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The impact of wildfire smoke on traffic evacuation dynamics

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ABSTRACT

This study investigates how reduced visibility due to wildfire smoke affects driving behaviour, specifically speed and headway, and the resulting implications for evacuation management and planning. Data were collected from participants immersed in a virtual environment through a driving simulator with a head-mounted display. Thirty-seven participants drove through scenarios simulating a rural highway. While driving visibility was systematically varied with virtual wildfire smoke. Participants were initially alone on the road to measure free-flow speeds and then proceeded to drive behind a convoy of cars. When visibility was low, driving speed was significantly reduced compared to the scenario with unrestricted visibility. Surprisingly, however, participants maintained similar distance headways in denser smoke compared to conditions with unrestricted visibility, suggesting that car-following behaviour was not affected. The collected data were used to develop a model that captures drivers' responses to reduced visibility due to smoke. The proposed model can be integrated into both macroscopic and microscopic traffic models, providing a tool for estimating evacuation times.

1. Introduction

Wildfires pose increasing health and safety challenges for communities in the wildland-urban interface (WUI) (Barros et al., 2023; Chen et al., 2024). For instance, the number and scale of wildfire-related community evacuations have increased continuously in the past decades around the world, e.g. in Canada (Christianson et al., 2024) or in the United States of America (Wong et al., 2020). The vast majority of evacuations rely on private vehicles (Wong et al., 2020; Zehra and Wong, 2024). Therefore, it is crucial to understand how environmental conditions can affect driving behaviour during a wildfire evacuation.

During wildfire evacuations, smoke from wildfires can travel miles ahead of the fire front (Goodrick et al., 2013). In some cases, the smoke can obscure the visibility along the evacuation routes. This puts populations near the wildfire at substantial risk during evacuation. In cases of rapid fire spread or delayed warning, communities may be forced to evacuate quickly and under dangerous conditions, such as heavy ember showers or reduced visibility due to smoke. The 2018 Camp Fire in the United States of America (Wong et al., 2020) and the 2018 Mati Fire in Greece (Kalogeropoulos et al., 2023) are examples in which smoke and poor visibility complicated the evacuation. Data on how these factors influence driving behaviour, and consequently, evacuation outcomes in wildfires, are unfortunately very scarce.

Previous studies have examined how to model traffic during an evacuation from a natural hazard using different methods, including geographical information systems tools or based on social network data, e.g., (Cova et al., 2024; Kim et al., 2021; Lindell and Prater, 2007; Pel et al., 2010; Sadri et al., 2017; Tamakloe et al., 2021; Ronchi et al., 2024). These data and tools can provide valuable insights into traffic dynamics. However, to the best of our knowledge, they are not tied to information on environmental conditions that can influence individual driving behaviour and aggregate traffic dynamics. For instance, precise data on visibility at the road level have rarely been reported.

Visibility often refers to the maximum distance at which an observer can perceive an object or scene (Yamada and Akizuki, 2016) and is, therefore, the result of interactions between the objects, the observer, the surroundings, the atmosphere and the light sources. Simple relationships have been established between the extinction coefficient K (which measures how a substance or medium attenuates or scatters light) and visibility as a distance, such as the inverse proportion by Jin (1978) and by Jin and Yamada (1985). Such relationships do not take into account the abovementioned interactions and are thus not

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universal. In this work, visibility conditions are studied by directly relating the smoke's extinction coefficient to the participants' driving behaviour. High extinction coefficients imply that the smoke absorbs and scatters the light as it passes through and interacts with the smoke particles and substances, leading to hazier conditions. Low extinction coefficients imply less interference.

Some studies have investigated the relationship between visibility conditions and walking speed (Akizuki et al., 2007; Frantzich and Nilsson, 2003; Fridolf et al., 2013; Jin, 1978; Ronchi et al., 2018). While most research concerns pedestrian walking speed, one study was found to relate fire smoke to driving speeds. In fact, Wetterberg et al. (2021) performed a virtual reality experiment and found that participants decreased their free-flow speed in reduced visibility conditions during a wildfire evacuation compared to conditions with optimal visibility. However, it is currently unclear how driving speeds are affected by reduced visibility when other traffic is present on the road and how related key variables for modelling purposes such as vehicle headways are impacted. Distance headway (the distance between a vehicle and the vehicle in front of it) is critical as it directly impacts traffic flows, network capacity and road safety. This research gap is relevant given that visibility conditions can significantly deteriorate during wildfires, potentially affecting the speeds evacuees can maintain.

As reliable real-world data on ground-level visibility and driving behaviour are virtually non-existent, controlled empirical studies in simulated environments may provide an opportunity to close this gap. Virtual reality driving simulators allow for the testing of behavioural hypotheses by comparing relative differences in results under safe and controlled conditions and thus offer a cost-efficient complementary tool to existing data collection approaches (Kinateder et al., 2014). Several studies have shown that virtual driving simulators can be a valid alternative to real driving experiments when measuring speed (Hartfiel and Stark, 2021), headways (Risto and Martens, 2014) and other driving behaviours, such as gap acceptance at intersections and roundabouts (Rossi et al., 2020). In the field of fire safety, studies have found similar pre-evacuation behaviours and route choice in both virtual reality and real experiments (Arias et al., 2022).

The present study sought to collect empirical data on how changes in visibility related to smoke influence driving behaviour. This driving behaviour is represented by the speed-density relationship (or equivalently the flow-density relationship) in macroscopic traffic simulations and follows from the car-following behavioural rules imposed on individual vehicles in microscopic traffic simulations. Representing the driving behaviour in the speed-density relationship or the behavioural rules is essential to assess evacuation times accurately (Wahlqvist et al., 2021) and to define precise trigger boundaries (Kalogeropoulos et al., 2023) through evacuation simulations. These simulations assist authorities in making well-informed decisions when planning and managing evacuations. The research team proposed the following hypotheses: when smoke is dense and visibility is poor, ….

1. participants who are alone on the road will drive slower (Wetterberg et al., 2021) and
2. participants who follow a vehicle ahead of themselves will keep a larger distance headway from that vehicle (Intini et al., 2022).

2. Methodology

2.1. Ethical aspects

The experiment was conducted in accordance with the Swedish Act (2003:460) on the ethical review of research involving humans. The study was approved by the Swedish Ethical Review Authority (dossier number 2023–04122-01). The study was pre-registered on *AsPredicted.org* (#162906), an online platform that allows researchers to pre-register their hypotheses, methods, and analysis plans before conducting their studies to increase transparency and reduce bias in scientific research.

2.2. Participants

A convenience sample of participants was recruited in Lund, Sweden. The experiment was advertised on accindi.se, an online platform for recruiting participants. Additionally, informational posters were distributed on the university campus and word-of-mouth advertising further promoted the study. As pre-registered, the sample size was limited to no more than 80 participants and data collection was scheduled to conclude by the end of June 2024. Eventually, 37 volunteers took part in the experiment, after it was confirmed that they met the following requirements:

- They were at least 18 years old.
- They had normal or corrected-to-normal vision.
- They had a driving license.
- They could communicate in English.
- They did not have a hearing aid incompatible with the over-the-ear headphones.
- They did not suffer from epilepsy.
- They did not suffer from severe motion sickness or car sickness.
- They did not suffer from migraines.
- They did not suffer from stress or anxiety-related disorders.
- They had never had a concussion before.

At the start of the experiment, participants signed an informed consent form and received a voucher worth 100 SEK (≈ 8.80 EUR). They were explicitly reminded that they could withdraw at any time without providing a reason. Participants cybersickness was monitored before the experiment (through a questionnaire), during the experiment (by a researcher) and after the experiment (through another questionnaire). The last questionnaire also included questions related to their experience in the simulator and demographics. All data were anonymised to ensure participant privacy.

2.3. Hardware configuration

The setup included the HTC Vive Pro 2 headset. The in-plane switching liquid crystal display screens with a combined resolution of 5 K (2448 × 2448 pixels per eye) offered a field of view of 120° (horizontally) and could operate at a refresh rate of 120 Hz. The Logitech G25 steering wheel and pedals were used for interaction within the virtual environment. These controls were mounted on a Playseat Sensation Pro. In addition, the steering wheel, seat, and seatbelt were sourced from a 1986 Honda Civic. This provided the participant with the feel of a real passenger car, rather than a race car. The cable of the head-mounted display was suspended with pullies to avoid restricting the participants' movements. Fig. 1 shows the setup.

The desktop computer powering the virtual reality system was equipped with an Intel Core i7-10700F CPU, operating at a base frequency of 2.90 GHz, with the capability to boost up to 4.8 GHz. This processor featured 8 cores and 16 logical processors and operated with a thermal design power of 65 W. The system included 32.0 GB of RAM, running at a speed of 3.2 GHz. The graphical performance was handled by an NVIDIA GeForce RTX 3080 graphics card. This card, built on the Ampere architecture, features 10 GB of GDDR6X VRAM and 8704 CUDA cores. It operated at a base clock speed of 1.44 GHz, with a boost clock speed of 1.71 GHz, and had a thermal design power of 320 W.

2.4. Software configuration

For this experiment, a dedicated virtual environment was developed in Unity 2021.3.22f1. Objects were designed in Blender and then imported into the game engine. Vehicle Physics Pro Community Edition (VPP) was used for modelling the player vehicle physics. This Unity asset

Fig. 1. Left: the hardware used for interaction with the virtual environment. Right: the virtual road and the virtual vehicle controlled by the participant. In this figure, the extinction factor K equals 0.05 m^{-1}.

managed driving and physics logic, including steering, braking, tyre friction, and engine parameters. The participant drove a pick-up truck included in this package. All vehicle settings were set to the default settings, except for the height of the mass (which was moved from 0.6 m to 0.3 m to make the vehicle more stable) and the gear shifting time (which was decreased to 0 s to prevent shift shocks). The vehicle is shown in Fig. 1 (exterior) and Fig. 2 (interior, participants perspective). The position of the virtual camera rig in the simulation was fixed to the driver's seat. Moreover, spin (rotation along the vertical axis) was fixed, ensuring the participant always looked out the front. However, tilt and roll were not fixed to reduce cybersickness and provide a more realistic experience: this design mimicked the natural compensatory movements of the hips, back, and neck muscles during driving.

The road was designed as a Swedish country road, with dimensions, markings and equipment (traffic signs and road poles) per the requirements for road and street design set by the Swedish Traffic Authority (Krav – VGU, 2022). The road was an undivided single-carriageway two-lane road with a width of 7.0 m (3.5 m per lane). The shoulders were 1.5 m wide (0.5 m continued asphalt and 1.0 m gravel). The total width of the open field of view, which included the lanes, shoulders, and grass verges, was approximately 14.5 m.

When driving in the virtual environment, the road was built procedurally, which means that the road never ended. In practice, the road consisted of four tiles, each 500 m long in the z-direction. The participant started at the start of the second tile. When they reached the third tile, the first disappeared and a fifth was generated. For each tile, the shape was defined by a "road sway", as indicated in Fig. 3. For each tile, a random road sway was chosen between 30 m and 100 m (leading to a

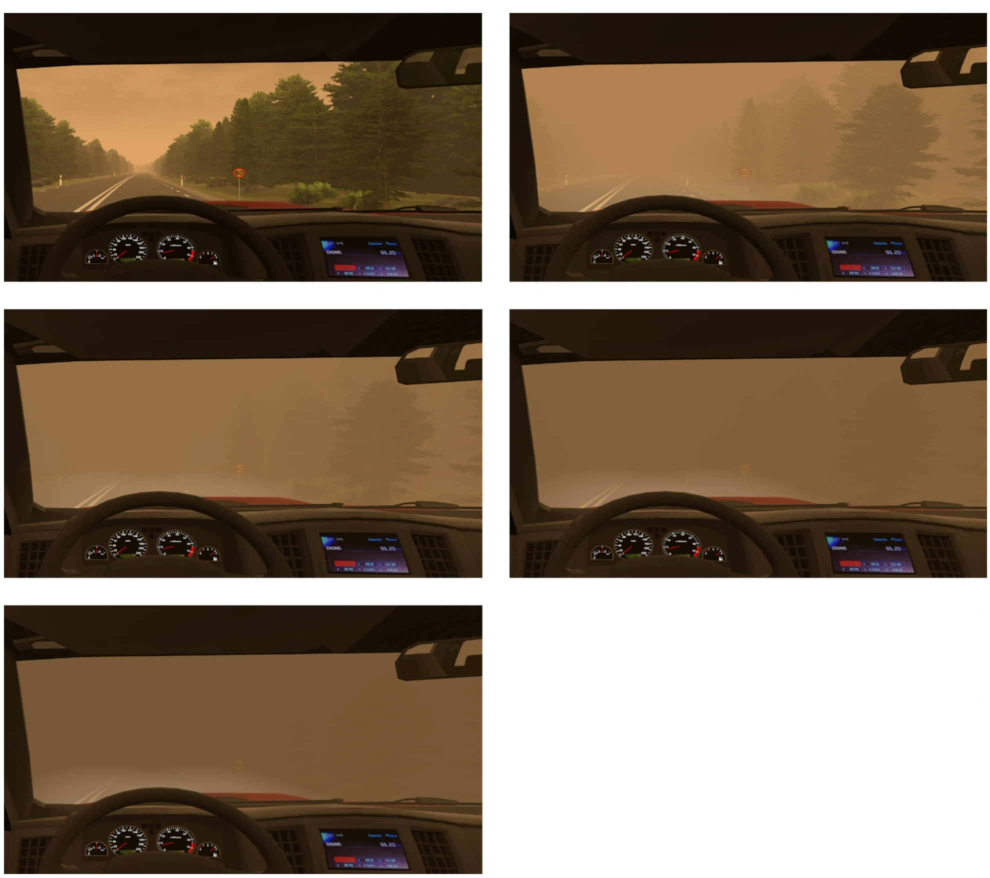

Fig. 2. Participants' view on the road for the five different smoke levels (arranged in reading order: $K = 0.003$, 0.05, 0.10, 0.15 and 0.20 m^{-1}).

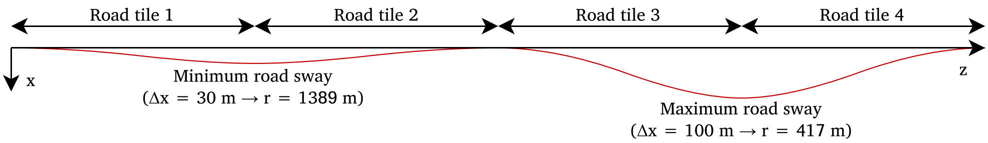

Fig. 3. Schematic presentation of the road tiles adopted in the roadway for the experiment.

turning curvature radius of 417 m to 1389 m). These turns obscured the horizon from the participants' view so that only 700 m of road needed to be rendered. To build the tiles, the Unity package "Dreamteck Splines" was used.

Special care was taken to create all game object meshes with low polygon counts and to avoid computationally heavy high-definition textures for objects further from the participants. These measures enabled the head-mounted display to refresh at a rate of 120 Hz (with a frame loading time of about 5.8 ms, well below the 8.33 ms available at 120 Hz). This high refresh rate was chosen to reduce discomfort and cybersickness.

The participants were not explicitly instructed to obey the traffic rules. They only received the instruction *"Please drive as you would in real life"*. A speed limit sign indicated the speed limit of 80 km/h every 2 km. Moreover, the following three measures were taken to discourage participants from overtaking (as it is not possible to study the participants' following behaviour after they have overtaken the vehicles in front of them): (1) The road was marked with a double solid line and traffic signs (repeated every 2 km) indicated that overtaking was not allowed. (2) A convoy of six lead vehicles was simulated, which was meant to convince the participants that they were part of a longer traffic jam, and that overtaking was futile. (3) Oncoming traffic passed randomly (every 2 to 5 min) to increase the participants' perception of the risk of collision when overtaking.

Implementing realistic fog or smoke light physics in real-time visualizations in Unity is challenging due to the computational costs involved in simulating complex light interactions, such as multiple scattering and volumetric effects (Wahlqvist and Rubini, 2023). Achieving accurate visuals for scattering, absorption, and emission of light within a dynamic, three-dimensional fog or smoke environment demands sophisticated calculations that may exceed the real-time processing capabilities of current hardware. Therefore, the fog and smoke were rendered using Unity's built-in fog function, which is applied post-process. Unity's fog function applies an interpolation between the "true colour values" and the colour of the smoke. The interpolation was set to exponential, equivalent to real light attenuation (the Beer-Lambert law). The built-in fog function processes rapidly and is commonly used by game developers and fire safety researchers (Davis et al., 2023; Wetterberg et al., 2021; Ronchi et al., 2024).

Unity fog does not simulate the interaction of light with the atmosphere or the environment. However, some efforts were made to counter the shortcomings of this implementation (Fig. 3 shows the simulated smoke from the participant's perspective). The colour of the smoke was derived from the assumed colour of sunlight (RGB: 240, 185, 120). Smoke typically absorbs the light of different wavelengths differently; the smoke colour was derived assuming the normalised mass-specific absorption of 1, 1.30 and 1.60 for the colour channels red, green and blue, leading to the smoke RGB colour 207, 152, 94. Due to the smoke above the road, less sunlight reached the player. The sunlight was manually dimmed by multiplying the light intensity by the factor e^{-10K}, where K is the extinction coefficient expressed in m^{-1}. This means that the direct sunlight was dimmed by a smoke layer equivalent to a homogenous layer of smoke with a thickness of 10 m. 40 % of this light was assumed to be scattered rather than absorbed and was therefore added to the ambient light. The exact ratio between absorption and scattering of real smoke depends on its composition: pure water vapour scatters light almost perfectly, while very sooty fuels produce almost perfectly absorbing smoke. The colour of the smoke was used as the colour of the direct sunlight and the ambient light. The same colour was used for the skybox, which lost its contrast as the smoke level increased (transitioning from a cloud texture to a plain smoke colour). Shadows were artistically reduced with increasing smoke levels (decreasing direct sunlight and increasing scattered light). Adjustments were also made to the standard shader (written in Microsoft's High-Level Shader Language HLSL and Unity's ShaderLab syntax) to prevent smoke from arising within the participant's vehicle. Unity's fog uses depth texture to assess the distance between the pixels and the camera and then interpolates between the pixel and smoke colour. However, these distances are only measured in the camera's forward direction. They are therefore inaccurate at the periphery of the image, especially for head-mounted displays with a large field of view, such as the HTC Vive Pro 2. To solve this issue, the rendering pipeline of Unity (written in Cg, a modified version of the High-Level Shader Language HLSL) was adjusted to calculate the depth based on the actual distance from the camera origin.

During pilot testing, the participants mentioned that the silence in the car was somewhat uncomfortable, and that, in real life, they would turn on the radio to get more information about the wildfire. Therefore, a radio excerpt from *Sveriges Radio* (the Swedish public radio broadcaster) played in the background. The excerpt dates from Friday the 20th of July 2018, 10:00 am and reported on the ongoing wildfires and evacuations all over Sweden. It did not provide any instructions. However, it did mention to look out for fleeing deer and other forest animals. All vehicles were equipped with engine sounds and tyre sounds.

2.5. Experimental procedure

The participants went through eight stages between arriving at the experiment and leaving. Fig. 4 illustrates the procedure. The entire procedure took about one hour for one participant.

Welcome: On arrival, participants were greeted and thanked for their interest in participating. A researcher gave an overview of the experiment.

Informed consent: Participants received detailed information about the experiment and were given the opportunity to ask questions. Participants then signed an informed consent form, indicating their voluntary participation and understanding of their rights. Participants then received a voucher of 100 SEK (≈ 8.80 EUR).

Questionnaire: Participants completed the Virtual Reality Sickness Questionnaire, developed by (Kim et al., 2018), to collect baseline data on their cybersickness symptoms. The sickness score of the experiment is then calculated from the changes in symptoms during the experiment.

Practice trial: After filling out the questionnaire, the participants were invited to sit down in the driving simulator. The car seat was adjusted (both by the distance from the wheel and the angle of the backrest) to the participant's comfort and the seat belt was fastened. The participants were introduced to the pedals, the steering wheel and the head-mounted display. The researcher ensured the display was correctly fitted by adjusting the fasteners and lens distances to match the participants' interpupillary distances. This adjustment was important to ensure optimal visual clarity and comfort and enhanced the overall experience. The participants were then asked to do a test drive to become familiar with the controls. They were instructed to drive as they would in real life: *"It is important to remember that this is not a* video *game, but a driving simulator. Please drive as you would in real life."*.

During this practice trial, a convoy of six vehicles (starting 300 m ahead of the participant) drove at 50 km/h. No smoke was present in the

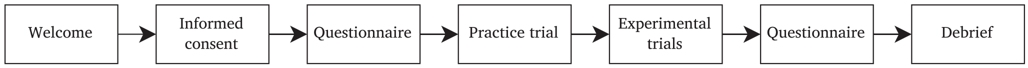

Fig. 4. Illustration of the experimental procedure in eight stages.

practice trial. One speaker of the head-mounted display was left open to enable the researcher and participant to communicate with each other. The participants were asked to continue until they felt comfortable with the controls.

Experimental trials: The participants received the scenario description, which was read out loud by the researcher: *"During a severe summer drought, Sweden has been hit by several large forest fires. Although firefighters are working day and night to extinguish the fires, many of these fires are still spreading. Some of them pose an immediate threat to life safety as they are spreading towards places where people live. The Swedish authorities have therefore decided that mandatory evacuations are necessary. You are currently close to a forest fire and have been ordered to evacuate to a safe place. You just need to follow the road to get there."*

Next, the participants went through five trials. All trials had an identical structure, but the smoke level differed in each scenario, with Unity smoke densities (equivalent to the extinction coefficient) varying between $K = 0.003$, 0.05, 0.10, 0.15 and 0.20 m^{-1}. These five trials can be ordered in 120 different ways (permutations). These permutations were randomised so that each participant completed the trials in a unique, random order. During each trial, the participants progressed through twelve phases (illustrated in Fig. 5):

1. Idling: The participant started in the idling vehicle on an empty road. This phase ended when the participant drove five metres.
2. Building up free-flow speed: The participant had time to speed up to their desired free-flow speed. This phase ended when the participant had driven one hundred metres and (125–250 K) seconds had passed, with K the extinction coefficient in m^{-1} (for example, 75 s for scenarios in which K equals 0.20 m^{-1}).
3. Measuring free-flow speed: For 30 s, the participants' desired free-flow speed was measured.
4. Inserting the leading vehicles: Next, a convoy of six passenger cars (leading vehicles) was inserted in the simulation, out of sight for the participant. The insertion distance was largest for the scenario without smoke (660 m) and shortest for the most dense smoke (34 m). The leading vehicles drove at a speed equal to 80 % of the free-flow speed, measured at Phase 3. The duration of this phase was set so that the participant had twenty seconds to establish a stable headway after catching up with the leading vehicle, assuming they maintained the speed measured in the previous phase.
5. Measuring headway at 80 % of the free-flow speed: For 30 s, the participants' distance headway was measured.
6. Slowing down the leading vehicles to 60 % of the free-flow speed: Next, the leading vehicles slowed down at a deceleration of 0.1 m/s, until they reached a speed that equalled 60 % of the participants' free-flow speed. Afterwards, this phase took twenty more seconds to allow the participants to establish a stable distance headway.
7. Measuring headway at 60 % of the free-flow speed: For 30 s, the participants' distance headway was measured.
8. Slowing down the leading vehicles to 40 % of the free-flow speed: This phase is similar to Phase 6.
9. Measuring headway at 40 % of the free-flow speed: For 30 s, the participants' distance headway was measured.
10. Slowing down the leading vehicles to 20 % of the free-flow speed: This phase is similar to Phase 6 and Phase 8.
11. Measuring headway at 20 % of the free-flow speed: For 30 s, the participants' distance headway was measured.
12. Finish: A message appeared on the screen that the scenario had ended. *"Thank you. You can now take off the headset."*

The fixed order of phases was chosen to address two key considerations. First, it ensured that the leading vehicle always travelled at speeds slower than the participant's free-flow speed and avoided situations in which the participant did not follow, as observed in previous studies (Broughton et al., 2007; Ronchi et al., 2024). Second, the decreasing speed sequence mirrored a natural scenario in which drivers encounter the end of a slowing traffic queue.

The duration of one trial depended on the smoke density (in dense smoke, the leading vehicles were inserted closer to the participants) and the free-flow speed (at high speeds, the leading vehicles took longer to slow down). Eventually, the average trial duration (from the start of the second phase till the twelfth phase) was about seven minutes. Between the trials, the researcher checked up on the participants' possible symptoms of cybersickness. They were invited to take short breaks between the scenarios and were offered a glass of water.

Questionnaire: After finishing the experimental trials, participants completed a post-experiment questionnaire. First, they filled out questions identical to those in the pre-experiment questionnaire: the Virtual Reality Sickness Questionnaire (Kim et al., 2018). Next, they were asked to reflect on their experience and driving behaviour. Last, the questionnaire gathered demographic information.

Debrief: The procedure concluded with a debriefing session. During this final step, the experimenter explained the purpose and expected outcomes of the experiment to the participants. Participants were also given the opportunity to ask questions and provide feedback on their experience, ensuring that they left the study with a clear understanding of its aims and their role in it. Lastly, they were thanked for participating and guided out of the lab.

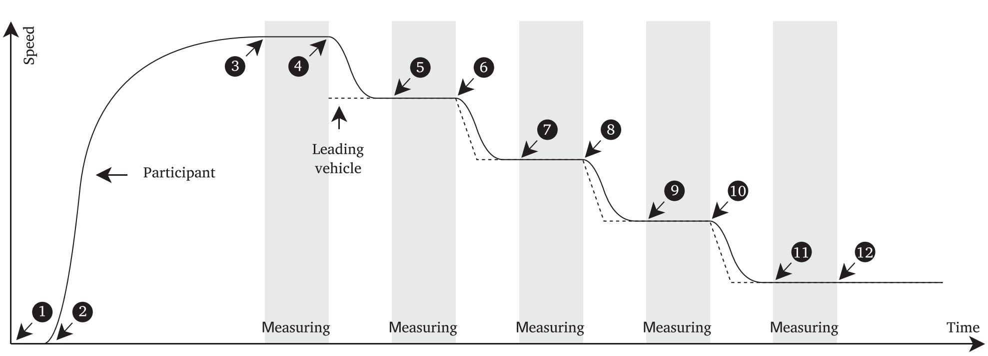

Fig. 5. Schematic representation of the vehicle speeds during a trial. The numbers represent the phases of the trial.

2.6. Data analysis and model calibration

Macroscopic traffic models describe the traffic dynamics of uninterrupted roads in terms of three aggregate variables: the traffic density k (veh/km/lane), the vehicle speed v (km/h) and the traffic flow q (veh/h/lane). The speed-density relationship (or its equivalent, the flow-density relationship) is an essential part of macroscopic traffic models. Many relationships exist. Here, the model by Daganzo (1994) was used (see Eqn 1), as it is a popular model that has been previously successfully fitted to evacuation data (Rohaert et al., 2023, Rohaert et al., 2022). The model consists of two regimes: a free-flow regime, in which drivers can drive at their desired (free-flow) speed, and a congested regime, in which drivers follow slower vehicles ahead whilst maintaining a safe distance.

$$v = \min\left(v_f, v_f \frac{\frac{1}{k_j} - \frac{1}{k}}{\frac{1}{k_c} - \frac{1}{k_j}}\right) = \min\left(v_f, v_f \frac{h_j - h}{h_c - h_j}\right) \quad [1]$$

where v is the vehicle speed, k is the traffic density and h is the distance headway, which is the inverse of the traffic density. The subscript f denotes free-flow conditions, c denotes critical conditions (when the flow is at peak capacity) and j denotes completely jammed traffic (total congestion).

Microscopic traffic models simulate the behaviour of individual vehicles on the road, focusing on the detailed interactions between them rather than using aggregate measures like speed and density. Instead of relying on a speed-density relationship, microscopic models generally use car-following models to obtain the speed of vehicles, as a function of headway. Under steady-state conditions, these car-following models become equivalent to speed-density relationships. In other words: speed-density relationships are not imposed but emerge from the rules individual vehicles use to follow leading vehicles. For instance, the car-following model (Krauss, 1998) used in the microscopic traffic model “Simulation of Urban Mobility”, better known as SUMO (Alvarez Lopez et al., 2018), is equivalent to the model by Daganzo (1994) when steady-state conditions are met (see Eqn 2).

$$v = \min\left(v_f, v_f \frac{h - h_j}{h_c - h_j}\right) = \min\left(v_f, \frac{h - h_j}{\tau}\right) \rightarrow \tau = \frac{h_c - h_j}{v_f} \quad [2]$$

For the virtual road of this experiment, the parameters can be estimated from the design values proposed in the Highway Capacity Manual (Dowling et al., 2016; Elefteriadou and Transportation Research Board, 2016). This leads to an estimated free-flow speed v_f of 88.5 km/h, a critical density k_c of 18.2 veh/km/lane and therefore a critical headway h_c of 55.0 m, a jam density k_j of 118 veh/km/lane and therefore a jam headway h_j of 8.47 m. The drivers’ desired minimum time gap τ is therefore 2.35 s.

To investigate how the speed-density relationship is affected by the smoke level, five data points were measured for each participant at each smoke level: the participant’s free-flow speed and the distance headway at four different speeds (80 %, 60 %, 40 % and 20 % of the free-flow speed of the participant). The free-flow speeds occurred at a zero traffic density and therefore have an infinite headway. Consequently, the free-flow regime results from the average free-flow speed and the car-following regime results from a linear fit to the headway-speed data. The relationship between speed, headway and extinction was fitted using mixed effects models, as the data points were dependent (multiple data points for each participant). The optimal parameters of the models were found by employing the Hastings-Metropolis algorithm (Comets et al., 2017), as implemented in the R package SAEMIX. In SAEMIX, the algorithm optimises the likelihood function of the nonlinear mixed-effects model.

3. Results

In total, 37 participants took part in the experiment. One participant experienced technical issues (loss of video signal due to poorly connected cables). Two participants experienced cybersickness and chose to terminate the experiment after two trials. Four participants had issues controlling the driving simulator; they unintentionally collided with the other vehicles and/or left the roadway. It is the researchers’ interpretation that this was due to the high velocity (up to 150 km/h) they were driving at, issues finding the pedals and – in one case – insufficient driving experience. All data presented below excluded these seven participants: the remaining thirty participants were considered in the analysis. On average, the thirty participants were immersed in the virtual environment for 34 min and 48 s each. This duration does not include the practice trial.

3.1. Sample demographics

The bar charts in Fig. 6 show the demographics of the thirty participants. Of all participants, 53 % identified as a man and 47 % as a woman. On average, participants were 34 years old and obtained their driving license 15 years before participating. Five participants reported not being used to driving in Sweden: they were most used to driving in Belgium (2x), the Netherlands, Hungary and the United States of America. Participants were also asked how prudently/aggressively they drive by comparing their speed and overtaking with other drivers. As shown in Fig. 7, participants reported maintaining similar speeds as others and overtaking as often as others. Fig. 8 shows how frequently participants drive and game. Most participants (70 %) indicated driving regularly – a few days a month or more often. Almost half of all participants (47 %) play video games a few days a month or more often, while only one participant (3 %) uses virtual reality a few days a month.

3.2. Cybersickness

Cybersickness was assessed using the virtual reality sickness questionnaire developed by (Kim et al., 2018). Fig. 9 shows the cybersickness score of the experiment. The average sickness score increased by 11.6 % (from 2.7 % before the immersion to 14.2 % after). The average oculomotor symptoms increased by 13.3 % and the symptoms of disorientation increased by 9.8 %. The increase can be partly explained by the duration the participants were immersed in the environment: on average immersion lasted 34 min and 48 s (with a standard deviation of 18 s). Despite the increased cybersickness score, it should be noted that only two participants out of thirty-seven (5.4 %) terminated the experiment due to sickness.

3.3. Free-flow speed

The participants’ free-flow speeds were measured during Phase 3 of each trial (see Section 2.5). The results are presented in Fig. 10 along with the only previous study of this kind by Wetterberg et al. (2021). Means and sample standard deviations are presented in Table 1. From Fig. 10 and Table 1, it is clear that the extinction coefficient has a noticeable effect on the free-flow speed, suggesting a monotonic decrease in speed with visibility. The statistical relevance can be shown by a “repeated-measures analysis of variance test” using least-squares regression ($p = 3.32E^{-25} < 0.05 \rightarrow$ statistical significance). Neither the normality nor the sphericity assumptions of the test appear to be violated (Shapiro-Wilk test: $p = 0.191 > 0.05$, Mauchly’s Test: $p = 0.172 > 0.05$).

The results by Wetterberg et al. (2021) show a trend to the results of this study: participants drive slower when smoke causes reduced visibility. However, in the study performed by Wetterberg et al. (2021), the speed reduction is greater than in this study. Three different monotone functions were fitted to the relative free-flow speed: a linear function, a

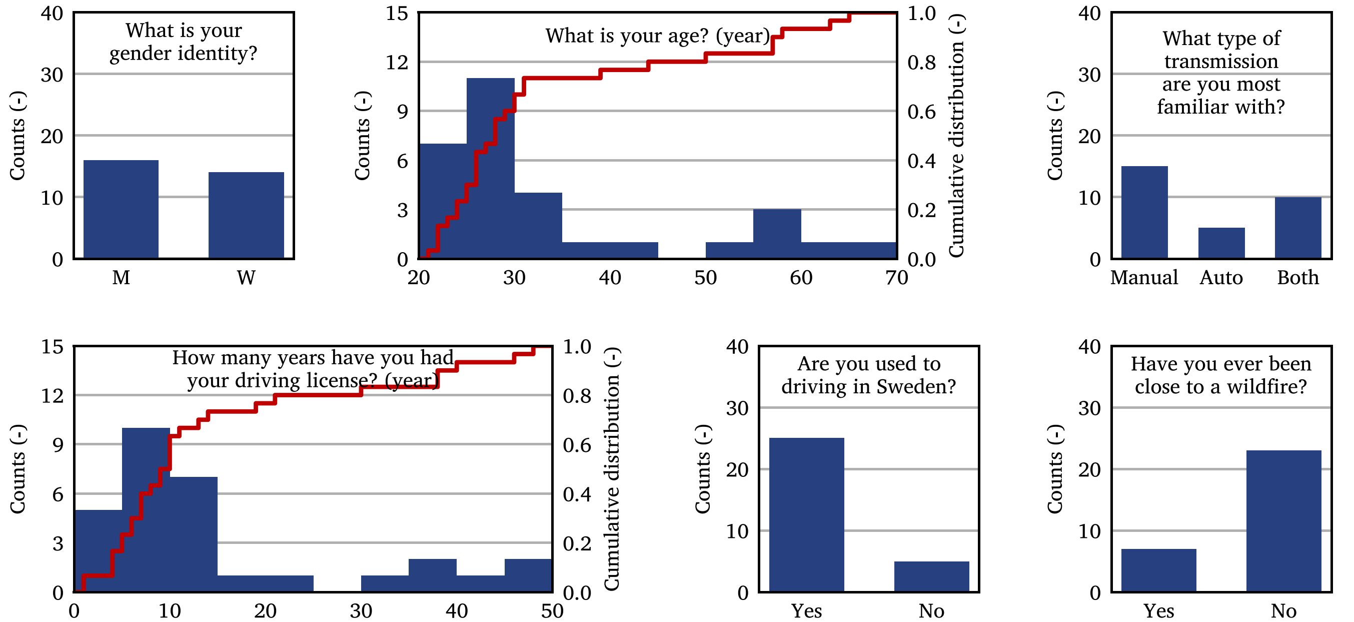

Fig. 6. Demographics of the participant sample. The histograms "What is your age?" and "How many years have you had your driving license?" also provide the empirical cumulative distribution (see the red curves). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

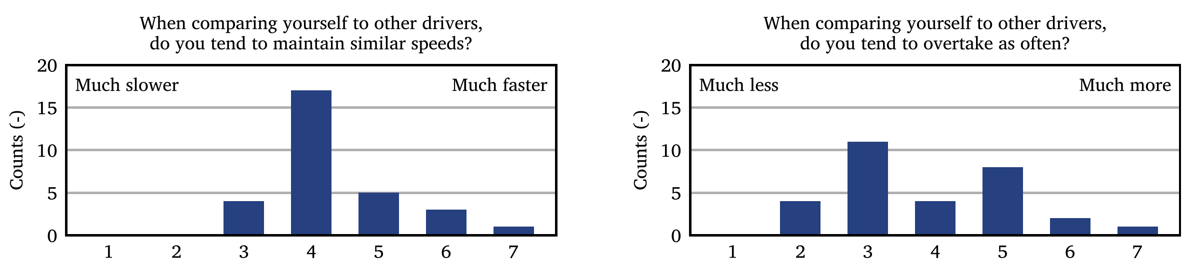

Fig. 7. Self-reported driving behaviour.

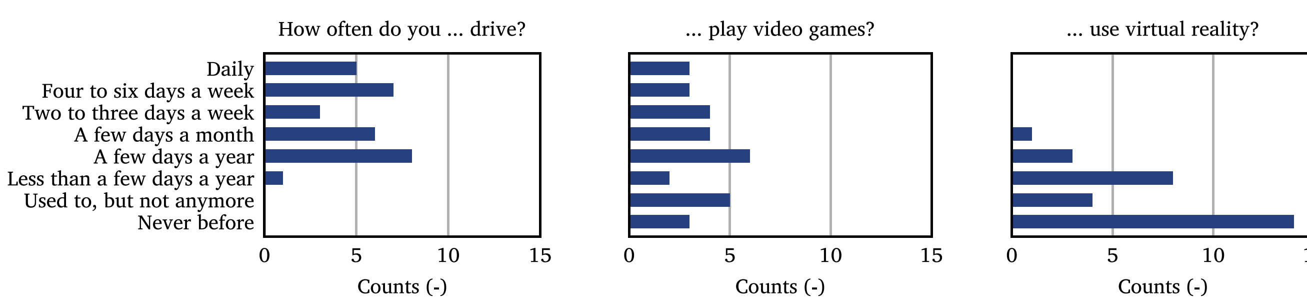

Fig. 8. Frequency at which participants drive, play video games, and use virtual reality.

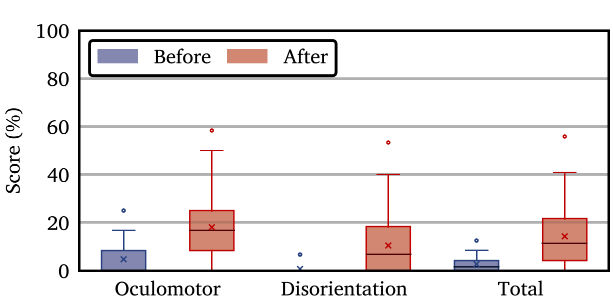

Fig. 9. Cybersickness score before and after the study.

power function and an exponential reciprocal function (see Table 2). Since the data points are not independent, with each participant being measured five times, a stochastic approximation expectation–maximization (SAEM) algorithm was employed to estimate the parameters in a mixed-effects model. Specifically, the Hastings-Metropolis algorithm was used, as implemented in R (Comets et al., 2017). The models include fixed effects to capture the population estimates of parameters c_1 and c_2 and the random effects on these parameters that capture the individual differences between participants. After optimising the parameters, the exponential reciprocal function has the lowest mean error on the prediction and fits best to the data. The function has been presented graphically in Fig. 11. Details on the fixed, random and residual effects are available in Appendix A.

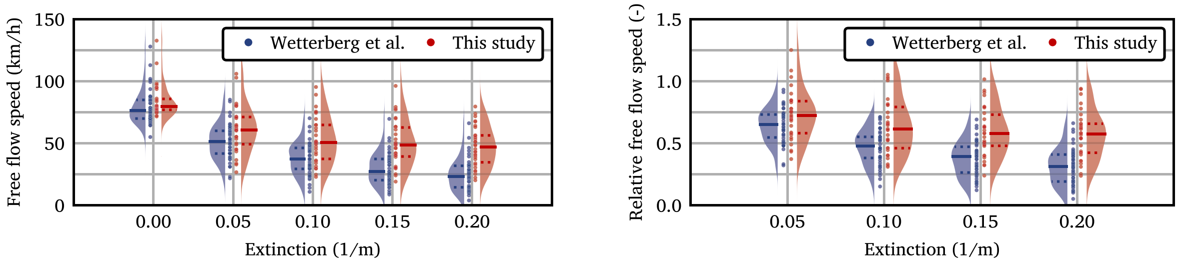

Fig. 10. Participants' free-flow speeds in the function of the smoke density (light extinction). The graph on the left shows absolute speeds, while the graph on the right shows speeds relative to the free-flow speed of the same participant during the no-smoke trial. The data in blue is obtained by Wetterberg et al. (2021), the data in red is obtained in this study. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
The means and sample standards deviation on the free-flow speed.

Extinction coefficient (m^{-1})	Mean (km/h)	Standard deviation (km/h)
0.003	84.0	13.2
0.050	61.1	18.8
0.100	52.8	19.1
0.150	49.8	18.7
0.200	47.0	16.2

For this study, the best fit exponential reciprocal regression is given by Eq. 3. Eq. 4 fits best to the data obtained by Wetterberg et al. (2021).

$$\overline{v}_f = 1 - 0.4967e^{-0.02910/K} \quad [3]$$

$$\overline{v}_f = 1 - 0.8619e^{-0.04786/K} \quad [4]$$

The free-flow speed from the no-smoke trials can be compared with the design value according to the Highway Capacity Manual (Elefteriadou and Transportation Research Board, 2016). The manual states that rough estimates of the free-flow speed can be made by adding 16 km/h to the speed limit. After applying a correction for the road geometry, this rough estimate equals 88.5 km/h, which is only 5.4 % higher than the observed speed (84.0 km/h). No statistically significant difference was found using a one-sample student's *t*-test ($p = 0.0725 > 0.05$). The Shapiro-Wilk test did not suggest a violation of the normality assumption of the *t*-test ($p = 0.338 > 0.05$).

3.4. Overtaking

Overtaking was not allowed on the road in the virtual environment (indicated by the double solid lines and the traffic signs). However, six participants overtook in a total of ten trials: six participants overtook once, and one participant overtook in four out of five trials. Six out of these seven participants overtook during the trial without smoke and six out of seven waited until the last (and slowest phase). This may indicate that participants are less comfortable overtaking when the visibility is poor and traffic is fast. Note that these observations are anecdotal and should be interpreted with caution. Although similar behaviour has been reported during real fires, despite traffic regulations (Carton et al., 2024), it remains unclear whether the participants in this virtual study shared the same motivations as evacuees or were simply bored, frustrated, or curious to explore the limits of the simulation.

3.5. Distance headway

Distance headway was measured at four different speeds during each trial, so there could be 600 data points (15 participants x 5 smoke levels x 4 speed levels). However, only 583 data points were gathered as headway could not be measured when participants overtook the leading vehicles. For every headway measurement, the corresponding driving speed was recorded. Fig. 12 illustrates this relationship through scatterplots, with each smoke level indicated in another colour. A linear curve was fitted to the headway speed data. This linear curve is the car-following regime of the model by Daganzo (1994), and the emergent steady-state relationship between headway and speed of the car-following model by Krauss (1998). A stochastic approximation expectation–maximization algorithm was employed to estimate the parameters in a mixed-effects model. The models include fixed effects to capture the population estimates of the jam headway and minimum time gap and the random effects on these parameters that capture the individual differences between participants. The optimised parameters are presented in Table 3 The negative two times the log-likelihood (−2LL), the

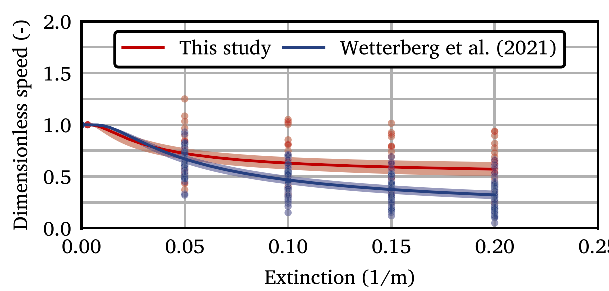

Fig. 11. Relative free-flow speed as an exponential reciprocal function of the extinction coefficient. The bands represent the 95% confidence interval of the data fit and are obtained from a Monte-Carlo simulation that employs the covariance reported in Table 2.

Table 2
Relationships of the free-flow speed $\overline{v}_f$ (−) and the extinction coefficient K (m^{-1}) fit to the data. All functions are chosen so that the relative speed is 1 for K equal to 0 m^{-1}. The negative two times the log-likelihood (−2LL), the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are computed by importance sampling. Lower values of these quantities indicate a better model.

Function	Parameter	Value	Covariance	−2LL	AIC	BIC
Linear $\overline{v}_f = 1 - c_1K$	c_1	2.664 E^{-0}	4.498 E^{-2}	−87.6	−81.6	−77.4
Power	c_1	1.051 E^{-0}	1.647 E^{-2} 4.398 E^{-3}	−154.6	−144.6	−137.6
$\overline{v}_f = 1 - c_1K^{c_2}$	c_2	4.950 E^{-1}	4.398 E^{-3} 2.093 E^{-3}			
Exponential reciprocal	c_1	4.967 E^{-1}	2.011 E^{-3} 9.136 E^{-5}	−185.1	−175.1	−168.1
$\overline{v}_f = 1 - c_1e^{-c_2/K}$	c_2	2.910 E^{-2}	9.136 E^{-5} 2.492 E^{-5}			

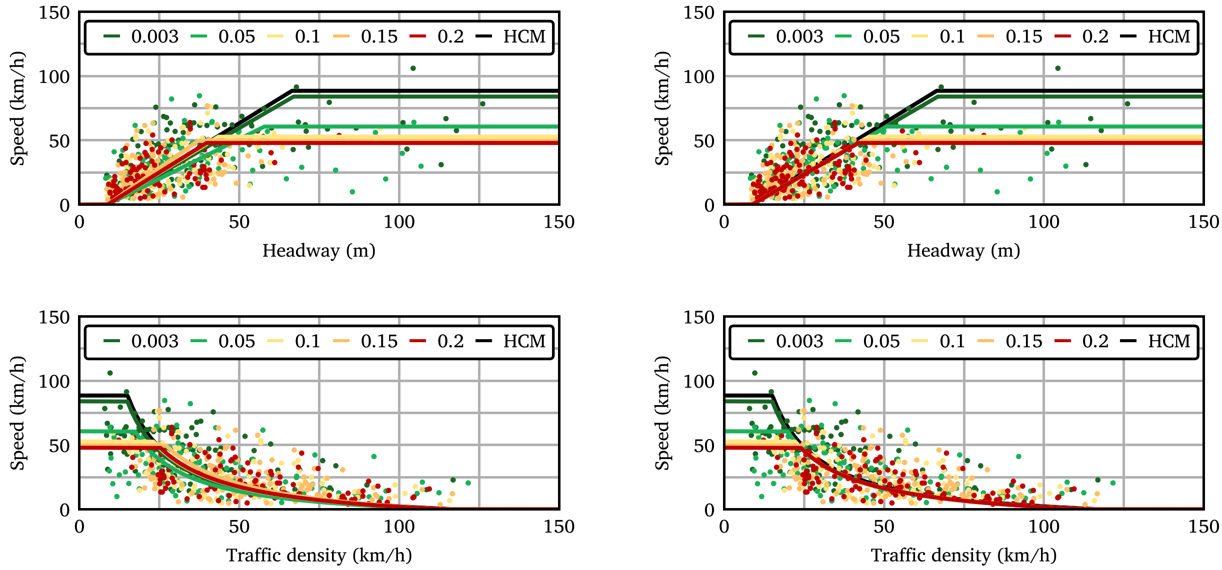

Fig. 12. Left: Steady-state relationship of the car-following model by Krauss (1998), equivalent to the speed density relationship by Daganzo (1994) fitted to the experimental data for each scenario separately. Right: Proposed speed headway and speed density curves for evacuation time simulations. The black curve corresponds to the curve derived from the estimated parameters proposed in the Highway Capacity Manual (Dowling et al., 2016; Elefteriadou and Transportation Research Board, 2016). The legend indicates the smoke level by the extinction coefficient (m^{-1}).

Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are computed by importance sampling. Details on the fixed, random and residual effects are available in Appendix A. The curves are also visualised in Fig. 12. It is reasonable to assume that drivers will leave the same gap between their vehicles when traffic is entirely jammed, regardless of the smoke level. Therefore, the parameters of all five linear fits were optimised simultaneously with separate minimum time gap (τ), but one jam headway (h_j). The car-following regime was joined with the free-flow regime, discussed earlier, to establish the entire model (Fig. 12).

Fig. 12 reveals that, when other vehicles are inserted into the virtual environment, the participants prefer to keep a shorter distance from the vehicles in front of them when the smoke is denser. An explanation for this behaviour might be that participants like to use the leading vehicles as a guide to position themselves on the road. This hypothesis is supported by the responses to the questionnaire (see below). This means that when the traffic is dense (and drivers are following the vehicles in front of them), the evacuation times might be shorter when smoke obscures the visibility of the road. Note, however, that this is not a monotonic trend. Fig. 13 visualises the distribution of the different minimum time gaps τ. Lower values translate to shorter distance headways.

The figure illustrates that the minimum time gap (and therefore the car-following behaviour) does not vary monotonically with the extinction coefficient. The overlapping distributions indicate a central trend: the car-following behaviour does not depend on the extinction coefficient. For this reason, we propose a conservative model for evacuation time simulations, which does not consider the possible "efficiency gains" in the car-following regime (Fig. 12). Instead, the car-following regime of the model is not affected by the smoke level. The vehicle speeds in the free-flow regime decrease according to the exponential reciprocal function (Fig. 11). To formulate this model mathematically, a speed-reduction coefficient (here represented by r) is introduced into the model by Daganzo (1994) used for macroscopic modelling, as illustrated in Eqn 4. Similarly, this reduction coefficient can also be introduced at the desired speed in the car-following by Krauss (1998). Moreover, the mathematical formulation of the model can also be easily explained by simple behavioural rules: drivers adjust their speed to reduced visibility or increased traffic. These factors do not interact.

Table 3
Relationships of the headway h (m) and the speed v (m/s) fit to the data. The values for the minimum time gap τ are expressed in seconds. If the speed is expressed in km/h rather than m/s, the value should be divided by 3.6.

Function	Parameter	Value	Standard error	−2LL	AIC	BIC
Five curves $h = h_j + \tau_K v$	h_j	8.756 E-0	1.826 E^{-0}	4269	4295	4313
	$\tau_{K=0.003m^{-1}}$	2.487 E-0	1.924 E^{-1}			
	$\tau_{K=0.050m^{-1}}$	2.898 E-0	2.683 E^{-1}			
	$\tau_{K=0.100m^{-1}}$	2.355 E-0	1.530 E^{-1}			
	$\tau_{K=0.150m^{-1}}$	2.042 E-0	1.235 E^{-1}			
	$\tau_{K=0.200m^{-1}}$	2.314 E-0	1.288 E^{-1}			
One curve $h = h_j + \tau v$	h_j	8.805 E-0	1.615 E^{-0}	4389	4399	4406
	τ	2.481 E-0	1.926 E^{-1}			

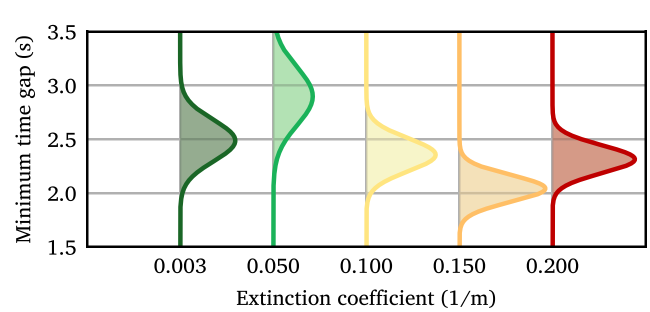

Fig. 13. Distribution of the estimated minimum time gap τ from the curve fit for the five extinction coefficients. The distributions represent the certainty of the best fit for all participants, considering the sample size and variation in the driving behaviour of the thirty participants.

$$v = \min\left(rv_f, v_f\frac{\frac{1}{k}-\frac{1}{k_j}}{\frac{1}{k_c}-\frac{1}{k_j}}\right) = \min\left(rv_f, v_f\frac{h-h_j}{h_c-h_j}\right) \text{ with } r = 1-0.4967e^{-0.02910/K} \quad [4]$$

As the car-following behaviour is assumed not to be affected by the smoke, the behaviour of all scenarios ($h_j = 8.81$ m and $\tau = 2.48$ s, see also Table 3) can be compared to the design values for this road for unrestricted visibility ($h_j = 8.47$ m and $\tau = 2.35$ s, see also Section 2.6). The design values for h_j and τ are respectively 3.9 % and 5.2 % lower than the observed values, which is considered a small difference. No statistically significant difference between the observed values and the design values was found (Mahalanobis distance test, a multivariate chi-square test: $p = 0.75 > 0.05$). Fig. 14 visualises that the design values indeed lie in the confidence intervals.

3.6. Participants' reflections

After using the driving simulator, participants completed a second questionnaire that included questions about their cybersickness symptoms, their reflections on the driving experience and demographic information. This section focuses on the participants' reflections.

Fig. 15 shows the responses to three questions related to the participants' risk perception. Twenty out of thirty participants (66 %) considered the possibility of being involved in a traffic accident (answered with 5, 6 or 7). The fact that such a high percentage of participants were aware of the risk suggests that the driving simulator provides an immersive environment that prompts participants to reflect on real-world driving risks. Despite the high level of awareness of the risk of a traffic accident, participants' perceptions of the urgency of evacuation and the threat of a wildfire were relatively low. Most participants did not perceive evacuation as urgent (only eight participants or 27 % answered 5, 6 or 7), nor did they perceive wildfire as a threat (only eleven participants or 37 % answered 5, 6 or 7).

This may be due to the static nature of the wildfire cues: a radio report and the constant extinction coefficient. After the experiment, several participants reported verbally that they expected to be surrounded by flames. Three participants wrote about this in the open-ended questions:

"If I had seen the fire, I would have been more inclined to drive faster." (translated).

"If I had seen animals running or the fire, I might have driven differently." (translated).

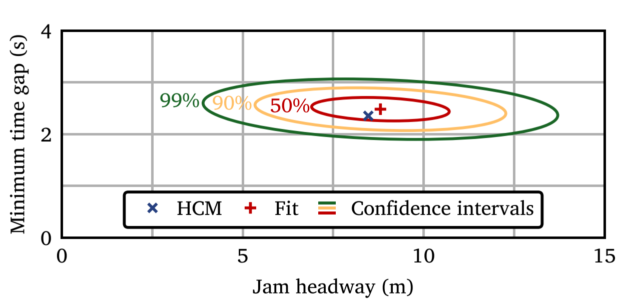

Fig. 14. The multivariate distribution of the two optimal car-following parameters. The confidence intervals are calculated from the χ^2 distribution and consider the estimated covariance matrix resulting from the mixed-effect model. As the design parameters of the Highway Capacity Manual (HCM) lie close to the optimal fit and within the confidence intervals, no significant difference could be found between the driving behaviour assumed in the Highway Capacity Manual and observed in our driving simulator.

"I drove as I would in real life. Only thing that would affect my driving is if I had a better idea of the immediate risk of fire in my vicinity."

To gain insight into behavioural realism, participants were asked if they would behave differently in real life ("Would you behave differently in real life? If so: What would you have done differently?"). Five participants mentioned they would drive faster, five participants said they might overtake more. Four participants thought they would drive slower. Eight participants thought they would be more stressed or anxious. However, most participants reported that the vehicle they drove behaved realistically and that the graphics in the virtual environment were realistic. Fig. 16 shows the responses to two questions relating to the realism of the simulator. Of all participants, twenty (67 %) reported that the vehicle physics and the graphics were realistic (answered 5, 6 or 7). Moreover, during the experiment, the researcher observed several participants trying to use the vehicle's turn signals, the horn, and the mirrors. Some participants also seemed frustrated with the slow queue. This suggests that the participants felt like they were "there" in the virtual environment.

Participants were also asked to reflect on how they drove. On the question "Did you change your driving speed, knowing you were evacuating? Why (not)?" eight participants (27 %) said they did. Five participants explained that they drove faster, due to the urgency. One participant explained that they drove slower as emergency services were occupied, and the consequences of an accident would be high during an evacuation: *"If I got in an accident the risks would be much higher and there would be no emergency assistance to help, or it would be taking away emergency resources from the fire"*.

Participants were also asked about their distance headway: "When following the car in front of you, did you change the distance between you and the car depending on how far you could see? Why (not)?". Six participants (20 %) reported they kept a larger distance. Two of them mentioned the risk of causing a multiple-vehicle collision when being hit from behind by another car (since they drove slowly in the thick smoke, one specified). Eleven participants (37 %) reported driving closer to the leading vehicles. Nine explained that they wanted to keep the vehicle in sight and two elaborated, explaining that the leading vehicle helped them position themselves on the road. This reported behaviour aligns with the observations from the fitted models (see above). However, a smaller portion of participants did the opposite (20 %); they prioritised safety by increasing their following distance.

4. Discussion

This study investigated how evacuees adjust their driving behaviour to the reduced visibility caused by wildfire smoke. While previous research has explored driving behaviour during evacuations (Dixit and Wolshon, 2014; Rohaert et al., 2023; Rohaert et al., 2022), the influence of wildfire smoke on car-following behaviour remained underexplored. Using a virtual reality experiment, this study specifically examined how different levels of smoke-related visibility affected free-flow speeds and following distances. The results showed that participants reduced their free-flow speeds as visibility deteriorated, supporting the hypothesis that dense smoke leads to slower driving. However, contrary to our expectations, participants did not adjust their distance headways according to a clear trend.

The results support the first hypothesis: participants decreased their free-flow speed when visibility was poor. Wetterberg et al. (2021) found a similar monotonically decreasing trend between free-flow speed and extinction coefficient, albeit more pronounced. This difference could be attributed to several factors. In the study by Wetterberg et al. (2021), the speed limit was lower (70 km/h compared to 80 km/h in the current study), the turning radii of the road were smaller (down to approximately 100 m, compared to 417 m in the current study), and participants were less experienced (96 % had their driving license for less than six years, while on average, the participants had their license for 15 years in

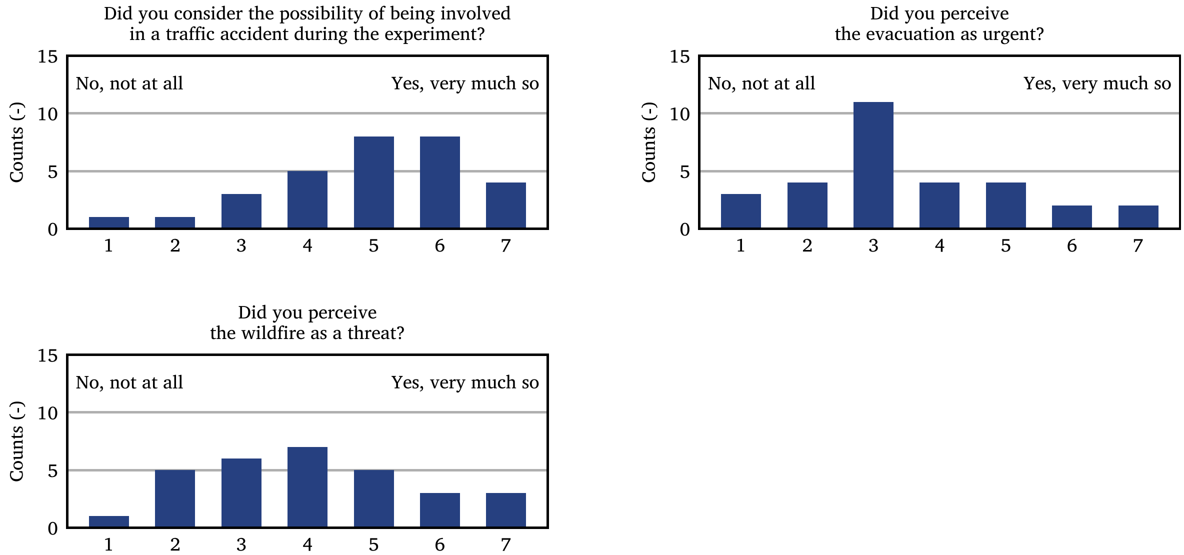

Fig. 15. Participants' responses to three questions related to risk perception.

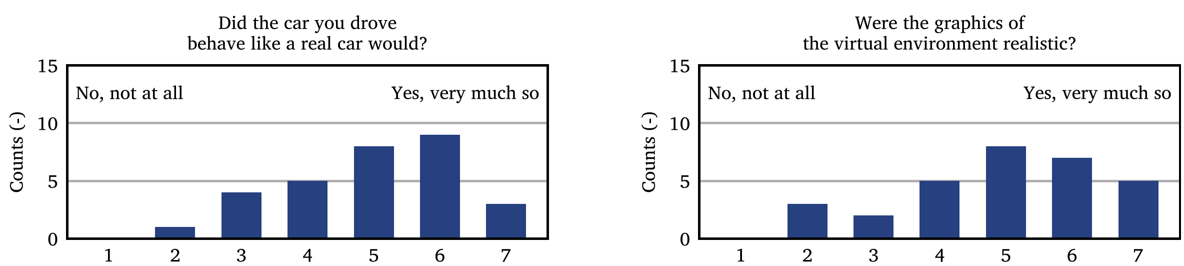

Fig. 16. Participants responded to two questions related to the realism of the simulator.

the current study) (Wetterberg, 2020). It is reasonable to assume that participants in both studies slowed down to reduce the increased risk of losing control of the vehicle, aligning with Fuller's task-capability interface model (Fuller, 2005), which suggests that drivers lower their speed to keep the task (controlled driving) within their capabilities. It should be noted that twenty out of the thirty participants of this study stated that they had considered the possibility of being involved in a car accident. This finding is critical in evacuation scenarios, where slower speeds may prolong evacuation times if smoke obscures the visibility on the road, increasing exposure to wildfire risks.

Surprisingly, the second hypothesis (participants follow vehicles at a greater distance when visibility is worse) could not be confirmed. In fact, participants kept the shortest distances in the three scenarios with the poorest visibility. This finding challenges conventional assumptions about how drivers respond to low visibility. One explanation for this behaviour might be that participants used the leading vehicles as a guide to position themselves on the road. In the scenarios with the poorest visibility levels, participants would need to stay closer to be able to see this leading vehicle. The responses to the questionnaire support this speculation. However, no clear monotonic trend was observed. Contrary to our findings, Intini et al. (2022) deduced that poor visibility would lead to larger headways. Their model was derived from an extrapolation of speed and flow reductions, observed in adverse weather conditions such as rain and snow: the observed reductions were limited to 12 %, but extrapolated to values between 35 % and 69 %. In addition, during these observations, drivers may have adjusted their speeds considering the wet or frozen road surface, rather than the reduced visibility. Moreover, drivers likely did not experience the same level of urgency as during wildfire evacuations. These differences in conditions and urgency might explain the discrepancy between their findings and ours. Broughton et al. (2007) used a driving simulator to investigate the effect of poor visibility on distance headway in the presence of fog. In their study, the speeds of the lead vehicles were not adjusted to the visibility conditions so two groups of participants formed: participants who followed and participants who did not. When the leading vehicles drove at high speed (80 km/h) through the fog, the following participants dramatically decreased their headway (down to 60 % of the headway in ideal visibility). However, at low speed (48 km/h), the following participants did not monotonically adjust their headway (down to 82 % in light fog but back up to 98 % in thick fog). This confirms our finding that in slow, congested traffic, drivers do not adapt their behaviour to changes in visibility.

The model we propose (Eqn 4) adapts the driving speeds in the free-flow regime to the smoke conditions, while the speeds remain unchanged in the car-following regime. The model is straightforward to implement in both microscopic and macroscopic traffic simulation software and can be easily explained using the task-capability interface model (Fuller, 2005), which suggests that drivers adjust behaviour to keep task demands within their capabilities. In the free-flow regime, participants reduced their speed significantly under poor visibility to maintain a comfortable level of task difficulty. However, in the car-following regime, difficulty was dictated by traffic density rather than environmental factors.

The ecological validity of the behaviour observed in virtual reality is often questioned. To achieve behavioural realism when performing experiments in virtual reality, the experiment must create two illusions which together qualify the "presence" of participants in the environment: the sense of physically being in a virtual environment and the feeling that the events within the environment are real and responsive to the participant's presence (Slater, 2009; Slater et al., 2022). In this study, participants rated the environment and the interaction with their vehicle as realistic. Moreover, the researcher observed several participants trying to use the vehicle's turn signals, the horn, and the mirrors and heard them sigh exasperatedly when the leading convoy drove slowly. Although this indicates the participant felt present (Slater, 2009; Slater et al., 2022), it does not prove that these results are useful for predicting behaviour during a real wildfire evacuation. Real validation of virtual reality can be established by comparing the results with observations in the field. Unfortunately, conducting a validation experiment for this study (driving in dense wildfire smoke) poses unacceptable health and safety risks. In addition, data from the real world on driving behaviour in smoke are harder to obtain, since smoke density levels are generally not measured at driver heights during wildfire scenarios. The level of experimental control achieved in a virtual environment is practically unattainable in real-world scenarios, especially when simulating extreme conditions such as those experienced during wildfire evacuations. However, both the free-flow speed under ideal visibility conditions and the parameters of the car-following regime were compared with the design values proposed in the Highway Capacity Manual (Dowling et al., 2016; Elefteriadou and Transportation Research Board, 2016). Differences between the observed values and the design values of the key parameters (v_f, h_j and τ) range from 3.9 % to 5.4 %. Moreover, no statistically significant difference was found between the observations and design values. This suggests the driving simulator accurately replicates realistic driving behaviour.

Despite the valuable insights, this study is not without limitations. During and after the experiment, some participants wondered aloud whether they would choose to drive in low-visibility scenarios at all. It should be emphasised that the experiment does not investigate this decision-making process, as the participants were instructed to evacuate and follow the road. Although the study provides a car-following model for reduced visibility, it does not answer the question of whether evacuees would still evacuate by car. Moreover, the results may not be very representative of real-life behaviour in dire situations. Only eight of our participants perceived the evacuation as urgent, and only eleven perceived the wildfire as a threat. Evacuees might adjust their driving style if they observe cues of a more prominent threat, such as flames nearby. Such clues would likely shift risk perception and lead to faster driving, as spontaneously reported by three participants. That said, this study aims to represent critical, yet not extreme wildfire conditions: scenarios in which smoke rather than flames or embers represent the threat. The findings aim to enhance traffic simulations for better planning and coordination of timely evacuations.

Future research should explore additional driving parameters, such as reaction time, acceleration, and deceleration, to better understand how these factors are influenced by reduced visibility and wildfire smoke. It would also be valuable to investigate the decision process of whether to drive at all in low visibility conditions, as this decision was not addressed in the current study but could have a significant impact on evacuation outcomes. Moreover, further studies should examine how drivers navigate differently in terms of wayfinding, lane changing, and overtaking under poor visibility conditions. Additionally, driving behaviour should be studied in different scenarios to understand the effect of the types of roads or the presence of flames and embers.

In summary, this study provides evidence that while evacuees tend to reduce their driving speeds in response to reduced visibility from wildfire smoke, they do not consistently adjust their following distances. These insights are critical for developing more accurate traffic models for evacuations.

5. Conclusion

The study provided insights into driving behaviour in reduced visibility caused by smoke. The results show that participants significantly reduce their free-flow speed in response to poor visibility, which is consistent with our hypothesis. This finding is critical to understanding evacuation times during wildfires, as it suggests that dense smoke can significantly slow the evacuation process. Contrary to our initial expectations, participants maintained slightly shorter distance headways in denser smoke conditions ($K > 0.100\ \mathrm{m}^{-1}$). However, the trend is not monotonic and the confidence intervals of the slopes of the headway speed graphs overlap. This suggests that car-following behaviour remains stable. These findings emphasise the importance of considering visibility.

The deidentified data gathered during this experiment is made publicly available in an open-access repository (Rohaert, 2024). The dataset includes the answers to both questionnaires (except for the demographic information) and the driving behaviour recorded during the experimental trials.

CRediT authorship contribution statement

Arthur Rohaert: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Maxine Berthiaume:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Max Kinateder:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization. **Jonathan Wahlqvist:** Supervision, Software, Methodology, Conceptualization. **Enrico Ronchi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Mixed-Effects model parameters

Table A1
Estimates and covariance of the mixed effects of the model fits to the free-flow speed.

Model	Effect	Estimate	Covariance matrix		
Linear	Fixed c_1	2.66E+00	4.50E-02		
	Random ω_1^2	1.02E+00	1.23E-01	−4.29E-04	
	Residual σ_ϵ^2	1.57E-01	−4.29E-04	1.03E-04	
Power law	Fixed c_1	1.05E+00	1.65E-02	4.40E-03	
	Fixed c_2	4.95E-01	4.40E-03	2.09E-03	
	Random ω_1^2	1.90E-01	4.46E-03	−2.64E-04	2.35E-05
	Random ω_2^2	7.55E-08	−2.64E-04	5.28E-05	−9.95E-06
	Residual σ_ϵ^2	1.17E-01	2.35E-05	−9.95E-06	5.92E-05
Reciprocal exponential	Fixed c_1	4.97E-01	2.01E-03	9.14E-05	
	Fixed c_2	2.91E-02	9.14E-05	2.49E-05	
	Random ω_1^2	4.41E-02	1.73E-04	−2.89E-07	−3.77E-07
	Random ω_2^2	9.49E-05	−2.89E-07	2.11E-08	−2.75E-07
	Residual σ_ϵ^2	1.00E-01	−3.77E-07	−2.75E-07	4.81E-05

Table A2
Estimates and covariance of the mixed effects of the model fits to the distance headway.

	Effect	Estimate	Covariance matrix						
One curve	Fixed h_j	8.81E+00	2.61E+00	−6.23E-02					
	Fixed τ	2.48E+00	−6.23E-02	3.71E-02					
	Random $\omega_{h_j}^2$	5.83E+01	3.76E+02	−2.13E-01	−2.38E-01				
	Random ω_τ^2	8.78E-01	−2.13E-01	7.61E-02	−2.57E-03				
	Residual σ_ϵ^2	9.31E+00	−2.38E-01	−2.57E-03	8.25E-02				
Five curves	Fixed h_j	8.76E+00	3.33E+00	−3.81E-02	−5.50E-02	−6.06E-02	−6.11E-02	−6.57E-02	
	Fixed $\tau_{0.003}$	2.49E+00	−3.81E-02	3.70E-02	3.89E-03	4.27E-03	4.29E-03	4.61E-03	
	Fixed $\tau_{0.050}$	2.90E+00	−5.50E-02	3.89E-03	7.20E-02	6.16E-03	6.13E-03	6.58E-03	
	Fixed $\tau_{0.100}$	2.36E+00	−6.06E-02	4.27E-03	6.16E-03	2.34E-02	6.91E-03	7.36E-03	
	Fixed $\tau_{0.150}$	2.04E+00	−6.11E-02	4.29E-03	6.13E-03	6.91E-03	1.52E-02	7.60E-03	
	Fixed $\tau_{0.200}$	2.31E+00	−6.57E-02	4.61E-03	6.58E-03	7.36E-03	7.60E-03	1.66E-02	
	Random $\omega_{h_j}^2$	8.38E+01	5.25E+02	−6.60E-03	−1.46E-02	−1.70E-02	−2.03E-02	−3.04E-02	−3.21E-02
	Random $\omega_{\tau_{0.003}}^2$	9.36E-01	−6.60E-03	7.41E-02	2.19E-05	1.22E-05	−1.82E-05	−5.06E-05	−1.77E-03
	Random $\omega_{\tau_{0.050}}^2$	1.77E+00	−1.46E-02	2.19E-05	2.77E-01	2.23E-05	−1.13E-05	−6.49E-05	−3.87E-03
	Random $\omega_{\tau_{0.100}}^2$	2.43E-01	−1.70E-02	1.22E-05	2.23E-05	1.88E-02	−1.29E-04	−1.78E-04	−3.74E-03
	Random $\omega_{\tau_{0.150}}^2$	3.87E-03	−2.03E-02	−1.82E-05	−1.13E-05	−1.29E-04	4.69E-03	−4.92E-04	−2.87E-03
	Random $\omega_{\tau_{0.200}}^2$	1.12E-05	−3.04E-02	−5.06E-05	−6.49E-05	−1.78E-04	−4.92E-04	6.07E-03	−3.53E-03
	Residual σ_ϵ^2	7.57E+00	−3.21E-02	−1.77E-03	−3.87E-03	−3.74E-03	−2.87E-03	−3.53E-03	6.55E-02

Data availability

The deidentified data gathered during this experiment is made publicly available in an open-access repository

References

Akizuki, Y., Yamao, K., Tanaka, T., 2007. Experimental study on walking speed in escape route considering luminous condition, smoke density and evacuee's visual acuity. Fire Saf. Sci. 7, 119.

Alvarez Lopez, P., Behrisch, M., Bieker-Walz, L., Erdmann, J., Flötteröd, Y.-P., Hilbrich, R., Lücken, L., Rummel, J., Wagner, P., Wiessner, E., 2018. Microscopic Traffic Simulation using SUMO, in: The 21st IEEE International Conference on Intelligent Transportation Systems. IEEE.

Arias, S., Mossberg, A., Nilsson, D., Wahlqvist, J., 2022. A Study on Evacuation Behavior in Physical and Virtual Reality Experiments. Fire Technol 58, 817–849. https://doi.org/10.1007/s10694-021-01172-4.

Barros, B., Oliveira, M., Morais, S., 2023. Continent-based systematic review of the short-term health impacts of wildfire emissions. Journal of Toxicology and Environmental Health, Part B 26, 387–415. https://doi.org/10.1080/10937404.2023.2236548.

Broughton, K.L.M., Switzer, F., Scott, D., 2007. Car following decisions under three visibility conditions and two speeds tested with a driving simulator. Accid. Anal. Prev. 39, 106–116. https://doi.org/10.1016/j.aap.2006.06.009.

Carton, H., Gales, J., Kennedy, Eric, B., 2024. Video analysis of human behaviour during wildfire evacuations. Canadian Journal of Civil Engineering. https://doi.org/10.1139/cjce-2023-0450.

Chen, B., Wu, S., Jin, Y., Song, Y., Wu, C., Venevsky, S., Xu, B., Webster, C., Gong, P., 2024. Wildfire risk for global wildland–urban interface areas. Nat Sustain 7, 474–484. https://doi.org/10.1038/s41893-024-01291-0.

Christianson, A.C., Johnston, L.M., Oliver, J.A., Watson, D., Young, D., MacDonald, H., Little, J., Macnab, B., Gonzalez Bautista, N., 2024. Wildland fire evacuations in Canada from 1980 to 2021. Int. J. Wildland Fire 33. https://doi.org/10.1071/WF23097.

Comets, E., Lavenu, A., Lavielle, M., 2017. Parameter Estimation in Nonlinear Mixed Effect Models Using **saemix** , an *R* Implementation of the SAEM Algorithm. J. Stat. Soft. 80, 10.18637/jss.v080.i03.

Cova, T.J., Sun, Y., Zhao, X., Liu, Y., Kuligowski, E.D., Janfeshanaraghi, N., Lovreglio, R., 2024. Destination unknown: Examining wildfire evacuee trips using GPS data. J. Transp. Geogr. 117, 103863. https://doi.org/10.1016/j.jtrangeo.2024.103863.

Daganzo, C.F., 1994. The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory. Transp. Res. B Methodol. 28, 269–287. https://doi.org/10.1016/0191-2615(94)90002-7.

Davis, C., Sole, C., Khan, H., Nilsson, D., 2023. Investigating movement through smoke in virtual reality. Fire Saf. J. 140, 103890. https://doi.org/10.1016/j.firesaf.2023.103890.

Dixit, V., Wolshon, B., 2014. Evacuation traffic dynamics. Transp. Res. Part C Emerging Technol. 49, 114–125. https://doi.org/10.1016/j.trc.2014.10.014.

Dowling, R., Ryus, P., Schroeder, B., Kyte, M., Creasey, T., Rouphail, N., Hajbabaie, A., Rhoades, D., National Cooperative Highway Research Program, Transportation Research Board, National Academies of Sciences, Engineering, and Medicine, 2016. Planning and Preliminary Engineering Applications Guide to the Highway Capacity Manual. Transportation Research Board, Washington, D.C. 10.17226/23632.

Elefteriadou, L.A., Transportation Research Board, 2016. Highway Capacity Manual 6th Edition: A Guide for Multimodal Mobility Analysis. National Academies Press, Washington, D.C. 10.17226/24798.
Frantzich, H., Nilsson, D., 2003. Utrymning genom tät rök: beteende och förflyttning [Evacuation in dense smoke: behaviour and movement] Technical Report 3126. Department of Fire Safety Engineering and Systems Safety, Lund.
Fridolf, K., Ronchi, E., Nilsson, D., Frantzich, H., 2013. Movement speed and exit choice in smoke-filled rail tunnels. Fire Saf. J. 59, 8–21. https://doi.org/10.1016/j.firesaf.2013.03.007.
Fuller, R., 2005. Towards a general theory of driver behaviour. Accid. Anal. Prev. 37, 461–472. https://doi.org/10.1016/j.aap.2004.11.003.
Goodrick, S.L., Achtemeier, G.L., Larkin, N.K., Liu, Y., Strand, T.M., 2013. Modelling smoke transport from wildland fires: a review. Int. J. Wildland Fire 22, 83. https://doi.org/10.1071/WF11116.
Hartfiel, B., Stark, R., 2021. Validity of primary driving tasks in head-mounted display-based driving simulators. Virtual Reality 25, 819–833. https://doi.org/10.1007/s10055-020-00496-w.
Intini, P., Wahlqvist, J., Wetterberg, N., Ronchi, E., 2022. Modelling the impact of wildfire smoke on driving speed. Int. J. Disaster Risk Reduct. 80, 103211. https://doi.org/10.1016/j.ijdrr.2022.103211.
Jin, T., 1978. Visibility through fire smoke. Journal of Fire and Flammability 9, 135–155.
Jin, T., Yamada, T., 1985. Irritating Effects of Fire Smoke on Visibility. Fire Science and Technology 5, 79–90. https://doi.org/10.3210/fst.5.79.
Kalogeropoulos, N., Mitchell, H., Ronchi, E., Gwynne, S., Rein, G., 2023. Design of stochastic trigger boundaries for rural communities evacuating from a wildfire. Fire Saf. J. 140, 103854. https://doi.org/10.1016/j.firesaf.2023.103854.
Kim, H.K., Park, J., Choi, Y., Choe, M., 2018. Virtual reality sickness questionnaire (VRSQ): Motion sickness measurement index in a virtual reality environment. Appl. Ergon. 69, 66–73. https://doi.org/10.1016/j.apergo.2017.12.016.
Kim, J., Park, J., Kim, K., Kim, M., 2021. RnR-SMART: Resilient smart city evacuation plan based on road network reconfiguration in outbreak response. Sustain. Cities Soc. 75, 103386. https://doi.org/10.1016/j.scs.2021.103386.
Kinateder, M., Ronchi, E., Nilsson, D., Kobes, M., Müller, M., Pauli, P., Mühlberger, A., 2014. Virtual Reality for Fire Evacuation Research. In: Presented at the 2014 Federated Conference on Computer Science and Information Systems, pp. 313–321. https://doi.org/10.15439/2014F94.
Krauss, S., 1998. Microscopic modeling of traffic flow: investigation of collision free vehicle dynamics. DLR Forschungszentrum fuer Luft- und Raumfahrt e.V., Koeln (Germany), Hauptabt. Mobilitaet und Systemtechnik, Germany.
Krav - VGU: Vägars och gators utformning, 2022. . Trafikverket, Borlänge.
Lindell, M.K., Prater, C.S., 2007. Critical Behavioral Assumptions in Evacuation Time Estimate Analysis for Private Vehicles: Examples from Hurricane Research and Planning. J. Urban. Plann. Dev. 133, 18–29. https://doi.org/10.1061/(ASCE)0733-9488(2007)133:1(18).
Pel, A.J., Hoogendoorn, S.P., Bliemer, M.C., 2010. Evacuation modeling including traveler information and compliance behavior. Procedia Eng. 3, 101–111. https://doi.org/10.1016/j.proeng.2010.07.011.
Risto, M., Martens, M.H., 2014. Driver headway choice: A comparison between driving simulator and real-road driving. Transport. Res. F: Traffic Psychol. Behav. 25, 1–9. https://doi.org/10.1016/j.trf.2014.05.001.
Ronchi, E., Wahlqvist, J., Rohaert, A., Kuligowski, E., Wu, J., Zhou, X., Singh, D., Rein, G., Mitchell, H., Kalogeropoulos, N., Gwynne, S., Xie, H., Thompson, P., Kinateder, M., Berthiaume, M., Benichou, N., & Kimball, A. (2024). *WUI-NITY 4: An Industry-Ready WUI Fire Evacuation Model* (FPRF-2024-08; p. 223). Fire Protection Research Foundation. https://www.nfpa.org/education-and-research/research/fire-protection-research-foundation/projects-and-reports/wunity-a-platform-for-the-simulation-of-wildland-urban-interface-fire-evacuation.
Rohaert, A., 2024. *Experiment dataset of people driving through simulated wildfire smoke using a driving simulator* [Dataset]. Zenodo. https://doi.org/10.5281/ZENODO.12579024.
Rohaert, A., Janfeshanaraghi, N., Kuligowski, E., Ronchi, E., 2023. The analysis of traffic data of wildfire evacuation: the case study of the 2020 Glass Fire. Fire Saf. J. 141, 103909. https://doi.org/10.1016/j.firesaf.2023.103909.
Rohaert, A., Kuligowski, E.D., Ardinge, A., Wahlqvist, J., Gwynne, S.M.V., Kimball, A., Noureddine Bénichou, Ronchi, E., 2022. Dataset of traffic dynamics during the 2019 Kincade Wildfire Evacuation. 10.5281/ZENODO.7410114.
Ronchi, E., Fridolf, K., Frantzich, H., Nilsson, D., Walter, A.L., Modig, H., 2018. A tunnel evacuation experiment on movement speed and exit choice in smoke. Fire Saf. J. 97, 126–136. https://doi.org/10.1016/j.firesaf.2017.06.002.
Ronchi, E., Wahlqvist, J., Rohaert, A., Kuligowski, E., Wu, J., Zhou, X., Singh, D., Rein, G., Mitchell, H., Kalogeropoulos, N., Gwynne, S., Xie, H., Thompson, P., Kinateder, M., Berthiaume, M., Benichou, N., Kimball, A., 2024. WUI-NITY 4: An Industry-Ready WUI Fire Evacuation Model (No. FPRF-2024-08). Fire Protection Research Foundation, Quincy, Maryland, USA.
Rossi, R., Meneguzzer, C., Orsini, F., Gastaldi, M., 2020. Gap-acceptance behavior at roundabouts: validation of a driving simulator environment using field observations. Transp. Res. Procedia 47, 27–34. https://doi.org/10.1016/j.trpro.2020.03.069.
Sadri, A.M., Ukkusuri, S.V., Gladwin, H., 2017. The Role of Social Networks and Information Sources on Hurricane Evacuation Decision Making. Nat. Hazards Rev. 18, 04017005. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000244.
Slater, M., 2009. Place illusion and plausibility can lead to realistic behaviour in immersive virtual environments. Phil. Trans. r. Soc. B 364, 3549–3557. https://doi.org/10.1098/rstb.2009.0138.
Slater, M., Banakou, D., Beacco, A., Gallego, J., Macia-Varela, F., Oliva, R., 2022. A Separate Reality: An Update on Place Illusion and Plausibility in Virtual Reality. Front. Virtual Real. 3, 914392. https://doi.org/10.3389/frvir.2022.914392.
Tamakloe, R., Hong, J., Tak, J., Park, D., 2021. Finding evacuation routes using traffic and network structure information. Transp. Res. Part D: Transp. Environ. 95, 102853. https://doi.org/10.1016/j.trd.2021.102853.
Wahlqvist, J., Ronchi, E., Gwynne, S.M.V., Kinateder, M., Rein, G., Mitchell, H., Bénichou, N., Ma, C., Kimball, A., Kuligowski, E., 2021. The simulation of wildland-urban interface fire evacuation: The WUI-NITY platform. Saf. Sci. 136, 105145. https://doi.org/10.1016/j.ssci.2020.105145.
Wahlqvist, J., Rubini, P., 2023. Real-time visualization of smoke for fire safety engineering applications. Fire Saf. J. 140, 103878. https://doi.org/10.1016/j.firesaf.2023.103878.
Wetterberg, N., 2020. A virtual reality experiment on driving speed in smoke during a wildfire evacuation. Lund, Sweden.
Wetterberg, N., Ronchi, E., Wahlqvist, J., 2021. Individual Driving Behaviour in Wildfire Smoke. Fire Technol 57, 1041–1061. https://doi.org/10.1007/s10694-020-01026-5.
Wong, S., Broader, J., Shaheen, S.A., 2020. Review of California Wildfire Evacuations from 2017 to 2019. University of California, Institute of Transportation Studies. https://doi.org/10.7922/G29G5K2R.
Yamada, T., Akizuki, Y., 2016. Visibility and Human Behavior in Fire Smoke, in: Hurley, M.J., Gottuk, D., Hall, J.R., Harada, K., Kuligowski, E., Puchovsky, M., Torero, J., Watts, J.M., Wieczorek, C. (Eds.), SFPE Handbook of Fire Protection Engineering. Springer New York, New York, NY, pp. 2181–2206. 10.1007/978-1-4939-2565-0_61.
Zehra, S.N., Wong, S.D., 2024. Systematic review and research gaps on wildfire evacuations: infrastructure, transportation modes, networks, and planning. Transp. Plan. Technol. 1–35. https://doi.org/10.1080/03081060.2024.2348713.