# EVACUATION SAFETY AND HUMAN EMOTIONAL RESPONSES IN SMOKE-FILLED TUNNELS FOR MACHINE LEARNING INSIGHTS

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**ABSTRACT**

To clarify the relationship between emotion and walking behavior in tunnel fires, we conducted evacuation experiments using model-scale tunnel with smoke and investigated participants' emotions, physiological signals, and walking speed. For applying machine learning to recognize emotions during evacuation in the future, we estimated the causal relationship using structural equation modeling and found that heart rate, systolic blood pressure, and standard deviation of N-N interval influenced the walking speed to be faster, while diastolic blood pressure influenced the walking speed to be slower.

*Keywords: Emotion, physiological signal, walking speed, smoke, tunnel fire.*

## 1. INTRODUCTION

When a fire occurs in a tunnel, which is an enclosed space, smoke fills the tunnel easily and users need to evacuate a long distance with reduced visibility due to smoke. In this situation, the users are at a high risk of becoming a victim. For future real-time evacuation guidance in a tunnel fire, understanding the psychological state and evacuation behavior of evacuees is considered as one of the important factors. Recently, studies on emotion recognition using machine learning have been conducted [1–3], however, there were no studies on emotion recognition during evacuation in our searching. In this study, we focused on the case of evacuation in smoke, classified emotions by combining heart rate with blood pressure, and investigated the relationship between emotions, physiological signals, and evacuation speed.

## 2. LITERATURE REVIEW

### 2.1. Emotion recognition by machine learning

Studies on negative emotion recognition using machine learning have been conducted [1–3] (Table 1). These studies used movies, documentaries, and TV shows to evoke participants' emotions. Subsequently, the type and degree of emotions were labeled by participants' self-report (subjective evaluation) [1–2] or by others such as the staff (objective evaluation) [3]. Finally, these studies used physiological signals such as electrocardiogram (ECG) to recognize emotions.

Table 1: Previous studies on negative emotion recognition by machine learning

| Author(s) | Methodology | Labeled by | Recognition tool |
|---|---|---|---|
| Jang et al. [1] | Movie<br>Documentary<br>TV show | Self-report | Electrocardiogram, electrodermal activity, skin temperature, and photoplethysmography |
| Park et al. [2] | Movie<br>Documentary<br>TV program | Self-report | Electrocardiogram, electrodermal activity, skin temperature, and photoplethysmography |
| Takeshita et al. [3] | Movie | Behavior observation by staff | Heart rate variability |

## 2.2. Emotion measurement

Early studies have been conducted to investigate the relationship between emotions and physiological responses such as heart rate (*HR*) and systolic (*SBP*) and diastolic (*DBP*) blood pressure [4–9].

Adstee et al. [4] reported that participants' *HR* and *SBP* had increased and *DBP* remained constant when the staff had judged them as anxious via the implications in the conversation as well as direct statements, and the observations of their gestures, facial expressions, blocking, and slips of the tongue, etc., in the stressful interviews. Nyklíček et al. [5] reported that *DBP* had increased in the anxiety by music and noise listening experiments. The anxiety state was determined by combining a pre-experiment investigation which emotion the music and noise had evoked, and the participants' self-report after the experiment.

Ax [6] conducted experiments which participants were asked to listen to music in a relaxed state to investigate physiological differences between those who with and without hypertension. Firstly, the staff had given the electric shocks to the participants, and then the sparks by the high-voltage short circuit had been shown to induce fear. Ax [6] reported that their *HR* had increased in fear state. Schwartz et al. [7] conducted walking-experiments which participants had been instructed to imagine a fearful situation from their past or future. The fear was determined by the participants' self-report and the staff's observation of the participants' behavior, such as facial expressions and body postures. Schwartz et al. [7] reported that their *DBP* had decreased in fear state.

Berntson et al. [8] proposed a quantitative bivariate model for chronotropic control of the heart in humans and mentioned an increase in *HR* when feeling stress. Sloan et al. [9] conducted experiments to measure participants' 24-hour electrocardiograms and found that when participants self-reported that they felt stress, their heart rate variability (HRV) decreased.

Zhang et al. [10] classified emotions by extracting key words from people's talk. Before classification, they referred to Bhargava and Polzehl [11] and determined that the heart rate should be in the range of 40–70 bpm in sadness and 80–150 bpm in anger. However, these studies were conducted in a stationary condition, such as in sitting.

In this study, we targeted the smoke-filled tunnel fire evacuation scenario and attempted to label emotions via physiological responses by the previous studies' results for future machine learning studies of emotion recognition in the evacuation.

# 3. EXPERIMENTS

## 3.1. Model tunnel

As same as Li et al. [12−13], a model tunnel (10 m long, 2 m wide, and 2 m high, with pitch-black interior) was used for the experiments (Figure 1). To set up evacuation routes, four check points (CP) were placed at a height of 1.5 m in the tunnel. Two smoke generators (PORTA SMPKE PS-2005, Dainichi) were placed diagonally at each end of the tunnel and three smoke density (extinction coefficient) measurements (laser sensor, LV-NH100, Keyence) were placed at 3 m intervals on the tunnel celling.

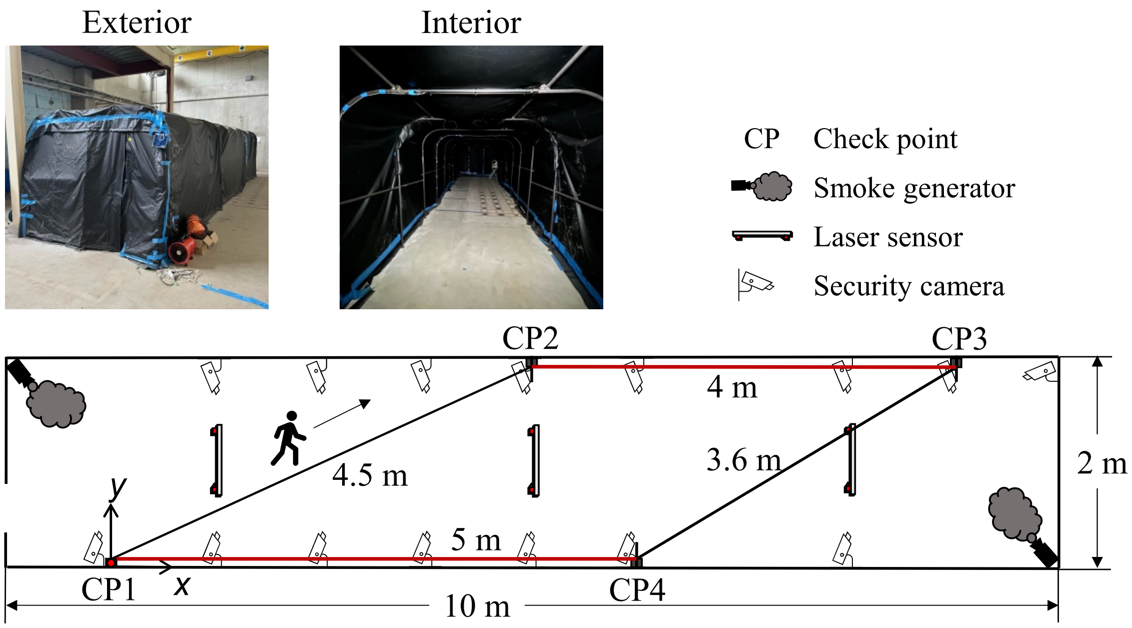


Figure 1: Model tunnel, evacuation route, and equipment

## 3.2. Methodology

Each participant evacuated a total of five times in different extinction coefficients (1st time: no smoke, 2nd to 5th times: light to dense). Walking speed was calculated by the evacuation time and distance, and extinction coefficient ($Cs$) was calculated using the following Lambert-Beer equation. We used the average value by the three measurements, for each route (from one CP to the next).

$$Cs = -\frac{1}{l}\ln\left(\frac{IL}{IL_0}\right)$$

where $IL_0$ is the incident light intensity (non-smoke), $IL$ is the intensity of light transmitted through the smoke, and $l$ is the distance traveled by the light through the smoke ($l$ = 0.8 m).

Before the evacuation, participants were provided with the following instructions: "A fire has occurred in the tunnel, and the space has become completely dark and filled with smoke. Please evacuate urgently (in Japanese)."

## 3.3. Participant

A total of 132 participants (91 males, age range: 20–64, mean age: 35.8; 41 females, age range: 20–63, mean age: 29) participated in the experiments. All the participants wore and used helmets, safety vests, masks, knee and elbow pads, small flashlights, and stopwatches.

### 3.4. Emotion definition

Proulx [14] proposed a stress model of decision-making in fires and mentioned that evacuees in a fire initially feel low-stress; subsequently, the emotion degree increases and transitions to stress, fear, worry (anxiety), and confusion. Based on this model, we focused on anxiety, fear, and stress, as same as Li et al. [12–13]. In addition, we defined as low-stress those that were excluded in anxiety, fear, or stress (see Table 2).

We defined the emotions using *HR*, standard deviation N-N interval (*SDNN*) (as one of the indicators of HRV), *SBP*, and *DBP*, by referring to the previous studies listed in Section 2.2 [4–9]. *HR* was recorded via a Wahoo Tickr WF124 heart rate monitor and *SDNN* was calculated from the standard deviation of *HR*. *SBP* and *DBP* were measured using an Omron HEM-6324T blood pressure monitor.

Table 2: Emotion definition in the present study

| Indicator | Description | Anxiety | Fear | Stress | Low-stress |
|---|---|---|---|---|---|
| *HR* change rate | Ratio of *HR* during / before the experiment | > 1 [4] | > 1 [6] | > 1 [8] | Others |
| *SDNN* difference | Difference of *SDNN* during – before the experiment | | | < 0 [9] | |
| *SBP* change rate | Ratio of *SBP* after / before the experiment | > 1 [4] | | | |
| *DBP* change rate | Ratio of *DBP* after / before the experiment | ≥ 1 [4–5] | < 1 [7] | | |

## 4. RESULTS

### 4.1. Walking speed vs. smoke by emotion

Figure 2 shows the results of walking speed vs. smoke density by emotion. To investigate the relationship between the walking speed and smoke density by emotion, we divided smoke

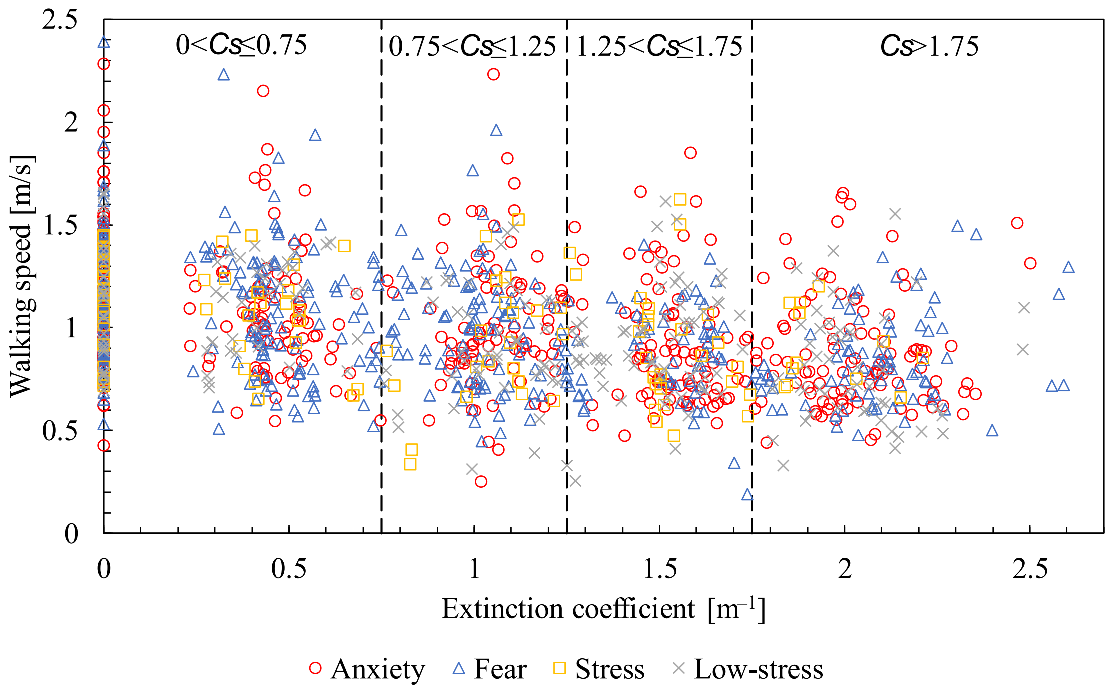


Figure 2: Walking speed vs. extinction coefficient by emotion

density into five ranges. Figure 3 displays the mean, maximum, and minimum walking speeds by emotions at each range. As smoke density increased, the mean walking speed decreased. The mean walking speed difference between the four emotions in five ranges were 0–0.10 m/s. The maximum and minimum walking speeds were always observed from anxiety and fear, but the maximum speed attenuation with smoke density increase in anxiety and fear was larger than in stress and low-stress.

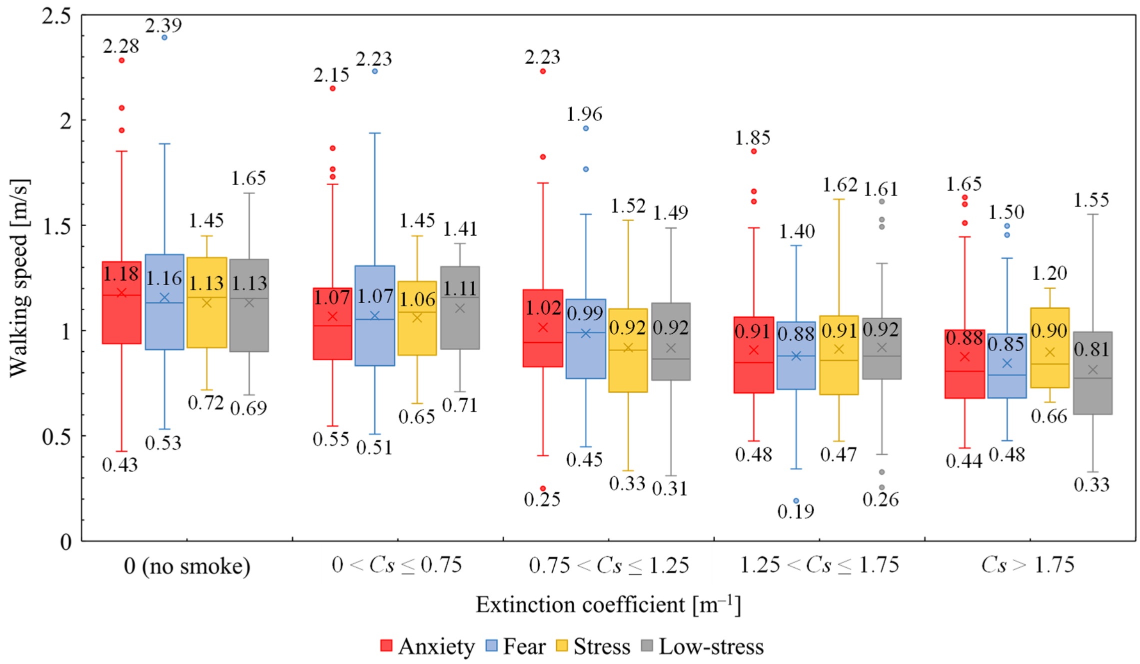


Figure 3: Mean, maximum, and minimum walking speeds at each smoke density range by emotion

## 4.2. Structural equation modeling

Applying the collected data to machine learning, we used Structural Equation Modeling (SEM) to investigate the causal relationship between emotions, physiological signal changes by emotions, and walking speed.

SEM comprises structural and measurement equations [15]. Structural equation analyzes the relationships between latent variables; measurement equation determines the impact of latent variables on the observed variables. In this study, we explored and verified the relationships between observed variables by regression equation.

The results are shown in Figure 4. GFI (Goodness of Fit Index, 0.870) and AGFI (Adjusted GFI, 0.725) indices showed that the model structure was acceptable.

**Hypothesis H1: Physiological signals impact walking speed**

The relationship between physiological signals and walking speed ($W$) considering smoke density ($Cs$) was calculated by the following regression equation.

$$G_{W,n} = \sum_{j} B_{j,W} \cdot Z_{j,n} + B_{Cs,W} \cdot Z_{Cs,n} + e$$

where $G$, $Z$, and $B$ are the observed dependent and independent variables and the parameter, in regression equation, respectively; $j \in$ {$HR$ change rate: 1, $SBP$ change rate: 2, $DBP$ change rate: 3, $SDNN$ difference: 4}; $n$ is the $n$th sample; and $e$ is the error term.

$B_{1,W}$ was 0.099 ($p < 0.001$) and accepted at the 0.1% level, while $B_{2,W}$ and $B_{4,W}$ were 0.057 ($p = 0.037$) and 0.059 ($p = 0.027$), respectively, and accepted at the 5% level. $B_{3,W}$ was –0.027 ($p = 0.320$) but the hypothesis was rejected based on the significance test.

**Hypothesis H2: Emotions impact on physiological signals**

The relationship between emotions and physiological signals was calculated by the following measurement equation.

$$F_{j,n} = \sum_i \Lambda_{i,j} \cdot \xi_{i,n} + e$$

where $F$, $\xi$, and $\Lambda$ are the observed dependent and latent exogenous variables and the parameter, in measurement equations; and $i \in$ {Low-stress: 1, Stress: 2, Fear: 3, Anxiety: 4}. The reference for emotion was set as low-stress.

**Anxiety (*i* = 4) impacts *HR* (*j* = 1), *SBP* (*j* = 2), and *DBP* (*j* = 3)**

Focusing on *HR*, *SBP*, and *DBP* in anxiety because of the definition in Table 2. $\Lambda_{4,1}$ (0.537), $\Lambda_{4,2}$ (0.437), and $\Lambda_{4,3}$ (0.277) were positive and accepted at the 0.1% level ($p < 0.001$). Hence, anxiety influenced *HR*, *SBP*, and *DBP* increase, which consistent with the previous studies' report [4–5], and had the largest impact on *HR* increase compared with fear and stress.

**Fear (*i* = 3) impacts *HR* and *DBP***

Focusing on *HR* and *DBP* in fear, $\Lambda_{3,1}$ (0.481) was positive and $\Lambda_{3,3}$ (–0.446) was negative and accepted at the 0.1% level ($p < 0.001$). Hence, fear influenced *HR* increase and *DBP* decrease, which consistent with the previous studies' report [6–7]. Schwartz et al. [7] reported that *HR* had increased approximately 10 bpm on average when imaging a fearful situation in a sitting condition. The mean *HR* increase in the present fear was 11.8 bpm, almost the same as Schwartz et al. [7].

**Stress (*i* = 2) impacts *HR* and *SDNN* (*j* = 4)**

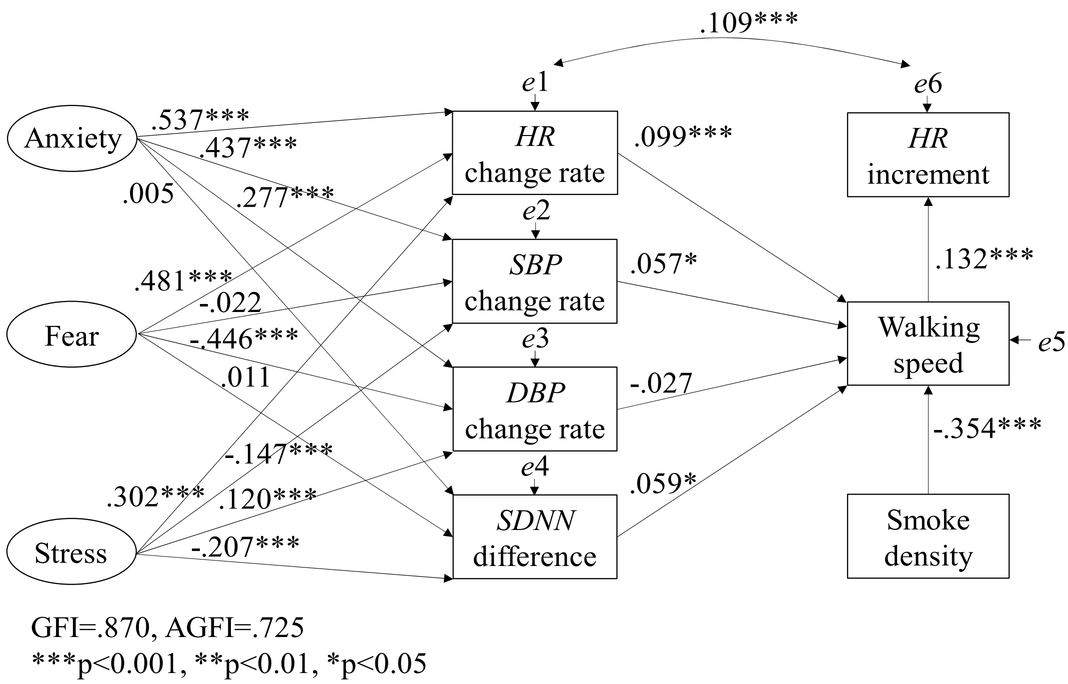


Figure 4: Standardized estimation results obtained through SEM

Focusing on *HR* and *SDNN* in stress, $\Lambda_{2,1}$ (0.302) was positive and $\Lambda_{2,4}$ (–0.207) was negative and accepted at the 0.1% level ($p < 0.001$). Hence, stress influenced *HR* increase and *SDNN* decrease, which consistent with the previous studies' report [8–9].

By combining the results of hypotheses H1 and H2, the indirect impacts from emotions on walking speed via physiological signals could be represented by $\Lambda_{i,j} \cdot B_{j,W}$. Therefore, anxiety increased walking speed via *HR* (0.053) and *SBP* (0.025) and decreased walking speed via *DBP* (–0.007), fear increased walking speed via *HR* (0.048) and *DBP* (0.012), and stress increased walking speed via *HR* (0.030) and decreased walking speed via *SDNN* (–0.012).

**Hypothesis H3: *HR* increase by emotion is larger than that by walking exercise**

To verify this hypothesis, we defined *HR* increment (*HRI*) as the walking exercise-induced *HR* increase. Here, *HRI* is the difference between the *HR* at the start CP (instantaneous value) and the mean *HR*, for each route. The influence of emotions on *HR* change rate ($\Lambda_{4,1}$, $\Lambda_{3,1}$, and $\Lambda_{2,1}$) was larger than the influence of walking speed on *HRI* ($B_{W,HRI}$ (0.132, $p < 0.001$)), consequently, hypothesis H3 was accepted.

## 5. DISCUSSION AND CONCLUSION

In this study, we conducted evacuation experiments using a model-scale tunnel filled with smoke, targeting a tunnel fire. The causal relationship between emotions, physiological signals, and walking speed was modeled and investigated by structural equation modeling with the aim of applying it to machine learning in the future. The results showed that *HR*, *SBP*, and *SDNN* influenced the walking speed to be faster, while *DBP* influenced the walking speed to be slower. And emotion-induced *HR* increase was larger than that induced by walking exercise. Hence, the next behavior might be able to predict from *HR* or *BP* via the present SEM and the optimal operational technical support or design decision to prevent the irrational behavior could be recommended.

Similar to the stress model of decision-making in fires proposed by Proulx [14], the present influence of emotions on *HR* were anxiety (0.537) > fear (0.481) > stress (0.302). As a future prospect, by setting the thresholds for increased *HR*, recognizing the emotion and predicting the next behavior might be possible. Accumulating and combining data such as physiological signals of evacuees recorded by their smartwatches and their evacuation behaviors from security cameras installed in tunnels, in actual tunnel fires, machine learning can be used to optimize the evacuation process and promote and help safe and rapid evacuation in the future.

The results of this study were obtained from evacuation experiments using a model-scale tunnel, further investigations such as full-scale tunnel experiments and further physiological signals such as LF/HF during an actual tunnel fire accident are needed in the future.

## 6. ACKNOWLEDGMENTS

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## 7. RESEARCH ETHICS

Ethical Committee for Epidemiology of Hiroshima University, E-2457.

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