Document Version
Final published version

Licence
CC BY

Citation (APA)
Xiao, T., Feng, Y., Chakraborty, S., Kiefer, P., Toups Dugas, P. O., & Raubal, M. (2026). Wildfire@Home: Personalized Immersive Training for Household Situation Awareness. In *Proceedings of the 1st International Conference on Human-Computer Interaction in the Alps, AlpCHI 2026* (pp. 87-95). (Proceedings of the 1st International Conference on Human-Computer Interaction in the Alps, AlpCHI 2026). Association for Computing Machinery (ACM). https://doi.org/10.1145/3780045.3780049

AlpCHI 2026: 1st International Conference on Human-Computer Interaction in the Alps
March 1 - 5, 2026
Ascona, Switzerland

SHORT-PAPER

Wildfire@Home: Personalized Immersive Training for Household Situation Awareness

TIANYI XIAO, Swiss Federal Institute of Technology, Zurich, Zurich, ZH, Switzerland

YAN FENG, Delft University of Technology, Delft, Zuid-Holland, Netherlands

SUVODIP CHAKRABORTY, Swiss Federal Institute of Technology, Zurich, Zurich, ZH, Switzerland

PETER KIEFER, Swiss Federal Institute of Technology, Zurich, Zurich, ZH, Switzerland

PHOEBE O. TOUPS DUGAS, Monash University, Melbourne, VIC, Australia

MARTIN RAUBAL, Swiss Federal Institute of Technology, Zurich, Zurich, ZH, Switzerland

Open Access Support provided by:

Swiss Federal Institute of Technology, Zurich

Monash University

Delft University of Technology

AlpCHI '26: Proceedings of the 1st International Conference on Human-Computer Interaction in the Alps (March 2026)
https://doi.org/10.1145/3780045.3780049
ISBN: 9798400719486

Wildfire@Home: Personalized Immersive Training for Household Situation Awareness

Tianyi Xiao*
ETH Zürich
Zürich, Switzerland
xiaoti@ethz.ch

Yan Feng
Delft University of Technology
Delft, Netherlands
Y.Feng@tudelft.nl

Suvodip Chakraborty
ETH Zürich
Zürich, Switzerland
schakraborth@ethz.ch

Peter Kiefer
ETH Zürich
Zürich, Switzerland
pekiefer@ethz.ch

Phoebe O. Toups Dugas
Monash University
Melbourne, Australia
Phoebe.ToupsDugas@Monash.edu

Martin Raubal
ETH Zürich
Zürich, Switzerland
mraubal@ethz.ch

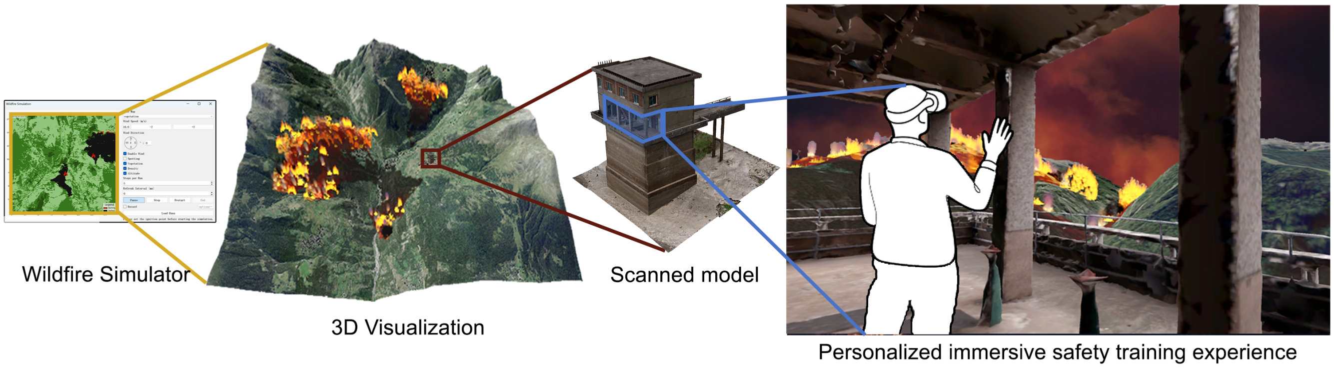


Figure 1: Overview of Wildfire@Home pipeline. A desktop wildfire simulator models fire spread behavior, which is then imported into a VR wildfire visualizer. Users scan their own homes, position them at real locations, and experience fire spread from first-person view in VR, enhancing situation awareness and decision-making within familiar surroundings.

Abstract

As wildfires become increasingly frequent and severe worldwide, at-risk homeowners face greater responsibility in assessing the fire situation and making safety-critical decisions. This requires specific training in situational awareness (SA). However, the effectiveness of conventional wildfire response training (WRT) methods (e.g., videos, brochures) is limited, as they cannot replicate the unpredictability of wildfires nor provide real-world context. This research introduces Personalized Immersive Training (PIT), a novel paradigm designed to embed WRT in real-world contexts. We implemented PIT in Wildfire@Home, intending to increase homeowners' SA capabilities. Learners first use a desktop wildfire simulator to build mental models of how terrain, vegetation, and wind shape fire spread. Then, experience a realistic and immersive 3D rendering of the simulation in a VR wildfire visualizer. Learners can personalize the training scenario by uploading 3D models and geospatial data.

CCS Concepts

• **Human-centered computing** → **Virtual reality**; *User interface design*; • **Security and privacy** → *Social aspects of security and privacy*.

Keywords

Wildfire simulation, wildfire visualization, virtual reality, personalization, situation awareness

ACM Reference Format:
Tianyi Xiao, Yan Feng, Suvodip Chakraborty, Peter Kiefer, Phoebe O. Toups Dugas, and Martin Raubal. 2026. Wildfire@Home: Personalized Immersive Training for Household Situation Awareness. In *1st International Conference on Human-Computer Interaction in the Alps (AlpCHI 2026), March 01–05, 2026, Ascona, Switzerland.* ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3780045.3780049

1 Introduction

Wildfires are increasing in frequency and severity, threatening lives, property, and ecosystems worldwide [36, 59, 66]. Climate change, policy constraints, and urban expansion into wilderness areas have created highly vulnerable wildland-urban interfaces that threaten public safety [7, 27, 55, 56]. Although evacuation as early as possible is the safest response to wildfire threats [44], many countries reject mandatory evacuation to preserve houseowners' autonomy

---

*Corresponding author.

AlpCHI 2026, Ascona, Switzerland

ACM ISBN 979-8-4007-1948-6/26/03
https://doi.org/10.1145/3780045.3780049

and avoid economic and displacement problems [47]. This shifts responsibility to at-risk homeowners, who must dynamically assess the situation and make safety-critical decisions. However, most residents delay action, often waiting until smoke is visible or hear the fire through the news media [45, 47], increasing the death rate from radiant heat or vehicle accidents [30].

One reason for this "last-minute evacuation" phenomenon is insufficient situation awareness (SA) of wildfire. SA is the perception, comprehension, and projection of evolving conditions that enable individuals to recognize risks and choose appropriate actions [13, 21, 29, 74]. Establishing and maintaining SA requires timely and continuously updated knowledge of multiple variables in a dynamic fire environment, such as the direction and speed of the fireline [13, 29, 74]. Improving SA skills has traditionally only been available to professionals through complex drills [13, 34, 50, 75]. In contrast, wildfire response training (WRT) for public preparedness is typically based on videos, brochures, and presentations, without embodied action [24, 31, 37]. Since these training methods cannot capture wildfire behavior, residents at risk often lack exposure until a real event occurs. Limited practice leads to poor threat identification, causing delay in action and an increased death rate.

Simulation with the right level of fidelity can replicate the psychological and physiological effects of real fire drills, promoting learning [65]. VR is increasingly becoming a vital method for developing critical SA skills [17, 24, 38]. This makes VR a low-cost, low-risk training supplement for citizen response training [18, 24, 33, 41]. However, few existing tools focus on the general public or support personalized training environments. The growing accessibility of consumer-grade headsets [12, 71] and advances in 3D reconstruction technologies [40] have enabled a shift toward Personalized Immersive Training (PIT). Rooted in situated learning theory [3], PIT embeds WRT in real-world contexts featuring spatial cues (e.g., terrain, vegetation) that help users assess fire proximity and determine evacuation necessity [45, 46].

We developed Wildfire@Home based on PIT, targeting the general public, who typically lack domain expertise and cannot access fire drills. The system comprises two components: a desktop-based wildfire simulator and a VR-based wildfire visualizer. The wildfire simulator uses a cellular automata (CA) model to show how environmental factors affect fire spread; it can be accessed by users without a VR headset. The wildfire visualizer transforms CA-generated simulations into 3D experiences, offering an immersive VR experience. Unlike traditional 2D visualizations, the VR environment provides spatial depth and a more intuitive understanding of fire behavior [34]. To achieve a personalized experience, users can scan their own homes and place them within real-world terrain, then observe fire conditions against the background of familiar surroundings.

As this study represents the first exploration of a PIT system, an overarching research question emerges: Does personalized immersive training (the proposed concept) enhance SA of wildfires compared to non-personalized 2D (baseline) and immersive training? A future user study will answer this question.

2 Related Work

We first address the importance of SA in responding to wildfires. We then consider simulation algorithms for wildfires, a necessary technology for our interface. Finally, we review prior approaches to immersive training.

2.1 Situation Awareness in Wildfire Response

Numerous studies have highlighted the importance of SA in firefighting operations, improving responders' chances of successfully managing the fire and, more importantly, safety and survival [46, 60, 64, 74]. Endsley's [21] three-level model indicates SA encompasses the perception of relevant environmental elements (Level 1), the comprehension of their meaning (Level 2), and the projection of their future status (Level 3). In the context of wildfires, these levels correspond to: (1) perceiving environmental and fire-related cues (e.g., nearby building numbers and locations, terrain features, fire origin); (2) comprehending the current fire situation (e.g., estimating fire size and identifying threatened areas); and (3) projecting future developments, such as the fire's likely trajectory or the potential need for evacuation [13, 20, 60].

Effective SA training requires more than the acquisition of factual knowledge; it also depends on perceptual learning, the ability to recognize critical environmental cues, and the development of mental models that accurately encode fire dynamics and progression [15]. VR has been shown to be an effective training method to increase SA skills [53]. For example, trainees can be placed within the visual, auditory, and even thermal/smoke environments of a virtual fire scene, activating their sensory and emotional capabilities to foster the development of SA behaviors [22]. The critical role of SA in fire prevention prompted this study to pose a research question aimed at comparing the impact of the PIT method versus non-personalized approaches for cultivating SA capabilities.

2.2 Wildfire Simulation Algorithms

Wildfire spread simulation algorithms can be grouped into four paradigms: empirical models, physics-based, raster-based, and machine learning (ML) approaches. Empirical models approximate fire behavior through parameterized formulas derived from historical data and controlled experiments; the most widely used is the mathematical model proposed by Rothermel [58], which underpins simulators such as FARSITE [43]. Physics-based approaches (e.g., WFDS [49], WRF-Fire [14]) solve fluid dynamics and combustion processes, offering high-fidelity insights into fire-atmosphere interactions, but they demand prohibitive computational resources and run orders of magnitude slower than real time [5, 25]. Raster-based approaches, such as CA models [1], simulate fire spread through cell-based state-transition rules, integrate efficiently with geographic information systems (GIS), and are computationally efficient, yet often produce unrealistic fire perimeters due to directional constraints [6]. ML approaches (e.g., decision trees, random forests [9]) capture complex non-linear relationships among environmental factors [8, 26], but require large datasets from remote sensing and meteorological records, and are difficult to interpret [73].

While low-fidelity simulations can be effective for learning, the goal of the present research is to help participants gain a better understanding of how a wildfire near their home might actually unfold. For this, we seek an algorithm of wildfire simulation within the constraints of an interactive, real-time, and context-rich method. Therefore, our system adopts a widely used CA model proposed by

Alexandridis et al. [1], as it provides rapid feedback and simulates terrain, wind, and vegetation effects on wildfire spread.

2.3 Immersive Wildfire Response Training

WRT aims to convey the characteristics, causes, effects, and prevention measures of wildfires to help individuals and professionals learn how to respond [15]. Recently, the growing evolution of immersive technology allows users to observe and explore fire events with a high degree of presence [13, 63]. For example, VFire enables users to modify fuel and weather conditions, and test firefighting strategies from a first-person perspective [35]. Vega et al. [66] developed a VR campfire game that guides users through building and extinguishing a campfire, using gamification to promote SA and safe behavior. However, compared to small-scale and enclosed fire scenarios, such as hospitals [23], coal mines [54], and train stations [68], there are relatively few immersive training interfaces specifically designed for wildfires.

Immersive WRT interfaces show a superior training experience and performance over traditional methods. For example, research shows that 360° immersive wildfire videos increased presence, risk perception, and emotional arousal compared to reading articles and watching videos [48]. VR training also simulates higher motivation and interest [69], yielding task performance comparable to real-world training, with both significantly outperforming the untrained condition [57]. Calandra et al. [10] integrated VR training with passive haptic feedback into a forest firefighting training course, finding that compared to video instruction alone, this approach significantly enhanced trainees' learning outcomes, motivation, and perceived quality of training.

Despite their innovation, most existing VR-based WRT systems rely on predefined scenarios [18, 19] and are designed primarily for professionals [16, 33, 39, 65, 67, 69]. While these approaches raise general awareness of wildfire hazards, they provide limited guidance on property-specific risks and tailored safety measures, making it difficult for users to apply what they learn to their own contexts. Recent advances in personalized VR experiences (e.g., healthcare [51], exhibitions [4], workspace [11]) inspired us to adapt this idea into the WRT system, Wildfire@Home, to address these gaps—particularly for the general public.

3 Formative Study

The present article is concerned with the technical design of Wildfire@Home, in particular, its simulation implementation. We briefly describe the light, formative study that we used to develop this novel system. The IRB board of ETH Zürich approved this study.

3.1 Methods

We conducted semi-structured interviews with nine experts in firefighting (E1–9; 6 men and 3 women), recruited through professional and social networks. Participants were selected based on a screening survey that collected demographic and professional information, as shown in Appendix B.1. They reported 2 to 15 years of working experience ($M = 6.0$, $SD = 3.9$). Roles included six field responders and three participants with both command/field experience (E2, E5, E7). More details appear in Appendix A: Table 1. All participants were compensated at local wage rates.

The interviews mainly covered their firefighting experiences, training methods, tools used in training, limitations of these tools, requests for improvements, and vision for future immersive training tools for citizens. A complete interview protocol is shown in Appendix B.2. The interview was conducted in Chinese and subsequently translated into English by the first author. Interview recordings were reviewed by the first author to gather insights, and findings were summarized using descriptive coding.

3.2 Results

All experts express a strong interest in VR-based training tools. They acknowledge its effectiveness and usefulness, but also indicate several limitations of the current VR experience. These insights directly informed the design of Wildfire@Home.

3.2.1 *Visualization.*

Experts mentioned that current training approaches rely mainly on static 2D or 2.5D maps. These representations force users to mentally reconstruct terrain and cannot represent dynamic fire behavior. In contrast, E2 highlighted that immersive visualization "*lets you see it directly from a first-person view,*" reducing cognitive load in interpreting elevation and slope.

3.2.2 *Fidelity.*

Experts emphasized the importance of simulation fidelity in training knowledge transfer, providing trainees with enhanced immersion and situation awareness. They noted that VR technology has significant potential to induce real-world stressors, allowing participants to make sound decisions under high-pressure conditions. For example, E6 argued that lifelike visuals increase applicability to real-world action, while E1 emphasized that "*people take more reasonable reactions about when to leave, where to go, and what to take in a realistic environment.*"

3.2.3 *Scenarios.*

E7 noted that "*training in people's own neighborhoods would be taken more seriously*"—a reflection of how several experts envisioned placing fire scenarios on the users' own properties. Existing systems only simulated small-scale, enclosed, and highly predictable scenarios. While such simulations are suitable for enclosed-space fire response training, they fail to prepare firefighters for the complex, multidirectional, and unpredictable nature of wildfire. The experts reported that current immersive training systems largely replicate outdated drills and practices, highlighting an urgent need for modernization. Unpredictable wildfires are viewed as exceptional and rare occurrences—though they are more common than ever—and thus excluded from most training exercises.

3.2.4 *Interactivity.*

Immersive systems allow users to observe both the external impacts of wildfire spread and the internal dynamics between wildfire variables. Experts stressed the value of active engagement. Instead of passively observing scenarios, users should be able to manipulate key parameters and observe the resulting changes in fire spread. Such interactive experimentation deepens understanding of fire spread.

3.3 Design Strategies

We derived four design strategies from these insights for Wildfire@Home, which support PIT and help us answer our research question: (1) provide immersive 3D visualization to reduce cognitive load; (2) render high-fidelity and realistic fire, smoke, and

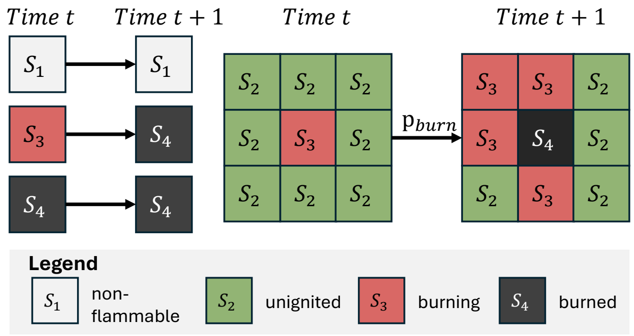


Figure 2: CA model state evolution rules: (1) S_1 remains S_1; (2) S_2 may ignite and transition to the burning state (S_3) if at least one neighboring cell is burning, with probability p_{burn}; (3) S_3 transitions to the burned state (S_4); (4) S_4 remains S_4.

terrain to enhance presence and SA; (3) support scenario personalization using user-specific and public geospatial data; and (4) allow parameter manipulation to reveal the underlying mechanisms of fire spread, thereby facilitating the construction of mental models.

4 Wildfire@Home

Wildfire@Home is designed for public preparedness and comprises a desktop-based wildfire simulator and a VR-based visualizer.

4.1 Desktop-Based Wildfire Simulator

The wildfire simulator component adopts a CA model [1]. The simulator can function independently, enabling users without VR equipment to engage with the tool. It allows intuitive manipulation of key parameters to explore how various factors influence wildfire spread, thereby supporting basic learning about wildfire dynamics.

4.1.1 Simulation Algorithm. The area is discretized into grid cells, each in one of four possible states (S): non-flammable (S_1), unignited (S_2), burning (S_3), or burned (S_4). The evolution rules between states are shown in Figure 2.

Fire propagates stochastically from burning to neighboring cells with a spread probability p_{burn} that integrates vegetation type, fuel density, wind, slope, and a baseline ignition probability:

$$p_{\text{burn}} = p_h(1 + p_{\text{veg}})(1 + p_{\text{den}})p_w p_s. \tag{1}$$

Baseline ignition probability (p_h). p_h represents the inherent likelihood of ignition under neutral conditions (e.g., flat terrain, no wind, average vegetation). It serves as a scaling factor and is typically calibrated in the range $[0, 1]$ based on empirical fire records or expert judgment.

Vegetation type (p_{veg}). Vegetation type influences combustibility. In the model, p_{veg} is discretized into categorical values (e.g., grasslands, shrublands, forests). Higher flammability vegetation is assigned larger p_{veg} values, whereas low-flammability vegetation (e.g., grasslands) receives smaller values.

Fuel density (p_{den}). p_{den} is likewise categorized into categorical values (e.g., sparse, normal, dense) corresponding to land-cover data. The spread probability is increased by denser fuels and decreased by sparser fuels.

Wind (p_w). Wind is modeled according to empirical wind-fire relations: $p_w = \exp(c_1 V) \cdot \exp\left(V c_2(\cos\theta - 1)\right)$,
where V is wind speed, θ is the angle between the wind direction and fire spread direction, and c_1, c_2 are constants. Spread rate is maximized when fire moves with the wind ($\theta = 0$) and minimized against the wind ($\theta = \pi$). Parameters c_1 and c_2 can be fitted by minimizing the difference between the simulated and observed burned areas.

Slope (p_s). Uphill increases the spread rate uphill due to the convective and radiative heating of unburned vegetation ahead of the fire front [32]. This effect is modeled as: $p_s = \exp(a\theta_s)$, where θ_s is the slope angle and a is an empirical constant. The positive slope increases p_s as the flames are closer to the surface, while the spread of the fire on the slope is reduced.

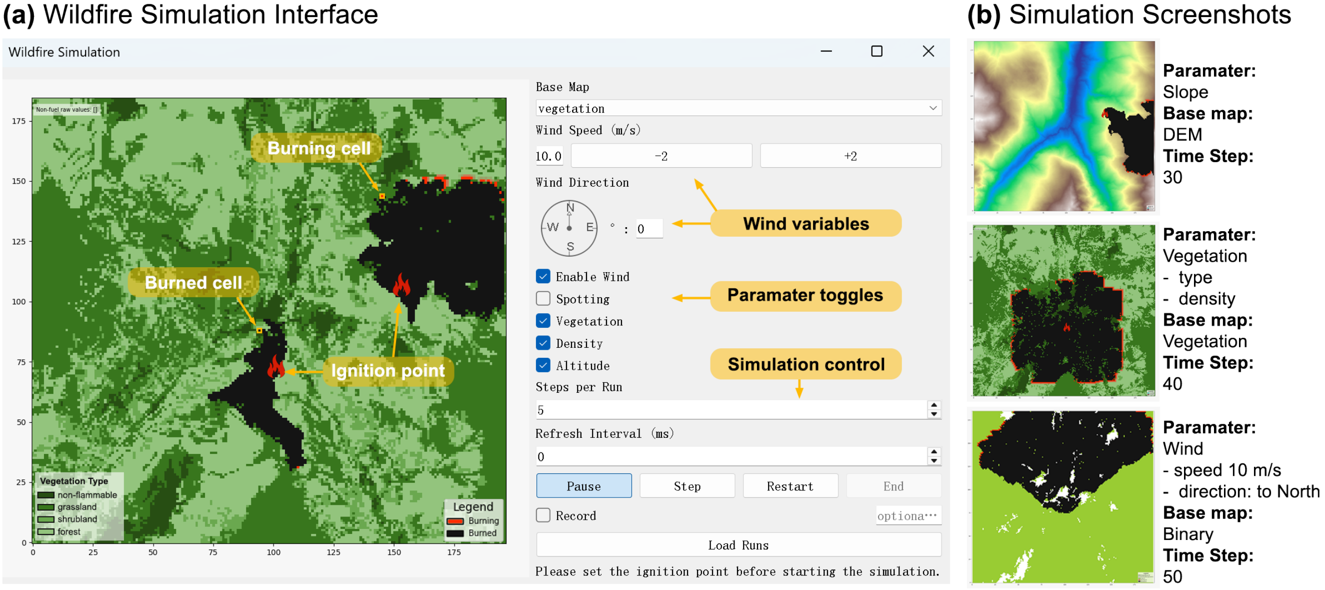
4.1.2 Simulation Data. The data used for wildfire simulation includes vegetation and digital elevation model (DEM) data (Figure 4). User can import datasets corresponding to their household location, using publicly available geospatial resources such as swissALTI3D [52]. Wind data may be obtained from local meteorological agencies' measurements of wind speed and direction.

4.1.3 Interface Design. The user interface (Figure 3) is designed to support novice users' interactive exploration of wildfire dynamics. The left panel displays the base map, which users can configure to show either a DEM, a vegetation map, or a binary map indicating flammable and non-flammable areas. The right panel allows users to manipulate key environmental parameters, such as *wind speed* and *wind direction*, and to toggle simulation factors including *wind*, *spotting*, *vegetation type*, *vegetation density*, and *altitude*. These toggles activate corresponding terms in the CA model [1] (see Equation 1), thereby directly influencing the probability of fire propagation p_{burn}. Simulation control panel includes *pause*, *step*, *restart*, and *end*, alongside adjustable parameters for *steps per run* and *refresh interval*. Users can also record simulation sessions as binary files that can be imported into the wildfire visualizer (Section 4.2) for an immersive training experience.

4.2 VR-Based Wildfire Visualizer

When combined with the wildfire simulator, the wildfire visualizer offers an immersive, first-person experience of the simulated fire, which is expected to enhance users' SA skills (Figure 5(a)).

4.2.1 Visualization Data. The visualization of the environment integrates personalized input data (Figure 4). User-scanned 3D models are captured with free applications such as Metaroom [2]. A 3D terrain model and building models were generated using the GIS Terrain Loader Pro plugin in Unity [28]. The terrain model was created based on DEM data and textured with satellite imagery, while the building models were constructed using vector building boundary data. A realistic rendering system is used to transform wildfire simulation generated from the wildfire simulator (Section 4.1) into an animation of fire's progression from ignition to extinction.


(a) Wildfire Simulation Interface

Wildfire Simulation

Base Map: vegetation

Wind Speed (m/s): 10.0 -2 +2

Wind Direction ° : 0

☑ Enable Wind
☐ Spotting
☑ Vegetation
☑ Density
☑ Altitude

Steps per Run: 5

Refresh Interval (ms): 0

Pause Step Restart End

☐ Record optiona…

Load Runs

Please set the ignition point before starting the simulation.

(b) Simulation Screenshots

Paramater: Slope
Base map: DEM
Time Step: 30

Paramater: Vegetation
- type
- density
Base map: Vegetation
Time Step: 40

Paramater: Wind
- speed 10 m/s
- direction: to North
Base map: Binary
Time Step: 50

Figure 3: A Swiss town, Stalden, was selected as our example location for its high wildfire risk. (a) The left panel presents fire progression dynamically on the base map, with actively burning cells shown in red and burned cells shown in black. Ignition points are marked with fire icons on the map and are interactively defined by the user. The right panel contains buttons and text input fields that allow users to configure simulation parameters. (b) shows the simulation results under different setups.

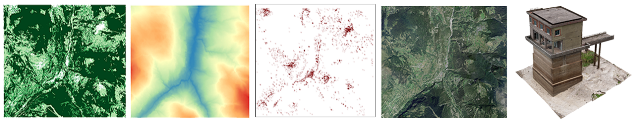

Vegetation DEM Buildings Satellite image Scanned model

Figure 4: Wildfire simulation and visualization data.

4.2.2 Realistic Rendering System. We use a hybrid method combining 2D textures as a base with 3D particles in Unity [62]. We support performance optimization through level-of-detail and selective rendering. The visualization and the wildfire spread process are shown in Figure 5(c)–(d).

The texture system applies color gradients based on the cells' states (Figure 5(c)), illustrating the fire lifecycle from bright flames (ignition) to dim embers (extinction). To reduce the blocky appearance caused by grid-based data, we apply a convolution kernel to smooth the texture. Simultaneously, a Gaussian filter is employed for temporal smoothing across time steps for better frame transition. To achieve a more natural flame appearance, subtle variations are introduced through Perlin noise and controlled randomness.

The 3D particle system and the texture data are correlated, synchronizing fire effects. The generation of particles is controlled by probability rules and spacing constraints to maintain visual density without overloading the system. Particle types include flames, explosions, dust, smoke, and ashes. Each particle undergoes three distinct phases: a vibrant flame stage with bright yellow colors, a transitional phase where hues gradually shift to deep red, and a final ember stage featuring towards black. Different particles will be randomly selected to fit the phase. The particle size and behavior evolve through a Gaussian distribution, lending the flames a more natural and lifelike appearance.

5 Planned User Study

We plan a between-subjects study with three WRT methods: non-personalized 2D training (C1, baseline), non-personalized immersive training (C2), and personalized immersive training (C3, proposed concept). The interface in C1 is limited to the wildfire simulator, while C2 and C3 offer the complete set of Wildfire@Home features. The dependent variables will be SA acquisition. Participants will be randomly assigned to one condition. Target participants are homeowners residing in high wildfire risk areas who possess traditional wildlife management experience.

The procedure is designed as follows: Participants will receive a digital consent form by email and, upon agreement, will sign and return it. Participants in the C3 condition will provide their homes' location and use a free mobile app to scan their homes. The experiment will be conducted in a controlled lab environment at the ETH Zürich, Chair of Geoinformation Engineering. When arriving at the lab, the participants will complete a demonstration questionnaire. The participants will then receive a 10-minute tutorial on the assigned interface. After the tutorial, the participants will follow 20 minutes of step-by-step, pre-defined standardized instruction to manipulate the parameters and learn how they affect the spread of the wildfire. The experimenter will assist them if any problem occurs. For C1 and C2, the experimenter will load a predefined location for the participant that they are not familiar with, while for C3, the experimenter will load the participant's home

Figure 5: (a) Training takes place from a first-person perspective in VR. (b) A third-person view shows the relations between the user, the scanned model, and the surroundings in the wildfire scene. (c) Wildfire visualization combines particles (flames, embers) with terrain textures indicating different fire states. (d) The wildfire spread process is simulated over time.

location and import the scanned home model into the wildfire visualizer. After completion of the training, participants will answer an SART Questionnaire [61]. Then, the experimenter will conduct a semi-structured interview to investigate general feedback on training effectiveness, perceived efficacy, and usability, while soliciting suggestions for interface design improvements. Data analysis will compare quantitative and qualitative metrics across conditions.

6 Limitations & Future Work

Our work primarily focused on Wildfire@Home's interface design. We have conducted internal testing, but have not yet validated it through real user evaluation. Moreover, current wildfire visualizations remain limited in realism. Future work could improve simulation fidelity in terms of physical, functional, psychological, and social aspects, as suggested in [42].

Another key direction for future work is to integrate eye tracking within VR for enhanced personalization. Unlike traditional methods, VR allows seamless capture of gaze data in 3D environments, providing insights into SA and cognitive load. This capability could enable personalized training by detecting gaze patterns and delivering adaptive feedback, such as highlighting overlooked hazards or reinforcing attention to critical areas. Metrics such as fixation duration, scanpath entropy, and pupil dilation could indicate whether trainees attend to critical uncertainty zones or are distracted by non-essential stimuli.

Embedding uncertainty maps and sketch mapping functions into VR simulations is another direction. Ensemble-based fire spread predictions or probabilistic exposure risks could be visualized as heatmaps, contour bands, or region opacity shifts, enhancing environmental literacy. When combined with eye tracking, these visualizations can reveal suboptimal behavior, such as avoidance of high-risk areas. VR-based sketch mapping technologies [70–72] can also be used to evaluate users' spatial understanding of the fire situation by indicating the fire perimeter and elements' location.

7 Conclusion

This paper introduced PIT, a paradigm that integrates wildfire simulation with immersive VR visualization for personalized WRT. We implemented PIT with Wildfire@Home, a system that enables users to explore cause-and-effect relationships between environmental conditions and fire behavior through direct manipulation and personalized immersive feedback.

Acknowledgments

This research was funded by the Swiss National Science Foundation (SNSF) under the grant 3D sketch Maps (Grant No. 202284).

Acknowledgment of Country (Toups Dugas)

I acknowledge the Traditional Owners and Custodians of Country throughout Australia and the lands on which I carry out my research, the Bunurong people of the Kulin Nations. I pay my respects to their Elders, past and present, and emerging leaders.

References

[1] A. Alexandridis, D. Vakalis, C. I. Siettos, and G. V. Bafas. 2008. A Cellular Automata Model for Forest Fire Spread Prediction: The Case of the Wildfire That Swept through Spetses Island in 1990. *Appl. Math. Comput.* 204, 1 (2008), 191–201. doi:10.1016/j.amc.2008.06.046
[2] AMRAX. 2025. Metaroom. https://amrax.ai/3d-room-models/

[3] John R. Anderson, Lynne M. Reder, and Herbert A. Simon. 1996. Situated Learning and Education1. *Educational Researcher* 25, 4 (1996), 5–11. doi:10.3102/0013189X025004005

[4] artsteps. 2025. Make Your Own VR Exhibitions. https://www.artsteps.com/.

[5] María Isabel Asensio, José Manuel Cascón, Diego Prieto-Herráez, and Luis Ferragut. 2023. An Historical Review of the Simplified Physical Fire Spread Model PhyFire: Model and Numerical Methods. *Applied Sciences* 13, 4 (2023), 2035. doi:10.3390/app13042035

[6] G. L. Ball and D. P. Guertin. 1992. Improved Fire Growth Modeling. *International Journal of Wildland Fire* 2, 2 (1992), 47–54. doi:10.1071/wf9920047

[7] A. Bento-Goncalves and A. Vieira. 2020. Wildfires in the Wildland-Urban Interface: Key Concepts and Evaluation Methodologies. *Science of The Total Environment* 707 (2020), 135592. doi:10.1016/j.scitotenv.2019.135592

[8] Sayed Pedram Haeri Boroujeni, Abolfazl Razi, Sahand Khoshdel, Fatemeh Afghah, Janice L. Coen, Leo O'Neill, Peter Fule, Adam Watts, Nick-Marios T. Kokolakis, and Kyriakos G. Vamvoudakis. 2024. A Comprehensive Survey of Research towards AI-enabled Unmanned Aerial Systems in Pre-, Active-, and Post-Wildfire Management. *Information Fusion* 108 (2024), 102369. doi:10.1016/j.inffus.2024.102369

[9] Karol Bot and José G. Borges. 2022. A Systematic Review of Applications of Machine Learning Techniques for Wildfire Management Decision Support. *Inventions* 7, 1 (2022), 15. doi:10.3390/inventions7010015

[10] Davide Calandra, Federico De Lorenzis, Alberto Cannavò, and Fabrizio Lamberti. 2023. Immersive Virtual Reality and Passive Haptic Interfaces to Improve Procedural Learning in a Formal Training Course for First Responders. *Virtual Reality* 27, 2 (2023), 985–1012. doi:10.1007/s10055-022-00704-9

[11] Yi Fei Cheng, Christoph Gebhardt, and Christian Holz. 2023. InteractionAdapt: Interaction-driven Workspace Adaptation for Situated Virtual Reality Environments. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (UIST '23)*. Association for Computing Machinery, New York, NY, USA, 1–14. doi:10.1145/3586183.3606717

[12] Luca Chittaro and Fabio Buttussi. 2015. Assessing Knowledge Retention of an Immersive Serious Game vs. a Traditional Education Method in Aviation Safety. *IEEE transactions on visualization and computer graphics* 21, 4 (2015), 529–538. doi:10.1109/TVCG.2015.2391853

[13] Rory M. S. Clifford, Timothy McKenzie, Stephan Lukosch, Robert W. Lindeman, and Simon Hoermann. 2020. The Effects of Multi-Sensory Aerial Firefighting Training in Virtual Reality on Situational Awareness, Workload, and Presence. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*. 93–100. doi:10.1109/VRW50115.2020.00023

[14] Janice L. Coen, Marques Cameron, John Michalakes, Edward G. Patton, Philip J. Riggan, and Kara M. Yedinak. 2013. WRF-Fire: Coupled Weather–Wildland Fire Modeling with the Weather Research and Forecasting Model. *Journal of Applied Meteorology and Climatology* 52, 1 (2013), 16–38. doi:10.1175/JAMC-D-12-023.1

[15] Carlos A. Tirado Cortes, Susanne Thurow, Alex Ong, Jason J. Sharples, Tomasz Bednarz, Grant Stevens, and Dennis Del Favero. 2024. Analysis of Wildfire Visualization Systems for Research and Training: Are They Up for the Challenge of the Current State of Wildfires? *IEEE Transactions on Visualization and Computer Graphics* 30, 7 (2024), 4285–4303. doi:10.1109/TVCG.2023.3258440

[16] Carlos Costa, Enrico Gomes, Nuno Rodrigues, Alexandrino Gonçalves, Roberto Ribeiro, Paulo Costa, and António Pereira. 2025. Augmented reality mobile digital twin for unmanned aerial vehicle wildfire prevention. *Virtual Reality* 29, 2 (2025), 1–15.

[17] Alison Crosby. 2025. *Developing a Virtual Reality Game to Support Wildfire Evacuation Awareness.* Ph.D. dissertation. University of California, Santa Cruz, Santa Cruz, CA.

[18] Alison Crosby, Mj Johns, Katherine Isbister, and Sri Kurniawan. 2025. Utilizing Virtual Reality for Wildfire Evacuation Training. *arXiv preprint arXiv:2504.12345* (2025).

[19] Alison Crosby, MJ Johns, Katherine Isbister, and Sri Kurniawan. 2025. Designing FEVR: A VR Game for Wildfire Evacuation Readiness. In *Proceedings of the 20th International Conference on the Foundations of Digital Games (FDG '25)*. Association for Computing Machinery, 1–4. doi:10.1145/3723498.3723766

[20] Viviana Maura Dos Santos and Changwon Son. 2023. Modern Firefighters' Three-Level Situation Awareness in Fire and Non-Fire Incidents. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 67, 1 (2023), 2335–2337. doi:10.1177/21695067231192647

[21] Mica R. Endsley. 1995. Toward a Theory of Situation Awareness in Dynamic Systems. *Human Factors* 37, 1 (1995), 32–64. doi:10.1518/001872095779049543

[22] Hendrik Engelbrecht, Robert W. Lindeman, and Simon Hoermann. 2019. A SWOT Analysis of the Field of Virtual Reality for Firefighter Training. *Frontiers in Robotics and AI* 6 (2019). doi:10.3389/frobt.2019.00101

[23] Sharon L. Farra, Matthew Gneuhs, Eric Hodgson, Burhan Kawosa, Elaine T. Miller, Ashley Simon, Nathan Timm, and Jackie Hausfeld. 2019. Comparative Cost of Virtual Reality Training and Live Exercises for Training Hospital Workers for Evacuation. *Computers, informatics, nursing: CIN* 37, 9 (2019), 446–454.

[24] Zhenan Feng, Vicente A. González, Robert Amor, Ruggiero Lovreglio, and Guillermo Cabrera-Guerrero. 2018. Immersive Virtual Reality Serious Games for Evacuation Training and Research: A Systematic Literature Review. *Computers & Education* 127 (2018), 252–266. doi:10.1016/j.compedu.2018.09.002

[25] Tiziano Ghisu, Bachisio Arca, Grazia Pellizzaro, and Pierpaolo Duce. 2015. An Optimal Cellular Automata Algorithm for Simulating Wildfire Spread. *Environmental Modelling & Software* 71 (2015), 1–14. doi:10.1016/j.envsoft.2015.05.001

[26] Sofia Giannakidou, Panagiotis Radoglou-Grammatikis, Thomas Lagkas, Vasileios Argyriou, Sotirios Goudos, Evangelos K. Markakis, and Panagiotis Sarigiannidis. 2024. Leveraging the Power of Internet of Things and Artificial Intelligence in Forest Fire Prevention, Detection, and Restoration: A Comprehensive Survey. *Internet of Things* 26 (2024), 101171. doi:10.1016/j.iot.2024.101171

[27] A. Malcolm Gill, Scott L. Stephens, and Geoffrey J. Cary. 2013. The Worldwide "Wildfire" Problem. *Ecological Applications* 23, 2 (2013), 438–454. doi:10.1890/10-2213.1

[28] GISTech. 2025. GIS Terrain Loader Pro. https://assetstore.unity.com/packages/tools/integration/gis-terrain-loader-pro-213428.

[29] Laila Goubran, Avi Parush, and Anthony Whitehead. 2016. Modelling Information Flow and Situational Awareness in Wild Fire Response Operations. In *Human Interface and the Management of Information: Applications and Services*. Springer International Publishing, 11–19. doi:10.1007/978-3-319-40397-7_2

[30] John Handmer and Amalie Tibbits. 2005. Is Staying at Home the Safest Option during Bushfires? Historical Evidence for an Australian Approach. *Global Environmental Change Part B: Environmental Hazards* 6, 2 (2005), 81–91. doi:10.1016/j.hazards.2005.10.006

[31] Jason Haskins, Bolin Zhu, Scott Gainer, Will Huse, Suraj Eadara, Blake Boyd, Charles Laird, JJ Farantatos, and Jason Jerald. 2020. Exploring VR Training for First Responders. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*. 57–62. doi:10.1109/VRW50115.2020.00018

[32] Suhaib M. Hayajneh and Jamal Naser. 2025. Wind and Slope Influence on Wildland Fire Spread, a Numerical Study. *Fire* 8, 6 (2025), 217. doi:10.3390/fire8060217

[33] Huang Heyao and T. Ogi. 2021. Assessing the Sense of Presence to Evaluate the Effectiveness of Virtual Reality Wildfire Training. *IEEE Conference on Virtual Reality and 3D User Interfaces* (2021), 1–9.

[34] Roger V. Hoang, Joseph D. Mahsman, David T. Brown, Michael A. Penick, Frederick C. Harris, and Timothy J. Brown. 2008. VFire: Virtual Fire in Realistic Environments. In *2008 IEEE Virtual Reality Conference*. 261–262. doi:10.1109/VR.2008.4480791

[35] Roger V. Hoang, Matthew R. Sgambati, Timothy J. Brown, Daniel S. Coming, and Frederick C. Harris. 2010. VFire: Immersive Wildfire Simulation and Visualization. *Computers & Graphics* 34, 6 (2010), 655–664. doi:10.1016/j.cag.2010.09.014

[36] Chad M Hoffman, John Canfield, Rodman R Linn, William Mell, Carolyn H Sieg, Francois Pimont, and Johannes Ziegler. 2016. Evaluating crown fire rate of spread predictions from physics-based models. *Fire Technology* 52, 1 (2016), 221–237.

[37] Edbert B. Hsu, Yang Li, Jamil D. Bayram, David Levinson, Samuel Yang, and Colleen Monahan. 2013. State of Virtual Reality Based Disaster Preparedness and Response Training. *PLoS Currents* 5 (2013).

[38] Tianqi Huang, Zhenan Feng, Daniel Paes, Fei Ying, Xilei Zhao, Max Kinateder, E. R. (Lisa) Langer, and Ruggiero Lovreglio. 2025. Gamification for Wildfire Education and Safety Training: A Systematic Literature Review and Meta-Analysis. *Journal of Computer Assisted Learning* 41, 5 (2025), e70108. doi:10.1111/jcal.70108

[39] Nicolas LaLone, Phoebe O. Toups Dugas, and Bryan Semaan. 2023. The Crisis of Designing for Disaster: How to Help Emergency Management During The Technology Crisis We Created. In *Proceedings of the 20th International ISCRAM Conference*. 126–143. doi:10.59297/IUGT6097

[40] Haitian Liu, Binglin Liu, Qianchao Hu, Peilun Du, Jing Li, Yang Bao, and Feng Wang. 2025. A Review on 3D Gaussian Splatting for Sparse View Reconstruction. *Artificial Intelligence Review* 58, 7 (2025), 215. doi:10.1007/s10462-025-11171-4

[41] Ruggiero Lovreglio, Vicente Gonzalez, Robert Amor, Michael Spearpoint, Jared Thomas, Margaret Trotter, and Rafael Sacks. 2017. The Need for Enhancing Earthquake Evacuee Safety by Using Virtual Reality Serious Games. In *Proceedings of the Joint Conference on Computing in Construction*. 381–389. doi:10.24928/JC3-2017/0058

[42] Heide Lukosch, Stephan Lukosch, Simon Hoermann, and Robert W. Lindeman. 2019. Conceptualizing Fidelity for HCI in Applied Gaming. In *HCI in Games*. Springer International Publishing, 165–179. doi:10.1007/978-3-030-22602-2_14

[43] Mark A. Finney. 2004. *FARSITE: Fire Area Simulator-model Development and Evaluation.* Number RMRS-RP-4. Rocky Mountain Research Station. doi:10.2737/RMRS-RP-4

[44] Sarah McCaffrey, Alan Rhodes, and Melanie Stidham. 2014. Wildfire Evacuation and Its Alternatives: Perspectives from Four United States' Communities. *International Journal of Wildland Fire* 24, 2 (2014), 170–178. doi:10.1071/WF13050

[45] Sarah McCaffrey, Robyn Wilson, and Avishek Konar. 2018. Should I Stay or Should I Go Now? Or Should I Wait and See? Influences on Wildfire Evacuation Decisions. *Risk Analysis* 38, 7 (2018), 1390–1404. doi:10.1111/risa.12944

[46] Jim McLennan, Glenn Elliott, and Mary Omodei. 2012. Householder Decision-Making under Imminent Wildfire Threat: Stay and Defend or Leave? *International Journal of Wildland Fire* 21, 7 (2012), 915–925. doi:10.1071/WF11061

[47] Jim McLennan, Barbara Ryan, Chris Bearman, and Keith Toh. 2019. Should We Leave Now? Behavioral Factors in Evacuation Under Wildfire Threat. *Fire Technology* 55, 2 (2019), 487–516. doi:10.1007/s10694-018-0753-8

[48] Marijn H. C. Meijers, Ragnheiður “Heather” Torfadóttir, Anke Wonneberger, and Ewa Maslowska. 2023. Experiencing Climate Change Virtually: The Effects of Virtual Reality on Climate Change Related Cognitions, Emotions, and Behavior. *Environmental Communication* 17, 6 (2023), 581–601. doi:10.1080/17524032.2023.2229043

[49] William Mell, Mary Ann Jenkins, Jim Gould, and Phil Cheney. 2007. A Physics-Based Approach to Modelling Grassland Fires. *International Journal of Wildland Fire* 16, 1 (2007), 1–22.

[50] Qingkuo Meng, Hao Lu, Yongjian Huai, Haifeng Xu, and Siyu Yang. 2023. Forest Fire Spread Simulation and Fire Extinguishing Visualization Research. *Forests* 14, 7 (2023), 1371. doi:10.3390/f14071371

[51] Ilias Miltiadis, Apostolos Skarlis, and Pavel Burko. 2025. The Role of Virtual Reality in Personalized Medicine: Advancing Prediction, Prevention, and Participation. *Journal of Medical Systems* 49, 1 (2025), 56. doi:10.1007/s10916-025-02191-2

[52] Federal Office of Topography swisstopo. 2025. swissALTI3D. https://www.swisstopo.admin.ch/en/height-model-swissalti3d.

[53] Joana Oliveira, Joana Aires Dias, Rita Correia, Raquel Pinheiro, Vítor Reis, Daniela Sousa, Daniel Agostinho, Marco Simões, and Miguel Castelo-Branco. 2024. Exploring Immersive Multimodal Virtual Reality Training, Affective States, and Ecological Validity in Healthy Firefighters: Quasi-Experimental Study. *JMIR Serious Games* 12 (2024), e53683. doi:10.2196/53683

[54] Shiva Pedram, Robert Ogie, Stephen Palmisano, Matthew Farrelly, and Pascal Perez. 2021. Cost–Benefit Analysis of Virtual Reality-Based Training for Emergency Rescue Workers: A Socio-Technical Systems Approach. *Virtual Reality* 25, 4 (2021), 1071–1086. doi:10.1007/s10055-021-00514-5

[55] V. C. Radeloff, R. B. Hammer, S. I. Stewart, J. S. Fried, S. S. Holcomb, and J. F. McKeefry. 2005. The Wildland-Urban Interface in the United States. *Ecological Applications* 15, 3 (2005), 799–805. doi:10.1890/04-1413

[56] Volker C. Radeloff, David P. Helmers, H. Anu Kramer, Miranda H. Mockrin, Patricia M. Alexandre, Avi Bar-Massada, Van Butsic, Todd J. Hawbaker, Sebastián Martinuzzi, Alexandra D. Syphard, and Susan I. Stewart. 2018. Rapid Growth of the US Wildland-Urban Interface Raises Wildfire Risk. *Proceedings of the National Academy of Sciences* 115, 13 (2018), 3314–3319. doi:10.1073/pnas.1718850115

[57] F. D. Rose, E. A. Attree, B. M. Brooks, D. M. Parslow, and P. R. Penn. 2000. Training in Virtual Environments: Transfer to Real World Tasks and Equivalence to Real Task Training. *Ergonomics* 43, 4 (2000), 494–511. doi:10.1080/001401300184378

[58] Richard C Rothermel. 1972. *A mathematical model for predicting fire spread in wildland fuels*. Intermountain Forest & Range Experiment Station, Forest Service, US Department of Agriculture.

[59] Harikesh Singh, Li-Minn Ang, Tom Lewis, Dipak Paudyal, Mauricio Acuna, Prashant Kumar Srivastava, and Sanjeev Kumar Srivastava. 2024. Trending and emerging prospects of physics-based and ML-based wildfire spread models: A comprehensive review. *Journal of Forestry Research* 35, 1 (2024), 135.

[60] Panayiotis Sophronides, Chrysaida-Aliki Papadopoulou, Maria Giaoutzi, and Henk J. Scholten. 2017. A Common Operational Picture in Support of Situational Awareness for Efficient Emergency Response Operations. *Journal of Future Internet* 2, 1 (2017), 10–35. doi:10.18488/journal.102.2017.21.10.35

[61] Richard M Taylor. 2017. Situational awareness rating technique (SART): The development of a tool for aircrew systems design. In *Situational awareness*. Routledge, 111–128.

[62] Unity Technologies. 2025. Particle System Component Reference. https://docs.unity3d.com/6000.2/Documentation/Manual/class-ParticleSystem.html.

[63] Carlos Alfredo Tirado Cortes, Mario Flores Gonzalez, Richard J. Hurley, and Dennis Del Favero. 2025. Designing an Immersive Wildfire Visualization System for Firefighters. In *Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems (CHI EA ’25)*. Association for Computing Machinery, 1–10. doi:10.1145/3706599.3719903

[64] Phoebe O. Toups Dugas and Andruid Kerne. 2007. Implicit coordination in firefighting practice: design implications for teaching fire emergency responders. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI ’07)*. Association for Computing Machinery, New York, NY, USA, 707–716. doi:10.1145/1240624.1240734

[65] Phoebe O. Toups Dugas, Andruid Kerne, and William A. Hamilton. 2011. The Team Coordination Game: Zero-fidelity simulation abstracted from fire emergency response practice. *ACM Trans. Comput.-Hum. Interact.* 18, 4, Article 23 (2011), 37 pages. doi:10.1145/2063231.2063237

[66] Jessica Vega, Sophia Rose, Christian Eckhardt, Liudmila Tahai, Irene Humer, and Krzysztof Pietroszek. 2017. VR Wildfire Prevention: Teaching Campfire Safety in a Gamified Immersive Environment. In *Proceedings of the 23rd ACM Symposium on Virtual Reality Software and Technology (VRST ’17)*. Association for Computing Machinery, 1–2.

[67] Jessica Vega, Sophia Rose, Christian Eckhardt, Liudmila Tahai, Irene Humer, and Krzysztof Pietroszek. 2017. VR wildfire prevention: teaching campfire safety in a gamified immersive environment. In *Proceedings of the 23rd ACM symposium on virtual reality software and technology*. 1–2.

[68] Zijia Wang, Zixuan Mao, Yongxing Li, Liang Yu, and Linmu Zou. 2023. VR-based Fire Evacuation in Underground Rail Station Considering Staff’s Behaviors: Model, System Development and Experiment. *Virtual Reality* 27, 2 (2023), 1145–1155. doi:10.1007/s10055-022-00718-3

[69] Steven G. Wheeler, Simon Hoermann, Stephan Lukosch, and Robert W. Lindeman. 2024. Design and Assessment of a Virtual Reality Learning Environment for Firefighters. *Frontiers in Computer Science* 6 (2024). doi:10.3389/fcomp.2024.1274828

[70] Tianyi Xiao, Yizi Chen, Sailin Zhong, Peter Kiefer, Jakub Krukar, Kevin Gonyop Kim, Lorenz Hurni, Angela Schwering, and Martin Raubal. 2025. Sketch2Terrain: AI-Driven Real-Time Terrain Sketch Mapping in Augmented Reality. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*. 1–24.

[71] Tianyi Xiao, Kevin Gonyop Kim, Jakub Krukar, Rajasirpi Subramaniyan, Peter Kiefer, Angela Schwering, and Martin Raubal. 2024. VResin: Externalizing spatial memory into 3D sketch maps. *International Journal of Human-Computer Studies* 190 (2024), 103322.

[72] Tianyi Xiao, Sailin Zhong, Peter Kiefer, Phoebe O. Toups Dugas, and Martin Raubal. 2025. CoNaviMap: Collective Navigation in Wilderness Search and Rescue Using Collaborative 3D Sketch Mapping. In *Workshop on Scaling Distributed Collaboration in Mixed Reality - The Blended Realities Collective at ACM CHI 2025*. doi:10.3929/ethz-c-000785080

[73] Haowen Xu, Sisi Zlatanova, Ruiyu Liang, and Ismet Canbulat. 2025. Generative AI as a Pillar for Predicting 2D and 3D Wildfire Spread: Beyond Physics-Based Models and Traditional Deep Learning. *Fire* 8, 8 (2025), 293. doi:10.3390/fire8080293

[74] Chuanjie Yang, Jianguo Chen, and Guofeng Su. 2016. Effective Situational Awareness to Wildfire Emergency Command Based on Multi-Model Forecasting System. In *Proceedings of the Second ACM SIGSPATIALInternational Workshop on the Use of GIS in Emergency Management (EM-GIS ’16)*. Association for Computing Machinery, 1–3. doi:10.1145/3017611.3017612

[75] Xiaolin Yang, Zhongliang Wu, and Yingchun Li. 2011. Difference between Real-Life Escape Panic and Mimic Exercises in Simulated Situation with Implications to the Statistical Physics Models of Emergency Evacuation: The 2008 Wenchuan Earthquake. *Physica A: Statistical Mechanics and its Applications* 390, 12 (2011), 2375–2380. doi:10.1016/j.physa.2010.10.019

A Characteristics of Experts

Table 1: Characteristics of experts involved in the semi-structured interviews. Abbreviations: F = field responder; C = commander; M = man; W = woman.

ID	Service Years	Role	Gender	Age
E1	7	F	M	41
E2	3	C/F	M	30
E3	4	F	M	29
E4	4	F	W	36
E5	10	C/F	M	50
E6	6	F	W	32
E7	15	C/F	M	36
E8	2	F	W	32
E9	3	F	M	25

B Formative Study Materials

B.1 Screening Survey

Part 1 – Participants Information and Firefighting Expertise

SS-1 Contact:________; Gender:________; Age:________
SS-2 Role: [Commander / Field Responder / Both / Other]
SS-3 Service years: ________

Part 2 – Availability

SS-4 What times are you typically available for an interview?
SS-5 Do you have any additional comments?

B.2 Interview Protocol

This interview served to generate our design strategists (Section 3).

IP-1 Can you briefly describe your primary responsibilities?
IP-2 What types of firefighting missions have you been involved in?
IP-3 Have you received fire response training? What content was covered? What tools were used?
IP-4 What challenges have you faced during training?
IP-5 How could tools be improved to better support fire response training?
IP-6 Do you see the potential for immersive technology to support (public) fire response training?
IP-7 Compared to traditional tools, what are the strengths and limitations of this system?
IP-8 In what scenarios would immersive technology be more useful than traditional methods?
IP-9 What features or capabilities would you expect in an immersive fire response training tool?
IP-10 Do you have any concerns about using such tools in practice?
IP-11 Is there anything else you would like to share?