# Modeling Wildfire Evacuation with Embedded Fuzzy Cognitive Maps: An Agent-Based Simulation of Emotion and Social Contagion

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**Abstract.** Wildfires are becoming increasingly dangerous, especially in densely populated fire-prone areas like California. People's evacuation decisions during wildfire events are influenced by many factors, including emotions such as fear or panic, which often affect people's decisions to evacuate. Traditional evacuation models often assume that individuals behave rationally. As a result, they tend to overlook the influence of emotional factors on evacuation behavior. To address this issue, this paper develops an agent-based model (ABM) combined with embedded fuzzy cognitive maps (FCM) to simulate residents' evacuation behavior during a wildfire event. The model focuses on how emotions of residents change over time, how they spread among people and how they affect evacuation decisions among different income levels of agents. Results from the model show that agents with different emotions behave differently during the evacuation process. In addition, the results suggest that income affects emotional responses. As such this study highlights the value of using ABM and FCM together to better understand evacuation behavior and thus more effective disaster response plans.

**Keywords:** Agent-Based Modeling · Emotional Decision-making · GIS · Fuzzy Cognitive Map · Wildfire Evacuation.

## 1 Introduction

Wildfires occur frequently worldwide, causing increasingly both casualties and property losses, and as such they have been attracting widespread attention from academia and policymakers (e.g., [22]). Take for example the 2018 Camp Fire in California which resulted in 85 deaths, making it one of the deadliest wildfires in the state's history [34]. Faced with the combined impact of multiple risk factors such as climate change, and the expansion of wildland-urban interfaces (WUI), improving people's response capabilities and evacuation efficiency during such extreme events has become an urgent and complex challenge [10]. Traditional models of wildfire evacuation typically consider people or vehicles as flows. For example, Vandaele et al. [33] studied a traffic flow model based on queueing theory. Although such models provide strong support for emergency management, they fail at capturing irrational decisions seen within individual behavior [20]. In recent years, agent-based modeling (ABM) has been gradually applied to disaster evacuation research due to its advantages in modeling individual heterogeneity and autonomous decision-making. However, most existing agent-based models of wildfire evacuation are mainly based on the rational choice assumption, ignoring the important role of human emotions in such extreme situations (e.g., [39])). Studies have shown that the emotions such as panic significantly affect an individuals' judgment and behavioral choices, especially in critical situations, where individuals" decisions tend to be more irrational. Although some studies have revealed the influence of these psychological factors through post-event surveys, there is currently a lack of modeling methods that can dynamically demonstrate the impact of emotions in ABM during emergency evacuations [32].

To fill this research gap, this paper proposes an integrated simulation framework that combines Fuzzy Cognitive Map (FCM) and ABM to explore how emotion propagation changes residents evacuation behavior. FCM, with its ability to express complex causal relationships and fuzzy reasoning, has been widely used in the modeling of social systems. For example, it has been used to characterize psychological models of individuals and groups in decision-making situations (e.g., [16]), as well as to simulate dynamic social psychological processes such as organizational behavior and stress (e.g., [9]) or public opinion dissemination (e.g., [14, 26]). In this study, we leverage the idea of FCM to construct the emotional state evolution path of affected individuals and coupled its output value as the key variable affecting the resident's evacuation behavior (e.g., departure time, path choice, whether to evacuate, etc.) within an agent-based model. This model is used to observe whether emotional factors influence the evacuation strategies of individuals. In addition, this study attempts to investigate whether there are differences in evacuation performance under the influence of emotions among different income groups. In the remainder of the paper, we will first briefly review the literature related to modeling evacuations (Section 2) before introducing the our model (Section 3). Section 4 will show simulation experiments and results, while Section 5 provides a summary of the paper and discusses avenues for future research.

## 2 Background

In recent years, due to the combined effects of climate change and WUI development, wildfires have exhibited characteristics of frequent outbreaks and high disaster severity in many regions worldwide. Research has shown that from 2000 to 2023, wildfires caused significant casualties, with low- and middle-income groups being the most severely affected, highlighting the inequalities in disaster response [22]. In wildfire risk management, the effectiveness of resident evacuation is a critical component of emergency response [28]. Therefore, understanding and simulating evacuation behavior in wildfire scenarios has become a key research topic. To support evacuation decisions, researchers often explore widlfre evacuations at the macro or micro scale.

Macro-level models view large-scale evacuations as a spatiotemporal evolution of network-level traffic flows, with the core focus on characterizing the traffic flow-speed-density relationship (e.g., [7, 25]). Micro-level models on the otherhand describe the details of traffic flow and the interactions that occur within it. These models are at the vehicle/individual scale. Primarily, such models focus on one of two directions. One type is a centered on the interaction between fire spread and traffic (e.g., [19]). While the second being evacuation models based on traffic simulation processes (e.g., [8]) Both styles of models prioritize evacuation efficiency and generally assume individual behavior is entirely rational, neglecting the effects of emotions and perceptions under emergency conditions.

While generally speaking ABM is also a micro-level modeling style, it differs from the ones above as it can simulate the heterogeneous behavior and decision making of individuals during an evacuation. As such this style of modeling enables researchers to capture dynamic phenomena such as route selection, evacuation behavior, and social interaction. However, most agent-based models of evacuations are rule-driven and lack modeling of individual internal psychological mechanisms (e.g., [35, 29]), particularly the dynamic feedback on typical emotional states such as "panic" and "anxiety." For example, in emergency evacuations, panic among evacuees may lead to irrational escape routes or even reversal. Traditional models often fail to reflect this level of uncertainty [12, 37]. By incorporating FCM within and agent-based model we can incorporate emotional responses under the influence of multiple factors and feed this dynamic feedback into behavioral decision-making [1].

## 3 Methodology

In this section we briefly describe our model which was created in NetLogo [36] to simulate the impact of emotional factors on residents evacuation decisions during wildfire evacuations. However, due to space constraints, a more detailed description of the model (including specific details of the FCM) following the Overview, Design concepts, and Details (ODD) protocol [17] along with the model, data required to run it is available at `https://github.com/ozzyzhou99/LA-Wildfire-Model`. We do this not only for readers to replicate what we present here but to extend the model if they so desire.

### 3.1 Study Area and Data

The simulation area chosen for this study is the Castellammare neighborhood of the Pacific Palisades, in western Los Angeles (LA), California. This area was damaged by the 2025 LA fires [27]. We chose this area as it has a "coast-hill-city" topography, which allows us to explore the interaction between coastline constraints, road bottlenecks, and wildfires. This model integrates multiple datasets as the basis for modeling wildfire evacuations as shown in Table 1. Household income data was obtained from the LA County Department of Public Health [21] which we used to construct proxy income categories. Damage Inspection (DINS) data from 2025 is sourced from CAL FIRE [3] documents. This dataset allows us to identify high-risk areas of Castellammare and serves as a spatial layout for modeling wildfire evacuation. The road network data is derived from StreetsLA[31] and is used to construct the accessible road network and to implement the wayfinding. All data is converted into a 10m x 10m raster data cells. Our rationale being this is equivalent to the typical cross-sectional width of urban roads in this area [13] and thus allows a single cell to represent a road or a small building.

The initial fire source points are randomly sampled based on historical fire distribution patterns [4]. Figure 1 shows the data used to set up the model experiments, which are household income, household location, and road network data. The model time step was set to one second (1 tick). Since ¿94% of evacuees during wildfire evacuation choose to drive [40], considering the size of the study area and the speed at which cars move, 1s per tick allows us to observe the complete evolution of fire spread and panic propagation.

**Table 1.** Input Data Sources

| **Data** | **Details** | **Resolution** | **Type** |
|---|---|---|---|
| Household income | By the Los Angeles County Department of Public Health | By Census Tract | .shp |
| Household location | DINS by CAL FIRE | Point | .csv |
| Street Data | Street Inventory by StreetsLA | 10m by 10m | .asc |

### 3.2 Brief Model Overview

The model explores three key questions: first, how do different income levels influence evacuation emotions? Are low-income groups more prone to making negative decisions? Research by Yabe et al. [38] indicates that income has a significant impact on evacuation capacity and choice, as low-income groups often face greater obstacles in accessing resources and transportation in emergency situations [38]. Second, how do different emotional states (i.e., calm-anxious-panic) spread through the population, and what chain reactions does it trigger on individual decision paths and overall evacuation patterns? By integrating a customized A* pathfinding algorithm with an FCM emotional propagation module, the model establishes a framework where individuals can respond in real-(simulation)-time to spatial layout of the fire and emotional contagion.

This model comprises three main entities: evacuees, responders, and the environment (i.e., patches). Evacuees represent residents driving private vehicles, with core state variables including income level, emotion level, current behavior mode, and pre-generated travel paths. Responders are designed to simulate police, fire, or other emergency personnel, dynamically switch between rescue and

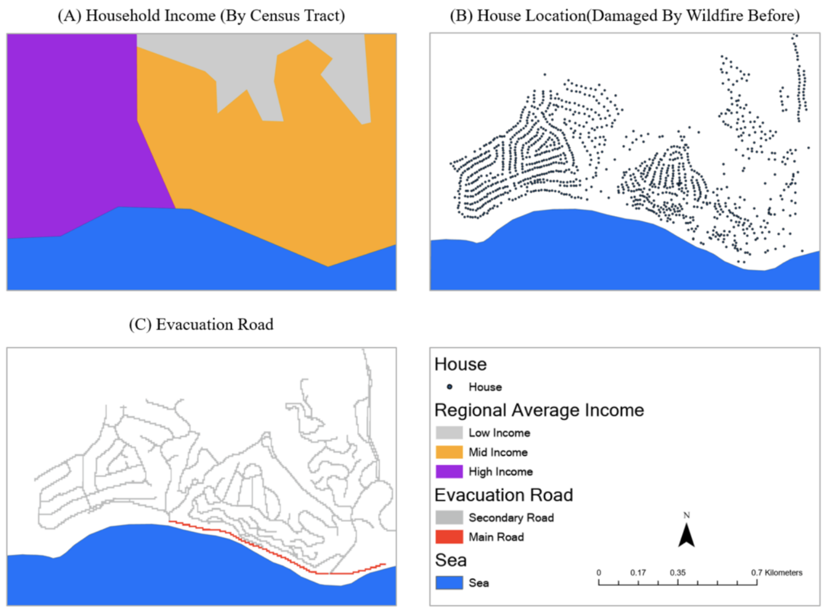


**Fig. 1.** Data used in the setting up the model experiment. (A) is household income data, (B) is location of previously affected houses, and (C) is evacuation road data.

evacuation operations. We also designed the rescuer here to insert a calm third party [23] as they can affect the evacuee's mood. By making evacuees calmer, they are guided to make rational evacuation decisions.

At each iteration, the model sequentially executes four phases. First, its expands the burning area based on the fire propagation speed and dynamically sets road pass-ability. Here, we use a simple fire spread model which spreads outward at a constant speed from the center of the fire. Since the focus of this model is not on fire spread, we feel this simple method is appropriate. The fire spread speed is set to the normal average speed of California fires in a light breeze, which is 2 km/h [30]. Next, the model calculates and updates the emotions and behaviors of evacuees which is shown at a high level in Figure 2. The arrows in this figure point to the central "Evacuees–Emotion" node, indicating that individuals receive a new emotion level denoted as **P** at each tick (which ranges from 0 to 1). The central and right-side groups of "Evacuees–Emotion" are connected by thick lines, illustrating "Emotion spreading among nearby evacuees." The circular 911–Calm node emits unidirectional arrows toward evacuees, representing the calming effect of rescuers on the crowd. The emotions are achieved by embedding a FCM into each agent. Figure 2 visually shows the submodels of social infection and emotion update in a closed-loop sequence: "Input factors → FCM calculation → individual emotions → social contagion loop." The social contagion loop also takes emotion levels from the surrounding agents. The "emotion level" outputed by the FCM is converted into an emotion state through a set of specific formulas. Emotional states control the actions of evacuees. Further details including the formulas of these submodels and can be seen in our ODD document.

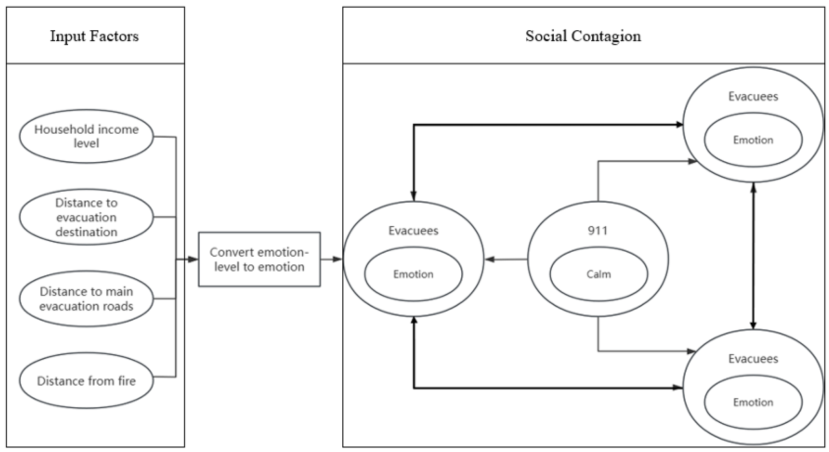


**Fig. 2.** Agent-level embedded FCM loop with social contagion.

Once emotions have been computed, agents update their behavior. The model a uses soft-max [15] mapping to convert **P** into three behavioral states: 1) Calm, means that evacuees will evacuate rationally (i.e., they will follow the pre-planned shortest path). 2) Anxious, means evacuees will act in a disorderly manner and 3) Panic, means that they will remain stationary. The workflow of this is shown in Figure 3A. The third step is to schedule the actions of the rescuers (see Figure 3B). Rescuers head toward the fire and if they encounter a road blocked by the fire, they re-plan their route. During this forward movement they scan for evacuees within an radius, pick them up one by one, until reaching the transport capacity limit (default 5 people). Finally, the forth step is update and record statistics .

## 4 Results

Before presenting our results, we will first discuss our efforts for verifying and validating our model. Verification was achieved via code review and unit testing of the models of critical processes (e.g., A* pathfinding, traffic capacity). Once the model had been verified we then set out to validate the model. Here we refer to Axtell and Epstein [2] four-levels of validation. Our aim is to achieve level 1 validation in which the model is qualitatively consistent with reality at the macro level. For example, consider traffic congestion. Long-term monitoring

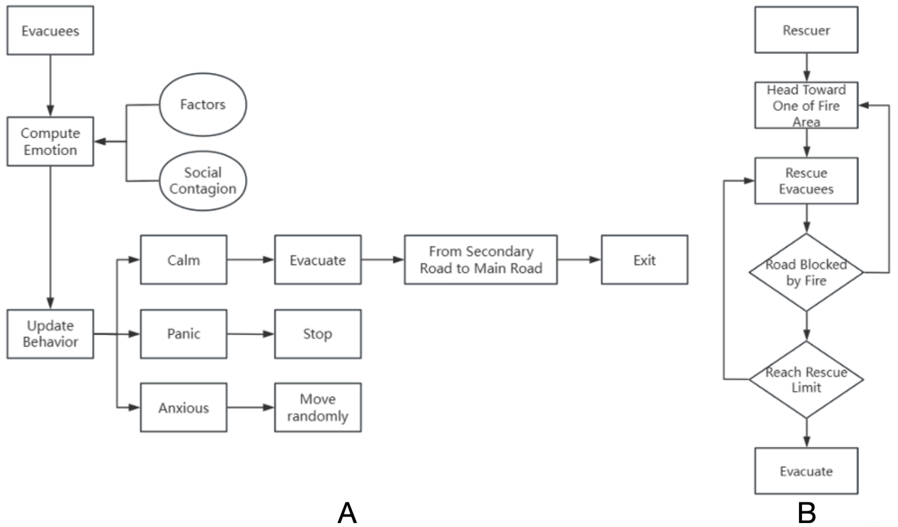


**Fig. 3.** Evacuees' Workflow (A), Rescuers" Workflow (B).

data from the California transportation data [6] shows that the intersections of Highway 1 and other secondary roads are most prone to sudden drops in vehicle speed during emergency evacuations. Our simulations observed that similar congestion hotspots at similar nodes. This indicates that the A* pathfinding, road capacity settings, and vehicle congestion avoidance strategies in the model accurately capture key network constraints. We also know socioeconomic differences influence emotions. Recent investigations into multiple wildfires indicate that low-income communities often initiate evacuations earlier to mitigate uncertainty caused by resource shortages [5]. In our model, we found that the average emotional level of the lowest-income group was higher than that of the other two groups. This result validates our assumption in the FCM, that income level influences emotional level. Further details on our verification and validation can be seen at `https://github.com/ozzyzhou99/LA-Wildfire-Model`.

Now turning to the results of the model, to recap, the model was designed to explore the influence of emotional factors on individual behavioral decisions, as well as the impact of income levels on emotions and behavior. In order to explore this, we set up three groups with increasing numbers of agents across different income levels, each undergoing 50 independent replicate experiments. The first group consists of 5 low-income individuals, 50 middle-income individuals, and 50 high-income individuals. The second group consists of 10 low-income individuals, 100 middle-income individuals, and 100 high-income individuals. The third group consists of 20 low-income individuals, 200 middle-income individuals, and 200 high-income individuals. Each experiment was run for 10,000 ticks, which is approximately 2.78 hours, or continued until all agents successfully evacuated (which we refer to as stop time). Figure 4 shows the time series of one representative run for each experiment.

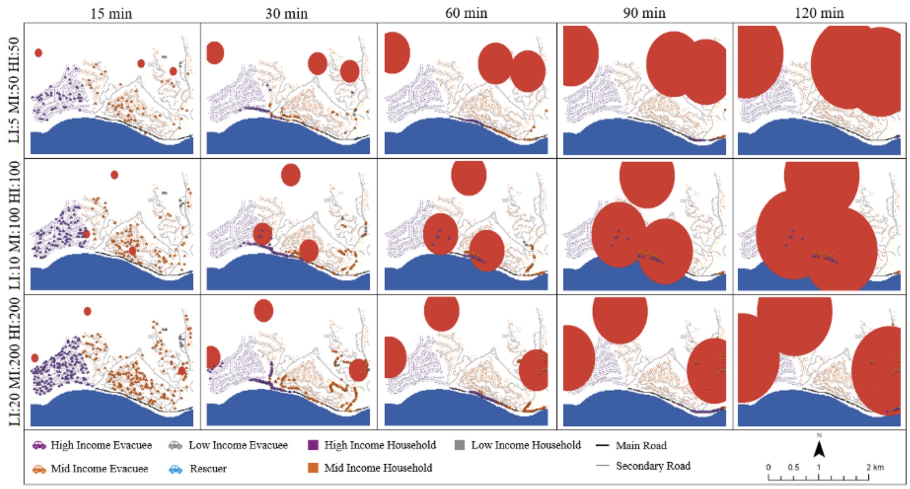


**Fig. 4.** Representative model time series diagrams, with the numbers on the left indicating the number of evacuees in each income bracket corresponding to each set of simulations. Low Income (LI), Middle Income (MI), High Income (HI).

**Emotional Levels and Behavioral Performance** By outputting the stop time and emotion level, we can observe the overall impact of emotions on the stagnation phenomenon in the model. The mean stuck time indirectly reflects the emotions of evacuees. This is because when evacuees are in a state of panic, they freeze in place due to excessive fear (i.e., they are stuck). We used Spearman's correlation test to establish the correlation between the overall average emotion (mean **P**) and the average stagnation time (stuck) collected in each experiment, obtaining $\rho = 0.915$ and $p = 4.67 \times 10^{-4}$, indicating a highly significant positive correlation between the two. As shown in Figure 5, when using the default inputs (10 low-income evacuees, 100 medium-income evacuees, and 100 high-income evacuees), an increase of 0.1 in mean **P** is associated with an approximate increase of 25 ticks in stuck (linear fit slope $\approx$ 250 ticks emotion$^{-1}$). These two analysis results indicate that emotion plays the role of in the evacuees behavioral decisions.

We also collected the number of route re-planning instances and the final evacuation time and analyzed them in conjunction with the average emotional level to examine the impact of emotions on route re-planning and final evacuation time in the model. Experimental results showed that the number of route re-planning instances was linearly correlated with the average P-value ($R^2 = 0.71$, $\beta \approx 5.2 \times$ Emotion$^{-1}$). The $P_{90}$ (90th percentile) of the final evacuation time was

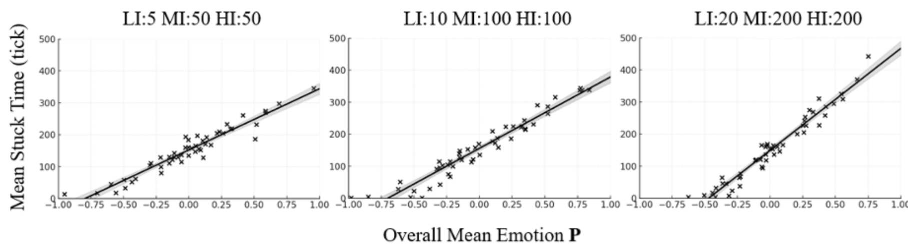


**Fig. 5.** The relationship between overall mean emotion **P** and mean stuck time to standstill ($\rho = 0.92$, p $\prec 0.001$). Shaded for 95 % confidence bands. Increasing number of people in each income bracket in the three groups from left to right. Low Income (LI), Middle Income (MI), High Income (HI).

also positively correlated with the average P-value ($\rho = 0.68$, p $= 0.03$). Among evacuees with high emotions (i.e., more prone to panic and anxiety), the bottom 10% of evacuees took up to 7,540 seconds, while those with low emotions (more likely to remain calm) only needed 800 seconds.

**Linkage of Income, Emotions and Behavior** We also analyzed the relationship between income and emotions using an average emotion sampling method. We conducted three experiments, each with an increasing number of evacuees at each income level, and each experiment was repeated 50 times. By sampling the average emotions of each group in each experiment, we obtained the box plots shown in Figure 6. It can be observed that the low-income group had the highest emotion levels, indicating that they were the least calm. Conversely, the high-income group exhibited lower emotional levels, indicating they remained more composed during the evacuation process. This aligns with social psychological observations that suggest that lower income correlates with stronger negative emotions (e.g., [18]).

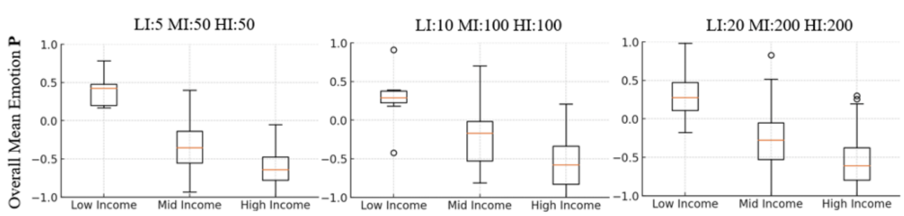


**Fig. 6.** Box plots of average emotions for three groups of experiments (50 repetitions each). From left to right, the number of people in each income group increases progressively. Low income (LI), middle income (MI), and high income (HI).

To explore the pathway of "income → emotion → behavior," we applied the Baron–Kenny method for mediation analysis, which involves three regression steps. This method tests the effect of the independent variable on the dependent variable, the effect of the independent variable on the mediating variable, and finally the indirect effect to determine whether the independent variable affects the dependent variable indirectly. The purpose of this is to determine whether income influences evacuation behavior indirectly through its effect on emotion, rather than directly. In the first step, the regression (income → behavior) showed that for each decrease in income level (high → medium → low), the stuck time increased by approximately 43 ticks, (p value = 0.07), showing a positive trend. In the second step, the regression (income → emotion) showed that income also had a positive effect on emotion ($\beta = +0.06$, p = 0.08). Finally, in the third step, when emotion level (mean $\mathbf{P}$) is included in the regression along with income, the coefficient for emotion is significant ($\beta = +620$ ticks, p ¡ 0.01), while the coefficient for income drops sharply and loses significance. This result indicates that income's influence on behavior is almost entirely mediated by emotion. In the sense, emotion is a complete mediating variable for income's effect on behavior: low income → higher negative emotion → longer stuck time and more frequent route re-planning.

## 5 Summary and Outlook

This study builds upon existing literature on fire evacuation by embedding fuzzy cognitive maps (FCM) into an agent-based model, with a focus on revealing the previously unquantified causal chain linking "income→emotion→ behavior." Experimental results indicate that low-income individuals exhibit significantly higher emotional levels than high-income individuals under identical external conditions. This finding aligns with post-disaster field surveys that identified a chain reaction among low-income households characterized by "low preparedness→high fear→disorganized action [24]." More importantly, Baron–Kenny mediation tests showed that the effect of income on delay time became non-significant after incorporating emotional state, confirming that emotional state fully mediates the impact of income on behavior. Therefore, simply adding lanes or extending mandatory evacuation windows is unlikely to mitigate the risks. Our results also explain the "early evacuation–high panic" paradox [11]: low-income residents often leave the fire scene earlier due to expectations of resource scarcity, but their emotions levels increase leading to a significant increase in the number of times they stall or retreat.

As with all models, there are numerous areas of further work. In reality, disparities in evacuation outcomes across income groups largely stem from unequal access to resources. Our model does not explicitly simulate such resource allocation; rather, it focuses on how emotional responses and contagion mechanisms influence evacuation behavior across groups. For example, we could explore how the fire speed or reducing exits can be used to test "panic-congestion". Also while this is currently a relativity simple model, we could reconstruct individual movement paths by utilizing mobile phone trajectories. In addition, we can also access interview data to record the reactions of different groups of people at different stages. Alternatively we could explore different types of interventions. For example in the early stages when the average emotion level approaches 0, using mobile push notifications, broadcasts, or volunteer announcements to quickly cool down the situation compared to simply deploying more police to manage traffic. One could also image a situation were one could incorporate emotional thresholds into real-time monitoring and intervention. For example, utilizing social media posts and traffic monitoring. Even with these areas of further work, this study demonstrates that in extreme events where evacuations occur we can move away from rationale choice or optimized traffic models to incorporate more human decision making into the evacuation process through the use of FCM.

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