Impacts of Anxiety in Building Fire and Smoke Evacuation: Modeling and Validation

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***Abstract*—Anxiety impairs evacuees' ability to select appropriate routes during building fire and smoke evacuations. Understanding anxiety is thus essential to provide proper guidance to evacuees. However, it is challenging to model how anxiety affects evacuees' decision-making process, and how to validate the resulting approach with very limited available data. In addition, mimicking anxiety in existing simulation packages is not easy because of the lack of appropriate features in simulators. This paper captures the impacts of anxiety on route choices and the interaction with other psychological features such as responses to guidance and herding. This is achieved by using an optimization framework where the number of planning steps and values of psychological parameters are affected by anxiety. To validate our approach, the levels of anxiety were manipulated by hazardous conditions and lengths of planning horizon are evaluated by comparing derived route choices against the data in virtual reality experiments. Impacts of anxiety on large crowds were also mimicked in Fire Dynamic Simulator + Evacuation with and without effective guidance. Testing results demonstrate that effective guidance help reduce negative impacts of anxiety on route choices.**

***Index Terms*—Impacts of anxiety, building fire and smoke evacuation, human factors and human-in-the-loop, virtual reality and interfaces.**

I. Introduction

FIRE disasters kill tens of thousands of innocent people every year worldwide [20]. One regrettable point is that evacuees may not always behave in a rational manner because of anxiety. Anxiety could lead to crying and yelling, pushing and shoving, and selecting improper routes which result in unnecessary deaths and injuries. For instance, the only casualties (one dead and 14 injured) during the fire event in Address Downtown Hotel (at Dubai, United Arab Emirates) were caused by stampedes at narrow passages, which were overcrowded with anxious evacuees at the new year's eve of 2015 [8]. As such, modeling impacts of anxiety is important to the study of evacuees' behaviors. With a better understanding of anxiety, proper guidance can be provided to increase survivability and the effectiveness of evacuation.

A major difficulty in studying anxiety is that it cannot be measured directly as a psychological state. Consequently, impacts of anxiety on evacuees' behaviors are not easily modeled and validated. To roughly assess anxiety, measurements of physiological markers have been utilized. Thus many hypotheses about impacts of anxiety on evacuees' behaviors can be tested. These hypotheses were tentatively summarized from records of past fire events. For instance, evacuees are more likely to follow the crowd (herding) under elevated levels of anxiety. Related findings were also tested in simulations where impacts of anxiety are partially incorporated. To test evacuation models with human participants, virtual reality (VR) experiments were developed and employed recently [9]. Studies about anxiety's impacts, evacuation models, and validation methods are reviewed in Section II. Despite many hypotheses about anxiety having been verified, impacts of anxiety on route choices remain difficult to assess.

From psychological findings, anxiety constrains perception and reasoning so that anxious evacuees become "myopic" when selecting a passage to safety. Impacts of anxiety on route choices are captured with the optimization framework for selecting a route. With a higher level of anxiety evacuees focus more on local information, consider fewer possible routes and think fewer time steps. Anxiety's interactions with other psychological features such as response to guidance and herding are captured by changing these features' biases in the objective function. The evacuees' objective function, impacts of anxiety, and the interaction with other features are incorporated in a network-flow model as presented in Section III.

To validate the evacuation model that incorporates anxiety's impacts, VR experiments were designed and results were analyzed in Section IV. Levels of anxiety were assessed by physiological data (heart rates and galvanic skin response) and hypotheses about factors that change levels of anxiety were aimed to be tested. Impacts of anxiety were then analyzed with the optimization on route choices in VR experiments. After assigning reasonable values for parameters in the objective function, expected frequencies about the length of planning

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This paper has supplemental downloadable multimedia material available at http://ieeexplore.ieee.org, provided by the authors. The Supplementary Materials contain an MP4 file showing the evacuation process in the virtual reality experiment (on the 3rd Floor) described in the paper. This material is 3.1 MB in size.

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

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horizons were calculated based on route choices recorded in VR experiments. Evaluated impacts on planning horizons are then verified with data from the other set of VR experiment.

Using the same parameters and the building layout as in VR experiments, evacuation processes are simulated by Fire Dynamic Simulator + Evacuation (FDS + Evac) to test effects of anxiety in Section V. Two independent variables varied in simulations: the length of planning horizon in the optimization framework and effects of guidance. Because there is no exact feature to mimic anxiety's impacts on route choices, route choice behaviors are computed with the optimization framework. Then derived route choices are associated with different exits and updated into FDS+Evac simulations. The results in indicate that with longer planning horizons, evacuees tend to select better routes and routing behaviors with a short planning horizon can be improved by effective guidance.

II. Literature Review

This section reviews studies about anxiety's impacts on evacuees, as well as methods of validating evacuation models. Factors that affect anxiety and models about impacts anxiety are reviewed in Section II-A. Methods of assessing anxiety and validating evacuation models are reviewed in Section II-B.

A. Anxiety in Evacuations

Anxiety is an emotional response of stress [13]. In building evacuations such as fire events, anxiety is often triggered by various stressors from the environment, e.g., smoke or fire alarm. Evacuees may interpret these stressors as threats. Meanwhile, they consider available passages and other route information to evaluate whether there are enough available passages to evacuate safely from the building [19]. The perception of hazards increases the anxiety level of evacuees. Conversely, the presentation of relevant, straightforward, and precise information can pacify evacuees' minds and alleviate their anxiety [18].

Anxiety affects evacuees' behaviors in many regards. Under a high level of anxiety, evacuees' cognitive ability is impaired and other mental and perceptual capacities are distorted. Anxious evacuees tend to focus more on the route information and hazards close to them rather than targets far away from them [4]. Anxiety also reduces people's ability to make decisions. Evacuees simplified their decision-making processes to make a quick decision. Evacuees also shift their decision mechanisms into following instincts (e.g., herding) when selecting a route under high anxiety [16]. Another impact of anxiety is the increase of pushing and shoving behaviors, which may cause severe blockages even without hazards [7].

Many evacuation models consider impacts of anxiety on evacuees. For example, in the model embedded in FDS+Evac the density of smoke speeds up the detection of fire and increases the speed at which the movement of evacuees can be triggered [10]. Evacuees' route choices are modeled as a decision-making process which includes 1) searching for possible options (routes); 2) anticipating the consequences; 3) weighing each consequences with preference; 4) choosing the most favorable route [16]. Route choices are then altered according to evacuees' instincts and crowding at exits (i.e., herding) [16], where evacuees' ability can be changed by anxiety [3]. Most of these models are heuristics summarized from disasters and tested with simulations, and there is no mathematical equation shown in them.

Anxiety's impact on pushing and shoving behaviors was modeled as the increase of desired velocities with the social-force model [7] and evacuees' "nervousness" can cause the accretion of desired velocity (denoted by v^d), i.e.,

$$v^d(t) = [1 - n(t)]v_0^d + n(t)v^{d,\max}, \tag{1}$$

where $n(t)$ represents the nervousness [7]. The corresponding variable of desired velocity for a group of evacuees was modeled as "desired flow rate" in the network-flow model in our previous work [15].

B. Validating Models About the Impacts of Anxiety

Levels of anxiety should be assessed before validating the model about impacts of anxiety. However, levels of anxiety are difficult to measure and record directly during fire evacuations. Several methods are developed: interpreting certain types of behaviors as an indicator of anxiety, collecting survey data, and analyzing physiological data [6]. Behaviors such as yelling and crying also reveal a high level of anxiety. Survey data provides a rough approximation of anxiety after events. Physiological markers such as galvanic skin response and heart rates can provide a more precise way to assess people's anxiety with data in high resolution.

Although it is inconvenient to obtain physiological data from evacuees during fire events, the physiological data can be collected conveniently with the assistance of VR techniques [9]. VR techniques provide a maximum of experimental control and are easy to replicate. One limitation in VR experiments is that VR cannot produce a completely realistic experience. Nevertheless, experiments with VR techniques are engaging in the long run, where their weaknesses are mitigated by the improvement of technologies. Apart from validation by VR techniques, impacts of anxiety were also investigated with data from real events. A notable example is the investigation report for the Station Nightclub Fire in Rhode Island in 2003 [5]. From the evidence collected in ruins, video clips, and interviews of survivors, simulations of agent-based models were run to reproduce the evacuation process, where serious blockages at the front door caused by herding behaviors were identified [1]. Although anxiety was not specifically mentioned, its impacts on route choices and desired velocities were well mimicked [5]. Another important factor, the information that guided people during evacuation was also partially simulated by fully trained leaders in [17].

III. Anxiety's Impacts in an Evacuation Model

In this section, impacts of anxiety on evacuees are captured in a network-flow model. The optimization framework for route choices are developed in Section III-A and impacts of anxiety in decision-making process on route choices are modeled in Section III-B.

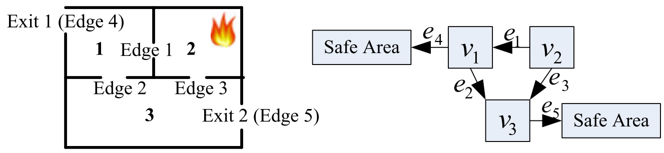


Fig. 1. A simple network-flow model.

A. An Optimization Framework for Route Choices

Evacuees want to select a safe route to evacuate quickly and this decision-making process is captured in an optimization framework in this section. The evacuees' movement and risks caused by fire are incorporated in a network-flow model, where levels of anxiety are also considered. An objective function of a group of evacuees is formulated at the end of this section.

A network-flow model is formed based on the layout of a building as a graph G(V, E), where rooms and areas are abstracted as vertices (denoted by set V) and passages are abstracted as edges (denoted by set E). A passage will be modeled as several connected vertices if it is very long. Fig. 1 illustrates the layout of a small building and the corresponding network-flow model. The evacuee's flow on edge e (denoted by $q(t, e)$) is embedded in the graph and the number of evacuees $x(t, v)$ at vertex v is updated by the flow rate $q(t, e)$ [15], i.e.,

$$x(t+1, v) = x(t, v) + \sum_{\mathrm{e}} b(v, e) \times q(t, e), \quad \text{for all } t = 0, 1, \ldots, T-1, \tag{2}$$

where $b(v, e)$ represents the direction of $q(t, e)$ and is determined by evacuees' route choices. The number of evacuees who intend to pass edge e at time t is called the desired flow rate and is denoted by $q^d(t, e)$ [15]. The flow rate $q(t, e)$ is computed by considering blocking effects when the desired flow rate $q(t, e)$ exceeds the passage capacity.

Risks caused by fire and smoke are also incorporated in the network-flow model. The status of fire on vertex v at time t is denoted by $x_F(t, v)$ and ranges from 0 to 1 to represent the magnitude of fire. The propagation of fire is modeled as a Markov process and the expected magnitude of fire can be calculated [15]. The probability that people get hurt on vertex v is derived from fire status and is denoted as $p_{\text{risk}}(t, v)$. The expected number of people injured on vertex v is defined as the risk $R(t, v)$ [2], where

$$R(t, v) = p_{\text{risk}}(t, v) \times x(t, v). \tag{3}$$

Levels of anxiety are modeled with the network-flow model. From psychological findings and our testing results in experiments in Section V, anxiety is modeled as two levels. Anxiety is in the high level when evacuees perceive hazards or cannot evacuate as fast as they expect due to blockage. On the other hand, when people evacuate without blockage or receive clear information about where to go, the level of anxiety is low [16].

The optimization framework for route choices is formulated based on the network-flow model. The objective function for a group of evacuees (group i) can be derived from the overall

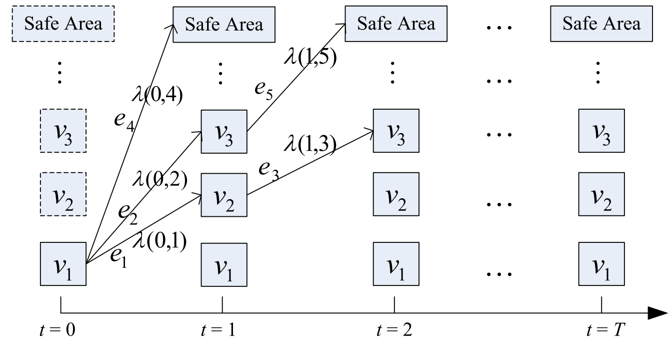


Fig. 2. The optimization framework with the planning horizon [0, T].

guidance optimization problem which aims at minimizing total risks by suggesting proper routes [14]. To reduce possible blocking effects, passage capacity constraints are added where desired flow rates at a passage should not exceed the passage capacity. After relaxing the passage capacity constraints with Lagrangian multiplier λ, the overall problem is decomposed into group subproblems, which form the objective function for different groups. As shown in Fig. 2, the route choice behaviors of group i (starting from vertex 1) are modeled as minimizing the objective function over a planning horizon [0,T]. The objective function consists of the total risks on vertices and the summation of marginal costs at edges evacuees go through, i.e.,

$$L^i(t) = \sum_{t=0}^{T} \sum_{v \in V} R^i(t, v) + \sum_{t=0}^{T-1} \sum_{e \in E} \lambda(t, e) q^{d,i}(t, e) \tag{4}$$

where $R^i(t, v)$ is the risk on vertex v and $\lambda(t, e) q^{d,i}(t, e)$ represents the marginal cost for group i at edge e. The marginal cost $\lambda(t, e) q^{d,i}(t, e)$ for group i can be derived from the Lagrangian relaxation framework given the crowd movement of all evacuees [15]. Values of $R^i(t, v)$ and $\lambda(t, e) q^{d,i}(t, e)$ are evaluated by the evacuees based on their observations, anticipations or the information provided by smart devices.

The optimization problem in (4) can then be solved by dynamic programming when the evacuees select an edge to move at a vertex. If there are many routes with similar costs, evacuees will have equal probabilities to select one of them, which is the "ε-optimization" in bounded rationality [12]. For example, if costs in the objective function for route 1 and route 2 are $L_1^i(t)$ and $L_2^i(t)$ and $|L_1^i(t) - L_2^i(t)| < \varepsilon$, where ε is a small positive constant, evacuees will have equal probabilities to select route 1 or route 2.

B. The Impacts of Anxiety on Route Choices

As mentioned in Section II-A, evacuees simplify their decision mechanism to select a route and pay more attention to the route information that are close to them under a higher level of anxiety. Thus one impact of anxiety is shortening the planning horizon in the optimization framework.

Anxiety also interacts with other psychological features when selecting a route. Psychological features such as response to guidance, familiarity and herding affect route choices and effects

Fig. 3. A participant in a VR experiment.

(a) (b)

Fig. 4. The virtual environment in the experiments.

are captured by biases on the perceived costs in (4). Magnitudes of psychological features' effects were modeled as parameters t_g, t_f and t_h, which represents the trust in routes because of guidance, familiarity and herding [14]. The values of the trust parameters range from 0 to 1, where "0" means no effect and "1" means complete trust. Trust parameters enlarge the tendency of using certain vertices and edges, and such effects are modeled by discounting the perceived cost in (4). For example, the bias caused by trust in guidance is modeled by discounting the perceived cost by $(1 - t_g)$,

$$\tilde{L}^i(t) = (1 - t_g)L^i(t). \tag{5}$$

Effects of guidance (t_g) are reduced if the guidance information is not easy to understand under a high level of anxiety [18]. Trust parameters from different features are unified together in the trust framework [14] before discounting $L^i(t)$.

IV. The VR Experiment

Two VR experiments were designed and conducted to test impacts of anxiety over individual participants. Individual human participants took part in VR experiments and as designed in Section IV-A. Hypotheses about conditions that affect anxiety are validated and impacts of anxiety on route choices are tested with the optimization framework in Section IV-B.

A. The Design of VR Experiments

VR experiments were designed to study evacuees' behaviors under conditions of high anxiety, where participants were immersed in a 3-D virtual environment with or without fire and smoke (see Figs. 3 and 4). A video clip that shows the evacuation process in VR has also been attached to this paper.

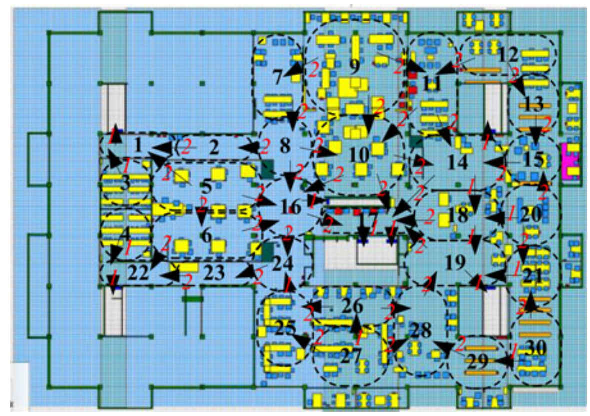


Fig. 5. The layout of 1st Floor in the library building.

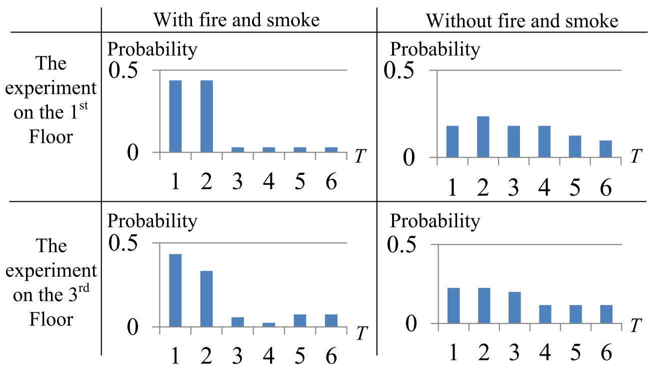


Fig. 6. The probability mass distribution of possible planning horizons.

The first VR experiment was to test evacuees' behaviors under different levels of hazardous conditions (with or without fire and smoke). The virtual environment was constructed according to the 1st floor of UCONN's library building [11] (see Figs. 4(a) and 5) and a large group of virtual avatars were simulated to evacuate with an individual participant. Thirty-three undergraduate students in the age range of 17 to 23 were recruited to participate in the experiment. Most of them are familiar with the main exits and about half of them are female. The independent variable is hazardous conditions, which are randomly assigned. The dependent variables are exit choices of participants. It is hypothesized that more participants tend to use main exits with a more hazardous environment. However, levels of anxiety under different hazardous conditions were not revealed in the first experiment.

To assess levels of anxiety, the second experiment was conducted with physiological measurements, including galvanic skin responses and heart rates. Of interest is how anxiety affects evacuees' route choices with or without providing the information about using peripheral exits. The information is either provided by a signage hung above the blocked passage or audio tracks which give no specific directions but inform participants about blockage at main exits and remind them to use other nearby exits. There were 27 male and 10 female undergraduate participants, whose physiological data and trajectories were recorded as dependent variables. The 3rd floor of the library building was selected as the virtual environment (see Figs. 4(b)

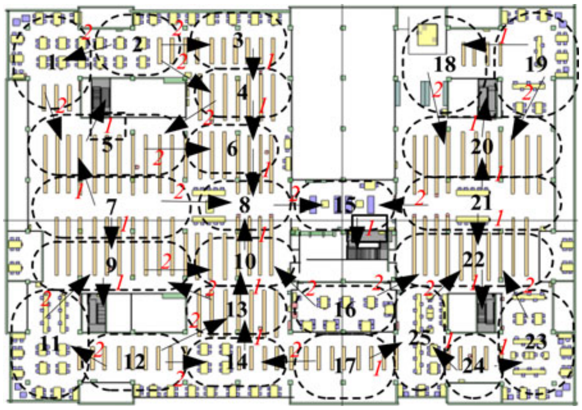


Fig. 7. The layout of 3rd Floor in the library building.

TABLE I
EVENTS THAT INCREASE ANXIETY

	Measure	Pre Mean	Post Mean	df	p
First alarm	GSR mean	6.942	7.221	26	0.003
	GSR max	6.999	7.559	26	<0.001
	HR mean	80.297	76.81	26	0.002
	HR max	82.463	81.927	26	0.623
First collision	GSR mean	7.549	7.468	25	0.18
	GSR max	7.59	7.669	25	0.111
	HR mean	82.968	83.707	25	0.111
	HR max	85.474	91.782	25	0.017
Hazards	PC1			$\mathrm{df1} = 2$	0.1046
	PC2			$\mathrm{df2} = 23$	

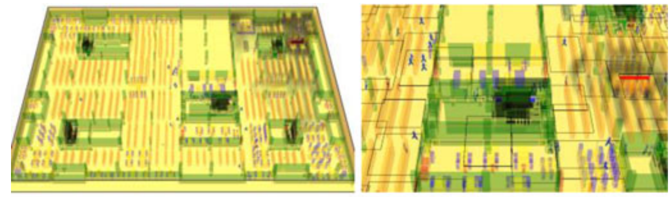
and 7). Participants were also asked to fill up a questionnaire which collects the information about their stressful feelings and other background information. They are also asked the knowledge about the building layout in the interview. It is hypothesized that anxiety levels will increase after facing hazards or encountering blockage. Therefore, galvanic skin responses and heart rates are hypothesized to increase after seeing fire, colliding with other avatars or hearing the fire alarm. Effects of anxiety on route choices are modeled as shortening the planning horizon in the optimization framework. Such effects are also tested after evaluating possible planning horizons, with which derived route choices match the trajectory data.

B. Results of VR Experiments

To analyze the physiological data, the mean value of the galvanic skin response ("GSR mean" in Table I) over a six-second window is extracted as the dependent variable and results from ANOVA suggest that GSR mean values were changed significantly after hearing the evacuation alarm. Likewise, maximum values of galvanic skin response ("GSR max"), mean values and maximum values of heart rates ("HR mean" and "HR max") are also analyzed by ANOVA. Results reveal that levels of anxiety are increased after hearing the evacuation alarm and colliding with others (see Table I). The "Pre Mean" and "Post Mean" in the first row of Table I are mean values of a measurement before and after certain events. The degree of freedom is abbreviated as "df" and type I errors are labeled by "p." Two principal components are extracted from the pooled variance matrix of dependent variables (GSR mean, GSR max, HR mean and HR max) by principal component analysis. Principal components can well represent the physiological data because they explain 89% of the total variance. They are analyzed together by MANOVA and marginally validate that the level of anxiety was increased by hazardous conditions.

After confirming that the level of anxiety can be manipulated by hazardous conditions, impacts of anxiety on route choices are focused. Effects of anxiety on planning horizon are difficult to test because the length of planning horizon cannot be measured. To evaluate possible planning horizons, optimized routes under different lengths of planning horizon are derived from the optimization framework and compared with the trajectory data. Corresponding to one trajectory, all possible planning horizons that result in the same route choice are assumed to have equal probabilities. After summing up and normalizing expected frequencies of planning horizons under a certain condition, the probability mass distribution of possible time windows are derived in Fig. 6.

Thus the hypothesis that anxiety shortens the planning horizon (T) is supported with different virtual environments. Risks in (5) are evaluated from the predicted fire status and marginal costs at passages are calculated from blocking effects. Parameters about psychological features are reasonably assigned based on questionnaires and interviews.



(a) (b)

Fig. 8. The virtual fire and evacuees in FDS+Evac simulations.

V. TESTING AND SIMULATION WITH FDS+EVAC

Following results from VR experiments, FDS+Evac simulations are designed to test impacts of anxiety over a crowd of evacuees in Section V-A. Impacts of anxiety on a crowd of evacuees under different levels of guidance are demonstrated by simulation results in Section V-B.

A. The Design of FDS+Evac Simulations

To test impacts of anxiety and guidance over a crowd of evacuees, a series of FDS+Evac simulations were run with the layout of the 3rd Floor (see Figs. 7 and 8). Since there is no anxiety feature in FDS+Evac, impacts of anxiety on route choices are mimicked by varying planning horizons for all simulated evacuees, and effects of guidance are mimicked by trusts in guidance in the optimization framework.

The two independent variables are lengths of planning horizon (denoted by "T" in Table II) and effects of guidance

TABLE II
EFFECTS OF GUIDANCE AND PLANNING HORIZONS

	The guidance without specific routes					
T	1	2	3	4	5	6
Evacuated at $t = 30$ s	43.4	56	65.6	85.4	91.1	97
Evacuated at $t = 60$ s	101	115	123	136	138	139
Clearance time	95.1	87.5	88.6	84.8	83.8	78
	The guidance with specific routes					
T	1	2	3	4	5	6
Evacuated at $t = 30$ s	111	107	114	105	112	111
Evacuated at $t = 60$ s	144	147	149	144	147	145
Clearance time	66.3	61.6	59.3	72.4	68.2	65.8

information. Lengths of planning horizon ranges from one to six time units, and the time window for all evacuees are the same. Effects of guidance are weak when guidance provides no specific routes to peripheral exits; effects of guidance are strong when specific directions (routes) are suggested by guidance. The movement of a group of evacuees is homogeneously affected by guidance, as well as other psychological features. Locations of fire were randomized among eight different parts on that floor and average values of the cases with different fire locations are listed in Table II. There were 150 evacuees randomly placed at the beginning of each simulation.

One inherent difficulty to manipulate independent variables is lack of appropriate features for planning horizons in FDS+Evac. To resolve this issue, evacuees' route choices are calculated with the optimization framework and then mimicked by "familiarity" parameters in FDS+Evac [14]. Decisions about route choices have to be made at each junction where original route choices may be altered. To update evacuees' route choices one simulation run is divided into several segments, where parameters about evacuees' positions are copied to consecutive segments. A technical detail is about setting initial positions of evacuees in the consecutive segment. Because evacuees' initial positions cannot be set as precise coordinates, "evac boxes" that prescribe their initial positions are set as small as possible (see Fig. 8(b)). When moving along different routes, exact trajectories of evacuees are computed by the social-force model embedded in FDS+Evac [10].

B. Results of the FDS+Evac Simulations

Several dependent variables are considered to assess the effectiveness of evacuation, such as numbers of evacuated people at different time points and the clearance time. Because it may take 60 to 100 s to evacuate all the people, the number of evacuated people at two time points ($t = 30$ s and $t = 60$ s) are particularly focused (See Table II). The clearance time is the time length it takes to evacuate all the avatars and is also listed in Table II. Fewer people are evacuated when the planning horizon becomes shorter if effects of guidance are weak. Results reveal that the evacuation process lasts for longer times with a shorter planning horizon because of anxiety. However, when effects of guidance are strong, impacts of varying planning horizon are very small because most evacuees select good routes by following the guidance. Effective guidance reduces negative impacts of anxiety by improving route choices.

VI. CONCLUSION

Impacts of anxiety on evacuees are modeled and validated with VR experiments in this paper. An optimization framework is developed to capture route choice behaviors considering anxiety. The analysis that combined physiological data with behavioral data in experiments validates changes of anxiety caused by different conditions and supports impacts of anxiety captured in the optimization framework. Numerical results suggest that guidance information with clear, specific directions can reduce negative impacts of anxiety.

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