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Analyzing Crowd Emotional Contagion in Metro Emergencies Through the Lens of the Weber–Fechner Law: Predictions Based on Computational Techniques Applied to Science

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Featured Application: Based on big data and public opinion analysis technology, control strategies for potential public crisis events have been explored. Based on the application of data technology, the transmission mechanism of public events has been predicted.

Abstract: The spread of panic can swiftly trigger group behaviors, leading to public security incidents and significant social hazards. Increasing attention is being paid to the impact of human psychology and behavior on the evolution and management of emergencies. Drawing on the Weber–Fechner Law, we proposed an emotional contagion model to explore the dynamics of crowd panic during metro emergencies, focusing on the interplay of emotional levels and stimuli. Key influencing factors such as crowd density, personality traits, official interventions, and evacuation rates are analyzed. Additionally, a case study is conducted to validate the model's effectiveness in quantifying emotions and characterizing the emotional contagion of crowd panic. Numerical results reveal that the initial intensity of panic stimuli significantly impacts peak panic levels, while contagion duration plays a minor role. Panic intensifies with increased crowd density, with sensitive individuals being more susceptible to extreme emotions, escalating negative contagion. Official intervention proves crucial in mitigating panic, though its effect is transient in enclosed environments. Evacuation rate minimally affects emotional contagion during the train's motion but becomes pivotal post-arrival. Highly panicked passengers evacuate quickly, necessitating timely interventions to prevent secondary panic on platforms. This highlights the importance of immediate, effective control measures to manage panic dynamics and ensure public safety.

Keywords: emergency event; group panic; emotional contagion; Weber–Fechner law; computational prediction applied science

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1. Introduction

As urbanization accelerates, the frequent occurrence of public emergencies has introduced significant instability to the normal functioning of society, prompting deep reflections on the emergency management strategies from various sectors. Among these emergencies, metro incidents hold a critical position due to the importance of metro systems as a primary means of transportation in modern cities. The narrow, enclosed, and highly trafficked nature of metro platforms and carriages easily suggests to the public that metro environments are prone to accidents and difficult to escape in cases of emergencies. Once an emergency occurs, panic is likely to ensue, potentially leading to behavioral disorders and even severe incidents such as stampedes and other harmful accidents [1,2]. Panic is a typical psychological response to crises. High-intensity individual panic and the spontaneous, polarized behaviors driven by it tend to spread rapidly at both the group and societal levels, evolving from individual to collective panic [3]. Group panic and irrational behavior complicate emergency management efforts, potentially exacerbating the risk associated with the initial emergency and triggering a series of secondary events with consequences more severe than the emergency itself. For instance, in 2017, a passenger on Shenzhen Metro Line 7 fainted due to discomfort, causing panic among nearby passengers. This panic led to a stampede as passengers rushed to escape, ultimately resulting in injuries to 15 people.

Managing passenger emotions is crucial in the emergency management of metro incidents. As early as 1884, William James [4] and Carl Lange proposed the periphery-feedback theory of emotion, describing a "bottom-up" mechanism of emotion generation, where physiological changes lead to emotional arousal. The intensity of emotional arousal is influenced by several factors. Firstly, the greater the discrepancy between changes in the surrounding environment and an individual's cognition, the higher the intensity of emotional arousal. Secondly, an individual's sense of control over the event significantly impacts emotional intensity; when perceived control is weak and the event is seen as beyond one's control, this leads to heightened negative emotional arousal [5]. Furthermore, the intensity of emotional arousal is also affected by the degree to which an individual's needs are satisfied. When these needs are inadequately met, the resulting negative emotional arousal becomes more intense [6]. Behavioral experimental data suggest that emotional responses elicited by negative information have shorter latency, are faster, and involve a higher degree of arousal. This explains why an individual's panic is highly susceptible to arousal when confronted with unexpected events [7]. In addition to high arousal, panic has group and social characteristics. It is highly contagious and can easily spread from individual to group emotion through relatively spontaneous communication behaviors in disordered situations [8].

Research on group panic in emergencies has predominantly been conducted from the perspective of social psychology. Various scholars have employed psychological experiments, empirical studies, and other qualitative methods to analyze the root causes of group panic, identifying emotional contagion [9,10], herd mentality [11], and extreme behavioral psychology [12] as the primary factors leading to panic behaviors. In emergencies, emotional contagion serves as a catalyst in the formation and evolution of group panic [13] and is considered the most critical factor. Emotional contagion, a phenomenon that is typically natural and unconscious [14], has garnered significant attention in the fields of psychology, sociology, and organizational behavior. Lundqvist and Dimberg [15] experimentally demonstrated the critical role of facial mimicry in emotional contagion. Barsade [16] conducted an experimental study on work groups, revealing that the spread of positive emotions significantly enhances group cooperation, reduces conflict, and improves task performance. Totterdell et al. [17] observed teams of nurses and accountants, confirming the interconnection of group emotions in shared tasks. Beyond laboratory research, studies conducted in real-world settings have provided evidence with greater external validity. Bartel and Saavedra [18] investigated emotional consistency within work groups, finding that emotional convergence among team members is closely associated with cooperative norms and social interdependence. Fowler and Christakis [19], through social network analysis, discovered that emotions could spread across three degrees of connection: friends, friends of friends, and friends of friends of friends. Kramer et al. [20] validated the existence of online emotional contagion through experimental studies conducted on social media platforms. This phenomenon manifests widely in both physical crowd evacuations [21,22] and virtual opinion dissemination [23]. Current research on the dynamics of emotional contagion emphasizes models that combine emotional valence within groups. For example, Faroqi and Mesgari [24] delineated emotional levels during emergencies, ranging from calm to hysteria, passing through stages such as anxiety, fear, horror, and panic. An increasing body of research integrates psychological findings on individual factors influencing emotional contagion and varying levels of emotional valence [25,26], with epidemiological models to simulate the spread of emotions in crowds. Incorporating personality traits into these models, Cao [27] developed the P-SIS (Personalized-Susceptible–Infected–Susceptible) model of emotional contagion by combining the OCEAN (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism) model with the traditional SIS (Susceptible–Infected–Susceptible) model. Similarly, Lv [28] utilized the SIR (Susceptible–Infected–Recovered) model to calculate a receiver's susceptibility based on the OCEAN model's five factors. Nizamani [29] expanded on the basic SIR framework, categorizing the crowd into five types of agents—"Upset", "Violent", "Sensitive", "Immune", and "Relaxed"—to address hatred issue-awareness. Further advancements include Wang's [30] introduction of a latent state group, resulting in the Susceptible–Latent–Infected–Recovered–Susceptible (SLIRS) model. This model formulates emotional contagion control as an optimal control problem, aiming to minimize the total costs of inhibiting emotional contagion. Liu [31], recognizing the importance of stabilization and control, incorporated an emotional control administrator into the contagion model. Meanwhile, Ni [32] introduced an emotionally stable node, representing a group that remains calm during emergencies and is less susceptible to event-related emotions, thereby stabilizing and regulating group emotions. Ni's model, known as the U-SOSPa-SPSO (Unsusceptible–Susceptible–Optimistic–Susceptible and Susceptible–Pessimistic–Susceptible) model, further refines the understanding of emotional contagion. Comparatively, Bosse [33] viewed the process of emotional contagion as analogous to heat dissipation in thermodynamics. He proposed the ASCRIBE model, where emotional changes in a receiver due to contagion are determined by two components: the ease with which emotion flows between agents and the emotional influence exerted by the sender. This model has inspired numerous variants [34]. Additionally, Rincon [35], drawing inspiration from Newtonian physics, proposed a dynamic emotional model for groups, expressing agents' emotions in three dimensions using the PAD (Pleasure–Displeasure, Arousal–Nonarousal, Dominance–Submissiveness) model. In this approach, emotional changes are conceptualized as kinetic processes similar to those in mechanics, providing deeper insights into the intricate dynamics of emotional contagion within groups.

Epidemiological models and thermodynamics-based models provide distinct approaches to modeling and analyzing emotional contagion. Epidemiological models, drawing analogies to the spread of diseases among individuals, offer a framework for describing how emotions propagate within a group, making them particularly useful for simulating both the speed and scope of emotional transmission. In contrast, thermodynamics-based models focus on the microscopic mechanisms of emotional flow from the perspective of energy transfer, making them well-suited for exploring the nuanced dynamics of emotional contagion. However, the representation of emotional computation within these studies remains somewhat ambiguous. According to the peripheral-feedback theory of emotion proposed by William James and Carl Lange, stimuli trigger activity in the autonomic nervous system, producing physiological changes that subsequently lead to emotional experiences. In perceptual psychology, the Weber–Fechner Law can be applied to explain visual, auditory, tactile, and other perceptual phenomena. This law describes a quantitative relationship between the intensity of physical stimuli and human sensation, stating that the human perception of physical stimuli is proportional to the logarithm of the intensity of those stimuli [36,37]. Emotion, in this context, can be considered a form of human perception of these physical stimuli [38]. Furthermore, the Weber–Fechner Law has also been validated in contexts such as negotiation interactions [39] and public opinion communication [40]. Thus, this study incorporated the Weber–Fechner Law into the investigation of emotional contagion to more accurately measure its intensity. By applying the Weber–Fechner Law, the intensity of emotional contagion is conceptualized as a logarithmic function of the emotional stimulus intensity. This allows for an improved quantification and comparison of emotional contagion across different contexts. As a result, this approach offers a robust quantitative tool for emotional contagion research, facilitating a more precise analysis of the dynamics of emotional contagion.

The Weber–Fechner Law is expressed as $S = K\lg(R)$, where S represents the sensation intensity, R is the stimulus intensity, and K is a constant. Additionally, McKay [41] suggested that the degree to which individuals are affected by emotional contagion varies due to individual differences, which can be characterized as emotional sensitivity. This study, therefore, accounted for these individual differences by introducing the concept of emotional sensitivity. An emotional contagion model based on the Weber–Fechner Law was proposed to describe the relationship between emotional levels and emotional stimuli. The study simulated and analyzed the process of emotional contagion during metro emergencies to explore the transmission patterns of group panic. Through numerical simulations, the research further examined the impact of factors such as crowd density, personality traits, official interventions, and evacuation rates on the mechanisms of emotional contagion. Extensive multi-agent simulations were conducted to model the propagation patterns of group emotions, with results closely aligning with observed phenomena. Furthermore, a specific case analysis validated the model's rationality and effectiveness in quantifying individual emotions and characterizing crowd emotional contagion. The primary aims of this study are not only to explore the propagation patterns of panic emotions during metro emergencies and to examine the roles of various factors influencing the emotional contagion process, thereby providing insights for effectively mitigating group panic and managing crises in such scenarios, but also, more importantly, to validate the rationality and accuracy of the proposed emotional contagion model, which quantifies emotional levels and describes the relationship between emotional stimuli and emotional states. This addresses the limitations of existing research in emotional computation and contributes to advancing the field.

The remainder of this paper is organized as follows. Section 2 provides a detailed explanation of the methods and processes used in this study's multi-agent emotion modeling, including the criteria for emotion classification, the emotion computation model, and the movement guidelines for the agents. Section 3 elaborates on the construction of the simulation environment and the design of the simulation steps. Section 4 presents the specific simulation results and analysis under various parameter scenarios. Finally, Section 5 offers a summary of the entire paper.

2. Methods

2.1. Emotional Classification

First, the emotional level e_i of passenger i is defined within the [0, 1] range, where a value of zero indicates that the passenger is in a calm state, unaffected by panic stimuli. Once panic stimuli appear in the scene, the emotional level e_i of passenger i within the affected range changes, triggering emotional contagion. These altered emotional levels also remain within the [0, 1] range. Additionally, due to varying levels of emotionality among individuals, the emotional levels of passengers are categorized into four stages: calm, slight panic, moderate panic, and intense panic, each corresponding to a different emotional state. The categories of these emotional levels are shown in Table 1.

Table 1. Emotional states corresponding to emotional levels.

Emotional Levels	Emotional States
0	Calm
(0, 0.4]	Slight panic
(0.4, 0.8]	Moderate panic
(0.8, 1.0]	Intense panic

2.2. Emotional Computation

We define an individual's emotional level as a combination of two components: (1) the initial cognitive appraisal of the environment and (2) the subsequent instinctive, unconscious emotional contagion [42]. Before delving into the details of cognitive appraisal and emotional contagion, let us first clarify how emotions are generally updated. At the initial moment (t = 0), passengers' panic is entirely derived from their own cognitive appraisal. However, over time, their panic is influenced not only by their own cognitive appraisal but also by emotional contagion. Building on Durupinar's research [42], weight coefficients ρ and $1-\rho$ are introduced to measure respective impacts of emotional contagion and cognitive appraisal. Based on Equation (1), we calculate the emotional level of passenger i at time t and normalize it to a value between 0 and 1:

$$e_i(t) = \begin{cases} f_i,\, t = 0 \\ (1-\rho)f_i + \rho\lambda_i(t),\, t = 1,2,3\ldots \end{cases} \tag{1}$$

where f_i is the appraisal contribution function and $\lambda_i(t)$ is the contagion contribution function. Here, ρ is related to the passengers' personality traits, represented by $pc = \{1,2,3\}$, where 1 indicates a sensitive type, 2 a neutral type, and 3 a conservative type [43]. The probability distribution of ρ can be expressed by ρ^{pc}. Let $\rho^{pc} = 1$ be randomly distributed over [0.6, 1], $\rho^{pc} = 2$ randomly distributed over [0.4, 0.6], and $\rho^{pc} = 3$ randomly distributed over [0, 0.4]. As the passenger's personality trait shifts from sensitive (pc = 1) to neutral (pc = 2) and, finally, to conservative (pc = 3), the influence of emotional contagion on the passenger gradually diminishes, while the impact of cognitive appraisal grows stronger.

When metro emergencies occur, they are often accompanied by visual or auditory sensory stimuli. As passengers assess their surroundings, these external stimuli can trigger feelings of panic. According to the Weber–Fechner Law, which is expressed as $S = K\lg(R)$, a formula for calculating the individual's cognitive appraisal of the environment is proposed as follows:

$$f_i = \alpha_i \lg(1 + N_i(0)) \tag{2}$$

where α_i is defined as the emotional sensitivity [44] of passenger i. The parameter α_i is associated with the passenger's personality traits, represented by $pc = \{1,2,3\}$, where 1 indicates a sensitive type, 2 a neutral type, and 3 a conservative type [43]. And it is assumed that the α_i for a sensitive passenger is equal to 1.2, for a neutral passenger is equal to 1, and for a conservative passenger is equal to 0.8. $N_i(0)$ denotes the initial intensity of environmental stimuli perceived by passenger i at the onset of an emergency. Given the mathematical properties of Equation (2), $N_i(0)$ is assumed to follow a uniform distribution between 0 and 9.

In an enclosed space, people instinctively mimic others' facial expressions, gestures, vocalizations, postures, and movements, synchronizing with them and ultimately achieving emotional alignment—a phenomenon known as emotional contagion. During the process of panic emotional contagion, sensory information conveyed through the expressions, speech, and actions of nearby passengers generates new sources of stimulation, leading to changes in passengers' emotions. Consequently, according to the Weber–Fechner Law, the changes in the emotion of passenger i during emotional contagion process can be expressed by Equation (3):

$$\lambda_i(t) = \begin{cases} 0, t = 0 \\ \alpha_i \lg(1 + N_i(t)), t = 1, 2, 3 \ldots \end{cases} \tag{3}$$

where $\lambda_i(0) = 0$ indicates that, at the moment that the emergency event occurs, passenger i has not yet engaged in any emotional contagion with the surrounding passengers. When $t = 1,\ 2,\ 3\ldots$, passenger i begins to interact emotionally with others, resulting in changes to their emotional level, $\lambda_i(t)$ represents the magnitude of this change. The definition of α_i is the same as above. $N_i(t)$ represents the intensity of stimuli received by passenger i at time t. The panic emotions of nearby passengers continuously generate new stimuli through their expressions, speech, and behaviors as sensory information. Given the cumulative effect of emotional stimuli [45], the intensity of stimuli perceived by passenger i at time t is defined as the aggregate of the emotions expressed by the nearby passengers, as shown in Equation (4):

$$N_i(t) = \sum\nolimits_{j \in patch_i} e_j(t-1),\ t = 1,\ 2,\ 3\ldots \tag{4}$$

where $patch_i$ refers to the set of all other passengers located in the same area as passenger i. Emotional contagion occurs only among passengers within the same area. $e_j(t-1)$ denotes the emotional level at time $t-1$ of passenger j, who is located in the same area as passenger i.

After some time, the official metro authorities stepped in, issuing various communications to guide and soothe the emotions of panicked passengers. As a result, passengers gradually regained emotional stability. As such, the rule for updating individual emotion level following the intervention of the metro authorities is as follows:

$$e_i(t) = (1 - R)e_i(t-1) \tag{5}$$

Here, $R \in [0,\ 1]$ represents the effectiveness of the official authorities' communications in regulating passenger emotions. The higher the authorities' credibility, the greater the value of R, and the more effectively they can suppress passengers' panic.

2.3. Movement Guidelines

Considering the influence of emotions on behavior, individuals with lower levels of panic are able to make swift decisions, while those experiencing higher levels of panic are more likely to engage in continuous searching behavior. The magnitude of changes in speed and direction intensifies progressively as individuals transition from states of calm to slight panic, moderate panic, and intense panic [46,47].

It is assumed that each passenger i has an intended direction, which is the position of the train door closest to passenger i, represented by the unit vector D_i of that direction and a feasible velocity sampling space S_i. When a passenger needs to take action, they will randomly sample a v_i within the space S_i. The sampling involves two components: a change in speed and a change in direction. The velocity sampling space of passenger i can be defined using a four-tuple as follows:

$$S_i = (\nu_{min}, \nu_{max}, \theta_{min}, \theta_{max}) \tag{6}$$

where ν_{min} and ν_{max} represent the lower and upper bounds of speed, while θ_{min} and θ_{max} define the minimum and maximum angles of deviation from the intended direction. Then, $\forall v_i \in S_i$, the following conditions hold true:

$$\nu_{min} \le \|v_i\| \le \nu_{max} \tag{7}$$

$$\theta_{min} \leq \text{angle}(v_i,\ D_i) \leq \theta_{max} \tag{8}$$

Equation (8) calculates the angle between v_i and D_i, where a positive value indicates the counterclockwise direction of D_i and a negative value indicates the clockwise direction of D_i. Together with D_i, these four parameters define a velocity sampling space, which forms an arc-shaped region extending from the point where the velocity is zero. The gray area in Figure 1 illustrates an example of such a velocity sampling space.

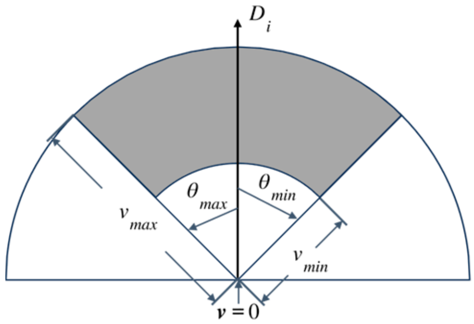

Figure 1. The gray area as velocity sampling space.

The velocity sampling space of an individual varies under different emotional states. First, let us define the changes in speed. According to research data, the comfortable walking speed for a crowd follows a uniform distribution between 0.9 m/s and 1.5 m/s. In the event of an emergency, individuals experience heightened tension, leading to a doubling of their walking speed, with a maximum speed reaching 3 m/s [48]. Based on this, the maximum speed for individuals in different panic states is set as follows: 1 m/s for the slight panic state, 2 m/s for the moderate panic state, and 3 m/s for the intense panic state. Additionally, while the train is in motion, passengers in a calm state do not move around freely, with their speed set to 0 m/s. Once the train comes to a stop, these passengers leave the carriage at a comfortable speed, with the maximum speed set to 1 m/s. Considering factors such as pushing, crowding, or encountering obstacles, the minimum speed for individuals in all emotional states is set to 0 m/s. Next, the changes in direction are defined. Referring to the approach in [47], a mirroring strategy is adopted for direction selection. Specifically, D_i serves as the central axis, and directions are symmetrically diffused outward on both sides. It is specified that $\theta_{max} = -\theta_{min}$, and the value of angle$(v_i, D_i)$ ranges between $-\pi/2 \sim \pi/2$. The directional change space for passengers in a slight panic state is defined as $-\pi/6 \sim \pi/6$, for those in a moderate panic state as $-\pi/3 \sim \pi/3$, and for those in an intense panic state as $-\pi/2 \sim \pi/2$. Additionally, while the train is in motion, passengers in a calm state have a velocity vector of 0, meaning that no directional dimension is defined. However, once the train has stopped, passengers in a calm state have a clear objective and move toward the nearest train door, resulting in zero directional change.

Based on the above information, the velocity sampling space for passengers during the two phases—when the train is in motion and when it is at a stop—are outlined in Tables 2 and 3.

Table 2. The velocity sampling space of passengers during the train's motion.

Emotional Levels	$[v_{min}, v_{max}]$ **(m/s)**	$[\theta_{min}, \theta_{max}]$
0	[0, 0]	—
(0, 0.4]	[0, 1]	$[-\pi/6,\ \pi/6]$
(0.4, 0.8]	[0, 2]	$[-\pi/3,\ \pi/3]$
(0.8, 1.0]	[0, 3]	$[-\pi/2,\ \pi/2]$

Table 3. The velocity sampling space of passengers after the train has stopped.

Emotional Levels	$[v_{min}, v_{max}]$ (m/s)	$[\theta_{min}, \theta_{max}]$
0	[0, 1]	[0, 0]
(0, 0.4]	[0, 1]	$[-\pi/6,\ \pi/6]$
(0.4, 0.8]	[0, 2]	$[-\pi/3,\ \pi/3]$
(0.8, 1.0]	[0, 3]	$[-\pi/2,\ \pi/2]$

3. Simulation Design

NetLogo [49] is a programmable modeling tool designed for simulating natural and social phenomena. It is particularly well-suited for multi-agent simulations, allowing the simultaneous control of thousands of agents. This makes it an excellent tool for modeling the behavior of individual agents at a micro-level and exploring the connections between micro-level behaviors and macro-level emergent phenomena. In NetLogo, there are static agents called "patches" and mobile agents referred to as "turtles". Relationships can be established not only among agents of the same type but also between different types of agents. For example, it is possible to determine which "turtle" is located on a specific "patche". The simulation interface represents a virtual world, where the entire interface is covered with "patches". Both the size of the patches and the dimensions of the world can be manually adjusted. NetLogo uses its own time unit called "ticks", where one tick represents the completion of a single update. In this simulation, ticks are used as the time unit and are not converted into real-world minutes. Given the excellent rapid prototyping facilities of Netlogo, arriving at a simulation environment for metro emergencies such as the one depicted in Figure 2 is an easy task.

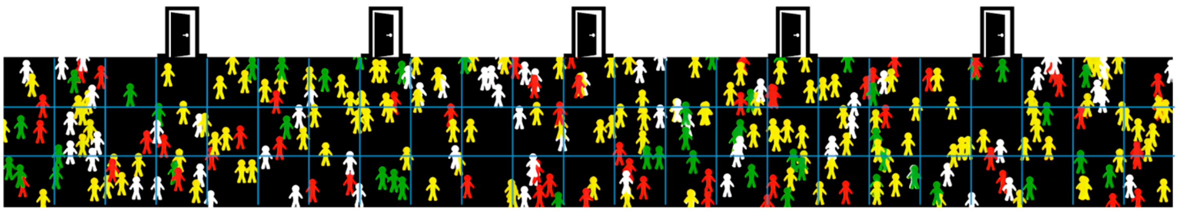

Figure 2. Simulation environment for metro emergencies.

Figure 2 illustrates the simulation environment of a metro carriage during an emergency scenario. The environment features miniature figures in various colors, representing passengers in different emotional states: white indicates a calm state, green represents slight panic, yellow signifies moderate panic, and red denotes intense panic. The doors are positioned above the carriage, and the grid layout depicts the distinct areas into which the carriage is divided. Since passengers can only move on a flat surface, the height dimension of the carriage is temporarily excluded from consideration. The carriage environment is modeled as a two-dimensional plane G with dimensions $L \times W$, where N passengers are randomly distributed. Referring to the A-type trains on Shanghai Metro Line 1, each carriage is 23 m long and 3 m wide, with a rated capacity of 310 passengers. And there are 10 doors—5 on each side. As metro train doors only open on one side, five doors are evenly spaced on one side with equal intervals. At any given time, passengers can only engage in emotional contagion with those within their emotional perception domain. For the emotional perception domain, we refer to the setup in [50]: "In a train carriage with a length of 114 m and a width of 2.8 m, during peak hours with 1500 passengers, the emotional perception domain for each individual is 4.5 m^2". In the scenario of this study, the simulation world is defined with dimensions L = 23 and W = 3, and the rated capacity is 310 passengers. Using proportional scaling, the emotional perception domain for each individual in this study is approximately 1 m^2. Coincidentally, in NetLogo, the world is divided into small square grids, each referred to as a patch. The default size of each patch is 1×1, meaning that the width and height of each patch are 1 unit. Therefore, we directly define the patch occupied by passenger i as their emotional perception domain. The two-dimensional plane G (23×3) is divided into M ($M = 69$) regions, with each region represented as a patch in the simulation software NetLogo (6.4.0). Let pm denote the m-th region; passengers within region pm can only interact with others in the same region. When the train arrives at a station and the doors open, crowding and waiting occur at the doors due to their limited size. To model this, a probability P ($P \in [0, 1]$) is introduced, where, at each moment t, passengers arriving at the door have a certain chance of leaving the carriage. If a passenger successfully exits at moment t, they disappear from the environment; if not, they continue to have a chance to exit at moment $t + 1$, until all passengers have left the carriage. Until they exit, passengers continue to interact emotionally with others according to the established rules. The value of P reflects the evacuation rate; a higher P indicates a greater likelihood of passengers leaving the carriage at each moment t, signifying a higher evacuation rate. Conversely, a lower P indicates a slower evacuation rate. As shown in Figure 3, the steps of the simulation experiment are as follows:

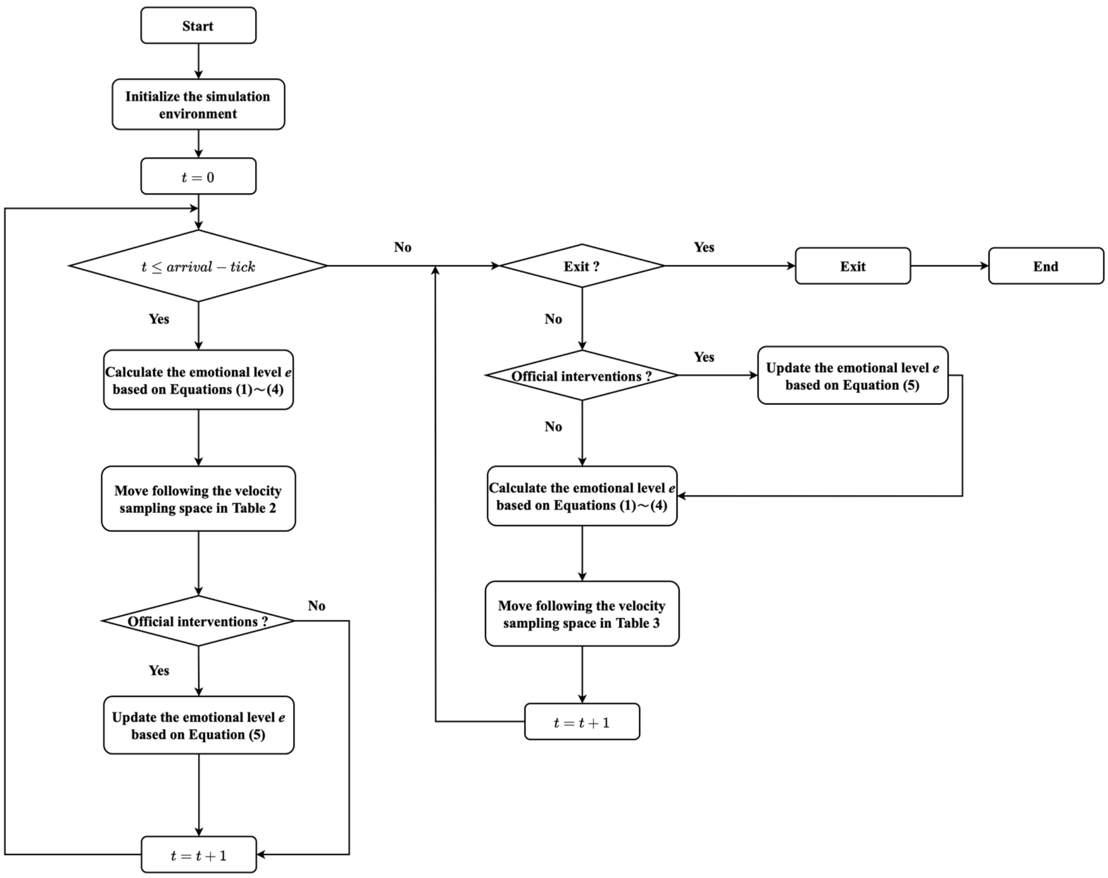

Figure 3. Simulation flowchart of passenger i's emotional evolution in metro emergencies.

Step 1: Initialize the simulation environment by setting $L = 23$, $W = 3$ and $M = 69$ to construct the metro carriage model. Configure the values for N, P, R, and *arrival-tick*. Define distribution schemes for three types of passengers: sensitive, neutral, and conservative. Assign emotional sensitivity values, denoted as α_i, to each passenger type and set the value of $N_i(0)$. Then, calculate f_i according to Equation (2); thus, $e_i(0)$ is obtained according to Equation (1).

Step 2: Before the train stops, all passengers inside the carriage engage in emotional contagion with other passengers in the same area. Calculate the emotional level based on Equations (1)–(4).

Step 3: All passengers move following the velocity sampling space specified in Table 2.

Step 4: Determine whether the authorities have implemented control measures. If they have, passenger emotions will decrease according to Equation (5); otherwise, proceed to Step 5.

Step 5: The simulation time advances by one tick. Repeat Steps 2~5 until the train comes to a complete stop.

Step 6: After the train stops, a random function generates a positive integer Q_i between 1 and 100 for each passenger i who has reached the door. If $Q_i \leq P \times 100$, passenger i exits the carriage and is removed from the simulation environment; otherwise, passenger i remains in the carriage and proceed to Step 7.

Step 7: Determine whether the authorities have implemented control measures. If they have, passenger emotions will decrease according to Equation (5); otherwise, proceed to Step 8.

Step 8: Passengers inside the carriage will continue to interact emotionally with other passengers in the same area. Calculate the emotional level based on Equations (1)–(4).

Step 9: All passengers move following the velocity sampling space specified in Table 3.

Step 10: The simulation time advances by one tick. Repeat Steps 6~10 until all passengers have exited the carriage, marking the end of the simulation.

4. Simulation Results and Analysis

Given that crowd density, personality traits, official interventions, and evacuation rates can influence the evolution of group emotions during metro emergencies, we conducted a series of simulation experiments to explore emotional contagion patterns from these four perspectives. To minimize the impact of anomalies from individual simulations, each parameter setting was simulated 30 times using NetLogo. The following conclusions were drawn based on the average results of these 30 experiments.

4.1. Crowd Density

Crowd density inside the carriage varies at different times of the day. During peak hours, the crowd density significantly increases, while it decreases during off-peak hours. Considering that the A-type train has a rated capacity of 310 passengers, we set the number of passengers to N = 60, N = 180, and N = 300, while keeping other parameters constant: P = 0.5, *arrival-tick* = 100, and an even distribution of the three personality traits, each making up 1/3 of the total. It was assumed that no intervention was made by the authorities, with R = 0. We observed the proportions of passengers in four emotional states (the number of passengers in a specific emotional state/N) within the group, as shown in Figure 4.

When $tick \leq 100$ (i.e., while the train is in motion), in different crowd density scenarios, the proportions of passengers in the four emotional states undergo rapid and significant changes within a short period after departure, quickly stabilizing into a clear distribution pattern. This illustrates the explosive nature of emotional contagion. Following this initial shift, the proportions of these emotional states fluctuate within a certain range. As crowd density increases, these fluctuations lessen, indicating that higher crowd densities positively contribute to the emotional stabilization of the group. The denser the crowd, the more stable the emotional states within the group tend to be. Previous studies have also confirmed the positive influence of crowd density in facilitating the convergence of passengers' viewpoints on rumors [51]. Further analysis shows that the proportion of passengers in a calm state exhibits an almost linear decrease from *tick* = 0 to *tick* = 1, rapidly falling from approximately 0.1 to 0. This is attributed to the presence of a few uninformed passengers at the onset of an emergency. However, under the effects of emotional contagion, panic quickly spreads throughout the carriage, prompting these passengers to swiftly shift from a calm to a panicked state. Concurrently, the percentage of passengers in slight panic decreases, while those in moderate and intense panic states rise, particularly in the intense panic state.

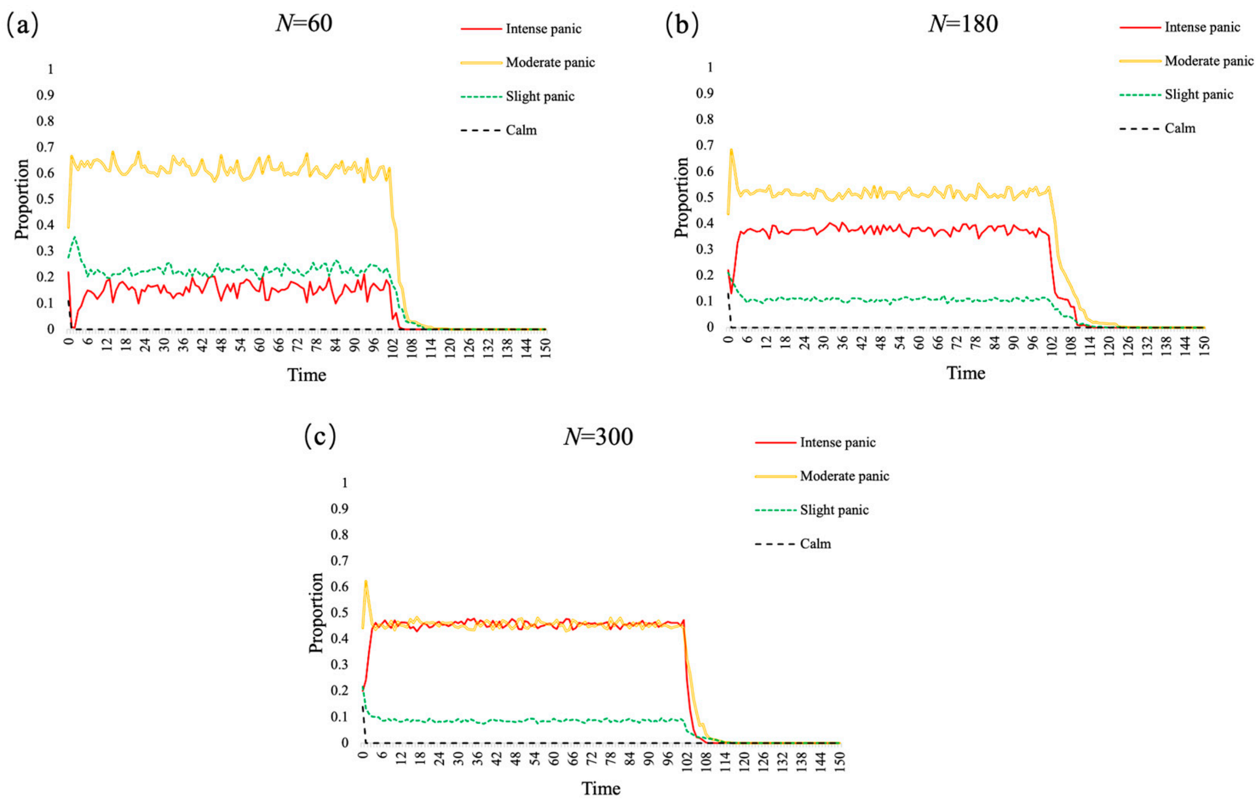

Figure 4. Emotional state proportions of passengers under different crowd density scenarios: (**a**) $N = 60$; (**b**) $N = 180$; (**c**) $N = 300$.

In Figure 4a, the moderate panic state dominates the crowd's emotions, with approximately 65% of passengers in this state. The proportion of passengers in intense panic initially decreases sharply over a short period, then begins to rise and shows oscillations. This pattern emerges because, in settings with lower crowd densities, passengers are more spread out within the carriage and are unable to promptly communicate with nearby passengers after being stimulated by a sudden event. As the initial emotional stimulus weakens, passengers' emotions gradually shift from intense to moderate and slight panic. Nonetheless, as the passengers' frantic search behavior persists, panic emotions build up, leading to a gradual increase in the proportion of passengers in intense panic. In Figure 4b, the moderate panic state remains predominant, although the proportion of passengers in this state has declined compared to the $N = 60$ scenario, now accounting for approximately 50%. Throughout the emotional contagion process, the proportions of passengers in both moderate and intense panic states have increased overall. Notably, the proportion of passengers in intense panic has risen significantly, indicating that the panic among passengers in the carriage is severe. In Figure 4c, the proportion of passengers experiencing intense panic rises sharply in a short period, soon matching the proportion of passengers in moderate panic. Together, passengers in these two emotional states make up approximately 90% of the total. Subsequently, intense and moderate panic levels display a trend of alternating fluctuations. In the N = 300 scenario, the panic among passengers in the carriage is extremely severe.

Comparing scenarios with varying crowd densities reveals that, as crowd density increases, the proportion of passengers experiencing intense panic also rises. Dense crowds exacerbate the panic among passengers because high crowd density contributes to greater chaos, more likely triggering emotional stimuli. This leads to a more intense and rapid escalation of panic, reaching an extreme state during the explosive phase of collective emotional release [52]. This phenomenon explains the frequent occurrences of mass panic events during peak metro periods.

After *tick* > 100, the doors open, and an increasing number of passengers exit the carriage until everyone is fully evacuated. During this phase, the proportions of passengers in each emotional state gradually decrease until they reach zero. The emotional states of passengers who leave the simulation environment are not within the scope of this study.

4.2. Personality Traits

To explore the influence of personality traits on the evolution of group emotions, the proportions of sensitive, neutral, and conservative passengers in the carriage are defined as follows: Personality Configuration I (proportion of sensitive passengers: 1/6; proportion of neutral passengers: 1/3; proportion of conservative passengers: 1/2), Personality Configuration II (proportion of sensitive passengers: 1/3; proportion of neutral passengers: 1/3; proportion of conservative passengers: 1/3), and Personality Configuration III (proportion of sensitive passengers: 1/2; proportion of neutral passengers: 1/3; proportion of conservative passengers: 1/6), while keeping other parameters constant (N = 300, P = 0.5, *arrival-tick* = 100). It was assumed that no intervention was made by the authorities, with R = 0. We observed the proportions of passengers in four emotional states (the number of passengers in a specific emotional state/N) within the group, as shown in Figure 5.

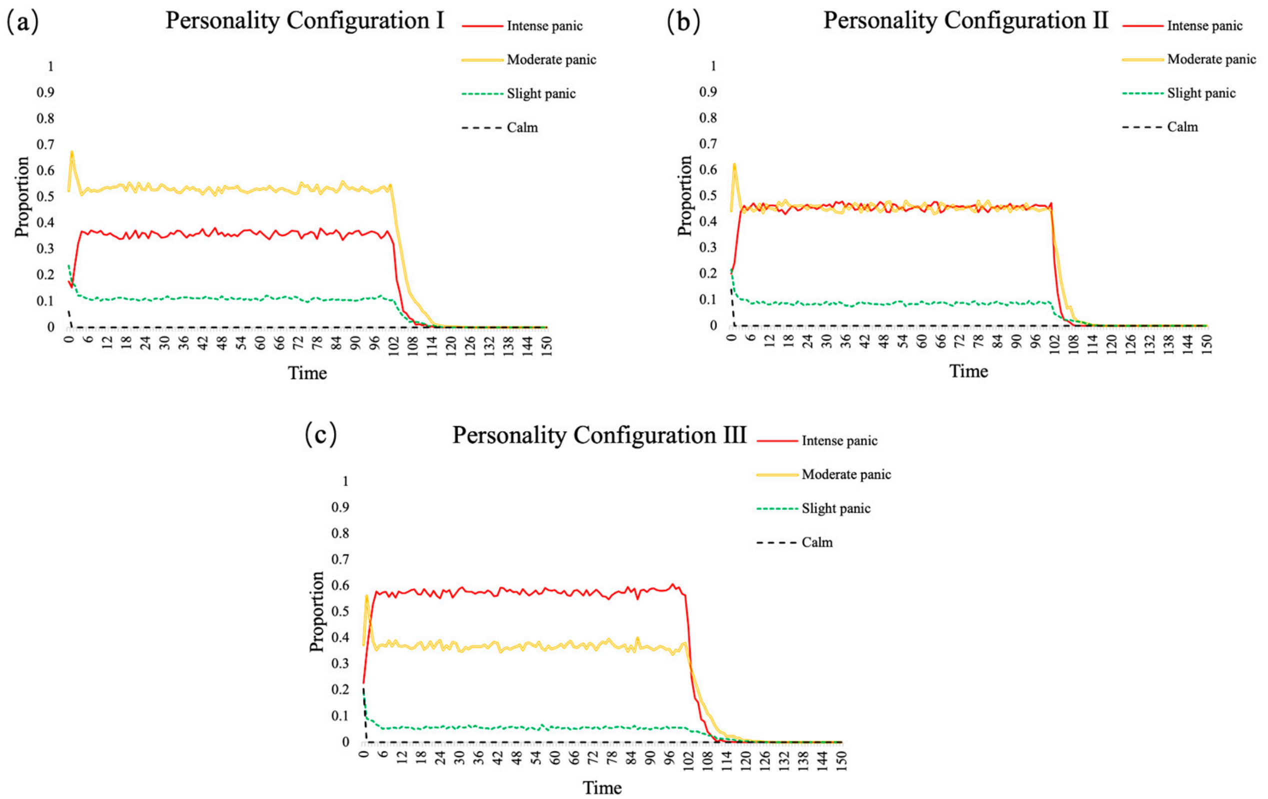

Figure 5. Emotional state proportions of passengers under different personality configuration scenarios: (**a**) Personality Configuration I; (**b**) Personality Configuration II; (**c**) Personality Configuration III.

Following the emergency, the proportion of passengers in calm state quickly drops to zero, with panic spreading throughout the carriage. The proportion of passengers in slight panic state decreases overall. Although the proportion of those in moderate panic state initially rises sharply, it soon declines back to the level observed at the onset of the emergency. Meanwhile, the proportion of passengers in intense panic state increases significantly. In Figure 5a, the moderate panic state dominates the crowd's emotions, with approximately 50% of passengers in this state. In Figure 5b, the proportion of passengers in intense panic is almost equal to those in moderate panic, with passengers in these two emotional states together accounting for 90% of the total. Meanwhile, in Figure 5c, the proportion of passengers in intense panic has overtaken those in moderate panic, with intense panic now dominating the crowd's emotions.

By comparing the initial proportions of passengers in four emotional states across the three scenarios, it becomes evident that, when a group contains more sensitive passengers, the initial proportions of passengers in intense panic and calm tend to rise, while the proportions of those in moderate and slight panic decrease. This suggests that sensitive passengers are more prone to experiencing extreme emotions during emergencies, which can be either positive or negative. However, as emotional contagion progresses, an increase in the number of sensitive passengers makes the evolution of group emotions more likely to escalate into intense panic. It is easy to see that sensitive passengers have a heightened capacity for emotional reception during the process of emotional contagion, which can amplify the spread of panic. Therefore, it is crucial to focus on sensitive passengers and implement preventive measures, such as enhancing safety education, to guide them positively. Providing targeted emergency management education to this sensitive group can help curb the spread of panic from the outset and be highly effective in controlling panic during metro emergencies.

4.3. Official Interventions

After an emergency, official departments should promptly intervene by releasing various information to calm passengers' panic. The role of official departments in regulating passengers' emotions is crucial for curbing panic, and the effectiveness of this regulation is reflected in their ability to manage passengers' emotions. To assess how the regulatory capacity of official departments influences the evolution of group emotions, the regulatory capacity is set at $R = 0.1$, $R = 0.5$, and $R = 0.9$, while keeping other parameters constant: $N = 300$, $P = 0.5$, *arrival-tick* = 100, and an even distribution of the three personality traits, each making up 1/3 of the total. Set the official interventions to begin at *tick* = 50. We observed the proportions of passengers in four emotional states (the number of passengers in a specific emotional state/N) within the group, as shown in Figure 6.

When $R = 0.1$, the regulatory capacity of the official departments is relatively low. As shown in Figure 6a, during the period from *tick* = 50 to *tick* = 100—when the official departments begin to take measures until the train arrives at the station—there is no significant change in the proportions of passengers in different emotional states within the group. This is due to passengers' lack of trust in the official departments, leading them to focus more on their own perceptions and emotional interactions with those around them. As a result, even though the official departments continuously release information, this fails to effectively control the situation's evolution. As shown in Figure 6b,c, around *tick* = 50, the proportions of passengers in intense panic, moderate panic, and slight panic exhibit significant fluctuations. The proportion of passengers in intense panic drops notably, while those in moderate and slight panic increase. Subsequently, the overall trend enters a phase of minor fluctuations. When $R = 0.9$, the decline in the proportion of passengers in intense panic is even more pronounced, and the increase in the proportion of passengers in slight panic is greater than that in moderate panic. This indicates that more passengers transition from intense panic to slight panic, significantly reducing the overall panic level among passengers in the carriage. This suggests that greater official regulatory capacity more effectively suppresses group panic. However, while this regulatory effect is immediate, it does not maintain sustained efficiency. Figure 6b,c shows that, after *tick* = 50, following a brief period of emotional regulation, there are no further significant changes in the distribution of passengers across the three emotional states of intense panic, moderate panic, and slight panic. This indicates that the official regulatory capacity does not have a lasting and efficient impact on reducing group panic. One possible explanation is that the enclosed environment of the carriage prevents passengers from accurately interpreting official information. As a result, the regulatory effect of official information on passengers' emotions diminishes over time, and instinctive emotional contagion gradually becomes the dominant influence.

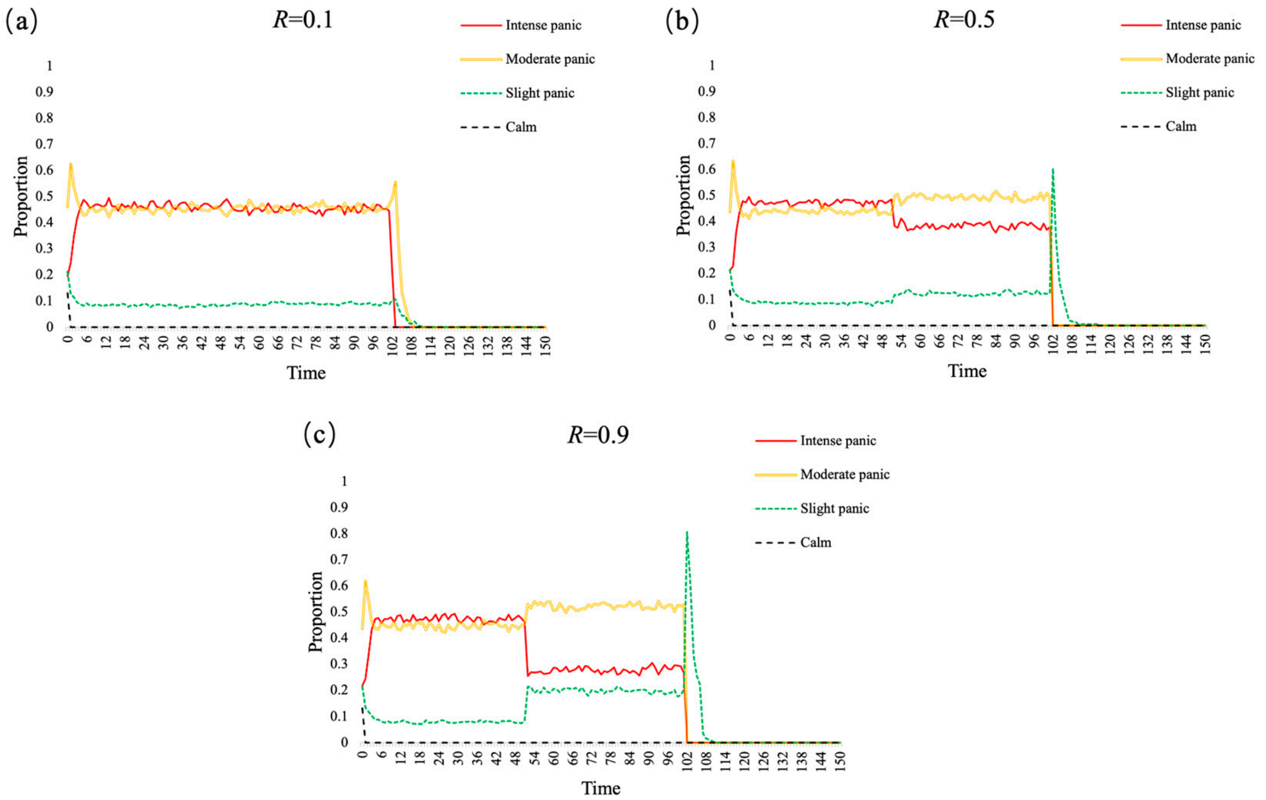

Figure 6. Emotional state proportions of passengers under different official interventions scenarios: (**a**) R = 0.1; (**b**) R = 0.5; (**c**) R = 0.9.

By comparing Figures 4c and 6a–c, it becomes evident that, after the train arrives at the station (i.e., *tick* > 100), during the evacuation process, the proportions of passengers in intense and moderate panic decrease more rapidly as the official regulatory capacity increases, assuming the same evacuation rate. This acceleration is due to a greater number of passengers transitioning to slight panic, which supports the notion that the enclosed environment can inhibit the effectiveness of official information. Therefore, it is crucial for official departments to actively release information after the train arrives at the station to calm passengers' emotions.

4.4. Evacuation Rates

In metro emergencies, it is common for passengers to rush toward the doors but be unable to exit the train carriage promptly due to overcrowding or door malfunctions. A slower evacuation process can lead to the congregation of a large number of passengers in a confined space, thus exacerbating the spread of panic. To investigate the impact of evacuation rates on the evolution of group emotions, we consider the following three scenarios: $P = 0$, where passengers cannot exit the train carriage due to door malfunctions or other reasons; $P = 0.5$, where passengers need some time to break free from the overcrowded space in order to exit the train carriage; and $P = 0.9$, where the passage is relatively smooth and passengers can exit the train carriage swiftly. We tested while keeping other parameters constant: $N = 300$, *arrival-tick* = 100, and an even distribution of the three personality traits, each making up 1/3 of the total. It was assumed that no intervention was made by the authorities, with $R = 0$. We observed the proportions of passengers in four emotional states (the number of passengers in a specific emotional state/N) within the group, as shown in Figure 7.

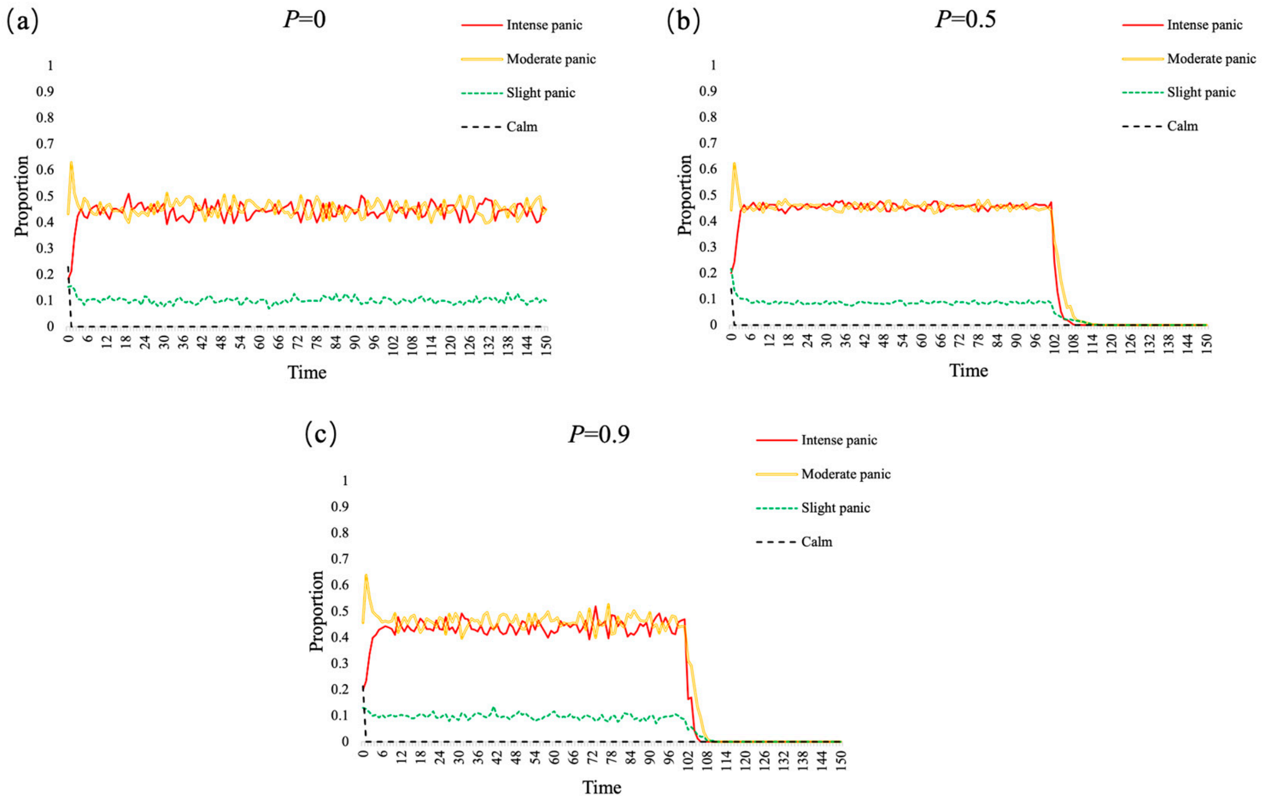

Figure 7. Emotional state proportions of passengers under different evacuation rate scenarios: (**a**) $P = 0$; (**b**) $P = 0.5$; (**c**) $P = 0.9$.

In the scenario where $P = 0$, passengers in intense panic and moderate panic states remain at consistently high levels throughout the observation period. In the scenarios with $P = 0.5$ and $P = 0.9$, when $t \leq$ *arrival-tick*, the intense panic and moderate panic states also remain at high levels. However, when $t >$ *arrival-tick*, the panic begins to subside, with intense panic subsiding first, followed by moderate panic, and finally slight panic. Passengers experiencing higher levels of panic tend to evacuate the train carriage more quickly. This underscores the critical importance of timely intervention and control after the train arrives at the station. Without prompt measures, these highly panicked passengers could potentially trigger another wave of panic on the platform upon disembarking. As the passenger density near the train doors gradually increases, metro authorities can station staff near the doors to provide orderly guidance and effectively direct passengers, thereby alleviating panic. Alternatively, installing train announcement systems directly above the train doors could ensure that passengers crowding near the doors receive timely and effective reassurance through official broadcasts. In the scenario where $P = 0.5$, all passengers exit the carriage by t = 119, while, in the scenario where P = 0.9, all passengers evacuate by t = 111. These results suggest that rapid evacuation can effectively eliminate panic within the train carriage.

When $t \leq$ *arrival-tick*, the passenger distribution across emotional states in Figure 7a–c is generally consistent across scenarios. This indicates that evacuation rate has minimal impact on emotional contagion during the train's motion. Sudden incidents are often characterized by their explosive nature, with panic emotions spreading rapidly and stabilizing within a short period. The initial intensity of the panic stimulus largely determines the peak level of group panic, while the duration of emotional contagion has limited influence. Unless official intervention is implemented, the level of group panic within the carriage remains relatively stable over time.

However, this does not imply that timely evacuation is unnecessary. Prolonged exposure to high levels of panic, coupled with passengers crowding densely near the train doors in confined spaces, significantly increases the risk of collisions, falls, and other safety hazards. This study does not account for the physical interactions between passengers and, therefore, does not incorporate the effects of such behaviors on panic emotions into the model. Future research could consider integrating a social force model to further explore panic dynamics at bottlenecks near train doors and provide a more comprehensive understanding of these scenarios.

4.5. Validating the Model via Comparative Case Analysis

To effectively demonstrate the authenticity of this model in simulating the spread of panic among metro passengers, the panic incident that occurred on Shenzhen Metro Line 7 at around 6:30 PM on 17 May 2019 is introduced as a comparative case study. Screenshots from the carriage surveillance video during the train's operation phase are shown in Figure 8, while screenshots from the platform surveillance video during the train's stop phase are presented in Figure 9.

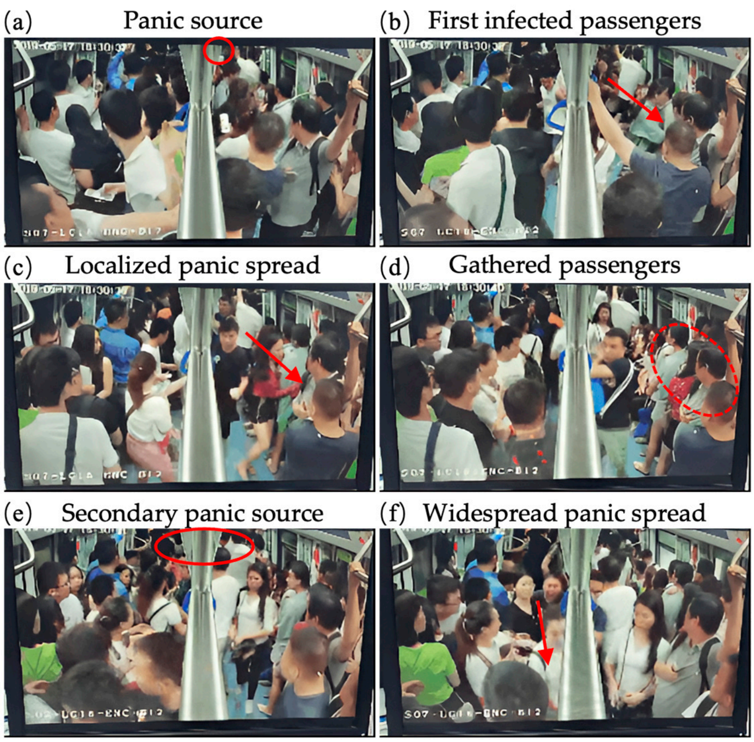

Figure 8. Panicked crowd in the carriage during the Shenzhen Metro 5.17 incident: (**a**) Panic source; (**b**) First infected passengers; (**c**) Localized panic spread; (**d**) Gathered passengers; (**e**) Secondary panic source; (**f**) Widespread panic spread.

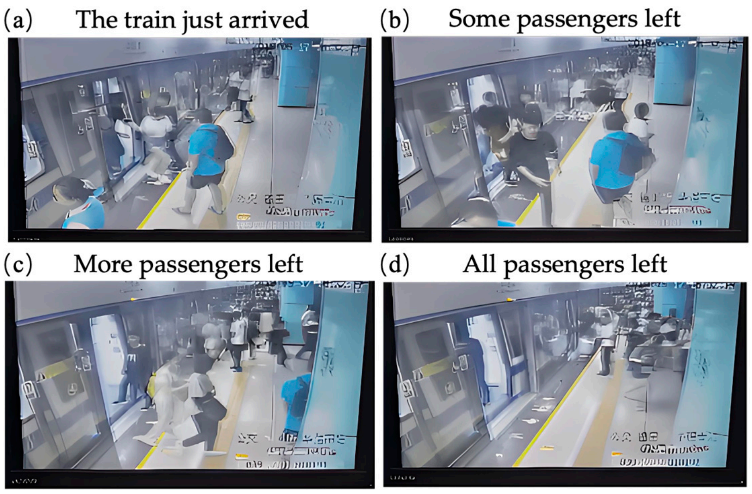

Figure 9. Panicked crowd on the platform during the Shenzhen Metro 5.17 incident: (**a**) The train just arrived; (**b**) Some passengers left; (**c**) More passengers left; (**d**) All passengers left.

During the train's operation, mass panic was triggered by a few passengers intentionally shouting and falsely claiming the presence of a weapon (as shown in Figure 8a, where the red circle marks the source of the panic). Passengers near the panic source were the first to perceive the visual or auditory sensory stimuli, leading them to believe that a potential terror attack might occur. This caused panic and prompted them to flee in the direction of the nearest train door (as illustrated in Figure 8b,c, with red arrows indicating the movement direction of the passengers). Since the train was still moving and the doors remained closed, these passengers gathered and crowded near the doors (as shown in Figure 8d, where the red dashed lines mark the areas near the doors). Meanwhile, other passengers who were farther away from the source, and thus did not perceive any visual or auditory sensory stimuli, remained unaware of the situation and did not take any action. However, the aforementioned passengers carrying panic emotions acted as secondary panic sources (as shown in Figure 8e, where the red circles highlight the secondary sources). While running in panic, they further spread and transmitted their panic to nearby passengers. These nearby passengers, upon perceiving visual or auditory sensory stimuli from the secondary sources, also experienced panic, sought the nearest train door, and fled in that direction (as depicted in Figure 8f, with red arrows representing the movement direction). Eventually, through emotional contagion, the panic rapidly spread. Each passenger carrying panic emotions had the potential to become a secondary panic source, transmitting visual or auditory sensory stimuli to others and escalating the mass panic. As a result, passengers flocked to the nearest train doors, waiting for them to open. When the train finally arrived at the station and the doors opened, passengers rushed to escape the train carriage (as shown in Figure 9).

The descriptive analysis of the surveillance video content above has validated the authenticity and effectiveness of the model's emotional contagion rules and passenger movement rules. Next, we further verify the model's validity by comparing the simulation results with real-world scenarios. In this case, Shenzhen Metro Line 7 operates A-type trains, which align with the simulation scenario described in Section 3. The parameters were set as follows: $L = 23$, $W = 3$, and $M = 69$. The incident occurred at 6:30 PM, during the evening rush hour, so the passenger count was set at $N = 300$, with the personality distribution of passengers assumed to follow an even split among the three traits, each accounting for one-third of the total. Based on the surveillance video, passengers had a high likelihood of leaving the train carriage once the doors opened, so the probability was set to $P = 0.9$. The recorded duration of the panic incident from the surveillance footage was approximately 2 min, leading to an *arrival-tick* value of 120. The initial panic source was identified as five passengers intentionally spreading terror-inducing information. Therefore, the model initialized with five adjacent passengers in a state of intense panic, with their initial emotional levels randomly distributed in the range of (0.8,1.0]. The remaining passengers were assumed to be in a calm state, with an initial emotional level of 0. During this incident, metro operators intervened only after all passengers had exited the train carriage. Consequently, it was assumed that no authority intervention occurred, setting $R = 0$. The simulation scenarios at different moments during the Shenzhen Metro 5.17 incident are depicted in Figure 10.

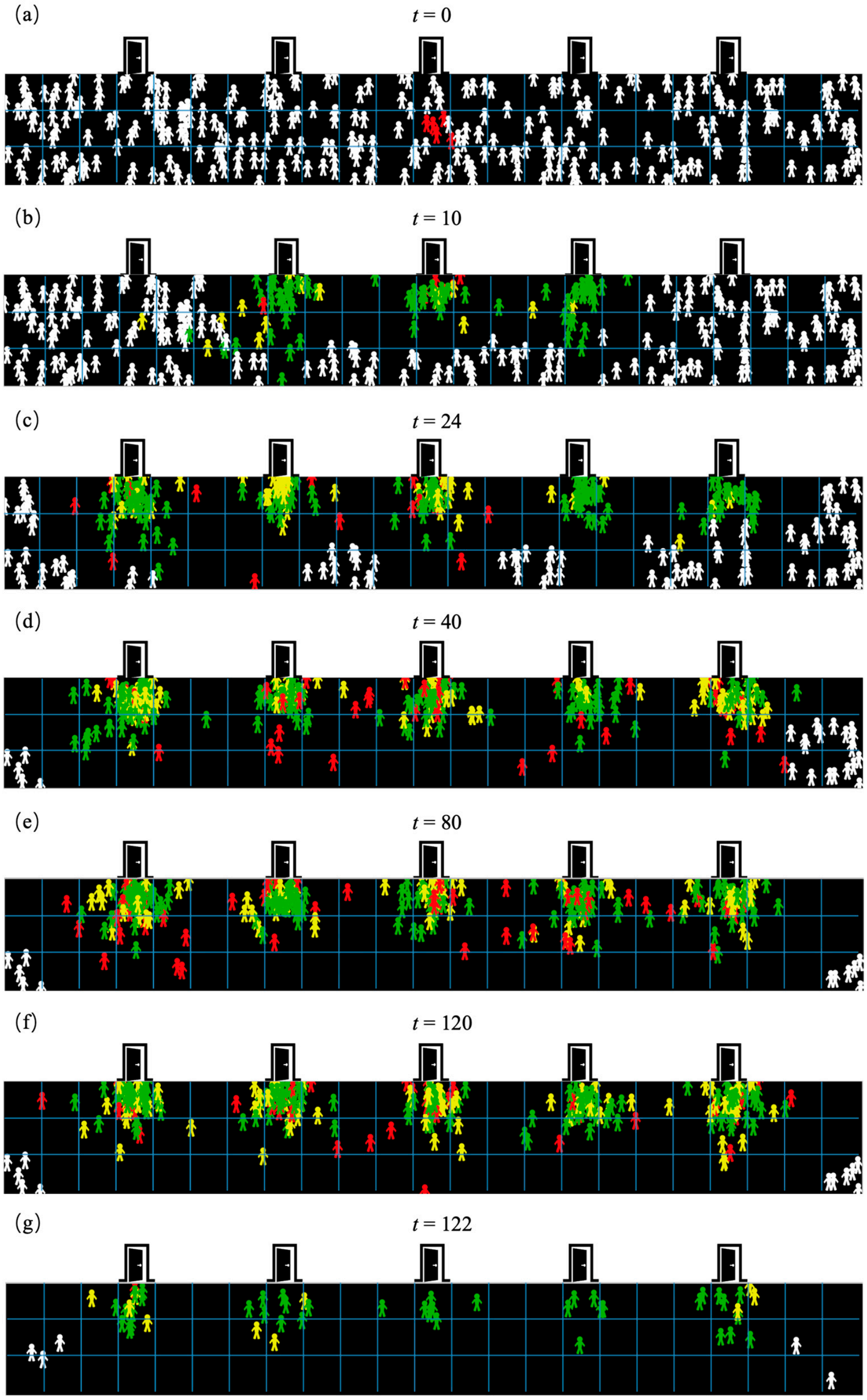

Figure 10. Simulation scenarios at different moments during the Shenzhen Metro 5.17 incident: (**a**) $t = 0$; (**b**) $t = 10$; (**c**) $t = 24$; (**d**) $t = 40$; (**e**) $t = 80$; (**f**) $t = 120$; (**g**) $t = 122$.

At the initial moment (t = 0), passengers were evenly distributed within the train carriage, with five passengers identified as the sources of panic for this incident (as shown in Figure 10a). By t = 10, passengers near the panic sources were the first to be affected, and panic began spreading within a small area. This process was manifested by calm passengers (represented by white figures) near the panic sources gradually transitioning to slight panic (represented by green figures), moderate panic (represented by yellow figures), and intense panic (represented by red figures). Three major crowd clusters formed around the panic sources, and these clusters began moving toward the nearest train doors (as shown in Figure 10b). As time progressed, these small crowd clusters continued to expand. On the one hand, they infected new calm passengers, and, on the other, the emotional interactions within the clusters intensified the panic. The density of these clusters increased gradually, with the number of green figures (slight panic state passengers), yellow figures (moderate panic state passengers), and red figures (intense panic state passengers) rising steadily. Meanwhile, the number of white figures (calm state passengers) steadily decreased (as shown in Figure 10c–e). Eventually, the distribution of passengers in the carriage showed a pattern of crowd clusters primarily gathering around the train doors. At the same time, a few calm passengers were scattered in the corners farthest from the panic sources (as shown in Figure 10f). When the train arrived at the station and the doors opened, passengers in the carriage quickly evacuated (as shown in Figure 10g).

Figure 11 illustrates the simulation of passenger emotional changes during the Shenzhen Metro 5.17 incident. The distribution of passengers across different emotional states is as follows: passengers in a slight panic state, moderate panic state, intense panic state, and calm state are in the ratio of 10:6:3:1. Overall, the level of panic remains relatively low. This aligns with the official report on the incident, which stated that it was caused by the spread of false information, posed no substantial harm, involved no injuries, and lasted for a short duration.

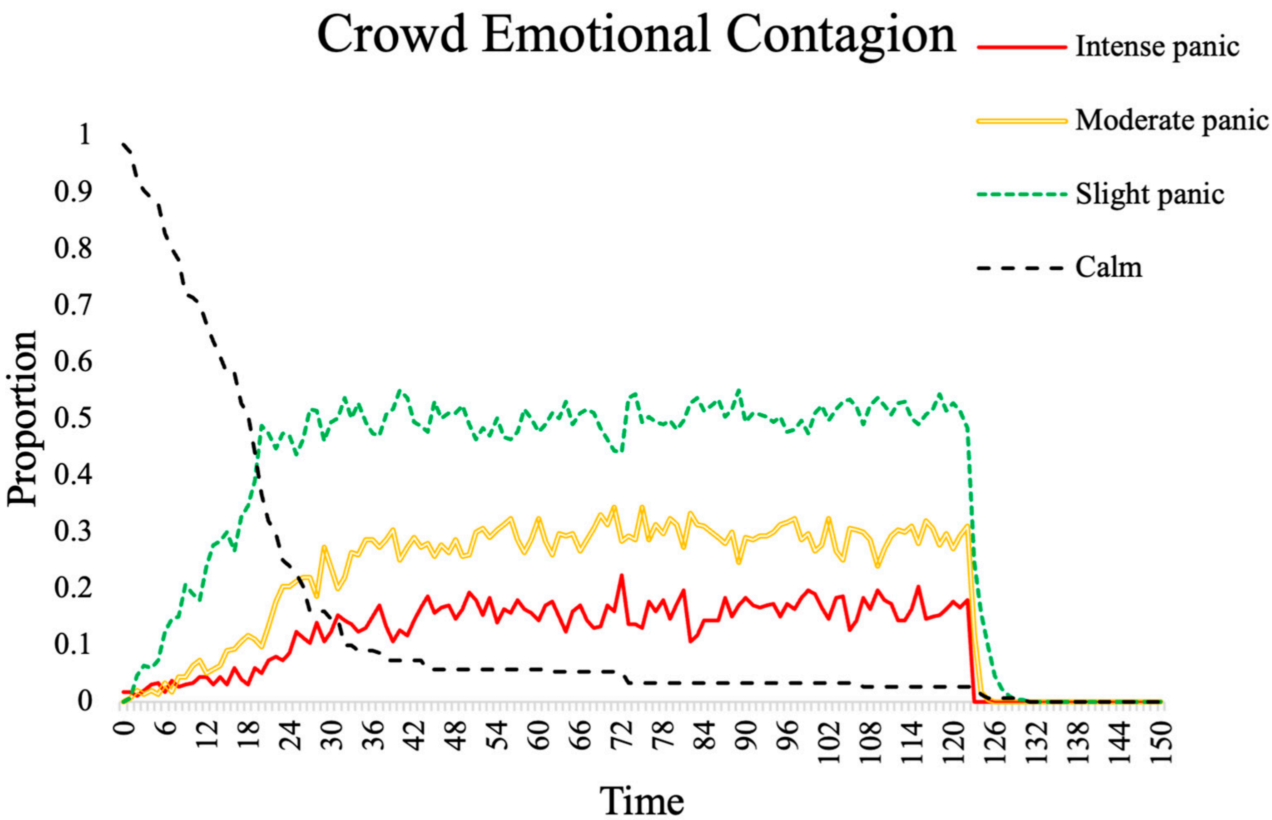

Figure 11. Crowd emotional contagion during the Shenzhen Metro 5.17 incident.

In summary, the simulation results of this model not only correspond with the footage from surveillance videos but also align with the official incident report. This demonstrates the model's accuracy and effectiveness in depicting and predicting panic emotion contagion in real-world scenarios.

5. Conclusions

The Weber–Fechner Law describes the quantitative relationship between psychological response and stimulus intensity. In the context of metro emergencies, this study addresses the limitations of existing research in emotional computation by proposing a group emotion contagion model that accounts for individual differences, based on the Weber–Fechner Law. Extensive multi-agent simulation experiments were conducted to model the evolution of group emotions, with the resulting trends closely aligning with observed phenomena. This confirms the model's effectiveness in explaining the contagion process of group emotions during metro emergencies. Additionally, this study provides a numerical analysis to explore the mechanisms by which crowd density, personality traits, official interventions, and evacuation rates influence emotional contagion, leading to the following conclusions.

Dense crowds exacerbate the level of group panic but also contribute positively to the stabilization of group emotions. Specifically, when crowd density is high, group emotions tend to stabilize at a heightened level of panic. It is therefore recommended that metro authorities remain vigilant during peak hours and promptly provide reassurance and guidance in the event of an emergency.

Sensitive passengers are more prone to extreme emotions during metro emergencies. These extreme emotions can be either positive or negative, but, without proper guidance, they may evolve into negative emotions under the influence of emotional contagion, amplifying the spread of panic. Therefore, it is advisable to strengthen metro safety education to help passengers make more rational assessments of emergencies, thereby curbing the spread of panic at its source. Additionally, after an emergency occurs, metro authorities should pay particular attention to this sensitive group when managing the situation's evolution.

Official interventions play a crucial role in curbing the spread of panic. When regulatory measures are implemented, group emotions quickly shift from a heightened state of panic to a lower one, with the effectiveness of this transition increasing with the strength of the official regulation. Thus, it is recommended that authorities focus on enhancing their credibility and improving the regulatory impact of official communications on passengers' emotions. However, this regulatory effect may not be sustained over time and is constrained by the enclosed environment. Consequently, it is particularly important for authorities to actively disseminate information once the train arrives at the station to calm passengers' emotions.

Although an efficient evacuation rate cannot reduce the peak level of group panic within the carriage, it can shorten the duration of panic by quickly dispersing the crowd, thereby preventing more severe safety incidents caused by crowding. Moreover, passengers with higher levels of panic tend to leave the carriage more quickly. If metro authorities fail to intervene and manage these highly panicked passengers promptly after the train arrives at the station, these individuals may trigger another wave of panic on the platform. During the train's motion, metro authorities must promptly investigate and release official information to reassure passengers and calm their emotions. Once the train arrives at the station, operational staff must be deployed to guide passengers for an orderly evacuation. The findings of this study provide a basis for optimizing evacuation strategies in metro operations, thereby improving the efficiency of emergency response.

Based on the simulation of the emotional contagion process during metro emergencies, this study reveals the propagation patterns of group panic and examines the impact mechanisms of factors such as crowd density, personality traits, official interventions, and evacuation rates on emotional contagion. Through numerical simulations, metro operators can adopt more targeted and efficient measures to curb the spread of crowd panic and effectively manage emergency crises. Moreover, this study introduces the Weber–Fechner Law from psychology to model individual emotions. According to the Weber–Fechner law, psychological quantities are logarithmic functions of stimulus intensity, with most perceptual stimuli following this law. Based on this, the study considers individual differences, introduces the concept of emotional sensitivity, and proposes an emotional contagion model that describes the relationship between emotional levels and emotional stimuli. This model innovatively quantifies emotional levels and has been validated through case analysis for its effectiveness in quantifying individual emotions and characterizing crowd panic emotional contagion. Therefore, the method of calculating emotions based on sensory stimuli such as vision and hearing in this model has broad application potential. In the future, it can be combined with machine learning models, integrating data from multiple sensors for multi-modal emotion recognition, and applied to the intelligent management of metro emergency crises, thereby enhancing the efficiency and accuracy of emergency response.

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