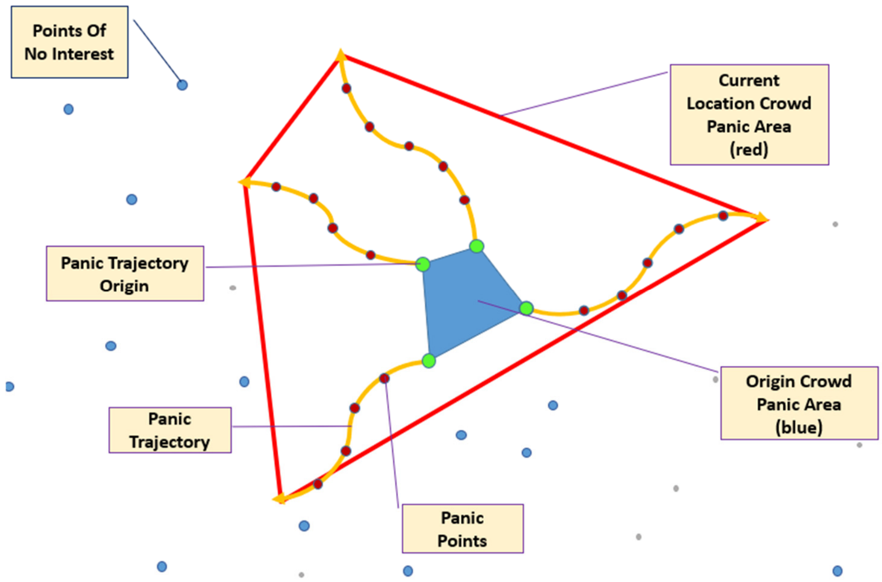

Figure 3. Data model's graphic representation.

Points of No Interest (PONI) are assigned an SPI of 0 and serve only to indicate the end of a sequence of Panic Points, while the Panic Points are assigned an SPI of 1 and represent highly stressed profiles. If Panic Points are isolated incidents and followed by a Point of No Interest, no further action is taken. However, if there are consequent Panic Points as expounded upon in the subsequent sections, they form a Panic Trajectory and the related Panic Trajectory Origin.

A Panic Trajectory (yellow arrows in Figure 3 above) denotes a consecutive sequence of Panic Points pertaining to a specific subject, persisting until the occurrence of one or more Points of No Interest, which act as interrupters, thereby terminating the trajectory. Likewise, the initiation of a Panic Trajectory can be determined by the criterion of monitoring either a singular or multiple Panic Points, triggering the creation of the trajectory. The selection of the number of essential initiation and termination points acts as a variable with a smoothing effect, regulating the sensitivity of our model toward noise generated by the Machine Learning classifier. We introduce this as a new characteristic called the Classifier Level of Trust (CLOT) and it is described in the next paragraph. In Section 4, which presents the experimental results, an in-depth investigation is conducted on distinct start-point and end-point windows for Panic Trajectories. This entails an exploration of the model's performance when two or more Points of No Interest become prerequisites for concluding a Panic Trajectory. Furthermore, we explore scenarios where two or more Panic Points are necessitated for the initiation of a Panic Trajectory.

Next, once a Panic Trajectory is initiated, the first point is considered as a Panic Trajectory Origin. The algorithm examines the Panic Trajectory Origins of various subjects to determine whether there is a spatiotemporal correlation between them. To establish a spatiotemporal correlation among Panic Points, the DBSCAN algorithm is employed. This algorithm is applied to the Panic Trajectory Origins, which are natively characterized by an SPI value of 1, as these are Panic Points that initiate a Panic Trajectory. These Panic Points serve as the starting points for the analysis. The algorithm initially sets a radius of 100 m and mandates a minimum of five Panic Points within this distance to classify it as a crowd. Additionally, the algorithm considers only Panic Points within a 10-s timeframe for the correlation analysis.

The use of time windows for analyzing physiological signals in stress and emotion recognition is a common practice, with various studies exploring optimal window lengths. In [17], Jarillo Silva et al. (2024) found that time windows between 2–15 s yielded better performance in emotion recognition using EEG signals, with 10-s windows particularly effective for between-subjects analysis. Sierra et al. (2010) in [18] demonstrated that stress detection systems using galvanic skin response and heart rate could accurately detect stress levels within 10 s. In [19], Rigas et al. (2012) employed specific window lengths for feature calculation in real-time driver stress detection, achieving 96% accuracy when incorporating driving event information. However, in [20], Fang et al. (2022) cautioned against using excessively long windows, such as 60 s with small shifts, as this may lead to redundancy and overfitting in stress detection analyses. These studies highlight the importance of selecting appropriate time windows for real-time physiological signal analysis in various applications and also justify our selection, showing that a 10-s window is well-suited for real-time monitoring in emergency contexts.

By including the time information and evaluating the live data within a time window of 10 s, the spatiotemporal correlation between Panic Points can be established, allowing for a better understanding of the patterns and trends of panic behavior. Specifically, the 10-s timeframe indicates that should a subject's most recent location fall beyond this 10-s window, it will not affect the evaluation. These parameters are adjustable variables that enable monitoring of the model's behavior under diverse circumstances. In the subsequent chapter focused on experimental results, we will showcase various runs involving alternative parameter values. Given that the above conditions are met, the creation of Crowd Panic Areas is triggered.

The Crowd Panic Areas are a set of dynamic polygon geometry features that play a critical role in detecting and responding to potentially dangerous situations in crowds. They are composed of two distinct areas: the Origin Crowd Panic Area (Origin CPA) and the Current Location Crowd Panic Area (Current Location CPA).

The Origin CPA and the Current Location CPA are spatial representations of potentially stressful events that may occur. The former is determined by tracing the origin of Panic Trajectories, whose starting points are spatially correlated, while the latter is based on the most recent point of each ongoing Panic Trajectory that is spatially correlated. The relationship between them along with the density of the phenomenon within them provide valuable insights into the ongoing phenomenon. The Domino Effect Index, introduced in the next section, is a comprehensive metric for evaluating the severity of panic-induced crowd behavior during emergencies.

3.3.1. Classifier Level of Trust (CLOT)

CLOT represents a numerical parameter ranging from 0 to 10. The CLOT value serves as a measure of confidence or reliability assigned to the classifier's output within the system. As the CLOT value approaches 0, the filtering of noise decreases, allowing for more immediate detection. In other words, with a lower CLOT value, the system prioritizes prompt detection over noise reduction. Conversely, as the CLOT value approaches 10, more noise is filtered, resulting in a reduction in false positives. However, it is important to note that this comes at the cost of slower detection speed. In summary, adjusting the CLOT value enables a trade-off between the speed of detection and the level of noise filtering within the system. This facilitates an exploration of the model's behavior under diverse configurations, enabling an examination of its response to varying degrees of noise.

In Figure 4, two illustrative examples highlight the influence of the CLOT parameter when set to a value of three. In the example on the left, the subject initially exhibits two Points of No Interest (green dots), indicative of a state of tranquility. Subsequently, a sequential occurrence of Panic Points (red dots) ensues. Employing real-time data monitoring, the system detects that the accumulation of these Panic Points attains the predetermined CLOT value of 3. Consequently, the system designates the third successive Panic Point as the Point of Trust (POT), signifying the initiation of Panic Trajectory creation. As long as the sequence of Panic Points remains uninterrupted, the trajectory extends further. After a duration of time, Points of No Interest commence their emergence. The system vigilantly assesses whether this sequence aligns effectively with the CLOT threshold. Once the requirement is met, affirming the presence of at least three consecutive Points of No Interest, the Panic Trajectory is terminated accordingly. Conversely, in the example on the right, an alternative subject exhibits a composed behavior, and the subsequent Panic Points fail to surpass the CLOT threshold of 3. Consequently, the system classifies them as noise, resulting in the absence of any trajectory formation.

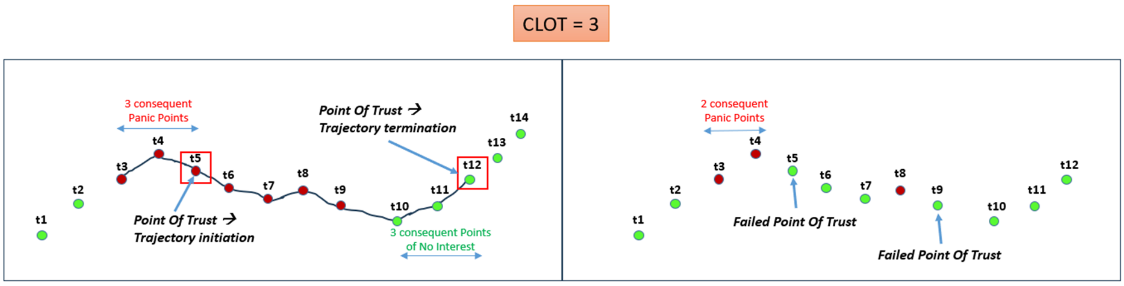

Figure 4. Example of CLOT = 3.

3.3.2. Domino Effect Index (DEI)

The DEI considers the rate of panic transmission, density of panicked people, distribution of new panic origins, area change rates of convex hulls, and alignment with the road network. The metric ranges between 0 and 5, with higher values indicating a more severe panic situation. This range is divided into a scale of 5, with DEI scale 1 representing the lowest severity and DEI scale 5 representing the highest severity. By integrating various factors that contribute to the domino effect, DEI provides a reliable assessment of the crowd's panic state, assisting decision-makers in devising appropriate emergency response strategies.

From the methodological point of view, the DEI is calculated using a combination of weighted normalized factors that influence panic spread in a crowd. These factors are summed up in the Table 1 below.

Table 1. DEI weighted normalized factors.

Factor	Description
Rate of panic transmission (w1)	The rate at which panic spreads among the crowd
Number of new panic origins within the panic origin convex hull (w2)	The distribution of new panic origins within the area where panic first emerged
Density of panicked people (w3)	The concentration of panicked individuals within the current location convex hull
Area-change rate of the panic origin convex hull (w4)	The rate at which the area of the panic origin convex hull changes over time
Area-change rate of the current location convex hull (w5)	The rate at which the area of the current location convex hull changes over time
Number of aligned clusters (w6)	The count of panic clusters aligned with the road network, which might indicate the crowd's tendency to use streets for escape

Each factor is normalized between 0 and 1 and then multiplied by a weight that reflects its importance in contributing to the domino effect. The DEI is then calculated as the sum of these weighted factors, as follows:

$$\mathrm{DEI} = \mathrm{w1} \times \mathrm{NRPT} + \mathrm{w2} \times \mathrm{NNPO} + \mathrm{w3} \times \mathrm{NDP} + \mathrm{w4} \times \mathrm{NACROH} + \mathrm{w5} \times \mathrm{NACRCLH} + \mathrm{w6} \times \mathrm{NACC} \quad (1)$$

- w1, w2, w3, w4, w5, and w6 are the respective weights assigned to each factor, determined based on their relative importance to the overall index;
- NRPT: Normalized Rate of Panic Transmission;
- NNPO: Normalized Count of New Panic Origins within the Origin Hull;
- NDP: Normalized Density of Panicked People;
- NACROH: Normalized Area Change Rate of the Origin Hull;
- NACRCLH: Normalized Area Change Rate of the Current Location Hull;
- NACC: Normalized Count of Aligned Clusters.

In the context of the DEI factor normalization, each contributing factor is normalized between 0 and 1 to ensure equitable comparison and synthesis of diverse numerical values. This normalization procedure entails three main steps. Firstly, the minimum and maximum values for each factor are established, representing the lower and upper bounds of the factor's range. Secondly, the actual value of the factor at a given time step is scaled to a normalized value within the 0 to 1 range using a formula that involves subtracting the minimum value and dividing by the range between the maximum and minimum values.

$$normalized\_value = \frac{current\_value - \min\_value}{\max\_value - \min\_value} \quad (2)$$

Additionally, a small constant (epsilon) is included in the denominator to prevent division by zero and enhance numerical stability. By undertaking this normalization process, the DEI computation amalgamates various factors, irrespective of their original scales, enabling a balanced assessment of their collective influence on the severity of the domino effect. These normalized values are then subjected to user-defined weights and combined via a weighted sum to yield the final DEI value, which quantifies the potential extent of panic propagation within a crowd and aids in prioritizing interventions to mitigate its repercussions.

Moreover, as stated above, the Domino Effect Index (DEI) is computed using a weighted sum of normalized factors, ensuring numerical stability through the inclusion of a small constant (ϵ) in the denominator to prevent division by zero. The formula for DEI is also expressed as follows to depict the use of this constant:

$$\mathrm{DEI} = \sum_{i=1}^{n} \mathrm{wi} \times \frac{x_i}{\max(x_i, \epsilon)} \tag{3}$$

where x_i represents the i-th factor (e.g., crowd density, heart rate variability), wi is its user-defined weight, and $\epsilon > 0$ ensures robust normalization across all scales. This approach integrates biometric indicators, spatial dynamics, temporal changes, and environmental conditions into a unified metric, allowing for a balanced assessment of panic propagation severity.

To determine the DEI scale, the DEI value is divided into five equal intervals (0–0.2, 0.2–0.4, 0.4–0.6, 0.6–0.8, 0.8–1), with each interval corresponding to a DEI scale from 1 to 5, as shown in Table 2.

Table 2. DEI scales.

DEI Scale	DEI Value
1	0–0.2
2	0.2–0.4
3	0.4–0.6
4	0.6–0.8
5	0.8–1

To assess the crowd's alignment with the road network, DBSCAN clustering is used to identify clusters of panicked individuals. DBSCAN is a popular clustering algorithm used to identify dense regions of data points in a given dataset. It is a classical density-based clustering procedure that has had tremendous practical relevance as stated by Jang et al. in [21]. For each cluster, the minimum area bounding rectangle (MABR) is calculated, and the axis ratio (smaller side length divided by the longer side length) is computed. If the axis ratio is below a certain threshold (e.g., 0.5), it is considered to be an aligned cluster. This information holds immense value as it suggests that when a considerable portion of a panicked crowd chooses to flee through the streets, the transmission of panic is likely to occur more rapidly.

The DEI metric and its associated scale are valuable for analyzing the severity of panic situations in real-world scenarios, such as during evacuations, natural disasters, or terrorist attacks. By quantifying the domino effect and categorizing it into five severity levels, emergency planners and responders can better understand crowd behavior and develop more effective response strategies to mitigate the risks associated with panic-induced crowd movements.

4. Experimental Setup and Results

To test the feasibility of the aforementioned methodology, we conducted a proof of concept by encompassing three distinct scenarios, each resulting in unique patterns of crowd panic behavior (ESCAPE, SHRINK, REPULSION). The study area is Syntagma Square, located in the downtown area of Athens, Greece.

Paths were designed for each individual in the crowd using points as locations and biometric values as attributes. All individuals start in a calm state but subsequently shift to a panicked state, simulating their reaction to a stressful event. This process initially creates an artificial crowd. Subsequently, a Python 3.9 script reads these points and moves each individual on the map, thus simulating their movement through space and time. These points are passed one by one through the classifier and are labeled as either 0 (Calm) or 1 (Panicked).

In the first scenario, the crowd encounters an aversive event that prompts individuals to disperse from the scene in various directions. The second scenario involves a peripheral threat, causing the crowd to contract toward the center of a defined area, such as a public square. Lastly, the third scenario entails a repulsive force; for instance, during a demonstration, law enforcement officers may initiate a dispersal maneuver, causing the participants to retreat in the opposite direction. These scenarios have been carefully designed to enable a comprehensive examination of diverse crowd panic behaviors, investigate the behavior of the DEI, and facilitate the development of appropriate response strategies.

To further understand the impact of different factors contributing to the DEI, varying weights have been applied across scenarios to analyze how changes in the relative importance of specific factors influence crowd behaviors and panic propagation. This approach provides researchers with nuanced insights into the interplay of elements driving panic and stress in group settings, ultimately contributing to the refinement of the DEI model and the development of more effective response strategies. The weights in the system are intentionally designed to be user-adjustable, allowing fine-tuning based on the specific characteristics and priorities of the monitored environment. This flexibility ensures that the algorithm can adapt to diverse scenarios, such as urban downtowns where crowd alignment with road networks is critical, or airports where other factors may take precedence. Additionally, this adjustability serves as a form of system training, enabling users to observe and understand the significance of each weight through iterative use. Over time, these insights will help clarify the relative importance of various factors, and as more data are collected, the system could evolve to automate weight assignments based on historical data and environmental characteristics. This evolution would enhance scalability and efficiency while retaining the system's adaptability to diverse environments.

The analysis of crowd panic behavior was conducted in real time using a custom Python script that processed data from wearable devices and smartphones. The script ingested biometric metrics like heart rate (HR) and variability (HRV) along with location data, extracting features such as the Normalized Panic Transmission and Recovery Rates, crowd density, and counts of stressed, calm, and recovered individuals. A pre-trained Gaussian SVM model classified data points as "calm" or "stressed", while the Domino Effect Index (DEI) dynamically assessed the severity and spread of panic.

For the real-time visualization of these scenarios, an ESRI ArcGIS Operations Dashboard, as shown in Figure 5, has been created to monitor and analyze the various factors at play. The dashboard is an essential tool for researchers and decision-makers, as it provides a comprehensive view of the unfolding situations and the group dynamics involved. The map background is provided by the following list of companies:

- ESRI—Redlands, CA, USA
- Intermap—Englewood, CO, USA
- NASA—Washington, DC, USA
- NGA—Springfield, VA, USA
- USGS—Reston, VA, USA
- Terra Mapping the Globe—Athens, Greece
- HERE—Eindhoven, the Netherlands

- Garmin—Olathe, KS, USA
- Foursquare—New York, NY, USA
- Geotechnologies—Tokyo, Japan

The Operations Dashboard consists of several components designed to offer a detailed understanding of the events as they transpire. These components include the following:

1. A map: This interactive map displays the location and movements of the individuals in each scenario, allowing researchers to observe patterns and group dynamics as they emerge;
2. DEI Current Value: The Domino Effect Index (DEI) index widget provides real-time values of the overall emotional state of the group, indicating the level of stress and anxiety experienced by the individuals;
3. DEI progress diagram: This diagram tracks the fluctuations in the DEI index over time, offering insights into the progression of the group's emotional state throughout the scenario;
4. Count of stressed, calm, and recovered individuals: This widget displays the current number of individuals in each emotional state, allowing researchers to monitor the distribution of emotions within the group;
5. Real-time charts for stressed, calm, and recovered individuals: These charts present the trends of the emotional states for each category, helping researchers identify the factors that influence the group's overall emotional state and individual transitions between states;
6. Panic transmission rate and recovery rate charts: These charts illustrate the rate at which panic spreads among individuals and the rate at which they recover from the state of panic. Monitoring these rates can provide valuable information on the effectiveness of interventions and the overall resilience of the group.

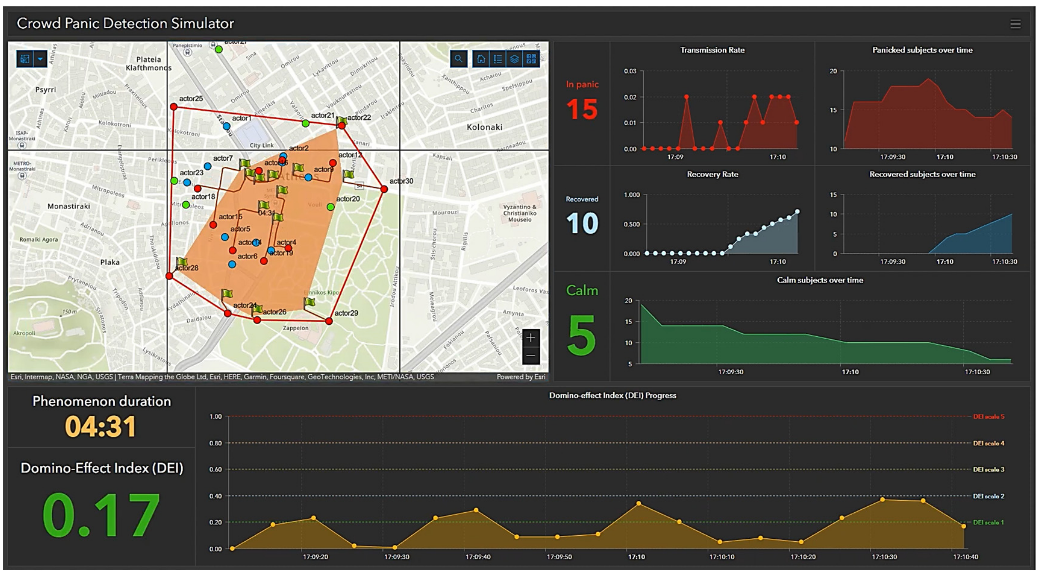

Figure 5. Sample screenshot of the Operations Dashboard.

The Operations Dashboard serves as a vital resource for researchers studying group dynamics and emotional contagion, as it offers a real-time view of the events and the opportunity to analyze the data as they are collected. By utilizing this dashboard, researchers can gain a deeper understanding of the complex interplay of factors that contribute to the spread of panic and stress within groups, as well as those that identify potential strategies to mitigate their impact in real-world situations.

The following scenarios encompass the execution of multiple tests. In the first two scenarios, a CLOT value of 0 is used, enabling the monitoring of Panic Points from their initial occurrence without noise filtering. The third scenario explores crowd panic detection across different CLOT values (0, 1, 3, and 4). This analysis sheds light on how different CLOT values impact the accuracy and effectiveness of crowd panic detection in the system.

4.1. Escape

In the first scenario, a group of about 30 individuals gather in a controlled environment, initially exhibiting a normal state of mind and behavior. The diverse group consists of people of different ages, genders, and backgrounds to ensure a wide range of responses. At the outset, the atmosphere is calm and the participants engage in various activities, such as conversing, playing games, or simply observing their surroundings. At a predetermined moment, an unpleasant situation is deliberately introduced nearby, catching some of the individuals off guard. The triggering event could be a loud startling noise, a heated argument, an unexpected physical disturbance, or even a terrorist attack. The initial group of affected individuals experiences a sudden onset of stress and panic, with physiological symptoms such as increased heart rate, rapid breathing, and heightened alertness. As the panic spreads, the individuals' emotional states begin to influence one another, causing a chain reaction. Those who are initially calm observe the panic-stricken individuals and, as a result, also become stressed and anxious. This phenomenon is known as emotional contagion, where emotions transfer from one person to another through nonverbal cues and social interactions. As Hatfield states in [22], emotional contagion is the ability of people to "feel themselves into" another's emotions. Over time, as the situation unfolds, panicked individuals instinctively seek escape in various directions. This propagation of panic spreads to distant individuals, causing them to also experience panic and respond accordingly, ultimately amplifying the scale and magnitude of the event. Figure 6 illustrates the precise quantities of weights employed in this particular scenario.

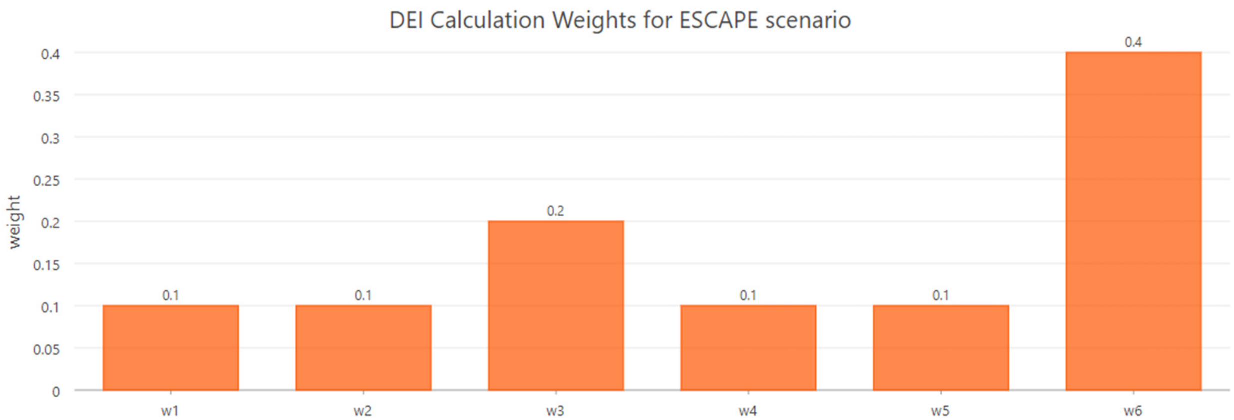

Figure 6. Scenario 1—Weights used.

In the subsequent figures (Figures 7–9), the maps illustrate the progression of the phenomenon over time. Panic Points are depicted as red dots, calm points as green dots, and recovered points as blue dots. Panic trajectories are represented by red lines, while the origins of these trajectories are marked by green flags. The shaded orange region denotes the Origin CPA (Common Panic Area), and the hollow red region indicates the Current Location CPA.

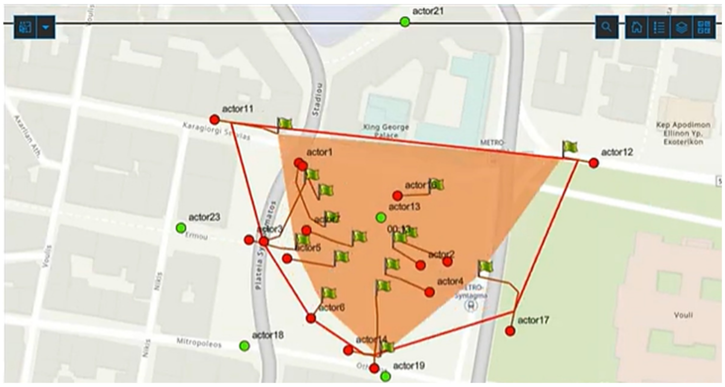

Figure 7. Scenario 1—initial expansion.

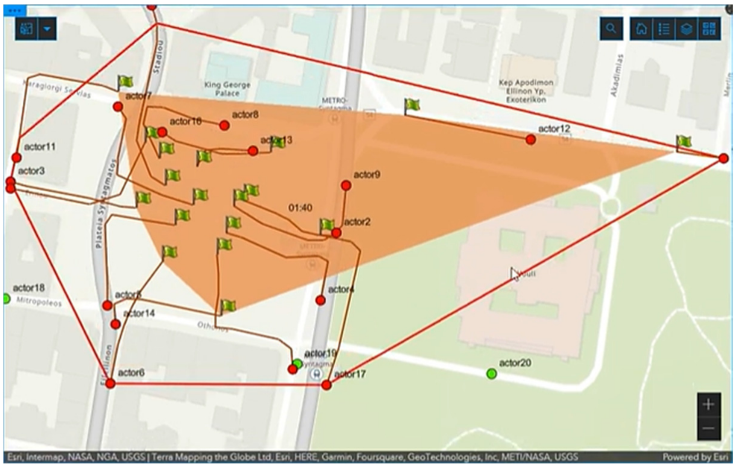

Figure 8. Scenario 1—panic starts to spread widely.

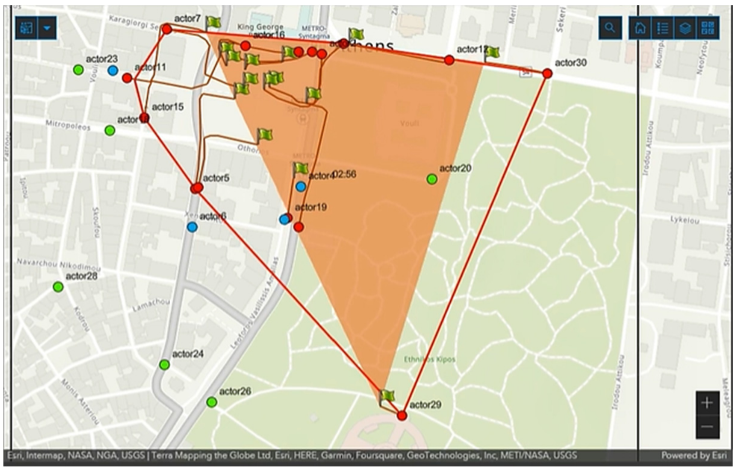

Figure 9. Scenario 1—after some time, it still expands but some subjects tend to recover (blue dots).

Next, in Figures 10–13, one can see the current count of individuals categorized as stressed, calm, and recovered, enabling effective monitoring of emotional distribution within the group. Real-time charts visually represent emotional trends for each category, aiding in the identification of influencing factors and individual transitions between emotional states. Moreover, the Panic Transmission and Recovery Rate Charts offer insights into the pace of panic propagation and the recovery rate, providing valuable information about intervention efficacy and overall group resilience. Additionally, the DEI Current Value provides real-time insights into the collective emotional state, reflecting stress and anxiety levels, while The DEI Progress Diagram tracks the evolution of the emotional state over time, shedding light on its progression throughout the scenario.

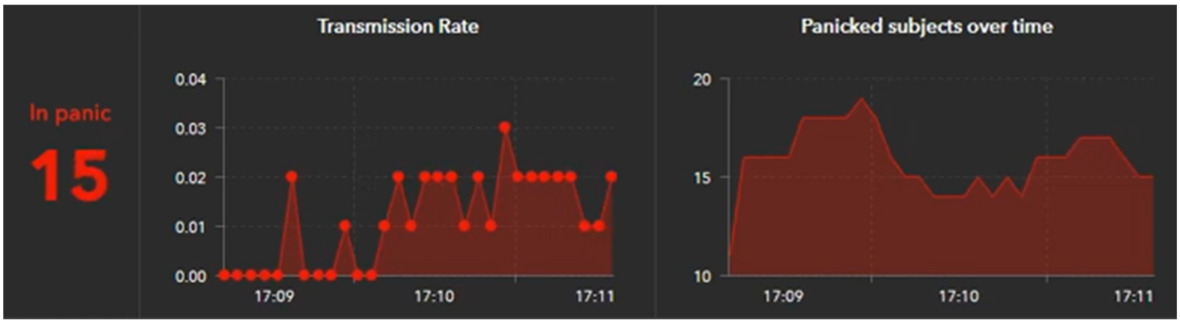

Figure 10. Scenario 1—transmission rate and panicked population.

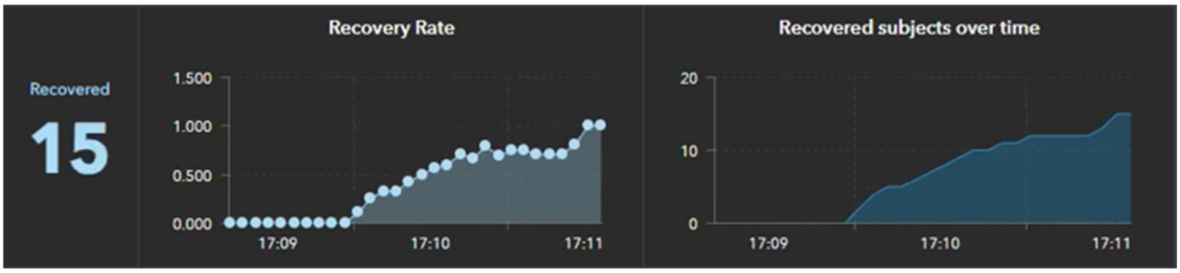

Figure 11. Scenario 1—recovery rate and recovered population.

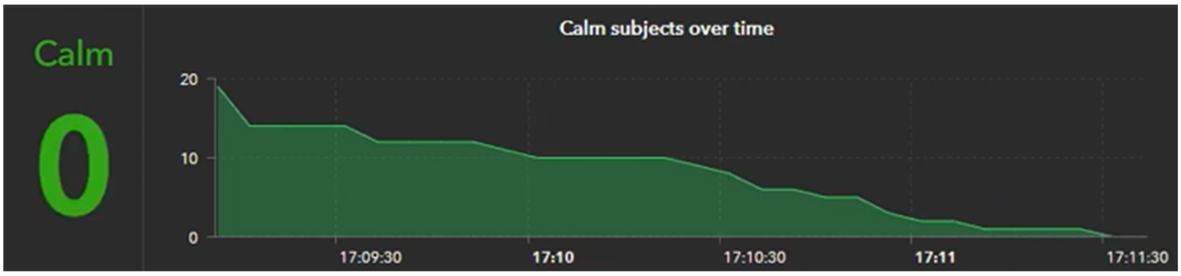

Figure 12. Scenario 1—calm population.

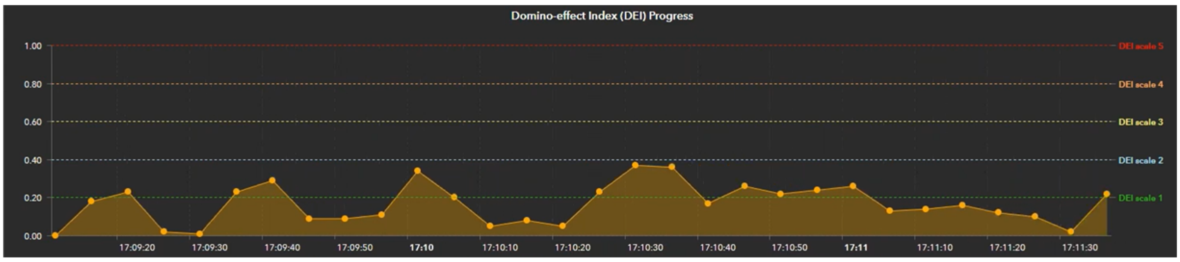

Figure 13. Scenario 1—evolution of DEI.

The count of recovered individuals demonstrates a progressive increase after a certain period, as evidenced by the recovery rate. Simultaneously, the number of calm individuals exhibits a noticeable decline, gradually approaching zero.

Ultimately, the comprehensive evaluation of the DEI reveals that, in this particular scenario, the phenomenon only marginally surpasses the threshold of 0.40, resulting in a DEI scale of 2.

In Figure 14, it is evident that the population of panicked individuals exhibits considerable fluctuations over time, indicating the arbitrary nature of the phenomenon's expansion and its variable impact on different individuals. During the initial minutes, the transmission rate remains predominantly low, as the panic has yet to propagate to a wider population. However, in subsequent stages, the transmission rate reaches higher values, signifying the widespread dissemination of panic.

Figure 14. Scenario 1—final state where the event has spread significantly, and multiple subjects are now in the recovery phase.

4.2. Shrink

In the second scenario, another group of individuals is presented, who, although initially calm, find themselves exposed to an unpleasant situation that envelops their surroundings. This group also consists of a diverse mix of ages, genders, and backgrounds to ensure a comprehensive understanding of various reactions and behaviors. The unpleasant situation could be a combination of factors, such as loud noises, a sudden change in environmental conditions, or the presence of perceived threats. These factors create an atmosphere of unease and anxiety, prompting individuals to instinctively seek safety and comfort in numbers. As the situation escalates, the group members respond by moving away from the sources of discomfort, causing the crowd to gradually shrink and gather in the center of the square, as shown in Figures 15–23. This movement results in a more densely packed cluster of individuals, reinforcing the sense of security that comes from being in close proximity to others. Figure 15 illustrates the precise quantities of weights employed in this particular scenario.

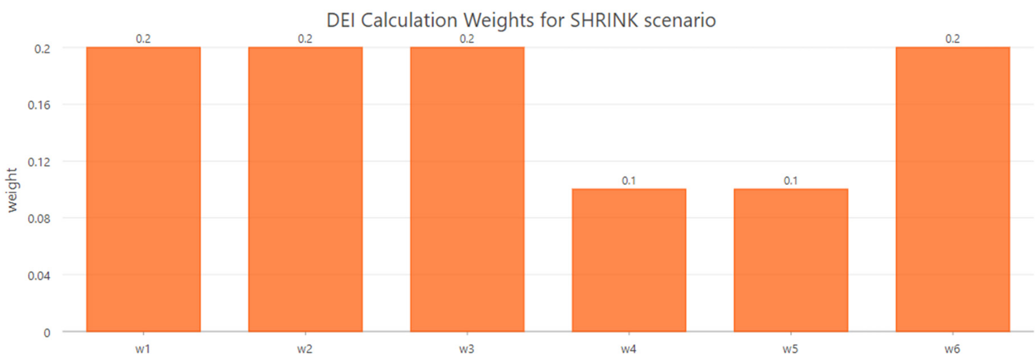

Figure 15. Scenario 2—weights used.

Figure 16. Scenario 2—initial reaction to the interior.

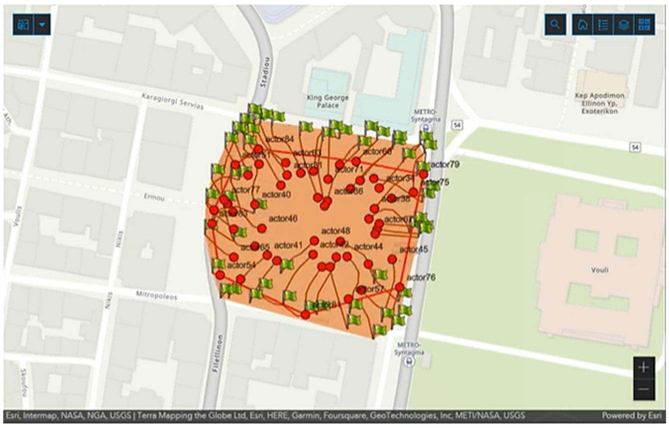

Figure 17. Scenario 2—crowd is intensively panicked and moves to the center of the square.

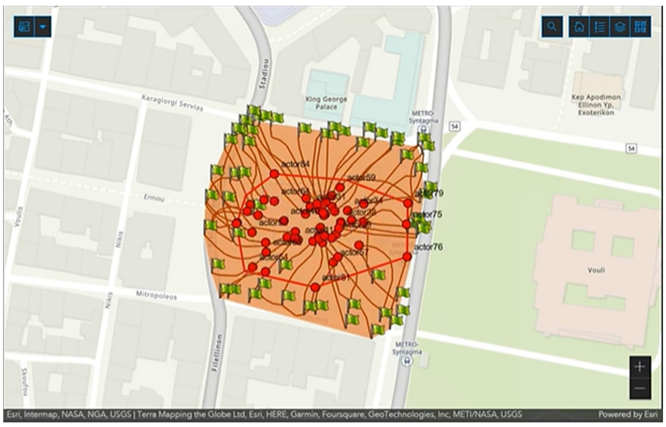

Figure 18. Scenario 2—crowd is still shrinking to the center.

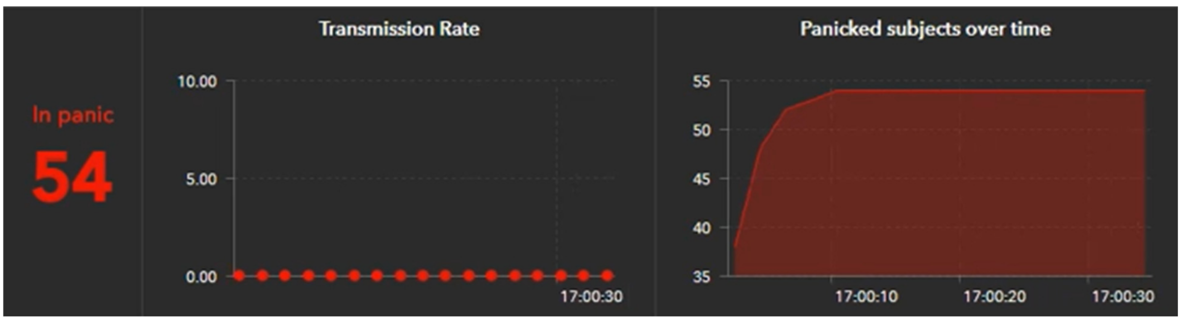

Figure 19. Scenario 2—transmission rate and panicked population.

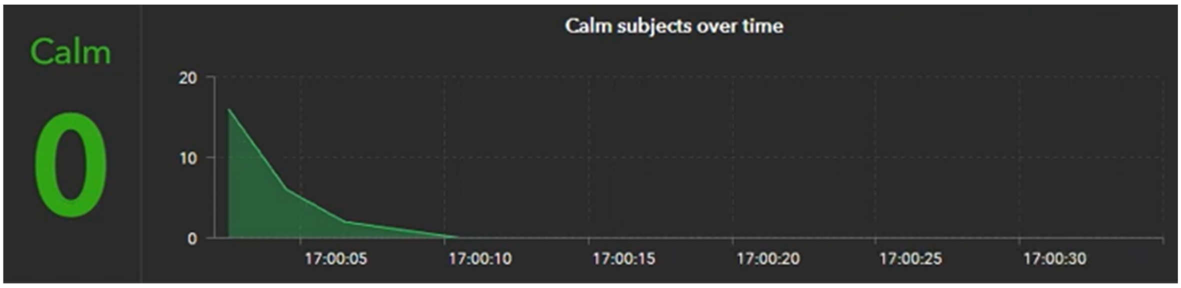

Figure 20. Scenario 2—calm population.

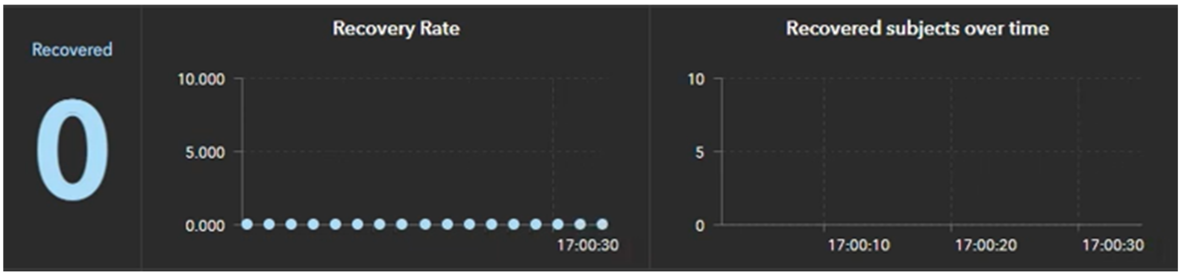

Figure 21. Scenario 2—recovery rate and recovered population.

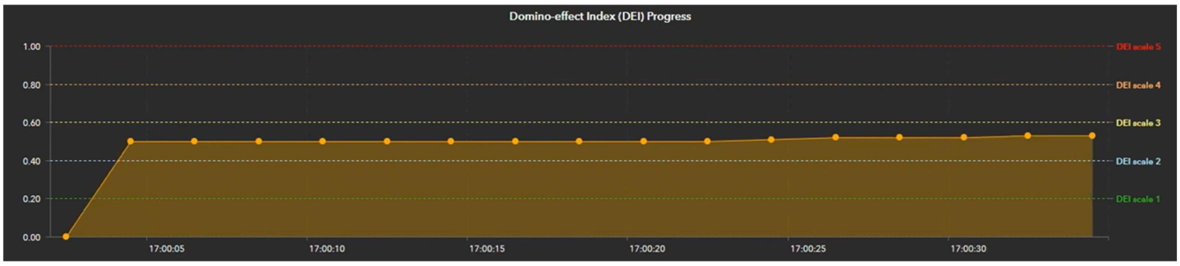

Figure 22. Scenario 2—evolution of the DEI.

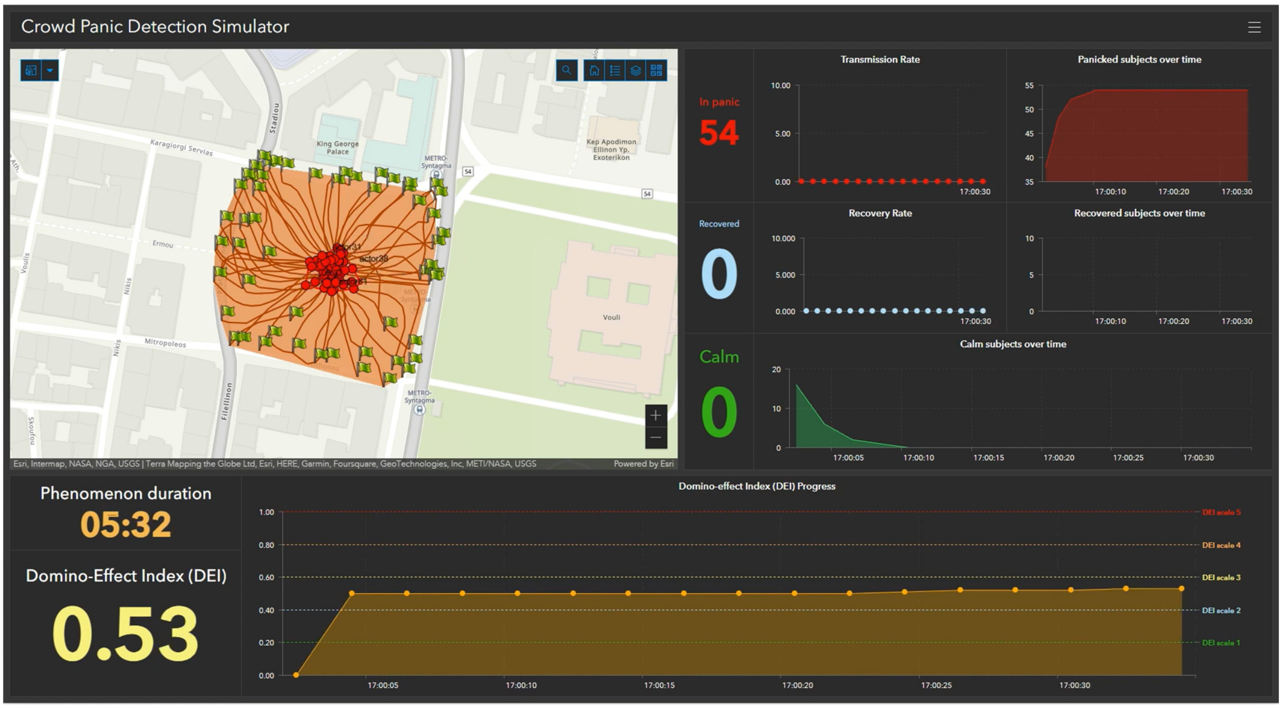

Figure 23. Scenario 2—final state, the crowd gathers at the very center of the square without signs of recovery yet.

In the subsequent figures (Figures 16–18), the maps again illustrate the progression of the phenomenon over time.

Next, in Figures 19–22, one can see the current count of individuals categorized as stressed, calm, and recovered, enabling effective monitoring of emotional distribution within the group. Real-time charts visually represent emotional trends for each category, aiding in the identification of influencing factors and individual transitions between emotional states. Moreover, the Panic Transmission and Recovery Rate Charts offer insights into the pace of panic propagation and the recovery rate, providing valuable information about intervention efficacy and overall group resilience. Additionally, the DEI Current Value provides real-time insights into the collective emotional state, reflecting stress and anxiety levels, while The DEI Progress Diagram tracks the evolution of the emotional state over time, shedding light on its progression throughout the scenario.

In parallel, the count of calm individuals undergoes a noticeable decline, swiftly approaching zero as a result of the widespread panic that engulfed the crowd early on. The count of recovered individuals and the corresponding recovery rates remain stagnant at zero, as the crowd remains in a panicked state throughout the entire duration.

Ultimately, a comprehensive assessment of the DEI reveals that, in this specific scenario, the phenomenon rapidly reaches a DEI scale of 3, as the panic spreads to the entire crowd and no instances of recovery are observed.

In Figure 23, it is evident that the population of panicked individuals experiences a significant and rapid increase from the initial moments, indicating the abrupt nature of the event and the immediate inundation of panicked individuals at the scene. Notably, the transmission rate remains at zero levels, indicating that the entire crowd became panicked right from the outset, leaving no individuals unaffected by the panic.

4.3. Repulsion

In the third scenario, a group of people is engaged in what appears to be a protest in front of police forces. The protesters, consisting of individuals from various backgrounds, ages, and genders, gathered to express their concerns and demand change. The atmosphere is tense, as both protesters and police officers stand their ground and face each other. Suddenly, a turning point occurs in the situation, compelling the protesters to retrace their steps and run away, changing their direction by almost 180 degrees. This shift could be triggered by various factors, such as the use of force by the authorities, the arrival of reinforcements, or the deployment of crowd control measures like tear gas or water cannons. In the initial phase, the crowd situated in close proximity to the police forces experiences a rapid onset of panic, prompting swift movement away from the immediate vicinity and toward the nearby square. This wave of panic transmission induces a similar response in the individuals already present within the square, resulting in the formation of a unified group exhibiting panicked behavior and moving in a synchronized manner in the same direction. Subsequently, the majority of individuals gradually regain composure and settle on the opposite side of the square, marking the recovery process from the state of panic (represented by blue dots). Figures 24–32 describe the above scene accordingly. Figure 24 illustrates the precise quantities of weights employed in this particular scenario.

In the subsequent figures (Figures 25–27), the maps again illustrate the progression of the phenomenon over time.

Next, in Figures 28–31, one can see the current count of individuals categorized as stressed, calm, and recovered, enabling the effective monitoring of emotional distribution within the group. Real-time charts visually represent emotional trends for each category, aiding in the identification of influencing factors and individual transitions between emotional states. Moreover, the Panic Transmission and Recovery Rate Charts offer insights into the pace of panic propagation and the recovery rate, providing valuable information about intervention efficacy and overall group resilience. Additionally, the DEI Current Value provides real-time insights into the collective emotional state, reflecting stress and anxiety levels, while The DEI Progress Diagram tracks the evolution of the emotional state over time, shedding light on its progression throughout the scenario.

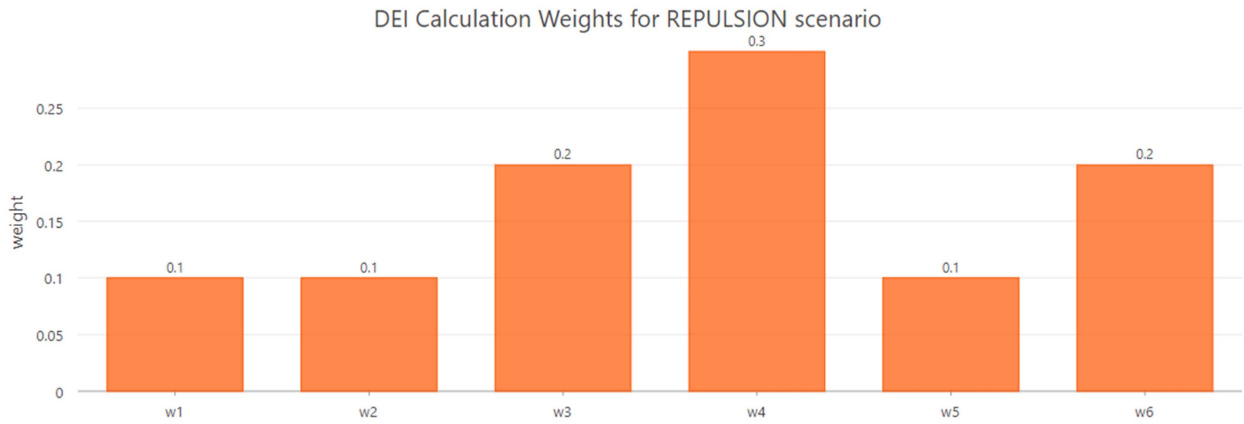

Figure 24. Scenario 3—weights used.

Figure 25. Scenario 3—initial reaction to the enforcement.

Figure 26. Scenario 3—repulsive reaction of the crowd, leading it in the opposite direction.

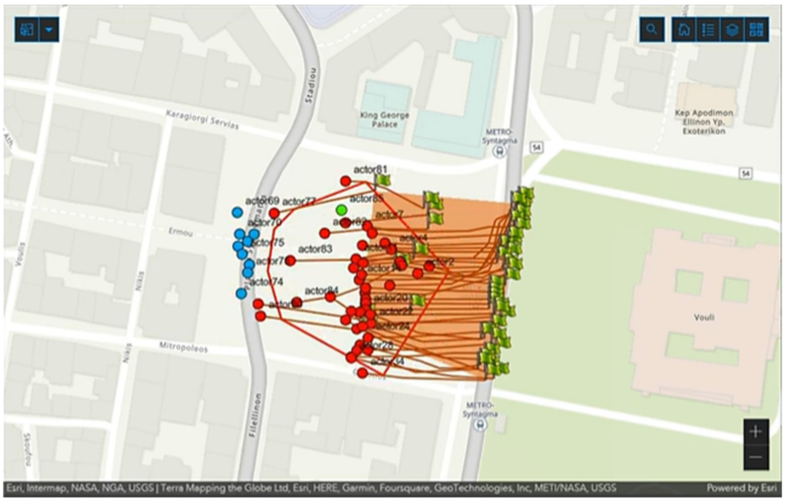

Figure 27. Scenario 3—the crowd moves away intensively as the first recoveries appear.

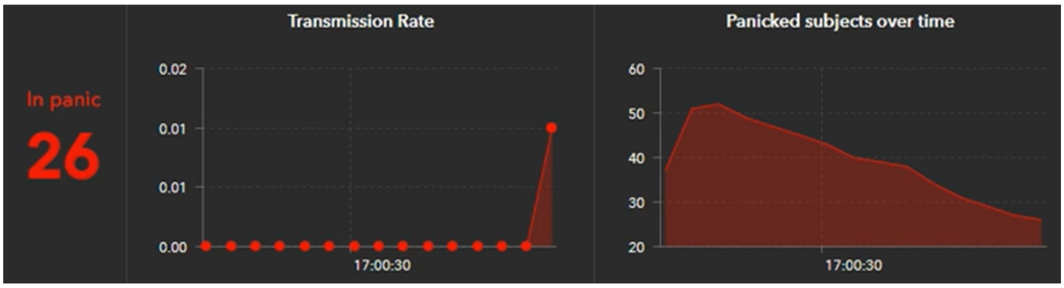

Figure 28. Scenario 3—transmission rate and panicked population.

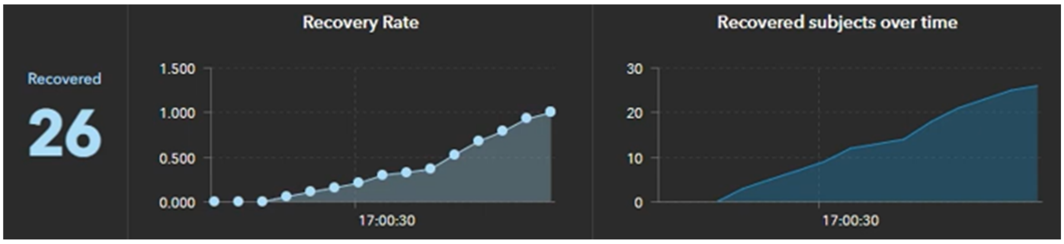

Figure 29. Scenario 3—recovery rate and recovered population.

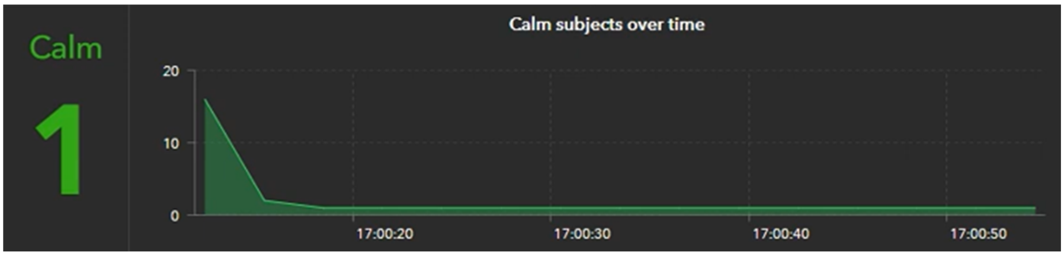

Figure 30. Scenario 3—calm population.

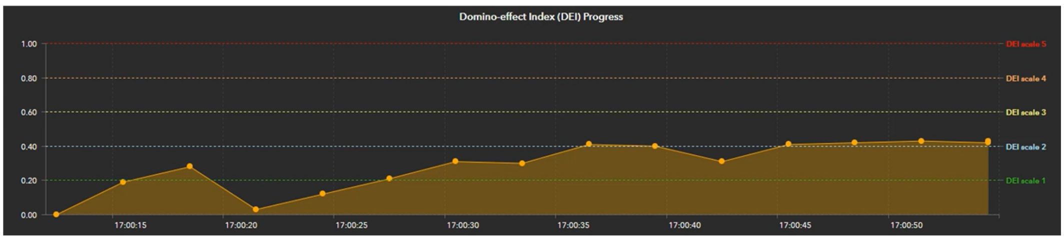

Figure 31. Scenario 3—evolution of DEI.

Figure 32. Scenario 3—final state where most of the crowd that is quite distant has recovered from the source of panic.

Notably, the transmission rate initially remains at negligible levels, implying that the entire crowd experienced panic from the very beginning. However, in the final minutes, there is a sudden surge in the transmission rate, reaching significantly higher levels, as the panicked crowd disperses and influences individuals on the opposite side of the square. Concurrently, the number of calm individuals experiences a noticeable decline, steadily approaching zero, as a consequence of the widespread panic that quickly permeated the crowd early on.

Ultimately, conducting a comprehensive assessment of the DEI reveals that, in this particular scenario, the phenomenon eventually reaches a DEI scale of 3 (0.42), albeit initially appearing to decline and calm at an earlier stage.

In Figure 32, it is evident that the count of panicked individuals undergoes a significant and rapid surge from the initial moments, indicating the abrupt and instantaneous nature of the event, leading to the immediate inundation of panicked individuals at the scene. However, over time, a steady decline in the count of panicked individuals can be observed, as many of them gradually recover from their panic as they distance themselves from the initial panic-inducing location. This recovery trend is also reflected in the measurements of recovery, where both the count and rate exhibit a clear upward trajectory.

Finally, pertaining to this particular scenario, the subsequent Figures 33–35 illustrate the outcomes observed when employing different CLOT values. Figure 33 represents a CLOT value of 0, which signifies the absence of noise filtering attributed to the Machine Learning classifier. Consequently, this leads to an immediate detection of crowd panic The blue line at the very right shows that the detection happens right at the beginning. However, it is important to note that such detection may encompass Panic Trajectory Origins that emerged from very limited sequences of Panic Points, even as few as 2 points. Thus, this scenario exhibits the maximum number of Panic Trajectory Origins contributing to the formation of the corresponding Crowd Panic Area.

Figure 33. CLOT = 0. No noise is filtered.

Figure 34. CLOT = 1. A Panic Point needs to have at least one consecutive.

Figure 35. CLOT = 3. A Panic Point needs to have at least three consecutives.

In Figure 34, which corresponds to a CLOT value of 1, a moderate level of noise filtering is implemented. Specifically, the number one means that each Panic Point should be followed by at least another one in order to be considered valid. As a result, the detection of crowd panic shows a slight delay compared to the scenario with a CLOT value of 0. In this case, the blue line appears slightly shifted to the left in comparison to Figure 33, illustrating this delay. The filtering process effectively reduces the occurrence of false positives but at the expense of a slightly later detection of panic events.

In Figure 35, denoting a CLOT value of three, a higher level of noise filtering is employed. Specifically, the CLOT value of three implies that each Panic Point should be succeeded by a minimum of two subsequent Panic Points for it to be deemed valid. This intensified filtering mechanism results in a more significant reduction in false positives, contributing to increased precision. However, the stricter criterion leads to a more significant delay in detecting crowd panic, as shown by the blue line shifting further to the left compared to the CLOT values of zero and one. While the filtering process enhances accuracy, the trade-off manifests as a slightly longer time frame before panic events are detected.

4.4. Discussion

In the above experiments, the participants are subjected to close monitoring, enabling the collection of comprehensive data regarding their behaviors, emotional states, and intricate interactions. By leveraging the data model entities described in the preceding section, these individuals and their interactions are effectively represented on a digital map, which serves as a powerful visual tool for elucidating the unfolding and dissemination of panic within the group. By examining the dynamic interplay of panic, vital insights are gained into the underlying mechanisms that drive group panic.

As the experiment unfolds, careful observation allows for the meticulous tracking of the formation and evolution of these data model entities on the digital map, revealing compelling patterns of behavior and group dynamics that come to the forefront. Notable clusters of stressed individuals are discerned, shedding light on the presence of localized panic hotspots, while also identifying those individuals who actively strive to diffuse the escalating tension or offer solace to their distressed counterparts. Through rigorous analysis of these emergent patterns and behaviors, the primary objective is to gain a deeper understanding of the fundamental mechanisms governing panic and stress propagation within groups.

The Domino Effect Index (DEI) is a novel metric introduced within the system's framework, designed to enhance its capability not only to detect but also to classify instances of crowd panic emergencies. The term "domino effect" refers to a chain reaction where one event triggers a series of interconnected events. The DEI assesses the severity of identified emergencies by considering crucial factors contributing to this cascading phenomenon, such as the pace of panic propagation, the density of distressed individuals, and alignment with the road network. By incorporating the DEI, the proposed system advances emergency detection and response. This index aids emergency responders in swiftly allocating resources, evacuating affected zones, comprehending event severity, and undertaking preventive measures to avert potential escalations.

The Classifier Level of Trust (CLOT) parameter plays a pivotal role in influencing the effectiveness of crowd panic detection. By adjusting the CLOT value, the balance between noise filtering and timely detection can be tailored to suit specific requirements. A lower CLOT value, such as 0 or 1, prioritizes immediate detection, allowing for quick identification of panic events but potentially including false positives. On the other hand, higher CLOT values, such as 3 or 4, emphasize stringent noise filtering, resulting in reduced false positives at the expense of a slightly longer detection delay. The choice of the appropriate CLOT value allows for fine-tuning the system's response, ensuring a balance between accuracy and responsiveness in crowd panic detection applications.

Furthermore, by unraveling the intricate dynamics at play and identifying effective strategies for mitigating the impact of panic and stress in real-world scenarios, the findings from these experiments hold immense potential for shaping the development of comprehensive interventions and response protocols. Armed with a refined understanding of group panic, emergency planners and responders can employ targeted measures to effectively manage and minimize the adverse consequences of panic-induced crowd movements in various critical situations, such as evacuations, natural disasters, or incidents of civil unrest.

5. Conclusions and Future Work

Bridging the gap between panic detection and actionable policy requires integrating real-time detection systems with emergency response infrastructures and establishing robust policy frameworks. Real-time data from wearable devices and smartphones can be transmitted to centralized monitoring platforms, triggering automatic alerts and guiding emergency responses such as evacuations or traffic rerouting through integration with smart city systems. Policies should include scenario-based response plans, regular emergency drills, and clear communication protocols to ensure efficient public engagement during crises. Challenges like data privacy, scalability, and bureaucratic delays can be mitigated with secure data handling, pre-approved action protocols, and cloud-based solutions. Public awareness campaigns and education on wearable device adoption and system alerts are essential to ensure cooperation and enhance the system's effectiveness in managing emergencies.

In conclusion, the real-time spatial analysis methodology presented in this article represents a step forward in monitoring and responding to panic conditions in crowds. By utilizing wearable devices and smartphones to collect spatiotemporal and biometric data, this methodology is able to provide real-time insights into the spatial extent and development of potentially dangerous situations. The resulting Panic Trajectories and Crowd Panic Areas can help authorities and emergency responders to make timely and effective decisions in response to emerging threats, ultimately ensuring the safety and security of individuals in high-stress or dangerous situations.

Moreover, the newly proposed Domino Effect Index (DEI) adds an additional layer of sophistication to this monitoring algorithm. By considering the potential for a small incident to trigger a cascading series of panic events, the DEI provides a more comprehensive understanding of the dynamics of crowd behavior. The DEI can help emergency responders identify and prioritize the most critical areas and individuals for intervention, ultimately leading to more effective responses to emergency situations.

The feasibility of this methodology and the DEI was tested through a proof-of-concept experiment, which demonstrated its ability to detect and respond to panic conditions in a simulated crowd environment. The results of this experiment indicate that the methodology and the DEI are both viable tools for real-time monitoring and response to panic conditions in crowds.

Overall, the real-time spatial analysis methodology presented in this article, combined with the newly proposed DEI, represents an advancement in the field of crowd safety and security. With its ability to provide real-time insights into the dynamics of crowd behavior, this methodology has the potential to save lives and prevent injuries in emergency situations.

Future work focuses on thoroughly examining bio-algorithms and mathematical models for measuring and analyzing the spread of panic in crowds. In particular, the spatial SIR (Susceptible-Infected-Recovered) model, commonly used to model the spread of infectious diseases, could be adapted and explored to estimate the spreading rate of panic in a crowd. To improve the accuracy of these models, other factors that could affect the transmission of panic could be considered, such as the density of the crowd, the level of noise, or the visibility of the panicked individual. The enhanced understanding of panic transmission gained from these investigations would contribute to the further development and refinement of the real-time spatial analysis methodology and its applications in crowd safety and security.

Moreover, machine learning approaches, such as Long Short-Term Memory (LSTM) networks, will be employed to capture temporal dependencies in biometric and spatiotemporal data, enabling predictions of panic progression over time. Graph Neural Networks (GNNs) will model crowd interactions as networks, providing deeper insights into how panic spreads through spatial proximity and individual connections.

Additionally, differential equation models will be explored to describe panic propagation more comprehensively. Reaction-diffusion models will combine local interactions with large-scale dynamics, while stochastic differential equations (SDEs) will account for randomness in individual responses under uncertain conditions. Coupled models will link biometric features, like heart rate variability, with changes in movement and density for realistic simulations.

To address computational challenges, numerical schemes such as Finite Element Methods (FEMs) will be applied to solve reaction-diffusion equations in irregular urban geometries, while Monte Carlo techniques will simulate random crowd behaviors and their influence on panic propagation. These advancements will collectively refine the system's predictive capabilities and its adaptability to diverse real-world scenarios.

Also, the Stress Profile Index (SPI) could be expanded to include intermediate values, allowing for a more nuanced classification of stress levels beyond the binary "calm" or "stressed/panic" states. By incorporating a gradient or range of SPI values, the system could capture varying degrees of stress, providing a more detailed understanding of individual and crowd behavior. This approach could enhance the precision of real-time interventions by tailoring responses to different stress levels, ultimately improving the system's adaptability and effectiveness in managing dynamic scenarios.

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References

1. Dong, E.; Du, H.; Gardner, L. An interactive web-based dashboard to track COVID-19 in real time. *Lancet Infect. Dis.* **2020**, *20*, 533–534. [CrossRef] [PubMed]
2. Malkani, D.; Malkani, M.; Singh, N.; Madan, E. Best Practices for the Design of COVID-19 Dashboards. *Perspect. Health Inf. Manag.* **2023**, *20*, 1b.
3. Mak, H.W.L.; Koh, K. *Building a Healthy Urban Environment in East Asia. Joint Lab on Future Cities (JLFC)*; Report No. 1; The University of Hong Kong: Hong Kong, China, 2021.
4. Jian, S.W.; Kao, C.T.; Chang, Y.C.; Chen, P.F.; Liu, D.P. Risk assessment for COVID-19 pandemic in Taiwan. *Int. J. Infect. Dis.* **2021**, *104*, 746–751. [CrossRef]
5. Lazarou, I.; Kesidis, A.L.; Hloupis, G.; Tsatsaris, A. Panic Detection Using Machine Learning and Real-Time Biometric and Spatiotemporal Data. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 552. [CrossRef]

6. Hao, Y.; Xu, Z.; Wang, J.; Liu, Y.; Fan, J. An Approach to Detect Crowd Panic Behavior Using Flow-Based Feature. In Proceedings of the 22nd International Conference on Automation and Computing, Colchester, UK, 7–8 September 2016; ISBN 9781862181328. [CrossRef]
7. Ammar, H.; Cherif, A. Deep ROD: A deep learning approach for real-time and online detection of a panic behavior in human crowds. *Mach. Vis. Appl.* **2021**, *32*, 57. [CrossRef]
8. Lu, S.; Chen, B.; Zhong, P.; Sheng, Y.; Cui, Y.; Liu, R. CrowdNav-HERO: Pedestrian Trajectory Prediction Based Crowded Navigation with Human-Environment-Robot Ternary Fusion. In Proceeding of the 30th International Conference (ICONIP 2023), Changsha, China, 20–23 November 2023. [CrossRef]
9. Bhowmick, D.; Winter, S.; Stevenson, M.; Vortisch, P. The impact of urban road network morphology on pedestrian wayfinding behaviour. *J. Spat. Inf. Sci.* **2020**, *21*, 601. [CrossRef]
10. Tsai, C.H.; Chen, P.C.; Liu, D.S.; Kuo, Y.Y.; Hsieh, T.T.; Chiang, D.L.; Lai, F.; Wu, C.T. Panic Attack Prediction Using Wearable Devices and Machine Learning: Development and Cohort Study. *JMIR Med. Inform.* **2022**, *10*, e33063. [CrossRef]
11. Kutsarova, V.; Matskin, M. Combining Mobile Crowdsensing and Wearable Devices for Managing Alarming Situations. In Proceedings of the 2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC), Madrid, Spain, 12–16 July 2021; pp. 538–543.
12. Alsalat, G.Y.; El-Ramly, M.; Fahmy, A.A.; Karim, S. Detection of Mass Panic using Internet of Things and Machine Learning. *Int. J. Adv. Comput. Sci. Appl.* **2018**, *9*, 5. [CrossRef]
13. Sun, H.; Hu, L.; Shou, W.; Wang, J. Self-Organized Crowd Dynamics: Research on Earthquake Emergency Response Patterns of Drill-Trained Individuals Based on GIS and Multi-Agent Systems Methodology. *Sensors* **2021**, *21*, 1353. [CrossRef] [PubMed]
14. Zhang, X.; Sun, Y.; Li, Q.; Li, X.; Shi, X. Crowd Density Estimation and Mapping Method Based on Surveillance Video and GIS. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 56. [CrossRef]
15. Albarakt, R.; Selim, G.; Iaaly, A. Reshaping Riyadh Alsolh Square: Mapping the Narratives of Protesting Crowds in Beirut. *Urban Reg. Plan.* **2021**, *6*, 126–133. [CrossRef]
16. Lazarou, I.; Kesidis, A.; Tsatsaris, A. Real-Time Monitoring of Crowd Panic Based on Biometric and Spatiotemporal Data. In Proceedings of the 18th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications, VISAPP, Lisbon, Portugal, 18–20 February 2023; Volume 5, pp. 1021–1027. [CrossRef]
17. Jarillo Silva, A.; Gómez Pérez, V.A.; Domínguez Ramírez, O.A. Study of the Length of time Window in Emotion Recognition based on EEG Signals. *Rev. Mex. De Ing. Biomé.* **2024**, *45*, 31–42. [CrossRef]
18. De Santos Sierra, A.; Avila, C.S.; Casanova, J.G.; del Pozo, G.B. A Stress—Detection System Based on Physiological Signals and Fuzzy Logic. *IEEE Trans. Ind. Electron.* **2011**, *58*, 4857–4865. [CrossRef]
19. Rigas, G.; Goletsis, Y.; Fotiadis, D.I. Real-Time Driver's Stress Event Detection. *IEEE Trans. Intell. Transp. Syst.* **2012**, *13*, 221–234. [CrossRef]
20. Fang, C.; Song, M.; Zhang, T. Real-time emotion classification using EEG signal with a 10-second feature map input. In Proceedings of the 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Virtual, 1–5 November 2021; pp. 5472–5475.
21. Jang, J.; Jiang, H. DBSCAN++: Towards fast and scalable density clustering. *Int. Conf. Mach. Learn.* **2019**, *97*, 3019–3029.
22. Hatfield, E.; Rapson, R.L.; Le, Y.C.L. Emotional contagion and empathy. In *The Social Neuroscience of Empathy*; MIT Press: Cambridge, MA, USA, 2011.