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RESPONSIVE ENVIRONMENTS WITH VIRTUAL REALITY EXPERIMENTS AND SIMULATIONS

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ABSTRACT

The safety and experience of the users of public infrastructure concern both them and the managers. Intelligent techniques such as virtual reality and computer simulations can enable environments to respond to users' needs. Such responsive environments can be designed to incorporate geographic information services based on pre-occupancy evaluations. For this dissertation, I investigate the potential of responsive environments in several scenarios, including crowd disasters, social wayfinding, and fire evacuation. The methodology of this dissertation combines behavioral science with computer science and engineering technologies. The results of this investigation show that intelligent interventions provide security, efficiency, and comfort for users within responsive environments. In general, this dissertation combines the technical perspective of computer science with the behavioral perspective of cognitive science to define the next generation of responsive environments. This approach can help public space organizers and event planners to better understand the effect of design on the behavior of individuals. Furthermore, it can provide users with assistance and advice. These series of studies may also help behavioral scientists, computer scientists, and public space designers better understand smart environment design and collective intelligence.

ZUSAMMENFASSUNG

Die Sicherheit und die Erfahrung von Nutzern öffentlicher Infrastruktur betrifft sowohl sie selbst als auch die Betreiber dieser Infrastruktur. Intelligente Techniken wie beispielsweise virtuelle Realität und Computersimulationen können Umgebungen befähigen, auf die Bedürfnisse der Nutzer einzugehen. Solche reaktionsfähigen Umgebungen können derart gestaltet werden, dass sie geografische Informationsdienste basierend auf 'pre-occupancy'-Bewertungen integrieren. In dieser Dissertation untersuche ich das Potential reaktionsschneller Umgebungen in verschiedenen Szenarien, einschliesslich Katastrophen in Menschenmengen, sozialer Wegfindung und Evakuierung bei Feuer. Die Methodik dieser Dissertation kombiniert Verhaltenswissenschaften mit Informatik und Ingenieurstechnologien. Die Ergebnisse dieser Untersuchung zeigen, dass intelligente Interventionen Sicherheit, Effizienz und Komfort für Benutzer innerhalb von reaktionsschnellen Umgebungen bieten. Im Allgemeinen kombiniert diese Dissertation die technische Perspektive der Informatik mit der Verhaltensperspektive der Kognitionswissenschaft, um die nächste Generation von reaktionsfähigen Umgebungen zu definieren. Dieser Ansatz kann Organisatoren von öffentlichen Räumen und Veranstaltungsplanern helfen, die Auswirkungen von Design auf das Verhalten von Individuen besser zu verstehen. Darüber hinaus kann er den Benutzern Hilfestellung und Beratung bieten. Diese Studienreihen können auch Verhaltensforschern, Informatikern und Gestaltern öffentlicher Räume helfen, intelligentes Umgebungsdesign und kollektive Intelligenz besser zu verstehen.

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CONTENTS

1 INTRODUCTION

Gentleness and kind persuasion win where force and bluster fail.

— Aesop

1.1 PREAMBLE

Almost all of us spend most of our lives in built environments. Consequently, our near-ceaseless interactions with these environments lead us to ask what our relationship is with them and how they influence and change our behavior. The ancient Greek storyteller Aesop tackled a similar question 2,500 years ago. In one of his stories, the north wind and the sun argued over which of the two was the stronger. They competed to see who could remove a wayfarer's cloak. The wind tried first. He blew a strong blast at the wayfarer, trying to blow the cloak off. It worked in the beginning due to the wind's fierce power. However, after the wayfarer realized what was happening, he grabbed his cloak and drew it closer to his body. The harder the wind blew, the tighter the wayfarer held onto his cloak. The north wind finally gave up. The sun started his attempt with a ray of pleasant sunshine. The wayfarer felt the warmth and loosened his grip on the cloak. As the temperature grew higher, the wayfarer finally took off his cloak and enjoyed the sunshine. How can an environment, whether natural or built, influence human beings' behavior? Aesop's clear answer appears in the quotation above.

1.2 MOTIVATION AND PROBLEM STATEMENT

As technology has developed, humans' capacity to influence our behavior has far exceeded what the north wind and sun achieved in Aesop's fable. We have created buildings for shelter and air conditioning systems to protect ourselves from both heat and cold. Nevertheless, the creators of built environments have repeatedly found their users misusing their creations [1], and the users often complain that the build environments are hard to understand and use [2]. There is certainly a gap between designers' initiatives and users' expectations. Designers of the public environment have suffered from such a disparity, the essential cause of which is the absence of users from the design process. After construction, the environments rarely incorporate feedback from their users' activities. They are not being *responding* to their users. Such important feedback is scarcely considered during the design process. The lack of feedback produces an environment that fails to actively answer the user's needs, thus leading to cumbersome scenarios. These scenarios have often failed to provide accessible information and/or have unintentionally created risky situations for users. Such failures have led to crowd disasters [3, 4], ineffective emergency evacuations [5–7], and traffic accidents [8]. These unfortunate events may also cause energy inefficiency [9], economic impact [10], and more severe consequences such as casualties [3, 11].

Recent developments in the research of the public environment have led to a renewed interest in integrating technologies into the design process. The rapid development of engineering technologies has enabled the environments to respond intelligently to their users through the evidence-based design. Conducting experiments in virtual reality enables the evaluations of the design even before the construction of the environments. Furthermore, computer simulations reveal the users' behavior patterns without massively collecting user' data in the real world thus violating privacy. Smart devices [12] and sensor technologies [13] are also used in the built environment in order to improve the perception of the entity and the experience of the users. In particular, these technologies allow the assessment of dangerous situations which are usually unethical if not impossible to study in the real world [14]. These prominent advantages of virtual experiments and computer simulations can help overcome a substantial proportion of such risks and inefficiency distribution of valuable resources. They provide pre-occupancy evaluations of the environment and help the designer to identify potential design flaws. With this assistance, environments that incorporate the user's behavior and feedback through empirical experiments and simulations can be referred as *responsive environments*. Such environments use information technologies to respond to their users' behaviors, thus avoiding some of the flaws generated by the traditional design procedure. Despite its importance, a systematic understanding of what consists of a responsive environment and how to validate its effect are still missing. Much uncertainty still exists about the relationship between the responsive environments and the design flaws that can be addressed. This dissertation will examine how to use virtual reality experiments and simulations to strengthen responsive environments.

1.3 PRIOR WORK

Previous research can be categorized into three areas: user behavior in built environment, responsive environment, and technologies for responsive environment. The investigation of user behavior begins by identifying the design flaws in the artificial environment and the consequences of such flaws.

1.3.1 *User behavior in built environment*

The design of environments affects the behavior of humans located within them in numerous ways. The infrastructure [5], spatial structure [15], and even lighting [16] and sound [17] can strongly influence individuals' behavior, since such design elements contain features that assist or hinder decision-making processes. Effective building infrastructure such as signage systems can function as the aid of the wayfinding [5]. Spatial structure influences the social effects through spatial foundations such as space syntax [15]. The lighting within buildings aims to balance amongst the glare, the thermal discomfort, and overheating risks [16]. The volume and source of background music positively affect the mood and the experience of the participants [17]. When poorly designed, a public environment with flaws can cause more severe consequences than influencing the users' experience and comfort. Such flaws are particularly fatal when emergent and dangerous hazard occurred, which requires the user to make prompt decisions with limited information and time. A considerable volume of literature has been published on the costs and consequences of a poorly designed environment for the socio-economic system. Severe consequences include wayfinding difficulties, crowd disasters, and evacuation failure.

WAYFINDING DIFFICULTIES Wayfinding refers to the human capacity to navigate in an environment in which the actions of determination, learning, and memorizing a route are required [18]. It is a complex process that involves a series of individual or group locomotion from one place to another [19]. Wayfinding decisions are made during the navigation process based on the perceived information by the subject. Due to the involvement of cognition and perception within wayfinding decisions, what we know about the relationship between indoor environment design and wayfinding decisions is largely based on studies from the environmental psychology community. Human wayfinding is a key consideration for the designer of public space to improve pedestrians' experience. The wayfinding strategies do not only depend on the individual spatial abilities but also on the structure of the environment [20, 21]. The accuracy and efficiency of this process can largely influence the user's viewpoint of an environment if the wayfinding experience is substantially compromised in this specific environment. Individuals' navigation strategies depend on various environmental features, such as landmarks, spatial layouts, and the floor arrangements of public space [22]. Researchers have demonstrated the importance of understanding users' spatial cognition when evaluating a public space design [23]. A combination of environmental structures can influence and alter the navigation behavior in various ways.

User-centered design [24] has a pivotal role in the design procedure. This concept emphasizes the importance of the user and the usability of the design. However, several lines of evidence suggest that the designed features are not always as helpful as they might be, especially in scenarios that involve wayfinding. Best [25] identified choice points, directional changes, and distances as factors that challenge the wayfinding procedure in complicated environments. Research has shown that users' abilities to integrate spatial information can be impaired by the misalignment of reference points [26]. The spatial structure of the environment can limit visual access [27], thus influencing users' trajectories and experience [28]. A multi-level building can be particularly challenging due to the presence of connection corridors and the stairs of the building. For unfamiliar users in a multi-level building, their wayfinding efficiency may depend on the building structures instead of their wayfinding strategies [29].

To overcome such challenges, geographic information services such as signage and maps are frequently provided in indoor environments. They are designed to convey relevant and accurate geographical information to the users in the environment, such as their orientations and locations [30]. A well-designed map can assist users to find a path to their desired target and improve navigation efficiency [31]. Though research has shown that a substantial proportion of signage and map is inefficient or does not deliver the information that it is intended to. They either provide misleading information [6] or are located in unfavorable positions and are thus neglected by users [32]. Such defective signage can delay the wayfinding procedure, contribute to unnecessary congestion, and generate large numbers of inquiries to staff at an information desk [33]. Collectively, these studies outline the critical consequences and the enormous potential cost. It can not be ignored that the traditional process of map and signage design contains potential deficiencies that result in wayfinding difficulties. In particular, investment in solving these wayfinding difficulties could create an economic return that benefits both users and managers. Rioseco and Berczuk [34] estimated that 3.7 US dollars could be gained for every dollar invested in the wayfinding system by providing benefits such as journey timesaving.

CROWD DISASTERS The behavior of a group of pedestrians in an unfamiliar environment is another vital component for the environment designer. The dynamic of a large crowd is depicted as a self-organizing system [35]. The high level of self-organization enables group behaviors that are hard to predict, which can potentially lead to the abnormal status of the crowd. Such abnormal status may further cause potential dangers, which in severe cases can develop into crowd disasters. Such human crowd disasters can be formed by unusual crowd densities [3], mass panic [36], and suboptimal decisions led by social contagion [37]. Irrational behavior at the individual level furthers the severity of such occasions [38]. Large gatherings are common venues at which crowd disasters have happened, including religious events [39], music festivals [3, 40], and sports events [41]. These venues share a common character that there are a large number of people gather or dismiss rapidly within an environment with limited space. The uncommon high volume of crowd flows results in unusual crowd density. When crowd density reaches a certain level, the danger from suffocating [42] and trampling [43] increases sharply to a point that produces severe injuries and death. Tragedies have occurred repeatedly in the past decade in Mina of Saudi Arabia [39], Duisberg of Germany [3], and Shanghai of China [40]. It is estimated that more than 2,000 people die annually because of crowd disasters [44]. The causes of such tragedies vary from case to case, but mismanagement is a common cause in most scenarios [45]. Such errors include but are not limited to defective field choices [3], wrongly signposted or limited entrance and exit locations [41], insufficient flow capacity [37], and inappropriate crowd management strategies [40]. Except for specific reasons such as religious events [39], most of the crowd disasters do not have the tendency to repeat at the same venue. These crowd disasters can be avoided by conducting careful evaluation and assessment in advance. It has been shown that pre-planning is crucial to prevent such tragedies [46];

thus the selection of a venue [47] that does not provide conditions for a crowd disaster is critical for large event organizers.

EVACUATION FAILURE Emergency evacuation is another scenario that requires the environment designer to take precautionary measures. When critical circumstances appear, such as fire, natural disasters, escapes of hazardous substances, and security threats, the users of a space are required to leave to avoid further risk. Fire is a common reason for emergency evacuation, with an estimated number of 7,000,000 to 8,000,000 incidents annually [11]. Most modern buildings have integrated fire evacuation systems (e.g. evacuations signage, emergency exit, fire sensors, etc.) to provide the necessary assistance to their users during unexpected fire accidents. However, research has found that design flaws could undermine the effectiveness of evacuation guidance thus threaten the safety of their users [5, 7, 48–50]. First, structural flaws such as narrow exits [49] and paths [3] limit the maximum flow capacity of the evacuees. Route choices are frequently suboptimal for the evacuees; the majority of people escape via the main entrance from where they enter the building, which is neither the shortest nor the signaled route [51]. Castle [50] observed that many buildings lacked specific evacuation plans. Furthermore, Elliott analyzed football stadium disasters in the United Kingdom and found that many evacuation tragedies were caused by insufficient attention to the exit plan design [49], even though emergency signs are placed in the public space to facilitate the evacuation procedure. Xie and colleagues found that evacuation signage was not as effective as it could have been [52], and more than half of signage was ignored by evacuees during the evacuation experiment [5]. From time to time, it is possible that the indicated route is blocked by the hazard or congested with traffic [53]. Most of these unfortunate circumstances are related to features of the environment, which could be improved with a new design or new technologies. However, another significant aspect of successful evacuations is the role of human behavior. Human perceptions and assessment of risk are challenged under critical circumstances [54]. If a collective phenomenon of escape panic appears, crowd stampede and trample can take place [38]. A clear understanding of wayfinding behavior is fundamental to designing a thorough and well-thought evacuation plan.

WAYFINDING BEHAVIOR IN VIRTUAL ENVIRONMENT Although generally studied in real environments [22, 27, 55–58], the analysis of wayfinding is not restricted to the physical world. Recent trends in extending wayfinding research to virtual environments have led to a proliferation of studies [59–65] due to the convenience and flexibility of this approach. Virtual environment technologies can facilitate the experimental control without compromising the validity of the findings in the experiment [66]. Despite the difference between a real and virtual environment, a previous study has demonstrated that practice with the virtual environment can reduce such differences [67]. There exists a strong correlation in wayfinding behaviors between real and virtual buildings [68]. Research using virtual environments has demonstrated that the spatial association of landmarks with certain targets can influence wayfinding decisions [55]. Compared to traditional behavioral studies in the real world, using virtual environments in a laboratory also facilitates the modification of experimental conditions. In virtual environments, researchers can systematically vary factors that are improbable in real life, including the variation of structural and visual factors [66]. For example, Bode and Codling [14] implemented a virtual evacuation task and put participants under stressful conditions. They found that people's route choices in stressful conditions were more directly determined by evacuation time than by a preference to avoid crowds. In another investigation, Bode and colleagues [69] have examined different media for conveying directional information from a top-down overview. They found that signs had a strong effect on the evacuation strategy used by participants in a virtual environment. Overall, the virtual environment may potentially be a more naturalistic medium to acquire spatial information for participants than a map and may thus require less effort during spatial information learning [70].

The cognitive properties of individuals play a vital role in the process of wayfinding. The spatial knowledge of the environment can be similar in both virtual and real environments. Theories and frameworks from cognitive science research can introduce a new perspective at the start of a design procedure to help avoid irrational decisions during indoor wayfinding. Cognitive scientists use the term "cognitive map" to refer to the spatial knowledge of the environment [71]. This spatial knowledge helps subjects to better reconstruct the environment in their memories and locate themselves. Based on the understanding of such a concept, therefore it is advisable to build the environment in a way that it can facilitate the building users to easily form a cognitive map. A location information system can vastly assist building users during navigation if a consistent spatial reference system is perceptible similar to a landmark at the center of a city, from several locations in a structure [26]. The effects of a global frame of reference on cognition were tested under stress [72]. Hölscher and colleagues [20] analyzed the usability of hot spots such as entrance hall, floors, stairways, and dead ends within a conference venue and observed their disadvantages for wayfinding from a cognitive-architectural perspective. They suggested that the consequences of rotation when using staircases to move vertically was the most problematic cause of wayfinding difficulties.

NAVIGATION AID In recent years, interest has been increasing in the role of navigation aids in wayfinding tasks [73–76]. Wireless Internet and personal devices (e.g. mobile phones, wearable devices, etc.) facilitate individual's access to real-time geographic information from anywhere conveniently. There is an urgent need to address questions raised about the usability of mobile phone navigators. In order to address these questions, it is essential to clarify the purpose and advantages of digital navigation systems. One study suggested that current navigation systems ought to incorporate varied and flexible information that ranges from detailed to abstract [77]. The same study has also emphasized the importance of interactivity in information delivery and responsiveness to users' prior experience [77]. Designing distinct methods to assess interaction with applications has been shown to be an effective approach to conducting usability tests. Rohs and colleagues [78] have demonstrated that an interactive device provides better map exploration performance than other methods such as static maps, virtual maps with joysticks, and physical movement with a grid map. Eye-tracking technologies enable quantitative evaluation of the wayfinding strategy with a focus on individual visual attention. It has been applied to evaluate the signage placement in Frankfurt Airport and identify the flaws of the current signage arrangement [79].

The media of navigation aids are no longer restricted to static offline maps. For example, network technology enables the sharing of information and knowledge on the social context between map users. Hirtle and Raubal [13] emphasized the importance of providing personalized services by exploring the interaction possibilities between users, environments, and mobile devices. Real-time information combined with social networking provides the possibility of spatially aware personal digital assistants. Applying collective intelligence to map design can also provide benefits of efficiency by assembling information. This is exemplified by a many-to-many mobile map that integrates information generated by numerous users or sensors to present more efficient and useful geographical information [13]. Navigation aids may also be distributed among users during cooperative wayfinding.

The study carried out by Reilly and colleagues [80] has also suggested that sharing mobile phones can be effective during cooperative wayfinding. They also found that users' navigation of the mobile phone's interface, the environment, and the collaborative predisposition of the participants can also influence performance.

Despite this, previous research suggests some disadvantages of relying on such navigation aids. Navigating with aids may be detrimental to the development of an accurate mental representation of the environment [81]. These aids may affect spatial memory while only providing marginal gains in navigation efficiency in familiar environments because they divide their users' attention [74]. If the service provider is offline or compromised by unexpected events, the strong dependence of wayfinding and navigation decisions on those applications can potentially create systemic failure. However, it can not be denied that our daily wayfinding activities, especially automobile navigation, have been strongly associated with personal smart devices. The increase in the availability and convenience of smart devices [12] means that people's reliance on smart devices for navigation is unlikely to cease. It is therefore worthwhile to investigate how to help pedestrians navigate more efficiently with mobile applications without diminishing their spatial abilities.

COLLECTIVE INTELLIGENCE As mentioned above, information sharing between users has recently become a focus of behavioral science studies. Collective intelligence represents the shared intelligence that is usually formed by collaboration within a team or competition between individuals. The generation of collective intelligence can help researchers to examine certain questions. In a social wayfinding study, three possible relationships between two related people were identified: leader and follower, independent, and collaborative [80]. The group dynamic and the social context largely determine the existence of a collaborative relationship. Numerous studies have attempted to reveal the benefits that collaborations can bring to a group. Malone and colleagues [82] used collective intelligence to learn that group decisions are as useful as individual decisions, especially when the knowledge necessary for making a decision is widely distributed among individuals in a group. Woolley and colleagues [83] demonstrated evidence for the effect of collective intelligence factors on a group's performance in experiments with video games and architectural design. Practitioners suggested that the inclusion of collective intelligence with isolated intelligence is beneficial even for traditional disciplines as architecture [84]. The form of collaboration can vary with context and social dynamics. Thus it is important to investigate whether this collective intelligence is continuous in virtual environments. Moussaid and colleagues [63] revealed the collective dynamics of herding under high density in a virtual evacuation task with 36 participants. Similar collaborative virtual environments have been implemented by Dodds and Ruddle [85], and they have found out that collaboration makes participants more efficient and travel significantly less in an urban planning task.

1.3.2 *Responsive environment*

DEFINITION Thus far, this dissertation has argued that design flaws and the complexity of wayfinding behavior both play critical roles in the research of artificial environments. There is an urgent need to address the absence of intelligence in conventional built environments. The need first arose among the architectural community. One of the first researchers to address this need was Christopher Alexander [86], who used the term *pattern* to describe problems that appear in the environment design procedure and the solutions corresponding to such problems. Bentley and colleagues [87] defined a responsive environment as an entity that can provide a democratic setting by maximizing the extent of freedom of its users. Krueger [88] popularized the term responsive environment by introducing computer technologies into the design of environments. He identified an "intelligent environment" as an entity that could perceive the actions of users and respond to them. Such a definition is further extended by Beilharz [89] with an emphasis on including technologies for smart buildings, networked sensors, and ambient visual and auditory systems. In this dissertation, I combine previous researchers' definitions and use *responsive environment* to refer to an environment that is able to use computer technologies to *answer* and *adapt* to the various needs of its users. There has already been a large volume of applications elaborating on the concept of a responsive environment. A wide range of applications benefits from such a concept, including health-related applications, transportation, education, entertainment, and smart offices [90].

APPLICATIONS Emergency response in hazardous situations has been a challenging task for building managers due to the unpredictability and complexity of those accidents. Conventional building managers often rely on external assistance (e.g. emergency response team, fire department, police station, etc.) when such hazardous events occurred. However, the dangerous nature of those hazardous incidents requires prompt reactions, which the external assistance often can not provide in time. The intelligence of responsive environments can enable both the safety [91–93] and the efficiency [94–96] of users in these hazardous accidents. Safety can be enabled through a pedestrian management system and citizen-based data collection. Pedestrian management systems are built to deliver route guidance information to users directly [92, 93, 97, 98]. The time-sensitive feature of such real-time management systems empowers the emergent needs of fast reactions in those hazardous events. On the other hand, citizen-based collection of data was suggested to be helpful for organizers coping with unforeseen natural disasters such as earthquakes, tsunamis, and floods. Personalized warnings and evacuation routes can be delivered to individuals directly through crowdsourcing [99]. Furthermore, information transparency and timely knowledge make public space managers become more efficient and effective when conducting difficult decision-making choices. For example, Bessis and colleagues [100] presented an information architecture with corresponding technologies that can enable more efficient disaster management. In their investigation, web Services and cloud computing technologies were demonstrated and integrated into various real-world disaster management scenarios.

In addition, a responsive environment can achieve far more than merely improving the safety level in disaster management scenarios. A smart home is built not only to increase its inhabitants' comfort but also to reduce its overall energy consumption [101]. In order to achieve such goals, the environment must be able to gain perceptions of the activities within itself. Sensor technologies are integrated to fulfill such purposes. The data collected by the sensors is used to analyze the ongoing activities and further to maximize energy efficiency and cut expenses [102, 103]. Computer networks enable cooperation between sensors and provide better judgment for decision making [104]. Information technology and computer simulation can achieve more than monitoring the environment. In an investigation into energy consumption, Peronato and colleagues [105] created a building simulation tool to simulate and visualize a building's energy usage performance. The responsive environments need to consider their users as well. Research recognizes the critical role played by users within the environment and focuses on analyzing their behaviors. Their feedback and activities can be included directly into the responses of an adaptive smart home [106]. Medical assistance can be provided through a responsive environment by monitoring and facilitating decision making by medics [107]. One longitudinal study found that mobility, health information, and social interactions can be monitored via smart devices to indicate physical and mental conditions in the elderly under medical treatment [108]. Mitchell and colleagues [109] developed an intelligent hospital system that facilitates remote consultation with the help of patient and equipment tracking and information notification. Together, these studies confirm the convenience and effectiveness of a responsive environment in modern environment design.

To date, most daily life involves few interactions between the environment and users that integrate information technologies. Currently, innovative approaches commonly involve a touchscreen that allows users to select from options and then displays the corresponding information on the screen [110, 111]. Research on the user interface design has mostly been restricted by the limited availability of interaction technologies. This concept has recently been challenged by the rapid development of human-environment interaction technologies. The context-aware shopping system now integrates the shopping list into the trolley, which improves the customers' experience [112]. Personal smart devices are ubiquitous and provide easy access to online information. Therefore, it is practical to progressively integrate smart devices into human-environment interactions. Anderegg and colleagues [113] used a smartphone as a controller to operate virtual characters in the environment. Bieber and colleagues [114] deployed a smartwatch to enable hands-free operations for maintenance technicians. Museum exhibitions become more vivid and interactive with both augmented reality [115] and virtual reality technologies [116]. The state-of-the-art interaction technologies make responsive environments more user-friendly and intuitive to connect.

Robotic technologies and artificial intelligence empower a responsive environment from another perspective. Robots have been deployed in public environments as a new medium of information, providing assistance [117] and entertainment [118]. In these specific scenarios, the environment can provide another communication channel between the user and the robot [119]. Matsumoto and colleagues [120] have built an intelligent wheelchair that can detect obstacles and automate its movement for patients. On the other hand, machine learning algorithms and artificial intelligence rationales have been broadly applied in pattern recognition and prediction of data, images, and natural language processing [121]. These prediction mechanisms can also help environment managers to gain better insights into the crowd and pedestrians. For example, Bera and colleagues [122] created a real-time pedestrian path prediction mechanism using Bayesian inferences and crowd videos from surveillance cameras. With proper state estimate methods and separation between global movement patterns and local movement patterns, they devised an algorithm that outperformed prior methods such as Bayesian reciprocal velocity obstacle and Kalman Filter [122]. Other researchers have used mobile data to predict the geographical location of crowds [123]. On the city scale, crowd movement prediction is also possible with large mobile phone Global Positioning System log datasets [124]. Data generated in social networks can be advantageous in the procedure of location prediction. Using Twitter to predict geographical location has been demonstrated with satisfactory accuracy as well [125]. Deep learning models, for example, recurrent neural networks [126], or convolutional neural networks [127], has been used for improving the prediction accuracy of the testing data set. Artificial intelligence helps to free valuable human resources from conducting repetitive jobs.

1.3.3 *Technologies for responsive environment*

DATA-DRIVEN DESIGN Multiple types of technologies are imperative to fulfill the requirements of the designers of responsive environments. In engineering disciplines, complex problems are often approached with data-driven methodologies. Such methods extract information directly from considerable amounts of recorded data [128], and they could potentially improve the design of environments and generate novel insights. For example, Nan and colleagues [129] used an image-based mapping method to assess the user experience of lighting conditions in an office environment. Merrell and colleagues [130] trained a Bayesian network to generate viable building layouts with a combination of machine learning and traditional blueprint optimization. One of the many advantages of such a generation procedure was that it did not need to take the specific requirements of location or client into account. One study has shown that the architectural solutions generated by an automatic architectural design tool outperformed the architectural solutions generated by handwork, given adequate user studies [131]. Dubey and colleagues [132, 133] used agents and information theory to model the interactions between signage and agents and thus optimize the locations of signs. If performed by human experts, those works could become extremely time-consuming.

Despite that previous research has established the importance of technology in the design procedure, due to practical constraints, users may not interpret the functionality of certain designs correctly. For this reason, even though automation may reduce the need for designers, human opinion is still an essential element during the design process [134]. One way to incorporate users' opinions into the smart environment is by modifying the environment set up to help the users concentrate and focus [135, 136]. When an architect is designing a public environment, the clustering of the users into a crowd is also an essential factor for strategic layout changes due to its effect on the movement patterns. Early consideration of the effects of crowds can benefit decision-makers and prevent particular risks such as crowd disasters. Massive crowd simulations play a vital role as a research method that could incorporate potential users' behaviors into the design procedure before the plan is executed [137, 138].

CROWDSOURCING Acquiring users' data from reliable sources is a fundamental step for these data-driven approaches. Additionally, a large training data set is advantageous for calibrating the algorithms [121]. This data collection requires a larger investment when conducted in a professional laboratory. In countries with high minimum wage such as Switzerland [139], recruiting and paying participants in behavioral studies are very expensive. Amazon Mechanical Turk provides a solution for collecting user measurements promptly with low costs through microtasks [140]. This web service links the researchers with microworkers by providing tasks that require human intelligence to complete [141]. Artificial intelligence scientists have already used Amazon Mechanical Turk as the data collection scheme to construct image datasets [142]. For a smart building, crowdsourcing can also provide insightful perspectives for disaster management [99]. While crowdsourced data is usually considered to be noisier than traditional data sources [143], machine learning techniques have been exhibited as robust mechanisms for dealing with noise [144].

VIRTUAL REALITY TECHNOLOGY Virtual reality (VR) technology integrates media such as computer hardware, head-mounted displays, and audio systems [145]. One of the many advantages of using VR to study environmental design is that it can avoid ethical and safety issues, such as putting participants through stressful emotional states in dangerous scenarios. Similarly, conducting studies within a virtual public space does not require access to the real environment. For example, the Visual Analytics

Science and Technology challenge of 2015 used a virtual amusement park that allowed participating researchers to use their own methods to visualize the simulated crowd data. Various successful projects have demonstrated the potential of using such virtual environments as reliable resources for analytic experimentation and validation [146]. Amongst them, Hofmann and colleagues [147] used software tools to visualize the communication patterns between visitors to investigate the group behavior of a crowd. They were able to detect malicious behaviors using visual cues generated by the software.

Computer power has evolved to allow plausible 3D environment rendering that can even operate on personal computers. More immersive systems and 3D graphic presentations extend the possibilities for psychological experiments. State-of-the-art VR devices such as Oculus Rift [148] provide a relatively cheap and accessible technology for research purposes. For example, Chamilothori and colleagues [149] used a virtual reality headset to assess the perception of daylight spaces in both real and virtual environments. Resources from the game engine and open source frameworks make using VR technology even easier. Game engines such as Unity [150] can facilitate VR development in many ways, including graphics rendering and animations. These existed resources and frameworks make it easier for researchers to quickly establish a work flow to conduct empirical studies in VR. One open-source framework, Experiments in Virtual Environments (EVE), allows researchers to deploy their VR experiment in a systematic way [151]. Using EVE, the researcher can easily implement a study protocol within Unity. Similarly, Becker-Asano and colleagues [152] proposed combining the Unity game engine with Oculus Rift to develop environment-aware wayfinding agents for evaluating the accuracy of their simulation heuristics.

Nevertheless, the technology has not escaped criticism from practitioners. The limitation of applying virtual reality can not be neglected. When studying crowds, the realistic feelings of physical interaction between individuals are often missing when the crowd density is high [65]. Photorealism, the requirement of producing images with the same visual response as the scene, is not always superior to the non-photorealism rendering approach [153]. The effect of crowdedness on wayfinding strategies may be hindered in VR [154]. The requirements of being comfortable, light, and mobile restrain it from being applied in real-world scenarios such as medical surgeries [155]. The challenge of motion tracking is another bottleneck of the massive application virtual reality technology [156]. Important factors such as visual [157] or thermal discomfort [158] are often absent in the virtual scene.

BEHAVIORAL STUDIES IN VR Based on these technologies and resources, various approaches to using VR have been exploited to study human behaviors. Prior studies have established platforms to observe the participants' behaviors in VR. Moussaïd and colleagues [63] validated a platform that allows synchronized participants in an immersive multiplayer virtual environment for studying crowd dynamics. Using a networked framework, they observed the participants' wayfinding behaviors under stressful evacuation. The choice of the avatars and interaction mechanism from their study have been successfully validated thus it is continued in this dissertation. The timing of navigational instructions provided to pedestrians is a factor vital to navigation behaviors in various environmental contexts [159]. Cooperative behavior during virtual evacuation scenarios can also be affected by the levels of danger experienced by participants [160]. Another advantage of using VR is to recreate dangerous situations, which are unethical to apply on real participants in the real world. Currently, the VR display is sufficiently real that researchers can use VR technology to replay accident scenes. For example, Kinateder and colleagues [161] found that using VR as a training method can improve the frequency and latency of self-evacuation in a road tunnel. Suma and colleagues [162] found that if a navigation task requires a large number of turns, the virtual experiment is an acceptable substitute for a real-world experiment. However, it can not be neglected that the behavior and feelings of walking in VR are different from reality in terms of control, speed, and collision avoidance, which can be reflected by the traveling time. The time that the participants need to travel to their destinations varies between different displays and control interfaces [163]. The control mechanism of VR is also relevant. Ruddle and colleagues [163] compared various control mechanisms including head-mounted display, joysticks, and treadmill; they found that the head-mounted display was the least natural method. It took the participants longer to walk when using a head-mounted display. This inconsistency may be due to the unnatural input method of the VR device or the low resolution of the capturing sensors.

Recently, interest in multiplayer VR research has been renewed. Previously, practitioners often conducted single-participant studies with VR. The experimental setting of one participant limits the capacity of networked devices for conducting collaborative and competitive studies. Capturing social dynamic and interactions between subjects are not possible in single-participant studies. By contrast, the expansion to multiple player setup allows more possibilities for researchers to conduct complex experiment. The appearance of the other people can also empower the feeling of being present and immersive for the participants. A framework that helps to process computer-assisted experiments allows technologies such as VR to be introduced to facilitate environment setup and data collection. Furthermore, such a system can give participants the feeling of "being together" [164]. There are some approaches to tackling this challenge. For example, Joslin and colleagues [165] presented the trends in studies of networked collaborative virtual environments . This approach sets a valuable technical standard for conducting networked studies in VR.

However, the limitations of VR should not be neglected; there is a large natural gap between real and virtual worlds. For example, navigation tasks were performed more quickly and efficiently in a real environment than in a virtual environment [162]. Another limitation of using VR is the restricted field of view. Facing a screen largely limits the visual exposure of the participants, which forces them to adopt this limited purview during the experiment [166]. It is also difficult to redirect participants' walking trajectories to avoid obstacles in an immersive VR environment [167]. It is important to bear in mind the possible discrepancy generated by the VR platform.

CROWD SIMULATION Besides first-person perspective studies, virtual environment technology can also be used for agent simulation. The rendering of massive crowd movement requires high-performance computing, which was not easily accessible for researchers until recently [168]. Nowadays, better computers are accessible to a broader audience, and they can handle much more complex and realistic simulations than those of decades ago. The purpose of a successful crowd simulation is to recreate realistic interaction laws between pedestrians. Moussaïd and colleagues [169] analyzed the laws that govern people's behavior during interactions by having them perform simple avoidance tasks. They have also used a heuristics-based model to study high-density situations during crowd disasters [170]. These approaches suggested improvements to an environmental setting for mass events to avoid crowd disasters. With the support of existing open-source frameworks, the implementation of such complex simulations becomes relatively easy. SteerSuite [171] is an open framework that allows users to simulate steering algorithms and crowd behavior easily by providing tools for facilitating, benchmarking, and testing. This framework can provide the core of an agent's navigation rationale, which is critical for successful crowd simulation. In addition, Singh and colleagues [172] demonstrated a single platform that combined a variety of steering techniques. Various test cases showed that this platform not only supported thousands of agents with low-latency reactions but also improved performance by reducing the frequency of updates for each phase of the computation. Kallman and Kapadia [173] reviewed the recent development of real-time planning for navigation in virtual worlds. Their analysis of applications of multi-agent simulation in virtual environments provides a comprehensive overview of various algorithms for path searching, which is helpful for researchers who want to implement their own discrete search algorithms.

SYNTHETIC CROWD Although simulations have been widely applied in the crowd research community, their applicability remains a challenge for most practitioners. This shortcoming can be overcome with synthetic crowd simulation, for example a data-driven simulation mechanism based on a real crowd trajectories was suggested by researchers [174, 175]. Torrens and colleagues [176] used simple trajectories to generate synthetic agent-based models automatically. An algorithm with an online tracker, which only used present or previous frames for real-time tracking, provided additional accuracy for data-driven crowd simulation [177]. Evidently, producing meaningful patterns from real-world trajectories requires sound computational models. Fruin and colleagues [178] quantified the space that people required for a range of situations such as walking, standing, and accessing facilities. They have also proposed many techniques for simulating large-scale autonomous virtual human crowds. Many methodologies exist for presenting detailed descriptions of synthetic crowds. A number of approaches have been explored for describing collision avoidance while navigating towards a target, including methods based on particle dynamics [179] and simple heuristics [180]. Metoyer and Hodgins [181] applied their motion-graph approach to generate 3D pedestrian locomotion from users' input for populating and directing pedestrians' routes. Their model produced correct behavior for most of the cases they examined.

1.4 RESEARCH OBJECTIVES AND QUESTIONS

The responsive environment has long been a question of great interest in a wide range of fields. Most studies using responsive environments have been limited to a small number of application areas. Prior works have focused on one or a few aspects when applying engineering intelligence to the environment. A systematic understanding of how the responsive environment concept contributes to various scenarios is still lacking, especially for hazardous events. Nevertheless, findings and rationales from the past demonstrated the great potential of expanding such a sophisticated concept into a broader perspective. The combination of virtual reality experiments and simulations has not yet been closely examined in the responsive environment, especially from the cognitive science's perspective. Individual reactions and responses to such environmental intelligence still need further investigation and validation.

The goal of this dissertation is to systematically examine the emerging role of the responsive environment using methodologies from both computer science and cognitive science research. By applying the methods into real-world scenarios of crowd disasters, fire evacuations, and emergency social wayfinding, I examine how responsive environments can help to prevent or minimize the danger and damage caused by these unexpected hazardous events. This can be relevant when designing the next generation of a public environment that is ought to be more resilient to unexpected accidents. A focus of this study is to understand the relationship between the responsive environments and its users, namely the behavior of the users in the responsive environments and the effects of interventions from the responsive environments on their users. Throughout the dissertation, I attempt to answer these three questions:

1. How can the social dynamic in hazardous accidents be investigated through simulation and virtual reality?

2. How can a responsive environment help to improve the safety of crowds in hazardous accidents?

3. How can the responsive environment design influence the individual and group behavior?

In order to answer them, a combination of research methods from computer science and behavioral science was used in this exploratory study. Whereas computer science methods contribute to the construction and design of responsive environments, methods from behavioral science research can help with understanding and analyzing the users' activity and responses to the environments. Multiple genres of responsive environments have been investigated throughout the dissertation. Based on the characteristics of the application scenarios of the responsive environment, I categorize them into two clusters.

First, the responsive environments are divided into dynamic and static types based on whether they can respond to users' needs in real-time. Whereas a dynamic environment refers to an intelligent entity that reacts and adapts in real-time, for instance by generating real-time notification and information, a static environment refers to the type that only applies the intervention measures ahead of time, for example for pre-occupancy evaluation. The nature of dynamic environments means they depend on advanced technologies such as computer networks, sensor technology, and real-time information services. In contrast, static-environment interventions can only be used as pre-occupancy methods, though they may be no less effective than dynamic interventions.

Second, another cluster refers to the measure of the responsive mechanism, which may be active or passive. Active measures represent intervention methods that are straightforward and proactive. These include pedestrian management strategies such as entrances, exits, and environment layout. Passive measures represent the type of interventions that are passive and implicit; these include geographic information displays on a digital screen and navigation aids. These two types of characteristics produce a total of four (2×2) types of responsive environments. Amongst these four types, the dynamic and active type does not apply to any real-world application, because it requires an impossible scenario of changing the environment layout in real-time. Thus, this dissertation focuses on the remaining three types: dynamic and passive, static and passive, and static and active. I use this convenient categorization to highlight various applications of a responsive environment to hazard accidents and social wayfinding scenarios.

The research objective of this dissertation is to provide an important opportunity to advance the understanding of responsive environment design. The main challenge faced by many researchers from this domain is the unpredictable nature of human behavior. Most such responsive environments remain as a prototype or theoretical approach that is never validated with empirical data. However, human behavior has a direct impact on the usability of such responsive environments. The purpose of this investigation is to explore the relationship between responsive environments and users. The findings make an important contribution to the interdisciplinary field of smart building and human-computer interaction.

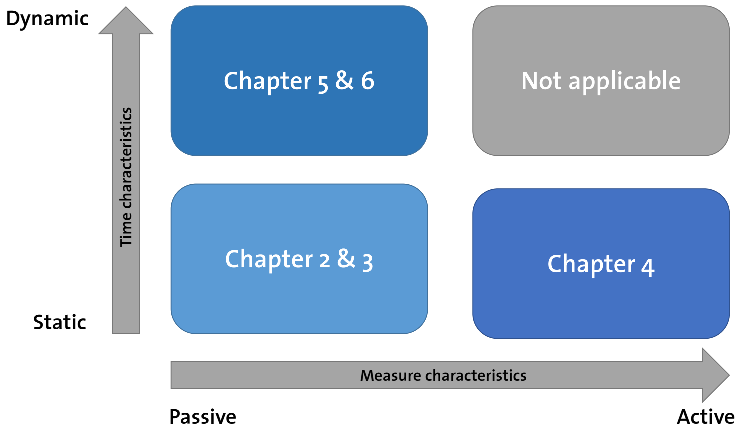

Figure 1.1: Categorization of each chapter of the dissertation.

1.5 ORGANIZATION OF THE DISSERTATION

The main content of the dissertation comprises five themed chapters, each of which corresponds to a study (see figure 1.1). The following publications are included in this thesis, including two that have not been published. The publication status and their corresponded chapters are presented in Table 1.1. The published chapters were adapted as post-print versions with permissions from their corresponded journals. At the end of the thesis, a publications list that contains all articles that were part of my PhD research is included, one of which is not covered in this thesis.

The first two chapters address the static and passive responsive environment with adaptive information services provided with maps. Chapter 2 aims at establishing a networked desktop virtual reality setup for the following multiple player studies. Investigating the interactions among multiple participants is a challenge for researchers from various disciplines, including the decision sciences and spatial cognition. With a local area network and dedicated software platform, experimenters can efficiently monitor the behavior of the participants that are simultaneously immersed in a desktop virtual environment and digitalize the collected data. These capabilities allow for experimental designs in spatial cognition and navigation research that would be difficult (if not impossible) to conduct in the real world. Possible experimental variations include stress during an evacuation, cooperative and competitive search tasks, and other contextual factors that may influence emergent crowd behavior. However, such a laboratory requires maintenance and strict protocols for data collection in a controlled setting. While the external validity of laboratory studies with human participants is sometimes questioned, a number of recent papers suggest that the correspondence between real and virtual environments may be sufficient for studying social behavior in terms of trajectories, hesitations, and spatial decisions. In this article, we describe a method for conducting experiments on decision-making and navigation with up to 36 participants in a networked desktop virtual reality setup (i.e., the Decision Science Laboratory or DeSciL). This experiment protocol can be adapted and applied by other researchers in order to set up a networked desktop virtual reality laboratory. This Chapter establishes the setup that will be employed in a variety of experiments in both decision-making and navigation studies in this dissertation. The results of experiment is only presented here as representative data, thus not fully extended and analyzed. The same data is used and expanded in Chapter 3.

Chapter 3 applies the networked virtual reality setup from Chapter 2 into an investigation of the navigation aid. A carefully designed map can reduce pedestrians' cognitive load during wayfinding and maybe an especially useful navigation aid in crowded public environments. In the present paper, we report three studies that investigated the effects of map complexity and crowd movement on wayfinding time, accuracy and hesitation using both online and laboratory-based networked virtual reality platforms. In the online study, we found that simple map designs led to shorter decision times and higher accuracy compared to complex map designs. In the networked VR setup, we found that co-present participants made very few errors. In the final VR study, we replayed the traces of participants' avatars from the second study so that they indicated a different direction than the maps. In this scenario, we found an interaction between map design and crowd movement in terms of decision time and the distributions of locations at which participants hesitated. Together, these findings can help the designers of maps for public spaces account for the movements of real crowds. This Chapter provides the evidence of capturing the studying crowd behavior with mixed human agent experimental settings, which can further elaborated in Chapter 6.

Chapter 4 further extends the scale of the studied crowd and uses computer simulations and virtual reality to assessing crowd management strategies. It is concerned with the static and active type of responsive environment and presents a case study of a crowd disaster and its responsive-environment interventions. Dense crowds in public spaces have often caused serious security issues at large events. In this paper, we study the 2010 Love Parade Disaster, for which a large amount of data (e.g., research papers, professional reports, and video footage) exists. In a many-year effort, we reproduced the Love Parade Disaster in a 3D computer simulation calibrated with data from the actual event and using the Social Force Model for pedestrian behavior. Moreover, we simulated several crowd management strategies and investigated their ability to prevent the disaster. We evaluate these strategies in Virtual Reality by measuring the response and arousal of participants while experiencing the simulated event from a festival attendee's perspective. Overall, we find that opening an additional exit and removing the police cordons could have significantly reduced the amount of casualties. We also find that this strategy affects the physiological responses of the participants in VR.

The next two chapters focus on user behaviors in dynamic and passive environments, emphasizing various aspects of adaptive signage (Chapter 5) and smart personal devices (chapter 6). Chapter 5 investigates the advantage of a decentralized adaptive sign system for fire evacuation. In the event of fires and other hazards, signs that support evacuation are critical for the safety of individuals. Current evacuation signs are typically non-adaptive in that they always indicate the same exit route independently of the hazard's location. Adaptive signage systems can facilitate wayfinding during evacuations by optimizing the route towards the exit based on the current emergency situation. In this paper, we demonstrate that participants that evacuate a virtual museum using adaptive signs are quicker, use shorter routes, suffer less damage caused by the fire, and report less distress compared to participants using non-adaptive signs. Furthermore, we develop both centralized and decentralized computational frameworks that are capable of calculating the optimal route towards the exit by considering the locations of the fire and automatically adapting the directions indicated by signs. Finally, we use an agent-based model to validate various fire evacuation scenarios with and without adaptive signs.

Chapter 6 examines the phenomenon of information exchange and collective intelligence in evacuations. The last two decades have seen a growing trend towards collective intelligence through sharing information via the Internet and social media. Sharing behavior can be extended into daily activities, such as wayfinding with digital maps. In emergency evacuations, the complexity of an unknown environment and the unpredictable locations of hazards hinder evacuees from identifying safe routes to exits. Successful crowd evacuation from locations impacted by fire or earthquake may depend largely on user-generated map information in the future. Sharing information with each other at such critical moments can benefit everyone, yet it requires a spirit of altruism in each individual. There is an urgent need to understand the relationship between altruistic behavior and collective intelligence. This research project investigates the social influence on altruism in information exchange. We use two multi-user studies in a virtual environment to examine altruistic behavior during an emergency evacuation. Allowing the participants to share spatial information about hazards and exits with each other enables us to examine how altruistic behaviors occur and may be propagated. We have found that participants were more cooperative when given incentives to be so, and demonstrated more altruism when there existed a lack of knowledge in the public information pool. The effect of collective intelligence has also been partly supported by the evacuation time and trajectory lengths of successful evacuees. Our enhanced understanding of altruism enables policymakers and event organizers to encourage efficient information sharing and collective intelligence during disaster evacuations. The experimental work provides some of the first indications of how collective intelligence can be observed and enhanced in a networked virtual environment. More broadly, the findings make an important contribution to the field of behavioral science.

In the last chapter, this dissertation is concluded with general discussions on the findings and results, followed with an outlook of future research directions.

Chapter	Publication details	Status
2	Zhao, H., Thrash, T., Wehrli, S., Hölscher, C., Kapadia, M., Grübel, J., Weibel, R. P., Schinazi, V. R. 2018 A Networked Desktop Virtual Reality Setup for Decision Science and Navigation Experiments with Multiple Participants. Journal of Visualized Experiments. (138), e58155. doi:10.3791/58155	Published
3	Zhao, H., Thrash T., Grossrieder A, Kapadia M., Moussaïd M., Hölscher C., Schinazi VR. 2020 The interaction between map complexity and crowd movement on navigation decisions in virtual reality. Journal of Royal Society Open Science. 7: 191523. doi:10.1098/rsos.191523	Published
4	Zhao, H., Thrash, T., Kapadia, M., Moussaid, Wolff, K., M., Hölscher, C., Helbing, D., Schinazi, V. R. Assessing crowd management strategies for the 2010 Love Parade Disaster using simulations and virtual reality. Royal Society Interface. 17(167). doi:10.1098/rsif.2020.0116	Published
5	Zhao, H., Schwabe, A., Schläfli, F., Thrash, T., Aguilar, L., Dubey, R.K., Karjalainen, J., Hölscher, C., Helbing, D., Schinazi, V. R. A Decentralized Adaptive Sign System for Fire Evacuation with Human and Agent Validation.	Unpublished
6	Zhao, H. The Social Influence of Spatial Collective Intelligence on Evacuees in a Mixed Human-Agent Experiment.	Unpublished

TABLE 1.1: Summary of publications and corresponding chapters

2

RESPONSIVE ENVIRONMENT FOR NETWORKED CROWDS

2.1 INTRODUCTION

Research on spatial cognition and navigation typically studies the spatial decision-making (e.g., turning left or right at an intersection) and mental representation of individuals in real and virtual environments [182, 183]. The advantages of VR include the prevention of ethical and safety issues (e.g., during a dangerous evacuation [63]), the automatic measurement and analysis of spatial data [151], and a balanced combination of internal and external validity [66, 184, 185]. For example, Weisberg and colleagues [59] extended previous research on individual differences in spatial knowledge acquisition by demonstrating that spatial tasks in VR can provide an objective behavioral measure of spatial ability. This study also suggested that navigation behavior in VR approximates real-world navigation because the virtual environment was modeled after the university campus used by Schinazi and colleagues [186] (see also the study of Ruddle and colleagues [187]). VR has also been applied to psychotherapy [188], clinical assessment [189], consumer behavior [190], and surgery [191, 192]. However, most VR systems lack proprioceptive and audio feedback that may improve presence and immersion [193–196], require training with the control interface [61, 64, 163], and lack social cues. Indeed, people in the real world often move in groups [169], avoid or follow other people [63, 197], and make decisions based on social context [160, 198].

At the same time, research on crowd behavior often focuses on emergent characteristics of crowds (e.g., lane formation, congestion at bottlenecks) that are simulated on a computer or observed in the real world. For example, Helbing and colleagues [199] used a combination of real-world observations and computer simulations in order to suggest improvements to traffic flow in an intersection by separating inflow and outflow with physical barriers and placing an obstacle in the center. Moussaïd and colleagues [170] used a heuristics-based model to study high-density situations during a crowd disaster. This approach suggested improvements to an environmental setting for mass events in order to avoid crowd disasters. With the aid of an existing open source framework, the implementation of such simulations could be relatively easy. SteerSuite is an open source framework that allows users to simulate steering algorithms and crowd behavior easily by providing tools for facilitating, benchmarking, and testing [171]. This framework can provide the core of an agent's navigation rationale, which is critical for successful crowd simulation. In addition, Singh and colleagues demonstrated a single platform that combines a variety of steering techniques [172]. While researchers can propose design interventions using such simulations, they are rarely validated with human participants in a controlled setting. Controlled experiments are rare in crowd research because they can be difficult to organize and dangerous to the participants.

VR has been employed to investigate social behavior using simple and complex virtual environments with one or more computer-simulated agents. In the study of Bode and colleagues [14, 69], participants were asked to evacuate a simple virtual environment from a top-down perspective among several agents and found that exit choice was affected by static signage and motivation. Presenting participants with a more complex environment from a first-person perspective, Kinateder and colleagues [198] found that participants were more likely to follow a single computer-simulated agent during escape from a virtual tunnel fire. In a complex virtual environment with multiple agents, Drury and colleagues found that participants tended to assist a fallen agent during an evacuation when they identified with the crowd [160]. Collectively, these findings suggest that VR can be an effective way of eliciting social behaviors, even with computer-simulated agents. However, some crowd behaviors may only be observed when there is a realistic social signal (i.e., when the participants are aware that the other avatars are controlled by people [63]). In order to address this shortcoming, the present protocol describes a method for conducting controlled experiments with multiple users in a networked VR setup. This approach has been employed in a recent study by Moussaïd and colleagues [63] in order to investigate the evacuation behavior of 36 networked participants.

Research on networked VR has focused on topics unrelated to navigation strategies [164, 165] and/or relied on existing online gaming platforms such as Second Life. For example, Molka-Danielsen and Chabada [200] investigated evacuation behavior in terms of exit choice and spatial knowledge of the building using participants recruited among existing users of Second Life. While the authors provide some descriptive results (e.g., visualizations of trajectories), this study had difficulties with participant recruitment, experimental control, and generalization beyond this specific case. More recently, Normoyle and colleagues [201] found that existing users of Second Life and participants in a laboratory were comparable in terms of evacuation performance and exit choice and different in terms of self-reported presence and frustration with the control interface. The findings from these two studies highlight some of the challenges and opportunities afforded by online and laboratory experiments. Online studies are capable of drawing from a much larger and motivated population of potential participants. However, laboratory studies allow for more experimental control of the physical environment and potential distractions. In addition, online studies may pose some ethical concerns regarding data anonymity and confidentiality.

As a networked desktop VR laboratory, the Decision Science Laboratory (DeSciL) at ETH Zürich is primarily used to study economic decision-making and strategic interactions in a controlled environment. The technical infrastructure at the DeSciL consists of hardware, software for laboratory automation, and software that supports the multi-user desktop VR setup. The hardware includes high-performance desktop computers with Microsoft Windows 10 Enterprise operating system, control interfaces (e.g., mouse and keyboard, joysticks), headphones, and eye trackers (see Table of Materials). All client computers are connected with Ethernet of one gigabit per second to the university network and the same network file share. There is no visible delay or lag when there are 36 clients connected. The number of frames per second is consistently above 100. Experiments are also managed and controlled with laboratory automation software based on Microsoft PowerShell (i.e., PowerShell Desired State Configuration and PowerShell Remoting). All relevant steps of the protocol are preprogrammed with PowerShell scripts called Cmdlets (e.g., Start-Computer, Stop-Computer). During the experiment, these scripts can be executed simultaneously and remotely on all client computers. This type of laboratory automation ensures an identical state of the client computers, reduces potential errors and complexity during scientific testing, and prevents researchers from having to perform repetitive manual tasks. For navigation experiments, we use the Unity game engine (https://unity3d.com/) in order to support the development of 2D and 3D environments for multi-user, interactive desktop VR. The 36 client computers are connected to a server via an authoritative server architecture. At the start of every experiment, each client sends an instantiation request to the server, and the server responds by instantiating an avatar for that user on all of the connected machines. Each user's avatar has a camera with a 50 degrees field of view. Throughout the experiment, the

Figure 2.1: Photographs of the DeSciL laboratory. (a) The control room contains the server that receives traffic from the 36 client computers and monitors the participants in their cubicles. This room can be isolated from the testing rooms in terms of sound and vision. Communication to participants is provided via microphone and speaker system. (b) The three testing rooms contain 36 cubicles. (c) Each cubicle contains a desktop computer, monitor, mouse and keyboard interface, headphones, and an eye tracker.

clients send user′ input to the server, and the server updates the movement of all of the clients.

In the physical laboratory, each computer is contained in a separate cubicle within three semi-independent rooms (see Figure 2.1). The overall size of the laboratory is 170 square meters (150 square meters for experiment room and 20 square meters for control room). Each of these rooms is equipped with audio and video recording devices. Experiments are controlled from a separate adjacent room (i.e., by providing instructions and initiating the experimental program). From this control room, experimenters can also observe participants in both physical and virtual environments. Together with the Department of Economics at the University of Zürich, the DeSciL also maintains the University Registration Center for Study Participants, which was implemented based on h-root [202]. The detailed experiment protocol is presented in the Appendix A.1.

2.2 REPRESENTATIVE RESULTS

For each client on each trial, experiment data from the DeSciL typically include trajectories, time stamps, and measures of performance (e.g., whether the participant turned in the "correct" direction at a particular intersection). A representative study investigated the effects of signage complexity on route choice for a crowd of human participants (with virtual avatars) in a

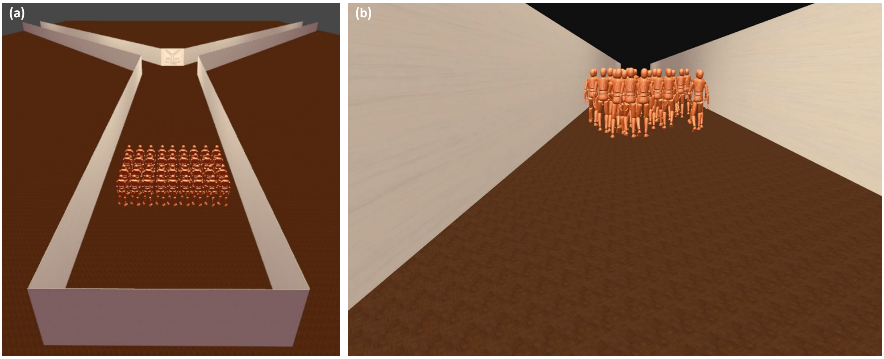

FIGURE 2.2: Views of the Y-shaped virtual environment. (a) From the server, researchers can observe participants moving towards the intersection. (b) From the clients, participants can view the virtual environment and other avatars from a first-person perspective during movement.

simple Y-shaped virtual environment. In this experiment, 28 participants (12 women and 16 men; mean age = 22.5) were given the same goal location (i.e., gate number) and were asked to choose the corresponding route option at the intersection using a map (see Figure 2.2).

Map complexity varied over 16 trials, and the hypothesis was that decision time and accuracy would be higher for maps that are more complex. While we expect decision accuracy to be relatively high overall, participants' trajectories can be used in future experiments to define the walking paths of agents that convey a realistic social signal (i.e., believable movements). The total experiment time was approximately one hour, including welcoming the participants, conducting the training session (for the control interface), and testing in the Y-shaped corridor. The obtained data are summarized in Table 2.1.

Figure 2.3 indicates the minimum and maximum completion times for each trial. These descriptive statistics provide an indirect measure of congestion during the trial. The obtained data also allows for the visualization of trajectories generated by the virtual crowd (see Figure 2.4). Spatial statistics can then be used to analyze changes in trajectories over trials. For example, researchers may be interested in how closely participants followed each other or how smoothly participants maneuver with particular control interfaces.

Table 1: Representative results from 16 experimental trials

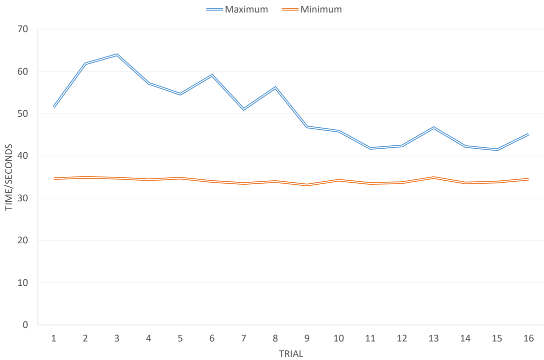

FIGURE 2.3: Representative results from 16 experimental trials. The maximum and minimum times are the times required by the fastest and slowest participants to reach the destination on each trial.

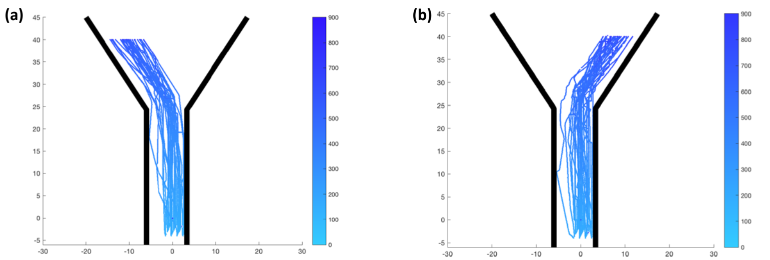

FIGURE 2.4: Participants trajectories from (a) trial 1 and (b) trial 16. The x- and y-axes represent the locations of the avatars in the crowd. The color bar represents time elapsed during the trial.

Representative results from 16 experimental trials.			
Trial No.	Map Type	Accuracy (%)	Average time/s
1	Simple	100	42.01
2	Complex	96.4	40.51
3	Simple	100	39.15
4	Complex	100	38.66
5	Complex	100	38.52
6	Complex	100	38.87
7	Simple	100	38.43
8	Complex	100	38.26
9	Simple	100	37.43
10	Simple	100	38.44
11	Complex	100	37.08
12	Complex	100	36.8
13	Simple	100	37.67
14	Complex	100	36.52
15	Simple	100	36.83
16	Simple	100	37.88

TABLE 2.1: Decision accuracy represents the percentage of correct choices (i.e., turning towards the correct gate) over all participants. Mean decision time is the mean time required to reach the destination (whether correct or not) over all trials.

2.3 DISCUSSION

In the present paper, we described a multi-user desktop virtual reality laboratory in which up to 36 participants can interact in and simultaneously navigate through various virtual environments. The experimental protocol details the steps necessary for this type of research and unique to multi-user scenarios. Considerations specific to these scenarios include the number of participants in attendance, the cost of seemingly small experimenter errors, rendering and networking capacities (both server- and client-side), training with the control interface, and data security. Overbooking participants is necessary in order to ensure a precise number of participants in an experimental session. If too few participants attend, then the cost of a failed experimental session is relatively high. Similarly, experimental errors can lead to a failed session because either the participants' data were contaminated before the error was detected, or the experiment cannot be conducted because of software or hardware failures. For example, if too much information is distributed through the network, then a relaunch of the entire system may be necessary. This is especially problematic if the experiment has already begun. In addition, participants in virtual navigation experiments require experience and/or training with the control interface because the controls are less intuitive than real walking [64] and interaction with the controls can interfere with spatial memory tasks [61]. Responsible data management also becomes especially important given the large amount of data obtained per session.

While there are many opportunities afforded by the DeSciL, at least three limitations remain. First, the current system is setup for up to 36 simultaneous participants. Experiments on larger virtual crowds may require computer-controlled agents, traces of human participants from several previous sessions, or the capability of including online participants. Second, future hardware upgrades (e.g., for better graphics cards and better processors) will be much more expensive than for the traditional, single-user system. Third, multi-user desktop virtual reality research cannot yet be conducted with control interfaces that are more similar to real walking. Thus, research on locomotion and the physical interactions among participants is limited.

Despite these limitations, the DeSciL offers several advantages over real-world studies, single-user laboratory studies, and multi-user online studies. Software automation gives researchers the abilities to adapt the experimental protocol with respect to their needs. Compared to both real-world and online studies, the DeSciL allows for more experimental control. For example, experiments in the DeSciL may employ systematic variations of the environment and provide direct observation of the participants in both virtual and physical worlds. Compared to single-user desktop virtual reality studies with computer-controlled agents, participants can interact with each other in real-time, and the emergent behavior of the virtual crowd is less reliant on the experimenter's preconceptions. Computer-controlled agents in VR often rely on scripted actions and do not adapt to users' movements in real time. In contrast, networked desktop VR provides a more ecological context in which human-controlled avatars affect (and are affected by) each other's movements. In addition, this approach can inform the movement parameters (e.g., walking speed and hesitations) of future agent-based models in crowd research (e.g., for evacuation scenarios [203]). In general, multi-user desktop virtual reality studies allow for more precise measurement of spatial behavior and the detection of patterns that may have previously been overlooked.

Recently, the DeSciL has been successfully employed in a series of decision-making [204, 205] and navigation studies [63, 64]. For example, Moussaïd and colleagues [63] used the multi-user desktop VR setup in order to study the effect of stress on crowd behavior during an evacuation. In this study, the "correct" exit varied from trial to trial, and only a proportion of the participants were informed of the correct exit. The results indicated that participants in the stress led to a more efficient evacuation, but this finding may be attributable to the way in which collisions were implemented. In addition, participants tended to follow other avatars under stress, suggesting that a social signal was conveyed among the participants despite lack of direct physical interaction. These results emphasize the advantages of multi-user VR compared to single-user VR with computer-controlled agents. Future studies will include the comparison of multi-user data acquired either online or in the laboratory, more complex environmental variations, and the addition of peripheral devices such as eye trackers or physiological devices. These advancements will allow for the collection of different types of complex behavioral data [206]. For example, low-cost eye trackers can be incorporated in order to monitor the participants' attention or detect coarsely areas of interest on the screen.

3

RESPONSIVE ENVIRONMENT FOR NAVIGATION AIDS

3.1 INTRODUCTION

Wayfinding refers to the decision-making component of navigation behaviour [207]. There are several sources of spatial information in an observer's environment that may facilitate decision-making, and people can flexibly switch from one source to another [208]. People may even convey spatial information to each other, either as part of the observer's immediate environment or via signage and maps (i.e., geographic information services). For the present study, we investigated the effects of cues in the immediate environment and from other people on decision-making during navigation through a virtual airport terminal.

Often in public spaces, the behaviour of other pedestrians can influence an observer's spatial decision-making by providing environmental cues [209–211]. For example, computer-controlled agents may cause a human navigator to hesitate while searching for an exit from a virtual tunnel [212]. Humans also have the tendency to follow other people within a small group or crowd [212–214], especially in stressful conditions. For example, Moussaïd and colleagues [63] found that individuals were more likely to follow others as a crowd during a stressful (virtual) evacuation than during a relatively calm wayfinding task. However, other studies have suggested that this type of following behaviour does not always occur during wayfinding [69], even during an emergency evacuation [215]. Such following behaviour has been previously defined as "herding", although Haghani and colleagues [216] suggest that this term is not consistently used in the literature. Here, we define "following behaviour" as conforming to the actions of the crowd.

Following behaviour may be similar to other socially contagious behaviours such as joint visual attention [213] and judgement propagation [217]. This type of conformity may also be considered a result of group or collective intelligence. On the one hand, this intelligence can generally lead to more accurate [83] and creative decisions [218]. On the other hand, previous research has found that collective judgement can supersede individuals' abilities to make accurate decisions [219], possibly representing mindless acquiescence and lack of original thought [214].

Typically, sources of spatial information in the immediate environment can be contrasted with maps and signage because of their purposeful design and reliable data sources [220]. Signage design can improve navigation efficiency and the accuracy of wayfinding decisions in public spaces and indoor environments [221–223]. In particular, maps can be designed to visually convey relevant and accurate geographic information such as landmarks [224] and orientations [30]. Indeed, visual variables [225] such as colour and contrast [226] can be used to represent geographic information in a perceptually salient manner [227] and to facilitate the user's understanding of this information [228]. In general, well-designed maps may improve navigation efficiency [31] and reduce cognitive load [229, 230], but inaccurate or misleading maps may result in getting lost [6, 231] or casualties [8]. In addition, the presence of landmarks on a map can improve user satisfaction [232] and help users learn the layout of the environment [233]. However, some researchers have shown that map design did not significantly affect wayfinding performance in real [234] or virtual environments [235].

Virtual Reality (VR) allows for experimental designs that would be difficult if not impossible to recreate in the real-world because of practical (e.g., cost) or ethical (e.g., safety) issues [66, 236]. Compared to most laboratory studies, VR also provides relatively high ecological validity [66, 237]. While navigation behaviour in VR can be unrealistic in terms of speed and collision avoidance [65], an appropriate control interface and training can mediate these difficulties [64, 163, 238].

Multi-user frameworks [63, 69, 239–241] and online studies [140, 142, 242] can extend traditional laboratory experiments by enabling the study of large groups and expediting data collection. For example, Moussaïd and colleagues [63] implemented a multi-user VR framework using a study of collective navigation and following behaviour during a stressful evacuation. In addition, the costs of a study can be reduced using online crowd-sourcing platforms such as Amazon Mechanical Turk (AMT) [140]. This web service allows researchers to give tasks to participants that require human intelligence [141]. For example, scientists in artificial intelligence have used AMT as a data collection scheme to construct image data sets [142].

In the present paper, we describe three experiments that employ a combination of multi-user and online platforms in order to investigate the impact of crowd movement and map design on wayfinding decisions. Across these three studies, we shift the focus of spatial cognition from individual decision-making in isolation to collective decision-making in social environments. Altogether, these findings may be used for the development of new guidelines for map design and public information services.

1. **Study 1:** We first studied the effect of map complexity in isolation. Towards this end, using AMT, we investigated whether a complex map would delay people's wayfinding decisions and reduce accuracy in a virtual airport.

2. **Study 2:** In the second study, we then tested for the effect of map complexity in a social environment. Here, we conducted a multi-user study in a networked desktop VR setup to collect the movement trajectories of a large group of participants in a simple virtual environment. Specifically, participants were asked to turn left or right at a Y-shaped intersection using a map that varied in complexity across trials. The trajectories and map design from the second study were also critical for the systematic variation of crowd movement in the subsequent study.

3. **Study 3:** In the third study, participants navigated through the same virtual environment amongst a crowd that was based on the trajectories from the second study, except that the crowd and the map indicated different directions. This conflict between the directions indicated by the map and the crowd allowed us to disentangle these effects on decision-making during wayfinding.

3.2 STUDY 1 - ONLINE MAP STUDY

The purpose of the first study was to examine the effect of map design on the time required to make a navigation decision at an intersection. The study was conducted using AMT because many participants could be recruited within a short period of time.

Participants Participants from AMT were selected based on two conditions. First, participants had to have finished at least three other AMT tasks so that they have experience in completing AMT tasks. Second, the participants could not be located in the United States, in order to eliminate the professional crowd source workers who could answer as fast as possible thus harm the quality of the study. The latter criterion is for excluding US citizens who have been to O'Hare airport. In total, we recruited 182 participants. Thirty-seven participants were excluded from analysis because they either did not complete the experiment or zoomed in or out during the video. Participants were not allowed to perform any zooming operation

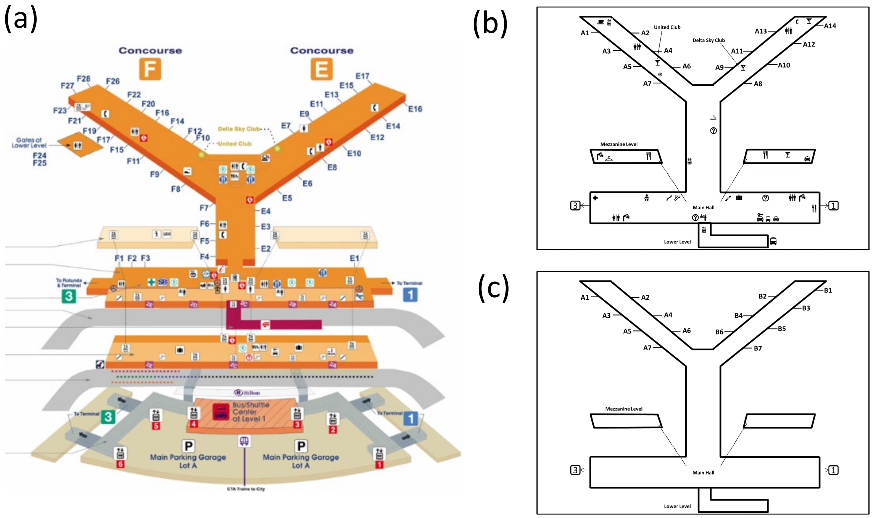

FIGURE 3.1: (a) O'Hare Airport Terminal 2 map. Source: http://airportczar.com/ohare/map/. (b) Complex map for the present studies. (c) Simple map, re-designed and simplified.

because changing the zoom level would influence their performance on the task. Of the remaining 145 participants (mean age = 36.31, range = 22 to 73), there were 93 men and 52 women. Participants were compensated with a base reward of 1.5 USD and two possible bonuses. Participants were given a bonus of 0.8 points if they answered correctly, and a bonus of between 0.0 and 0.2 points that depended on the time between the start of the trial and their final decision. The sum of these two bonuses was multiplied by the base reward, averaged over trials, and added to the base reward. Overall, participants were compensated between 1.5 and 3 USD (mean = 2.78) for approximately 20 minutes of participation. Due to the nature of the online survey, the same age requirement was not applied here.

Materials We generated an abstract map based on the real map of O'Hare Airport Terminal 2 (see Figure 3.1). Airport terminals were chosen by previous researchers because of their size and complexity [243–245]. This specific terminal was chosen because of its Y-shape and other design elements (e.g., annotations, gate numbers). Indeed, the Y-shaped environment allows us to conduct studies in which only a binary choice can be made. Four types of maps were created from the real map, including a simple map design with limited annotations and symbols, a complex map with rich annotations

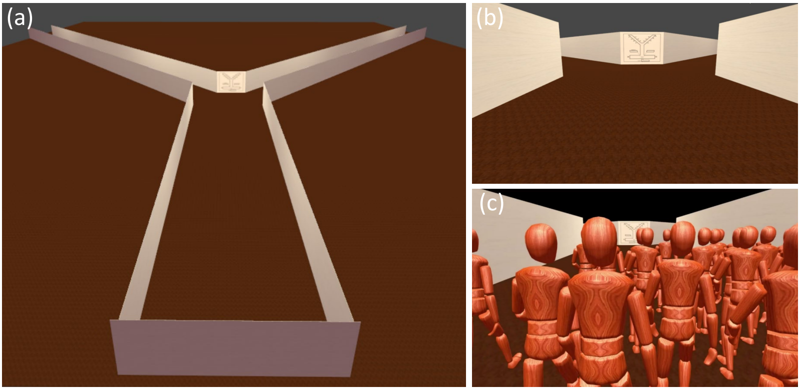

FIGURE 3.2: (a) Overview of the virtual environment used for all three studies. (b) View of the front wall of the intersection from an avatar's perspective during one of the videos in Study 1. (c) View of the other avatars from a first-person perspective during Study 2.

and symbols, a mirrored version (left to right) of the simple map, and a mirrored version of the complex map (see Figure 3.1). The complexity of the map was additionally reflected by the gate indexing system. The gate indexing of simple map design contains only variations of numbers, whereas the complex map design contains both alphabetic and numerous variations. We converted the 3D map into 2D map because the original maps from O'Hare represent multiple floors that we did not have in the virtual environment. Without these additional floors, the maps look 3D but do not provide any additional information. The virtual environment was developed using the Unity 3D game engine [246] (see Figure 3.2). Videos of movement through the corridor were recorded from the perspective of an avatar that was controlled by a researcher. The virtual avatar was animated using the ADAPT [247] framework, which facilitates the designing and authoring of virtual human characters in the Unity game engine. In each video, the avatar walked from a first person perspective at full speed (1.3 m/sec) from the bottom part of the main corridor to the forking of the Y-shaped intersection (see Figure 3.2). The avatar stopped moving in front of the wall containing the map. We created four videos that were identical except for the map design on the wall of the intersection. Each video lasted 30 seconds.

Procedure Participants were first asked to digitally sign a consent form, to read an information page that introduced the task, and to complete a training trial that familiarised them with the main task. The main task required participants to watch each video and decide whether to turn left or right at the Y-shaped intersection as quickly as possible. Participants were instructed that faster decision-making resulted in higher compensation. Before the start of each video, participants were instructed to choose whether to turn left or right to reach a selected gate (e.g., A2). After clicking the start button, the video started playing. While the video was playing, participants could choose to go left or right by clicking buttons on the computer screen. As the avatar moved closer to the map wall, participants gained a better view of the map, which should have made it easier to make a decision. They were allowed to change their decisions throughout each trial. Each participant was asked to respond to eight types of videos (i.e., simple/complex map designs by original/mirrored map orientation by left/right correct responses) for each of three trials. The three trials for each video type only varied with respect to the gate number of the goal. The order of these 24 trials was predetermined and randomised for each participant.

Design The only independent variable of interest was map type (simple versus complex; within-subjects). The three dependent variables were the amount of time from the beginning of each video to each participant's final decision, the percentage of errors in participants' final decisions, and the number of mouse clicks recorded during each trial. Two-tailed, paired-sample t-tests were used to analyse the effect of map type on these three dependent variables.

Results Simple maps resulted in lower values (compared to complex maps) for all three dependent measures. Levene's test revealed no difference between the variances of the two groups in terms of time to final click ($p = .611$), percentage of errors ($p = .071$), or number of clicks ($p = .959$). The paired-sample t-tests revealed that the difference between simple and complex maps was not significant in terms of time to final decision, $t(144)=0.36$, $se=0.38$, $p=.721$, $d=.019$. However, we found significant differences between simple and complex maps in terms of percentage of errors in participants' final decisions, $t(144)=3.30$, $se=0.01$, $p=.001$, $d=.204$, and number of clicks during the trial, $t(144)=1.99$, $se=0.01$, $p=.049$, $d=.113$. In addition, there was a significant linear effect of trial on time to final decision, $F(1,144) = 35.966$, $MSE = 115.362$, $p < .001$, $d=.830$, suggesting that participants improved over trials.

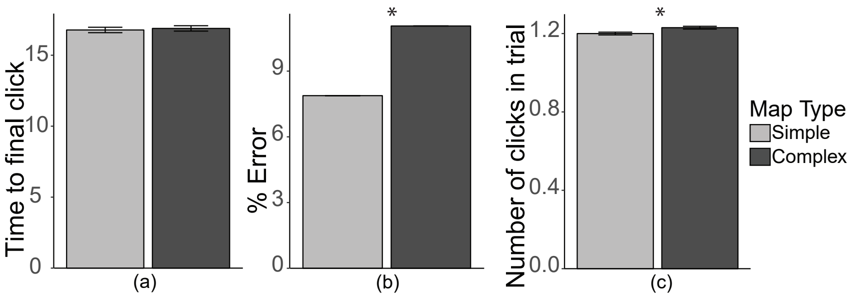

FIGURE 3.3: Results from Study 1. For all three graphs, the error bars represent standard error of the difference between means. (a) Difference between simple and complex maps in terms of time to final click (p = .721). (b) Significant difference between simple and complex maps in terms of percentage of errors in participants' final decisions (p = .001). (c) Significant difference between simple and complex maps in terms of number of clicks (p = .049). There are 145 data points in total represented by each bar. The asterisks '*' denote a significant effect.

3.3 STUDY 2 - MAP EFFECT STUDY

Study 1 provides evidence that map complexity can affect navigation decisions. In order to observe and collect crowd movement data, Study 2 was designed so that participants could control their own movement through the virtual environment amongst a crowd of other human-controlled avatars.

Participants Twenty-eight participants (16 men and 12 women) were recruited via the University Registration Center for Participants (http://www.uast.uzh.ch). All of these participants were between 20 and 29 years of age (mean age = 24.3). Each participant was paid between 25 CHF and 30 CHF, depending on their performance.

Materials For Study 2, we used the same Y-shaped virtual environment from Study 1. Participants had the first-person perspective of the avatar and were able to move through the virtual environment by using the arrow or the "WASD" keys (e.g., the up arrow or "W" for forward movement) on the keyboard. The maximum forward movement speed was 1.3 m/sec, and the maximum backwards and sideways movement speeds were 0.6 m/sec. Participants could also use the mouse to rotate their field of view up to a maximum angular velocity of 120 degrees/sec. Participants could see each of the other participants' avatars that were within their field of view. These avatars were represented by wooden mannequins with an eye height of 1.8 m and a collision radius of 0.25 m. Also, the design of the simple/complex maps and the selection of target gates were the same as in Study 1.

The experiment was conducted in the Decision Science Laboratory (DeSciL) at ETH Zürich. The DeSciL is a laboratory that consists of 36 cubicles, each of which is equipped with a desktop computer. This networked computer setup has been used previously for studies on group decision-making in both game theory [248] and crowd dynamics [63] contexts. The lab and experiment set up were explained in detail by Zhao and colleagues [241]. Each participant performed the experiment on a Dell Optiplex 980 computer running Windows 7 Enterprise SP1 X64 and connected to a 19-inch diagonal Dell 1909W monitors with a resolution of 1920 x 1080 pixels. The application frame rate was at least 30 frames per second, and network latency was approximately 67 milliseconds.

Procedure After reading and signing an informed consent form, participants were shown how to use the mouse-and-keyboard control interface using an interactive tutorial [63, 64]. For each trial, participants were given a gate number and were asked to move down a virtual corridor towards a Y-shaped intersection. Their task was to turn left or right at this intersection in order to reach the given gate. All of the participants were located in the same virtual corridor at the same time, and the other participants' avatars were visible. However, participants were not instructed as to whether the other participants were given the same gate as a goal (even though they were given the same gate within one trial). For the training trial at the beginning of the experiment, no map was displayed in order to familiarise participants with the environment and control interface. During this training trial, the participants were simply asked to move to the left at the intersection.

For 16 subsequent trials, the map randomly varied between simple and complex designs, and each avatar's starting location was randomly selected from a grid of 36 locations. During each trial, the virtual reality system automatically recorded the time and the coordinates of all participants' avatars between 20 and 60 times per second (depending Unity's update rate).

Design As in Study 1, the only independent variable of interest was map type (simple versus complex; within-subjects). The two dependent variables were the percentage of errors and time required to reach the end of the corridor. We analysed the effect of map type on each dependent variable using two-tailed, paired-sample t-test.

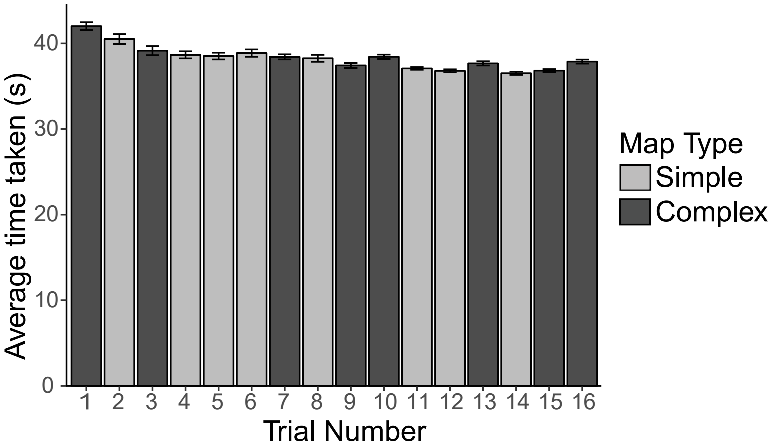

FIGURE 3.4: Mean time required to finish each trial for Study 2.

Results
Only one error was committed throughout the entire experiment, so the analyses were focused on the time required to reach the end of the corridor in the two map conditions. The corresponding t-test revealed that trials with complex maps (mean = 38.48s) did not require significantly more time to finish than trials with simple maps (mean = 38.15s, see Figure 3.4), *t(26)=-1.29, se=0.253, p=.208, d=.131*. In addition, we found a significant linear effect of trial on time required to complete each trial, *F(1,28) = 16.31, MSE = 36.37, p < .001, d=1.969*. We speculate that this effect may be attributable to familiarity with the control interface in VR [249, 250].

3.4 STUDY 3 - CROWD TRAJECTORY STUDY

In Study 3, we replayed the trajectories of participants from Study 2 and, for some trials, reversed the direction of crowd movement. This manipulation caused the direction indicated by crowd movement to conflict with the direction indicated by the map. Participants moved through the same virtual environment individually amongst these replayed trajectories.

Participants Twenty-nine additional participants (20 men and 9 women) were recruited via the University Registration Center for Participants (http://www.uast.uzh.ch) and paid 30 CHF upon completion of the experiment. All participants were between the ages of 18 and 27 (mean age = 22.38).

Materials The same virtual environment and physical apparatuses from Study 2 were used in Study 3. However, participants performed Study 3 individually amongst computer-simulated agents. These agents' trajectories were equivalent to those recorded from the participants of Study 2. The participants were told that the crowd movements were from real people. We excluded the trajectories of the participants from Study 2 who made incorrect choices. In order to avoid collisions between the individual participants' avatars and the computer-simulated agents, the participants' initial position was behind all of the agents (at least 3 m). Four different types of trials were designed to include the combination of two map types (simple versus complex) and two different crowd movements (original versus reversed). "Original" crowd movement refers to a crowd that moved in the same direction as indicated by the map, and "reversed" crowd movement refers to a crowd that moved in the opposite direction. To simulate a reversed crowd, we flipped the indicated destination. For example, if gate A2 was indicated as the correct destination in one trial in Study 2, B2 could be used as the correct destination in the corresponding trial of Study 3. In this example, the crowd would still move towards A2.

Procedure The procedure for Study 3 was similar to that for Study 2, except for the order of the trials and the addition of trials in which the direction indicated by the crowd was different from the direction indicated by the maps. Participants underwent the same training procedure as Study 2 before completing 32 testing trials. For the order and types of the trials, see Figure 3.5.

In order to ensure that participants would consider crowd movement as a reliable cue, the first eight trials only contained the original crowd without the conflict between cues. If the conflict between crowd movement and the map appeared earlier, then participants would likely deem crowd movement as an unreliable cue. The remaining trials (9 through 32) were in the same random and predetermined order for all participants.

Design The two within-subjects independent variables were map type (simple versus complex) and crowd movement (original versus reversed). The dependent variables were the number of errors (with respect to the direction indicated by the map), the time taken to finish the trial, the number of hesitation points within the entire y-shaped corridor, and the number of hesitation points within the area from which the map was visible.

	Df	Df.res	F	p
Effect of Map	1	28	1.3633	.25
Effect of Crowd Movement	1	28	34.9435	<.001*
2x2 interaction	1	28	2.5140	.12

TABLE 3.1: Two-way ART ANOVA results for number of errors from Study 3. The asterisk denotes a significant effect.

According to Filippidis and colleagues [251], such an area can be defined as the visible catchment area (VCA). We first compared trial 9 (i.e., the first trial in which participants faced reversed crowd movement) to all of the preceding trials and all of the subsequent trials in terms of number of errors using two separate one-proportion Z-tests. For each of the four dependent variables, we then conducted separate two (map type) by two (crowd movement) analyses of variance (ANOVAs). When Levene's tests revealed heterogeneity of variance amongst the experimental conditions, we also performed an aligned rank transform analysis of variance (ART ANOVA) [252]. The ART ANOVA is a non-parametric version of the typical ANOVA that computes each main effect and interaction by first aligning the data with respect to a specific effect and then converting the data to ranks. Hesitation points were defined as successive data points within the same m^2 and within a time window of 0.13 s (i.e., 10% less than the mean amount of time between two successive data points within the same m^2). The VCA was defined as a set of locations from which the map could have been visible [251]. For our purposes, this value (15.58m from the front of the map) was derived from Study 1 by inferring the average location at which the final decisions were made. Specifically, we considered the radius of the VCA as the mean distance from the map where participants made their final click in Study 1, indicating their final decision. Kernel density estimates (KDE) were then used to compare the distributions of hesitation points within the VCA between pairs of experimental conditions [253]. KDE is a multivariate kernel discriminant analysis that compares two distributions of data [253, 254]. In order to simplify the KDE analyses, locations within the VCA were excluded if they did not contain any hesitation points.

Results The number of errors for trial 9 was significantly higher than the eight preceding trials, $Z=4.52$, $p<0.001$, and all of the subsequent trials (in aggregate), $z=3.99$, $p<0.001$ (see Figure 3.5a). In addition, trial 9 tended

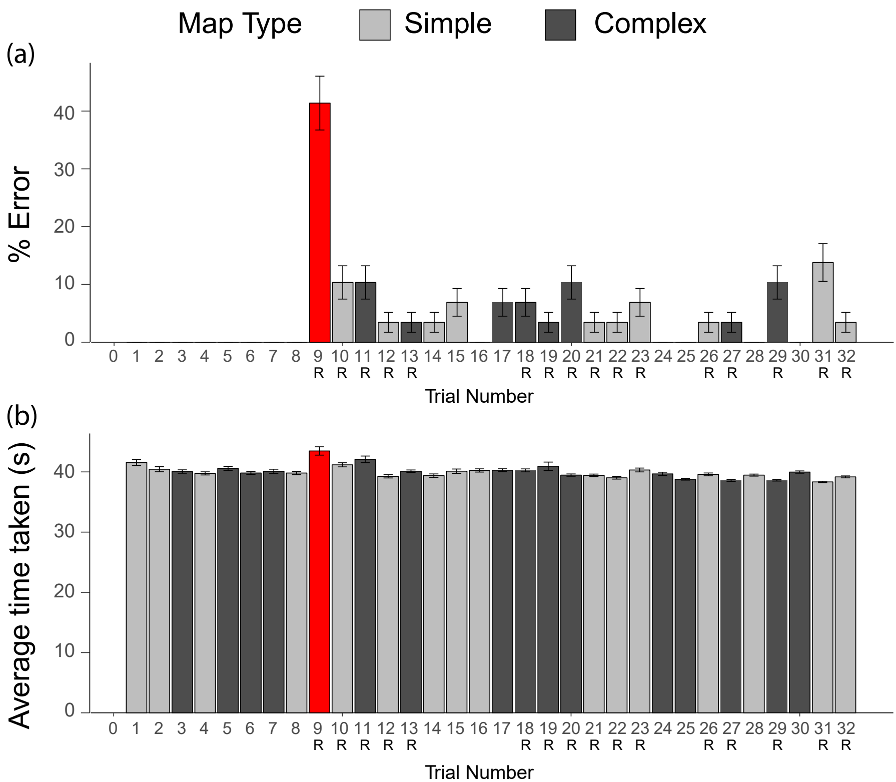

FIGURE 3.5: (a) Mean number of errors for each trial in Study 3. (b) Mean completion time for each trial in Study 3. For some trials, the original crowd from Study 2 was employed (e.g., trial 1 to 8), but for reversed trials (e.g., trial 9 to 13), the crowd indicated a different direction than the map. The red highlighted trial 9 is the first trial in which the crowd trajectories were reversed. The trials with reversed crowd movement are annotated with an "R" below the trial number. The trials without an "R" represented the original crowd movement.

Measure	Contrast	F	MSE	p
Number of Errors	2x2 interaction	10.755	0.135	0.003*
	Effect of Crowd movement	4.717	2.239	0.038*
	Effect of Map	9.108	0.115	0.005*
Time	2x2 interaction	8.591	1.003	0.007*
	Effect of Crowd movement	0.003	2.056	0.958
	Effect of Map	2.189	1.680	0.150
Number of Hesitation Points	2x2 interaction	1.926	14.799	0.176
	Effect of Crowd movement	1.670	17.364	0.207
	Effect of Map	1.021	29.396	0.321
Number of Hesitation Points inside VCA	2x2 interaction	1.919	33.004	0.177
	Effect of Crowd movement	1.815	16.406	0.189
	Effect of Map	2.620	49.957	0.117

TABLE 3.2: Two-way ANOVA results for all four dependent variables from Study 3. The asterisks '*' denote a significant effect.

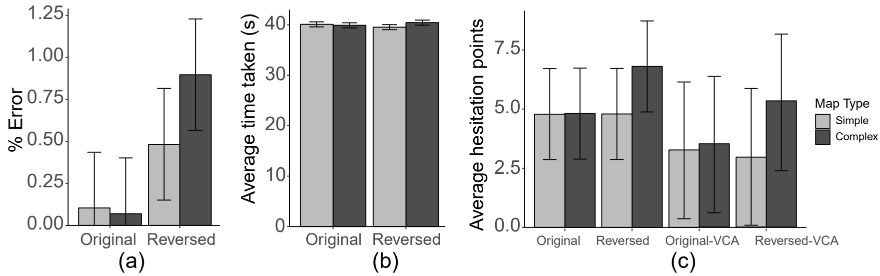

FIGURE 3.6: (a) Mean percent error for each experimental condition. (b) Mean completion times for each experimental condition. (c) Mean number of hesitation points for the full environment and inside the VCA. Error bars represent standard error. Original and Reversed represent original and reversed crowd movement, respectively.

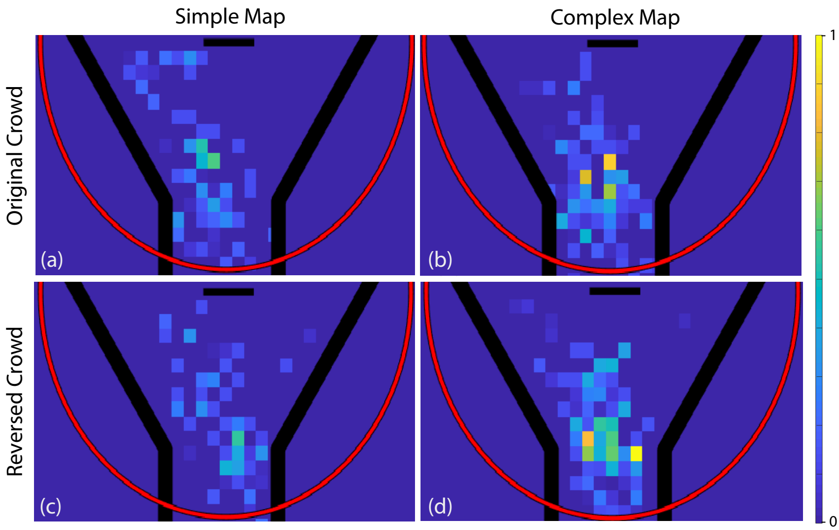

FIGURE 3.7: Normalised density maps of hesitation points. The red semi-circle represents the boundary of the visible catchment area. The scale ranged from 0 (no hesitation points) to the maximum number of hesitation points for any location across the four experimental conditions. For all density maps, we combined trials with goal locations to the left and right. (a) Simple maps and the original crowd movement. (b) Complex maps and the original crowd movement. (c) Simple maps and reversed crowd movement. (d) Complex maps and reversed crowd movement. There is a significant difference between simple/reversed and complex/reversed conditions (p=0.02). The size of each cell is 1X1 meter.

to require more time (43.48s) than all of the other trials (mean = 40.12, see Figure 3.5b). The results of the 2x2 ANOVAs for number of errors, completion times, number of hesitation points, and number of hesitation points within the VCA are presented in Table 6.2. Because of heterogeneity of variance, number of errors was also analysed using an ART ANOVA (see Table 3.1). Both parametric and non-parametric analysis revealed a main effect of crowd movement on number of errors, whereas the effect of map types on number of errors was only revealed by the parametric analysis. In addition, there was a significant interaction between crowd movement and map complexity in terms of time ($p=0.007$) and number of errors ($p=0.003$). Percent error (see Figure 3.6a) and the mean number of hesitation points (see Figure 3.6c) were both highest for trials with reversed crowd movement and complex maps. Time required per trial was similar for all four types of trials (see Figure 3.6b).

In order to visualise hesitation points within the VCA, we created "Normalised" density maps to weigh each hesitation point according to its (temporal) length, and higher values represent more hesitation in general (see Figure 3.7). Each cell is of the size of 1 meter X 1 meter because the hesitation point is defined with the same size scale. From these two sets of density maps, the complex/reversed condition clearly exhibits the most hesitation. Accordingly, the KDE analyses for normalised density maps revealed a significant difference between simple/reversed and complex/reversed conditions ($p=0.02$). However, this effect was not confirmed using the aggregated density maps ($p=0.14$). All of the other comparisons were not significant, including simple/original versus simple/reversed (aggregated $p=0.51$, normalised $p=0.57$), simple/original versus complex/original (aggregated $p=0.53$, normalised $p=0.39$), and complex/original versus complex/reversed (aggregated $p=0.50$, normalised $p=0.51$).

3.5 DISCUSSION

In the present studies, we investigated the effects of map design and crowd movement on spatial decision-making in VR. First, we used an online crowd-sourcing platform to present videos of movement through a Y-shaped intersection from a ground-level perspective and asked participants to decide whether to turn left or right. Study 1 revealed that a complex map design led to longer decision times and more mistakes compared to a simpler map design. In the next study, we collected participants' trajectories as they moved together through the same Y-shaped intersection using a networked VR laboratory. Study 2 revealed a very low number of errors and slower decisions with complex map design than with the simple map design, but the results were not significant. Study 2 also allowed us to collect crowd trajectories for the final study. In the third study, we flipped the indicated destination to produce a conflict between the direction indicated by the map and the direction indicated by the crowd. The results from Study 3 demonstrated a significant effect of conflicting crowd movement on the number of incorrect decisions. Study 3 also showed that a complex map design can lead to a higher number of incorrect decisions and a different distribution of hesitation points in the environment when in conflict with crowd movement.

Together, these three studies demonstrated the expected differences between simple and complex maps. Consistent with O'Neill [31], we found that simple maps may help people make more accurate spatial decisions. However, these findings may appear to conflict with previous research that did not find an effect of different map designs on decision-making [234, 235]. While Soh and colleagues [234] varied other aspects of map design, Devlin and Bernstein [235] varied the amount of detail in the maps as in the present studies. In Devlin and Bernstein [235], participants navigated through a complex environment with several intersections rather than a simple one-intersection environment. This complex environment may have allowed participants more time and space to make a decision or correct for a previous decision [235]. In addition, the less-detailed maps from Devlin and Bernstein [235] were still relatively more complex than our simple maps in terms of both the absolute number of details and the number of details per unit of space. Because the differences between maps in the present study were more pronounced, the effect of map design on decision time and accuracy might have been easier to detect.

We did not find an effect of map design on decision accuracy in Study 2, but this result is due to the very low number of incorrect decisions overall. This low number of incorrect decisions in Study 2 may be attributable to the co-presence of participants in the same virtual environment. This co-presence allowed participants to "physically" interact with each other by reacting to each other's visually depicted movements in real-time. Moussaïd and colleagues [63] found that following behaviour could lead to incorrect collective decisions during navigation in VR. In the present study, these interactions between participants may have led to more accurate decisions via collective intelligence [83], although both studies were conducted in the same laboratory. Notably, participants in Study 1 were alone in the environment, and participants in Study 3 were immersed with computer-controlled avatars.

Despite the avatars in Study 3 being controlled by the computer, participants sometimes followed the virtual crowd as if it were controlled by other participants. Indeed, the conflict between the direction indicated by the map and the direction indicated by the virtual crowd led to significantly more incorrect decisions (with respect to the map). Although we only tested for following behaviour using one group of participants, this finding is consistent with previous research that found that participants tended to hesitate before responding to a similar conflict between the direction indicated by an computer-controlled avatar and the actual direction of an emergency exit [212]. Both findings indicate that the computer-controlled avatars were somewhat believable, despite lack of direct communication between the participants and avatars. In the present study, these avatars also lacked visual communication cues such as eye contact and hand gestures. While these features may be added in future studies to improve believability, the social signal produced by our relatively simple avatars was sufficient to elicit following behaviour.

We also observed an interaction between the direction of crowd movement and map design for both the time required to complete a trial and the distribution of hesitation points. In both cases, there was only a difference between simple and complex maps when the direction of crowd movement was reversed. We interpret this interaction as an indication that the conflict trials resulted in higher cognitive load than trials without this conflict. Despite the habituation effect, it is worth noting that this should not affect our interpretation of the difference between simple and complex signs because the order of trials was randomized. Thus, these findings support the notion that map designers should simplify maps by reducing the number of extraneous icons, especially in cases of high cognitive load [229]. In addition, maps may be personalised by only including icons that are relevant for each person with a specific task. The convenience and ubiquity of smartphones allows for maps in airports to be displayed with an interactive digital device on which information regarding other types of locations can be presented for different tasks (e.g., searching for the nearest bathroom, finding a restaurant). The findings from our study can inspire such map designs to be simplified and more task-specific for each individual user.

Another important finding was the difference in the distribution of hesitation points caused by the more complex map design and crowd movement. Previous research has already shown that hesitations by pedestrians can increase the probability of collisions and decrease the moving speed of a crowd [255, 256]. Such involuntary slowing down of crowds can create unexpected obstacles and lead to congestion [257]. This finding reinforces the idea that the task-specific and individualised presentation of map information may influence hesitation.

One issue that has not been addressed in the present study is whether the effects of crowd movement and map complexity would apply to more complicated wayfinding tasks that require more than just binary choices from the participants. Future research can complement the present studies by introducing manipulations of time pressure, task difficulty, and visual noise. Time pressure can be introduced in order to simulate the stress associated with finding a terminal gate. We would expect time pressure to increase the size of the effect of map complexity. This idea is consistent with previous research [63], which has found that people are much more likely to follow others in an evacuation scenario with additional time pressure. In addition, adding visual noise (e.g., smoke from a simulated fire) would probably reduce the size of the effect of map complexity and increase following behaviour. Following vision-based models of collective motion [170, 210, 211], we would expect, especially with low visibility, for objects closer to the navigator to affect the navigator's behaviour more than objects further from the navigator. Adding noise to the virtual environment (e.g., additional signs on the ceiling and walls) could decrease the observed effect of map complexity, especially if these signs are irrelevant to the task. Finally, looking at the interaction between task difficulty and map complexity would be interesting because we could expect the effect of map complexity to either decrease or increase with task difficulty. Task difficulty could be increased by having participants find the actual gate instead of turning left or right. On the one hand, the effect of map complexity could decrease with task difficulty because the task would be longer and involve more decisions along the route to the destination. On the other hand, the effect of map complexity could increase with task difficulty because the time required to find the destination is amplified by each decision along the route.

Another possible limitation of the present study is participants' habituation to the VR task over trials, which may help explain some of the main effects for map type and crowd movement that we originally obtained. Unfortunately, for our experimental design, we could not test for a higher order interaction between map type, crowd movement, and trial number. For a future study, we could include additional trials after trial #9 and exclude trials before this probe trial in order to maintain a balance among the various experimental conditions.

Prior studies have revealed the importance of map design [31, 234, 235, 258–260] and crowds [63, 69, 212, 215, 261] as wayfinding cues, but to our knowledge, the present studies represent the first investigations of the interaction between these two factors. These studies also contribute to the literature by demonstrating that map design can affect human decision-making in VR and that crowd movement can affect spatial behaviour, even when the individual avatars are computer-controlled. Both of these contributions may inform future studies on collective intelligence, especially in situations with high cognitive load. For example, maps may need to be designed more simply in public spaces with larger crowds. In the future, a similar approach can be used for the preoccupancy evaluation of indoor environments.

4

RESPONSIVE ENVIRONMENT FOR CROWD DISASTER

4.1 INTRODUCTION

Crowd disasters during large-scale events are a primary concern for event security because of the related casualties and chaos. However, the investigation of conditions that lead to crowd disasters in real environments is often infeasible because of practical and ethical issues. In contrast, computer simulations can contribute to our understanding of crowd disasters by providing a framework for the formal analysis of an event. In addition, VR experiments allow researchers to investigate individuals' responses to simulated crowds, the physical and social conditions surrounding the event (e.g., exiting barriers or fences), and to precisely measure participants' physiological reactions and spatial behaviour. Both simulation and VR approaches may facilitate the development of disaster prevention methods.

The goal of this paper is to employ the combination of simulation and VR methods to gain a better understanding of crowd management and help organisers avoid similar future disasters. Specifically, we investigate interventions that might have been able to prevent the disaster at the 2010 Love Parade music festival in Duisburg, Germany. First, we reproduce the events of the 2010 Love Parade disaster with a simulation based on the Social Force Model [262] calibrated with available data (https://loveparade2010doku.wordpress.com/). We then test several possible crowd management strategies, including the removal of physical obstacles and the separation of inflow and outflow. These strategies are evaluated with respect to crowd density, throughput, congestion, and the number of simulated casualties. While the results of this simulation appear to match observations from the actual event, our approach focuses on the density of the event within a simplified crowd behaviour framework. More sophisticated models incorporating local behaviours are possible and can be the focus of future research. Second, we conduct a VR experiment in order to investigate differences in the simulated first-person experiences of the original disaster and the best-performing crowd management strategy using a head-mounted display. Here, individual participants are immersed in one of two crowd scenarios as we measure their physiological arousal and self-reported level of stress.

4.1.1 *Computer simulations of crowd behaviour*

Many researchers have attempted to address the conditions that lead to crowd disasters using computer simulations [4, 39, 199, 263], real-world observations [3, 264, 265], real-world experiments [266], and virtual reality experiments [162]. Computer simulations of real events have been used to study crowd disasters because of their versatility and relatively low cost. Simulations provide the ability to predict crowd behaviour in new and unseen environmental conditions, allowing researchers to conduct "what-if" experiments [4]. Computer simulations typically employ steering algorithms for individual agents and are evaluated with respect to the behaviour of a large number of agents [263]. For example, the Social Force Model (SFM) describes the self-organisation of pedestrian movement using a microscopic model of pedestrians [199, 262]. Inspired by the Newtonian law of motion, this model has been successful in reproducing several common crowd phenomena such as lane formation and crowd turbulence [38]. In order to evaluate the outcome of the simulations, density [39], congestion [267], and crowding [268] have been used as metrics to assess the level of risk.

4.1.2 *Real-world observations and experiments*

Based on observations of the Love Parade Disaster, a number of studies have begun to examine the management of the event [3, 269]. In order to prevent future disasters, Helbing and Mukerji [3] have suggested the separation of inflow and outflow, the removal of obstacles (e.g., fences, police cordons), and the provision of additional entrances/exits. Klüpfel [269] has assessed the underlying causes and consequences of the Love Parade disaster and has suggested that the proximate causes of overcrowding include the late opening of the entrance. Lian and colleagues [270] focus on extracting pedestrian movement patterns from publicly available video footage of the disaster. Krauzs and Bauckhage [271] extend this work by using the video footage to automatically detect the timing of the congestion. Pretorius and colleagues [4] simulate several management strategies in a model of the Love Parade disaster and find that a one-directional flow might have prevented injury compared to the original event.

In general, data corresponding to real-world events is often difficult to obtain and may violate the individuals' privacy. In comparison, experiments in real environments can be costly and difficult to organise, especially for large crowds, and their scope is limited to situations that do not endanger health or lives. Nonetheless, researchers have developed crowd behaviour detection and flow computation [265] methods that are capable of capturing aggregate behaviour without tracking specific individuals. By applying a similar approach, Moussaïd and colleagues [169] have analysed the organisation of social groups to predict walking patterns from video footage. Laboratory experiments have also been used to study local crowd movement patterns at critical regions such as turning corners [272, 273] or stairs [274]. For example, Dias and colleagues [273] observed crowd turning behaviour and found that higher turning angles can reduce flow rates and velocities under normal congestion. Similarly, Burghardt and colleagues [274] found that areas of high density can precede a turning point at the stairs where congestion forms. Such empirical evidence can be further used to calibrate data-driven models for pedestrian simulations. Dias and Lovreglio [275] represented the floor as a continuous field in order to better model pedestrians' navigation of a corner and validated these field representations with the observation of walking behaviour during a laboratory experiment. In addition, Crociani and colleagues (Crociani et al., 2018) proposed an algorithm to reproduce smooth trajectories at corners and validated this algorithm with the laboratory experiment data.

Real-world data from crowd disasters (e.g., during a Hajj event in Mina [39]) can be used to calibrate and validate computer simulations in order to help predict future disasters. Extracting continuous crowd movements from segmented video clips has been a major challenge for acquisition of crowd data from cameras. Recently, Khan and colleagues successfully used an unsupervised clustering algorithm to generate crowd flows from segmented video clips and then compared to other tracking techniques from the literature [276]. Automatic tracking techniques for coarse-grained data analysis can also benefit from reflexive markers carried by crowd members [266]. Some researchers have also employed a more traditional approach by manually extracting data from videos in order to improve head counting methods [277].

4.1.3 *Virtual reality experiments*

Compared to real-world experiments, VR studies of crowd behaviour allow for greater experimental control [278] and opportunities for crowd visualisation [173]. This type of visualisation provides a first-person perspective that can guide the organisers towards better decisions and help patrons to experience the scenario within the crowd. When conducting single-user studies, VR researchers must consider the manner in which the crowd is visualised [173]. Depending on the application, these visualised crowd may need to be representative (e.g., with human-like bodies and movements [63]) or realistic (e.g., with human-like faces and clothing [279]). Despite the opportunities provided by VR for experimental control, crowd visualisation, and multimodal assessment, there are a few notable limitations. These limitations include but are not limited to constraints on task complexity (e.g., the number of turns along a route) [162], motion sickness [280], lack of interaction with real social agents [281], and the lack of real-time proprioceptive feedback (e.g., collisions between avatars) [278].

4.1.4 *Crowds and physiological arousal*

Crowds may influence individual self-reported affective [282], behavioural [283], and physiological states [284]. In terms of behavioural effects, virtual crowds can be used positively as a social signal for finding an unobstructed exit [63] or negatively as an obstacle blocking a potential path to safety. Realistic crowd visualisation in VR also provides opportunities to investigate changes in psychological states resulting from dangerous scenarios such as crowd disasters. For example, the presence of a standing avatar has been found to lead to a higher physiological arousal than the presence of a running avatar [285], and the appearance [286] and distance [287] of virtual avatars have been found to positively correlate with physiological arousal. Physiological responses such as electrodermal activity (EDA) [288] and heart rate variability (HRV) [289] have been used to study stress/distress [290], user experience [291], attention, and other aspects of cognition [292]. EDA and HRV both reflect the activity of the autonomic nervous system. While EDA reflects sympathetic arousal, (normal) HRV results from a balance between sympathetic and parasympathetic activity [289]. Questionnaires can also be used to distinguish between affective states [293].

4.1.5 *Overview of the Love parade crowd disaster*

The Love Parade was a popular German music festival that was first organised in 1989. The Love Parade disaster occurred in Duisburg on July 24, 2010 [3]. The festival area was approximately 100,000 m^2 and was constrained by railway tracks to the East and by a freeway to the West (see Figure 4.1). A tunnel from an old freight station funnelled visitors to a main ramp that led to the festival area. The narrowest diameter of the tunnel was

20 m. The festival area could only be entered and exited from this tunnel, although a side ramp was available as an additional (reserve) exit. The main ramp was 26 m wide at its narrowest point, but with a local effective width of only 10.59 m due to the presence of temporary fences. The entire festival area was surrounded by fences.

A detailed analysis of the festival area revealed potential safety issues in the event planning, including the limited maximum capacity and the use of the tunnel as the only entrance and exit [3]. The use of the main ramp was temporarily restricted by police cordons that were added to control traffic at 15:50 during the festival. Around this time (between 15:30 and 16:00), congestion around the main ramp began to form. As congestion increased, people began climbing fences, billboards, and poles in order to escape from the dense crowd. The fences were removed at approximately 16:20 in an attempt to relieve the congestion [3]. This, however, could not prevent the crowd disaster, which killed 21 people and injured 500 festival attendees. The primary cause of death was suffocation.

4.2 SIMULATION AND INTERVENTIONS

4.2.1 *Love parade crowd disaster simulation*

To simulate the 2010 Love Parade disaster, we use publicly available online data from video surveillance cameras (https://loveparade2010doku.wordpress.com/), a 3D model of the festival area, and computer-controlled agents to represent the moving crowd. We then extend this simulation by modelling various crowd management scenarios and compare these simulations in terms of congestion and simulated casualties. We use the Unity 3D Game Engine (http://www.unity.com) to construct a true-to-scale 3D virtual environment of the festival area and all potential entrances and exits (see Figure 4.2). This environment was created based on the description from Helbing and Mukerji [3] and publicly available maps, plans, and other documents. For the simulation, we use a simple version of the environment without lighting and texture details. The texture and lighting were later added for the VR experiment and modelled based on the surveillance videos (i.e. https://loveparade2010doku.wordpress.com/), of the real environment.

We compute a triangulated representation of the walkable areas in the environment to form a navigation mesh. The starting point and the destinations of the crowd flows were determined from the surveillance videos. A

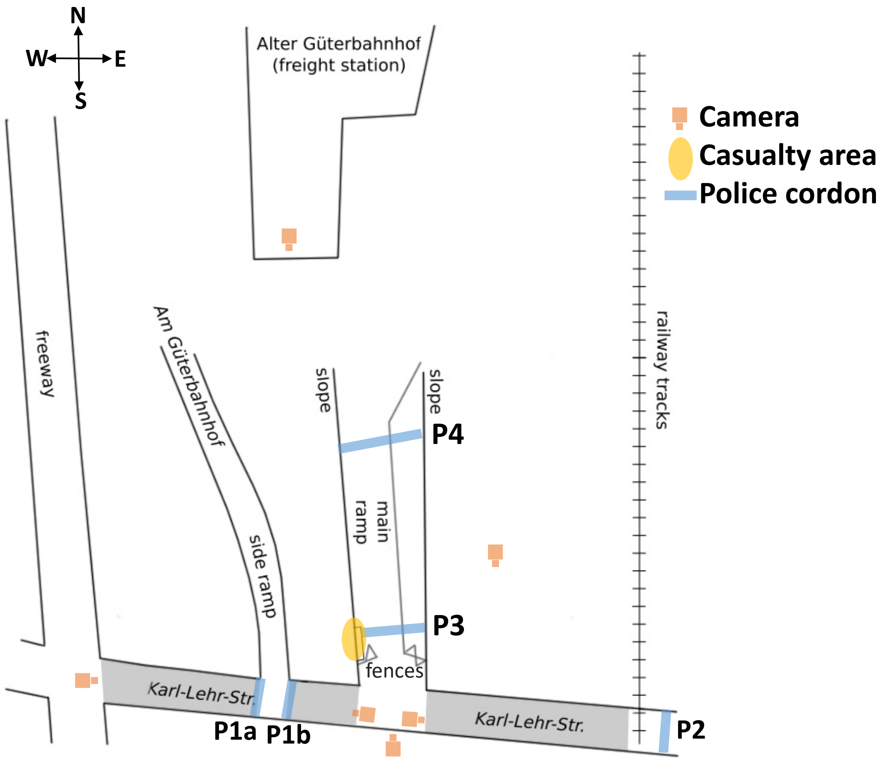

FIGURE 4.1: Illustration of the festival area including the locations of the surveillance cameras used for the simulations, the police cordons (P1 through P4), and the casualty area. Adapted from an image created by Helbing and Mukerji [3].

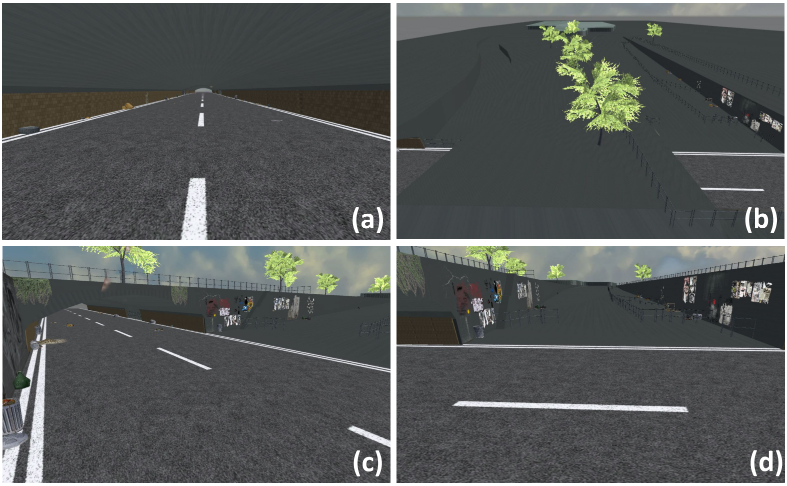

FIGURE 4.2: Four different views of the virtual environment. (a) View of the tunnel. (b) View of the overall area with both the main and side ramps. (c) View of the tunnel and a narrow staircase from the entrance to the main ramp. (d) View of the main ramp from a similar position as the videos recorded by surveillance camera 13.

search graph was constructed on the navigation mesh (nodes are the centroids of triangles, and edges connecting adjacent triangles). The A* search algorithm [294] was used to perform path finding operations on the search graph to find sequences of way points between origins and destinations of agents. The SFM [199] was used to steer the agent along this computed path while avoiding collisions with the environment and other pedestrians.

The analysis of the surveillance videos also provided estimates of inflow, outflow, density, and individual velocities at different times. Videos from surveillance cameras were used instead of videos from visitors' mobile phones because they were more stable over time and often of higher quality. Given the availability of the data, each surveillance video was separated into segments of 20 minutes except for the first three segments (7, 6, and 17 minutes, respectively). Because of technical problems with the recording, some frames were missing, and the effective length of the video segments were shorter than the duration they represented by up to four minutes.

In order to estimate visitors' velocities in meters per second ($\mathcal{V}(t)$) as a function of density (ρ(t)), we used the fundamental diagram proposed by Weidmann [295].

$$\mathcal{V}(t) = 1.34 \times (1 - e^{-1.913 \cdot (1/\rho(t)) - 1/5.4}) \tag{4.1}$$

Density can also be estimated by the combined inflow and outflow per second and meter ($\mathcal{Q}$(t)) divided by velocity ($\mathcal{V}(t)$).

$$\rho(t) = \frac{\mathcal{Q}(t)}{\mathcal{V}(t)} \tag{4.2}$$

The solutions of Equation 4.1 can be determined numerically using Newton's method [296]. We used the velocity of the crowd after 15:20, which remains at 0.7 m/s constantly during the simulation. We computed the flow values for the centre of each time interval based on the total width of the main ramp (irrespective of the fences).

Based on these estimates, we generated a crowd of agents to populate the virtual environment and to simulate the effects of different crowd management scenarios in terms of density, congestion, throughput, and simulated casualties. Similar to the real event, the agents entered the main ramp from inside the tunnel and exited from the end of the main ramp towards the festival area. The simulations represented estimates of the real event from 15:20 to 16:40.

The SFM represents systematic forces (i.e., attraction and repulsion) exerted by targets, obstacles, and other pedestrians that influence the agents' movements [199]. Specifically for agent α, these forces include an acceleration force $\vec{f}^0_\alpha(\vec{v_\alpha})$, a repulsive force $\vec{f_{\alpha i}}(\vec{r_\alpha})$ caused by obstacles and boundaries, and repulsive interactions $\vec{f_{\alpha\beta}}(\vec{r_\alpha}, \vec{v_\alpha}, \vec{r_\beta}, \vec{v_\beta})$ between the agents [199]. The index of obstacles is i, and β represents the other agents (see Equation 4.3).

$$f = \vec{f}^0_\alpha(\vec{v_\alpha}) + \vec{f_{\alpha B}}(\vec{r_\alpha}) + \sum_{\beta(\neq\alpha)} \vec{f_{\alpha\beta}}(\vec{r_\alpha}, \vec{v_\alpha}, \vec{r_\beta}, \vec{v_\beta}) + \sum_i \vec{f_{\alpha i}}(\vec{r_\alpha}, \vec{r_i}, t) \tag{4.3}$$

The acceleration force $\vec{f}^0_\alpha(\vec{v_\alpha})$ is defined by the direction of the next destination $\vec{e_\alpha}$, desired speed v^0_α, and the current speed $\vec{v_\alpha}$ according to:

$$\vec{f}^0_\alpha(\vec{v_\alpha}) = \frac{1}{\tau_\alpha}(v^0_\alpha \vec{e_\alpha} - \vec{v_\alpha}) \tag{4.4}$$

Other obstacles i (i.e., fences and walls) define the repulsive forces. In equation 4.5, $\vec{r}_\alpha - \vec{r}^\alpha_i$ is the distance between an agent and the obstacle, and V_i represents a potential repulsive force (see Equation 4.5).

$$\vec{f_{\alpha i}}(\vec{r_\alpha}) = -\nabla_{\vec{r}_\alpha} V_i(\|\vec{r}_\alpha - \vec{r}^\alpha_i\|) \tag{4.5}$$

Repulsive forces between the agents are defined as follows:

$$\vec{f_{\alpha\beta}} = A_\alpha exp[(r_{\alpha\beta} - d_{\alpha\beta})/B_\alpha]\vec{n}_{\alpha\beta} \tag{4.6}$$

A_α represents interaction strength, and B_α is the range of the repulsive interactions. $d_{\alpha\beta}$ is the distance between the centres of the mass of agent α and β and $r_{\alpha\beta}$ is the sum of their radii r_α and r_β. $\vec{n}_{\alpha\beta}$ represents the normalized vector pointing from agent β to α. We used the parameters $A_\alpha = 0.045$, $B_\alpha = 0.2$, r_α=r_β=1, and v^0_α = 1.3m/s.

Each agent within the crowd was assigned a series of navigation targets (see Figure 4.3). These potential targets lied along the edges of Regions 1 and 2. The crowd entering the festival area was first directed towards Region 1 and then Region 2. The crowd exiting the festival area was first directed towards Region 2 and then the tunnel to their left or right. To avoid an unrealistic amount of congestion at the corners of each intersection, we defined these navigation targets probabilistically and separately for each agent. The point at which each agent entered or exited an intersection was selected from four discrete targets with equal probability. There were five meters between each of these four potential targets. Figure 4.3 illustrates the

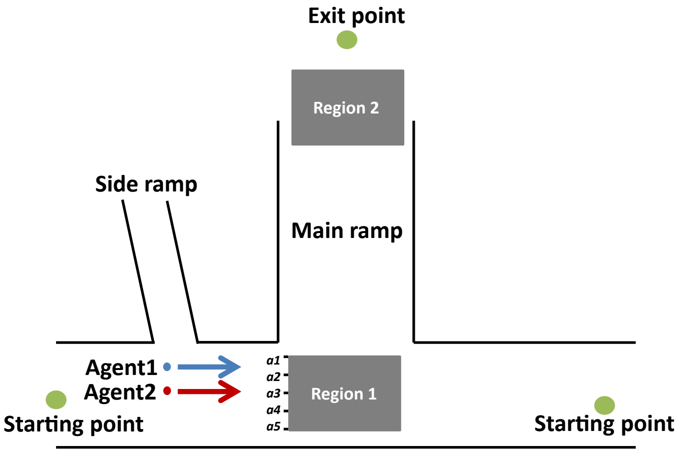

FIGURE 4.3: Overview of the targets and trigger areas on the ramp to navigate agents.

case in which two agents first moved towards the Western edge of Region 1. Agent 1 has an equal probability to choose from *a1* through *a4* on the edge of Area 1 as first navigation point, whereas Agent 2 has an equal probability to choose from *a2* through *a5*. Similar mechanisms were applied for the northern edge of Region 1 and the southern edge of Region 2. We tested two other targeting mechanisms, one in which agents attempted to take the shortest path and one in which agents moved directly towards the closest target, but neither of these extremes produced realistic crowd behaviour.

4.2.2 *Intervention scenarios simulation*

After the simulation of the original crowd disaster, we simulated nine alternative crowd management scenarios based on the recommendations of Helbing and Mukerji [3]. These nine scenarios were based on five different variations of the original simulation. First, we varied the presence of the police cordons. The original police cordons were simulated using obstacles that could not be walked through. The idea was that removing the police cordons might reduce crowd density by removing unnecessary obstacles. Second, we varied whether the main fences were present at the beginning of the simulation because the fences may have been unnecessary obstacles increasing crowd density. Third, we varied whether the side ramp was

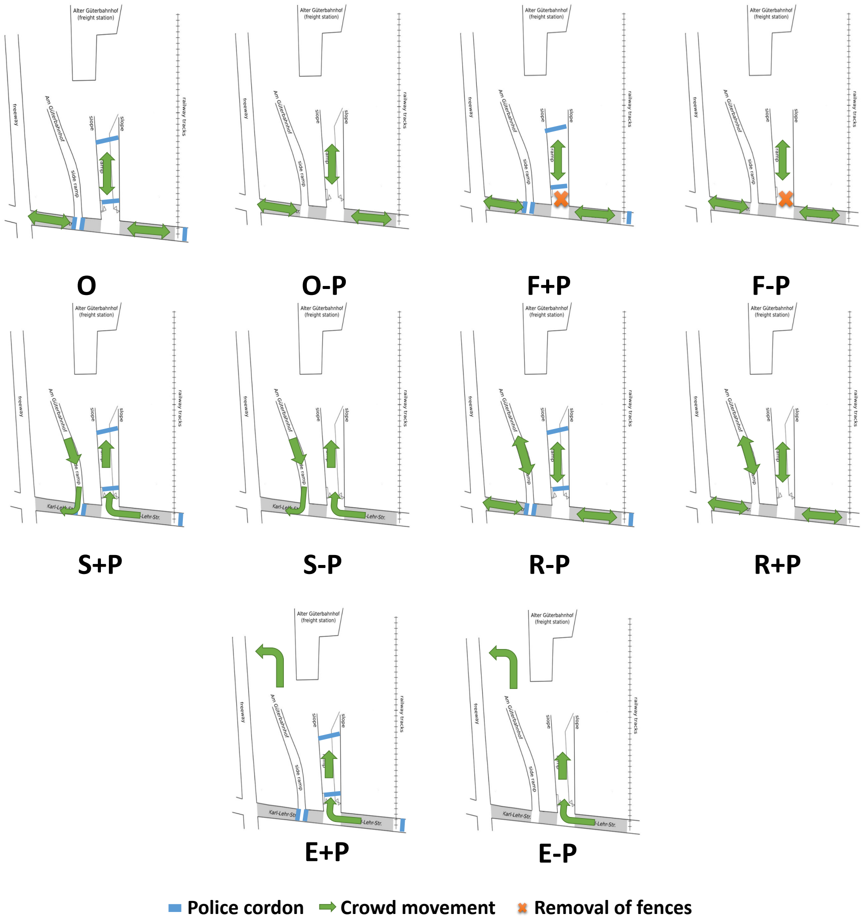

FIGURE 4.4: Illustration of the ten simulated scenarios. Green arrows represent the in- and outflow of the crowd. Blue lines represent the police cordons, and the orange crosses represents the removal of the main fences along the main ramp. Scenario O represents the original simulation, the F scenarios represent the removal of fences, the R scenarios represent the inclusion of the side ramp, the S scenarios represent the separation of inflow and outflow, and the E scenarios represent opening the additional exit. Each of these intervention scenarios has two conditions, either with (+) or without (-) police cordons (P).

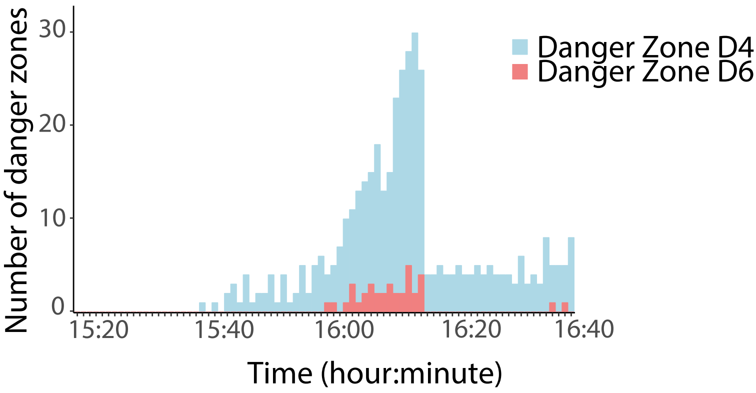

FIGURE 4.5: Change in the number of danger zones (D_4 and D_6) for the first repetition of the O simulation from 15:20 to 16:40. The number of danger zones increases over time until 16:15 and then suddenly decreases because of the removal of the main fence. This graph peaked at 27 danger zones around 16:15.

open. We expected that this might reduce the density by decreasing the number of people attempting to move through the same channel. Fourth, we varied whether inflow and outflow were separated or not using both ramps or just the main ramp. The separation of inflow and outflow can avoid confrontations of opposite flow directions. Fifth, we varied whether there was an additional exit near the festival area because this might remove the limitations related to the restricted width of the ramps. In total, we devised ten scenarios (see Figure 3): The original simulation (O), the original simulation without police cordons (O-P), the removal of fences while police cordons were present (F+P), the removal of fences and of police cordons (F-P), the separation of inflow and outflow in the presence of police cordons (S+P), the separation of inflow and outflow without police cordons (S-P), the inclusion of the side ramp while police cordons were present (R+P), the opening of the side ramp and no police cordons (R-P), use of an additional exit with police cordons (E+P), and an additional exit and no police cordons (E-P).

These scenarios were each repeated 10 times (conducted simultaneously on various computing units with the same simulation program) and compared in terms of maximum occupation (Max), simulated casu-

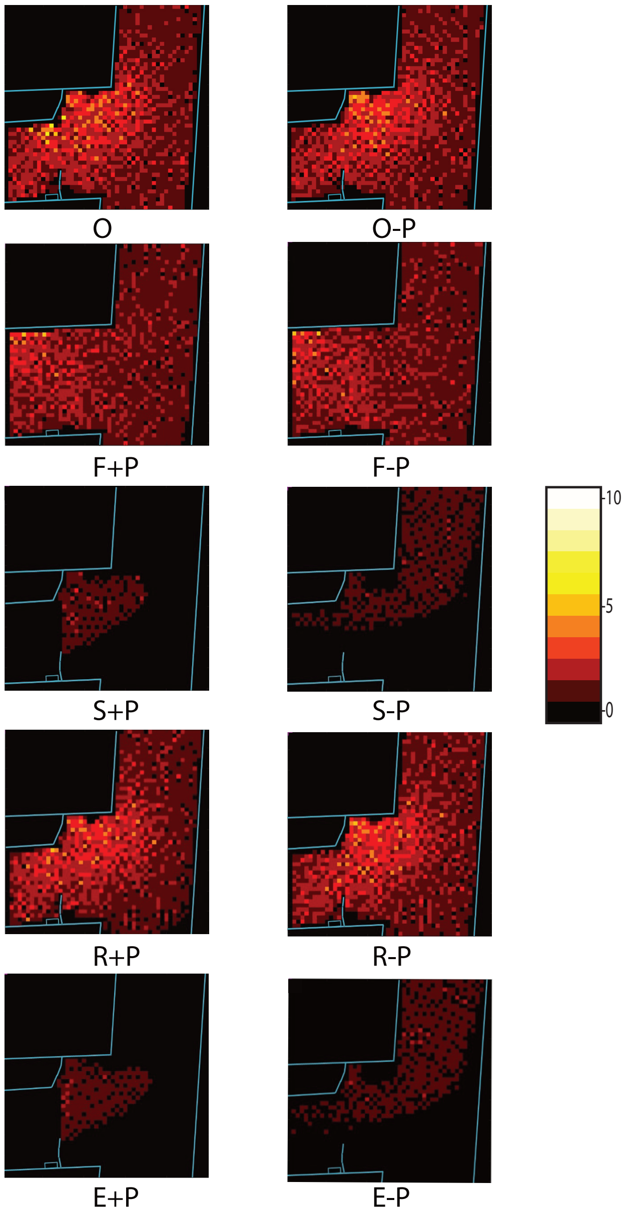

FIGURE 4.6: Density maps of the general ramp area at 16:00 for the first repetition of each scenario. The blue lines represent walls and fences. The red dots represent the numbers of pedestrians in each grid cell. The colour bar on the right reflects the number of people in each cell.

alties, throughput (TP), general crowd density near the main ramp, and congestion. Consistent with the literature [3], we assumed the possibility of casualties when crowd density exceeded four agents per m^2 (i.e., danger zones; D_4). Since conditions with four agents per square meter are not necessarily deadly, we additionally determined extreme danger zones (D_6), where the crowd density exceeded six agents per m^2, although other researchers have defined danger zones differently [297]. The throughput was considered to be the number of agents that successfully exited the festival area over the course of the entire simulation. General crowd density was computed as the number of agents per m^2, recorded once every simulated minute and averaged over minutes. Congestion was defined as the number of agents who did not move at least 1 m in 60 seconds. Cronbach's α was computed for each of these dependent measures in order to assess its consistency across repetitions. We also conducted 2 (with or without police cordons) by 5 (scenario) between-groups ANOVAs in order to test for systematic differences among the scenarios in terms of each dependent measure.

4.2.3 *Simulation results*

Overall, there were very few unrealistically high densities in these simulations. Numerically, all of the alternative crowd management scenarios led to less density, less congestion, more throughput, and fewer expected casualties than the simulations of the original event (see Table 4.2). There was also extremely high consistency across repetitions for each dependent measure (Cronbach's α >.989). The removal of police cordons resulted in the largest differences compared to the Original scenario in terms of the reduction of congestion and danger zones. The removal of fences and the use of the side ramp also reduced the number of danger zones, but the most effective scenarios were those that separated inflow and outflow or added another exit near the festival area. These observations were confirmed by a series of ANOVAs. The ANOVA for all dependent measures revealed a significant main effect of police cordons, a significant main effect of scenario, and a significant interaction (see Table 4.1). The assumption of homogeneity was violated for each ANOVA, so we confirmed each result using a non-parametric ART ANOVA [252]. In addition, Figure 4.5 represents the first repetition of the O scenario in terms of the number of danger zones over time, and Figure 4.6 illustrates the crowd densities for all ten scenarios around the accident area at 16:00.

DV	Effect	F	MSE	p
Max	Police cordons	163.636	0.611	<.001
	Scenario	309.625	0.611	<.001
	Interaction	29.495	0.611	<.001
D4	Police cordons	116.584	714.914	<.001
	Scenario	744.874	714.914	<.001
	Interaction	32.211	714.914	<.001
D6	Police cordons	189.153	12.384	<.001
	Scenario	101.953	12.384	<.001
	Interaction	55.153	12.384	<.001
TP	Police cordons	5313.469	4230.030	<.001
	Scenario	342056.024	4230.030	<.001
	Interaction	2216.595	4230.030	<.001
Density	Police cordons	4.183	0.00008	.044
	Scenario	32322.325	0.00008	<.001
	Interaction	9.603	0.00008	<.001
Congestion	Police cordons	3759.747	735.106	<.001
	Scenario	8110471.825	735.106	<.001
	Interaction	1489.341	735.106	<.001

Table 4.1: Results of the ANOVAs based on simulation data for each dependent variable (DV). Across all DVs, there are reliable effects for the presence of police cordons and other variations across scenarios.

Scenarios	Max	D_4	D_6	TP	Density	Congestion
O	11.1(1.8)	357.8(39.2)	28.7(6.8)	13.1(9.7)	0.889(0.004)	35220.5(19.9)
O-P	6.6(0.5)	192.3(32.5)	1.4(1.5)	9.1(5.8)	0.899(0.012)	35231.1(18.4)
F+P	8.2(0.8)	392.1(33.8)	19.5(5.0)	17.5(6.1)	0.826(0.007)	35259.9(28.2)
F-P	7.6(0.5)	338(46)	13.8(5.4)	20.9(10.0)	0.832(0.005)	3526 (37)
S+P	3(0)	0(0)	0(0)	10581.1(73.5)	0.203(0.003)	4255.9(14.3)
S-P	2.4(0.5)	0(0)	0(0)	13568.8(146.3)	0.195(0.002)	3313.8(43.4)
R+P	9.8(0.9)	189.3(31.8)	15.8(4.6)	29.4(8.0)	0.836(0.013)	35200.9(32.1)
R-P	6.2(0.4)	120.2(16.8)	0.4(1)	31.1(7.1)	0.856(0.019)	35203.2(30.8)
E+P	3(0)	0(0)	0(0)	17174.2(89.6)	0.205(0.002)	3997.2(13.4)
E-P	2.3(0.5)	0(0)	0(0)	18926.3(84.1)	0.195(0.001)	3261.7(14.5)
Cronbach's α	.994	.997	.989	.999	.999	.999

TABLE 4.2: Means and standard deviations (in parentheses) of simulation results for all ten replications. Scenario O represents the original simulation, the F scenarios represent the removal of fences, the R scenarios represent the inclusion of the side ramp, the S scenarios represent the separation of inflow and outflow, and the E scenarios represent opening the additional exit. Each of the intervention scenarios has two conditions, with (+) or without (-) police cordons (P). The measures reported here include maximum occupation (Max), simulated casualties (D_4 and D_6), throughput (TP), general crowd density (Density) near the main ramp, and congestion (Congestion). Cronbach's α represents the consistency of these measures across the ten replications.

Our simulations reproduced the crowding effect in the original scenario at approximately the same time and location it was observed in the video footage. Our complementary results suggest that other crowd management strategies may have led to fewer or no casualties by decreasing density and congestion and increasing throughput. These results support the strategies suggested by Helbing and Mukerji [3]. Specifically, we found that the removal of physical obstacles (i.e., fences and police cordons) and the separation of inflow and outflow substantially reduced the expected number of simulated casualties.

4.3 VIRTUAL REALITY EXPERIMENT

While the simulation results provide evidence for the efficacy of these strategies for collective behaviour, they do not by themselves reveal the mechanisms underlying individual reactions to the crowd. In order to

FIGURE 4.7: Screenshots from (a) the O (original) scenario and (b) E-P scenario (additional exit without police cordons) in the virtual reality environment.

compare the best (E-P) and worst (O) scenarios in terms of individuals' physiological and behavioural responses, we devised a VR experiment in which participants experienced the simulation from a first-person perspective (see Figure 4.7). We expected participants in the O condition to be more physiologically aroused than participants in E-P condition with respect to EDA and HRV. We also expected participants in the O condition to report higher levels of distress and produce more head movements than participants in the E-P condition.

4.4 PARTICIPANTS

Participants were recruited via the University Registration Center. A total of 58 participants (27 females; mean age = 27, range = 19 to 39) participated in the study. Two participants were excluded from the study because of equipment failure. All participants received 15 CHF for approximately 45 minutes of participation. Before each experimental session, participants were given an information sheet and asked to complete an informed consent form. After this consent procedure, the experimenter helped the participant attach the three electrocardiogram electrodes. Next, participants completed the demographics questionnaire, video game experience questionnaire, and the pre-test questions from the SSSQ. The experimenter then attached two electrodes to the participants' fingers to collect EDA data and placed the HMD on the participant's head. After adjusting the HMD, participants completed a training procedure in which they were asked to look left and right and then look towards a button that was shown at a specific location on the display. After training, a seven minute nature video was presented to participants in order to record a baseline measure of their physiological activity. During the testing phase, the participants viewed four identical replays of one simulated scenario from a first-person perspective. Each replay was two minutes long, and participants had small breaks between replays. The video sequences did not contain any distressful content.

Participants were randomly assigned to one of two groups (O or E-P), each of which represented a scenario from the simulations above. Specifically, we compared replays of the O scenario with replays of the E-P scenario. These simulated scenarios were thus the only between-subjects independent variable. Our dependent variables included responses to the video game experience questionnaire, the three subscales of the Short Stress State Questionnaire (SSSQ), EDA, HRV, and the magnitude of head movements derived from the gyroscope in the head-mounted display (HMD).

EDA, HRV, and head movement data was aggregated across trials, and all of these measures were compared between the O and E-P scenarios using two-tailed, independent-samples *t*-tests.

4.4.1 *Materials*

The VR system consisted of a high-end gaming computer (Dell Alienware Area 51 Base; i7-5820K processor at 3.8 GHz overclocked; dual NVIDIA GeForce GTX 1080 video cards; 32 GB of SDRAM; Windows 10 operating system), a head-mounted display (Oculus Rift SDK2; https://www.oculus.com/rift), and physiological data equipment (Powerlab 8/35 recording device with FE116 GSRAmp and FE132 Bio Amp signal amplifiers; https://www.adinstruments.com). Finger electrodes (MLT118F) connected the GSRAmp to the medial phalanges of the index and ring fingers of each participant's non-dominant hand. In addition, we used three disposable electrocardiogram electrodes (MLA1010) to collect data for HRV analyses. These electrodes were placed on the second intercostal space below the middle of the clavicle on the right and left side of the chest and below the ninth left rib.

The VR experiment was implemented using Unity and the Experiments in Virtual Environments (EVE) framework [298, 299]. The virtual environment was based on the environment described above. Additional decals and game textures from the Unity Asset Store (https:// assetstore.unity.com/) were placed along the walls of the tunnel and main ramp in order to improve optic flow and provide a more realistic setting. In addition, we used LabChart 8.14 (https://www.adinstruments.com/) for collecting the physiological data, Matlab R2017a (https:// www.mathworks.com) for exporting and segmenting the physiological data, Ledalab 3.49 (http://www. ledalab.de) for processing the EDA data, and Kubios HRV 3.1 (https://www.kubios.com) for analysing the HRV data.

Participants have read and signed consent in all experiments. Participants were recruited via the University Registration Center for Study Participants (http://uast.uzh.ch). Participants completed a demographics questionnaire, a video game experience questionnaire, and the SSSQ. The demographics questionnaire contained questions regarding participants' gender, handedness, vision, and experience with head-mounted displays. The video game experience questionnaire asked participants to judge the number of hours per week that they had played video games in each of several categories (e.g., first-person shooters, sports games) [300]. The Short Stress

State Questionnaire (SSSQ) consists of 24 pre- and post-test items that can be divided into three subscales (i.e., distress, engagement, and worry) [293]. The distress subscale of the SSSQ is an indicator of positive arousal and negative valence, while the engagement subscale refers to positive arousal and positive valence. The worry subscale represents self-focused attention and intrusive thoughts.

4.4.2 *Design and analyses*

Our physiological data included both electrodermal activity (EDA) and heart rate variability (HRV). While EDA reflects sympathetic arousal, (normal) HRV results from a balance between sympathetic and parasympathetic activity [289]. For each trial, we exported the EDA data from LabChart to Ledalab. In Ledalab, this data was then downsampled from 1000 Hz to 10 Hz and visually inspected for artefacts. No artefacts were detected. We used Continuous Decomposition Analysis in order to extract the number of peaks in the EDA data (nSCR) and the sum of the amplitude of these peaks (AmpSum) [301]. Experiments in which the timing of the evocative stimulus depends on participant behaviour often measure the frequency of nSCR [302]. For this analysis, the parameter estimation algorithm was optimized twice in order to model the impulse response function. The threshold for each individual peak was 0.01μs. After subtracting the baseline, both nSCR and AmpSum should represent overall reactivity for each trial.

HRV can be assessed in time or frequency domains. Researchers often consider decreases in the high frequency band (i.e., 0.15 to 0.40 Hz) as an indicator of stress [303]. The electrocardiogram data was sampled at 1000 Hz and exported from LabChart to Kubios HRV for analysis. After automatic beat detection and artefact correction, the time series of interbeat intervals for each trial were visually inspected for additional artefacts. In total, we removed one participant completely and 4 trials (.02%) from the remaining 57 participants due to missing or misaligned beats [304]. Each participant had at least three trials for further analysis. This data was then processed using a very low threshold filter (0.45 sec) and a smoothness prior filter for detrending (λ = 500, cut-off frequency = 0.035 Hz). We then used a Fast Fourier transform that was focused on power in the high frequency range (0.15 to 0.4 Hz) that typically reflects parasympathetic nervous system activity [305, 306]. The absolute values for high frequency power were natural log transformed (Log(HF)) in order to produce a measure of stress, panic, anxiety, and/or worry.

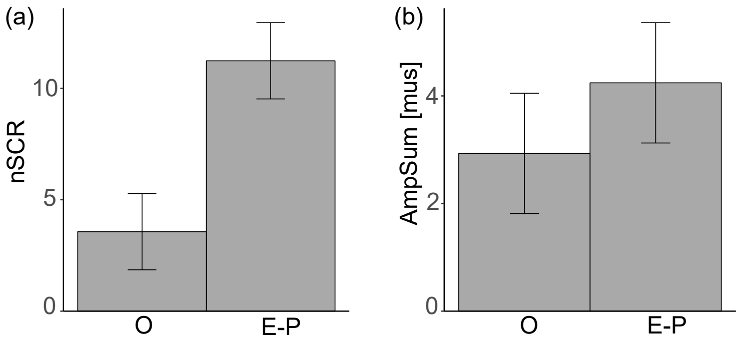

FIGURE 4.8: Difference between O and E-P scenarios in terms of (a) nSCR (non-specific skin conductance responses) and (b) AmpSum (the sum of the amplitude of skin conductance response peaks). The error bars represent the standard error of the difference between the two groups. Although both trends are in the same direction, we only found a significant difference in terms of nSCR ($p = .029$).

4.5 RESULTS

Results of the VR experiment showed that for the SSSQ, there were no significant differences between the O and E-P scenarios in terms of distress (O = 0.66±0.71, E-P = 0.54±1.31), t(56) = 0.444, se = 0.277, p = .659; engagement (O = -0.30±0.82, E-P =-0.08 ±0.97), t(56) = -0.93, se = .236, p = .357; or worry (O = -0.26±0.76, E-P = -0.15±0.96), t(56) = -0.489, se = 0.227, p = .627. For EDA, we found a significant difference between the O and E-P scenarios in terms of non-specific skin conductance responses (nSCR) (O = 3.57±13.91, E-P = 11.24±12.09), t(56) = -2.241, se = 3.422, p = .029, but not in terms of the sum of the amplitude of these peaks (AmpSum) (O = 2.93±10.57, E-P = 4.24±5.76), t(56) = -0.586, se = 2.237, p = .560 (see Figure 4.8). This suggests that the frequency (but not the magnitude) of skin conductance responses was higher in the E-P scenario than in the O scenario. For the HRV data, there was no significant difference between the O and E-P scenarios in terms of Log(HF) (O = -0.27±0.79, E-P = -0.12±0.50), t(53) = -0.894, se = 0.176, p = .375. In addition, there was not a significant difference between the O and E-P scenarios in terms of head movements (O = 1150.22±635.17, E-P = 1267.46±527.22), t(56) = -0.765, se = 5.837, p = .448. During the course of the whole experiment, no participants reported motion sickness or interrupted the procedure because of discomfort.

The results reveal that, when viewing from a first-person perspective, participants had higher non-specific skin conductance responses in the effective intervention group (E-P) than viewing the original (O) simulation. The simulation of the Original crowd disaster may have been less stressful than in reality because, due to ethical and technical reasons, we could not simulate and present the participants with animations of crowd members falling and stepping on each other. In addition, our design cannot be used to disentangle the effects of crowd movement and visual exposure to the virtual environment. This limitation makes it difficult to interpret the observed effect of management strategies on individual physiological arousal. In order to explain this effect, future research could systematically vary crowd movement and exposure to the environment. However, this approach would require the experimenter to control the viewing direction of the participants during the replays. Future research can also address the possibility of an interaction between motion sickness [303] and stress resulting from differences between the crowd scenarios, although we did not observe any motion sickness in the present study.

4.6 DISCUSSION

In this paper, we present the results of computer simulations and a VR experiment that investigated the effects of possible interventions during the 2010 Love Parade disaster on simulated casualties and physiological arousal in VR. We simulated the original event along with several other scenarios, including the removal of the main fences and/or police cordons, the opening of a side ramp for entering or exiting, the separation of inflow and outflow using the main and side ramps, and the opening of an additional exit near the festival area. These simulations revealed that, compared to the original scenario, all of these interventions led to less congestion, more throughput, and fewer or no simulated casualties. Our simulations provide a mechanism to assess previous disasters and may support event managers devise strategies to avoid future crowd disasters. Specifically, we demonstrate that crowd simulations based on the SFM and rendered in Unity can be used to determine possible causes of disasters. The application of the SFM was effective for recreating the physical properties and dynamics of the observed crowd. The application of the SFM and its simulated results present the "what-if" scenarios that could have been implemented in this tragedy. Our introduction of the danger zone metrics allowed us to easily assess the risk level of the simulated event. Our simulation of various management strategies demonstrated that alternative organisational decisions regarding crowd control during the event could have helped to prevent the disaster. In addition, rendering these simulations in Unity may help event managers visualise the effects of specific interventions on the crowd. Our VR experiment revealed that the best (E-P) and worst (O) scenarios significantly differed in terms of the frequency of skin conductance responses.

With respect to the simulations, we found that the most effective strategy for reducing simulated casualties was a combination of removing of police cordons and opening an additional exit from the festival area. Most previous research specifically focused on the detection of crowd movement patterns during the Love Parade disaster [265, 270, 271]. We extended these approaches by simulating several interventions suggested by previous assessments of the organisation and operation of this event [3, 269]. Our results support the potential of these interventions for saving lives. However, the scope of our finding is limited in terms of using density as a proxy to estimate critical crowded conditions. The simulation of more realistic crowd behaviours such as falling and stepping upon other might would help one to establish a greater degree of accuracy in this respect in the future, but there are ethical issues to be concerned.

Consistent with Pretorius and colleagues [4], we found that the separation of inflow and outflow (resulting in one primary direction of motion) increases throughput and reduces congestion in the simulated crowd. However, unlike in our study, Pretorius and colleagues [4] did not find any benefit of removing the police cordons. Due to several differences between the implementations and analyses of the two studies, we cannot identify the exact reason for this difference in results. In our study, the effect of the removal of police cordons was extremely consistent across measures and most scenarios. Indeed, the removal of police cordons in the present simulations decreased the maximum occupation, decreased the number of danger zones, increased throughput, decreased density, and decreased congestion. Such an effect is also consistent with recent official expertise [307, 308]. Importantly, our study extended Pretorius and colleagues [4] by including a measure of simulated casualties based on danger zones. As decreased throughput and increased congestion do not necessarily always result in more danger zones, event planners may adopt metrics such as danger zones in order to gain a better understanding of the potential benefits of particular interventions in the future.

With respect to the VR experiment, we found that viewing a simulation of an effective intervention from a first-person perspective led to higher non-specific skin conductance responses than viewing the original simulation. One possible explanation of our results is that participants in the E-P group moved further along the ramp and were exposed to more variation in the virtual environment than participants in the O group. This additional visual exposure may have increased arousal by inducing engagement or curiosity. The skin conductance results by themselves cannot disentangle these possibilities. Previous research in VR has found that the idle behaviour of a single avatar [285], the presence of a group of avatars [286], and smaller distances between avatars and the observer [287] increased physiological arousal. Furthermore, Llobera and colleagues [287] also found that more moving avatars led to higher physiological arousal, but the number of avatars in their study (maximum 4 agents) was much lower than in the present study (up to 2,000 agents in the Original group). Our two VR scenarios were similar with regards to avatar presence and distances, and the main difference between scenarios is the level of congestion. However, congestion was negatively related to avatar motion. Thus, our finding that idle avatars lead to lower physiological arousal may be inconsistent with Fox and colleagues [285]. The VR experiment was also limited in terms of the presence of the simulated crowd in that it did not reproduce crowd turbulence from the original disaster. Hence, the absence of crowd turbulence and the time pressure are likely to have caused participants to experience less stress from the first-person perspective than they would have experienced during the disaster. Future research can focus on explaining the exact mechanisms underlying the significant difference between scenarios by systematically varying crowd parameters (e.g., density, congestion) and environment parameters (e.g., spaciousness, visual noise).

Since the study was limited to a simplified crowd behaviour model, it was not possible to completely reproduce the complex phenomenon and spontaneous crowd movement patterns of the Love Parade crowd disaster. One limitation of our simulations is that rendering simulations in Unity is time intensive and prohibits a large number of replications. As a result, parameters in the SFM were difficult to optimise with respect to the original video data. Nonetheless, conducting 10 repetitions of each scenario allowed us to assess the consistency of each measure and the statistical significance of differences across scenarios. In future studies, one way to overcome this limitation would be to conduct the crowd simulation on a lighter platform and then only render the simulated crowd with optimised trajectories in

Unity. Another possible limitation is the manual extraction of crowd data from video footage. In the future, computer vision technology may be used to extract more precise estimates of in- and outflows. Lastly, the simulated crowd is notably less intelligent than members of the real crowd and do not necessarily reflect the spontaneous behaviours of people reacting to a dangerous situation. Many aspects of the crowd behaviour (e.g., realistic turning behaviour at the corners, crowd turbulence) could have augmented this simplified model and improved the veracity of the simulations. Future research can propose and attempt to validate these more sophisticated models of pedestrian dynamics for large crowds and environments [275, 309, 310].

Despite these limitations, we demonstrate a novel methodology for the research of crowd disasters and their prevention. To our knowledge, this is the first study to combine simulations and experimentation in VR of a crowd disaster of this complexity and size. We expect that follow-up work will further increase the sophistication and precision of this approach and thereby underline its huge potential and value. In conclusion, the coordination of crowd simulations and VR technologies can help event managers to assess potential dangers more realistically and to make more effective decisions about crowd management strategy in advance.

5

RESPONSIVE ENVIRONMENT FOR FIRE EVACUATION

5.1 INTRODUCTION

Fire is an exceedingly dangerous but common hazard in private and public spaces. Worldwide, it is estimated that 7,000,000 to 8,000,000 fire incidents occur annually, which lead to 70,000 to 80,000 fire deaths and 500,000 to 800,000 fire injuries [311]. Whereas it is usually easier to evacuate from familiar properties [312], it can be more difficult to navigate through unfamiliar public environments when signs provide incorrect or incomplete spatial information [313]. Indeed, it has been demonstrated that the conventional (non-adaptive) exit sign is not fully visible in unfamiliar environments [5] or helpful for evacuees when poorly designed [7]. Despite these findings, little progress has been made for human-building interaction technologies such as intelligent evacuation systems.

Animation, adaptation, and decentralization can be used to improve existing signage systems. Animations on signs can attract evacuees' attention and indicate a particular direction [314]. The direction indicated by a sign or signage system can also adapt to the location of the hazard by indicating the safest route [315]. These systems can be centralized or decentralized in that control malfunctions may or may not affect other components of the system, respectively [316]. In this paper, we specifically test the utility of adaptation and decentralization for signage systems during evacuation.

To design such a system, we established a workflow that included a lab experiment with human participants and agent-based modeling to validate the computational framework. First, we designed a prototype of the adaptive signage system and examined its utility using a desktop Virtual Reality (VR) experiment. Second, we implemented an automatic computational framework for the adaptive signage system, using graph-based algorithms and either centralized or decentralized computational structures. Third, we used an agent-based model to verify the effectiveness of the system.

5.2 RELATED WORK

Previous research has identified three key factors for successful fire evacuations: evacuation efficiency [317], information that supports wayfinding [318], and the emotional stability of the evacuees[319]. One of the main causes of casualties during fires is exposure to toxic fumes. Indeed, there are two times more fatalities caused by smoke inhalation than fatalities caused by burns [320]. To avoid the danger of smoke, a fast and efficient evacuation is vital. Since the stress of facing dangerous fire situations could affect the cognitive processes and decision making abilities of evacuees, it is important to ensure that they evacuate as quickly and calmly as possible [319]. Here, an adaptive signage system may be designed to solve such issues by highlighting the direction of the optimal route considering both path distance and safety.

To overcome the shortcomings of traditional exit signage, numerous researchers have attempted to devise a more intelligent system based on sensor and network technologies [92, 321–326] to collect information regarding the locations of fires [327] and individual evacuees [328] and to deliver route guidance information [92, 98]. For example, Hsu and colleagues [97] implemented a digital panel to provide route guidance during an evacuation. Other researchers have used sensors to detect the locations of fires and indicate a safe route using blinking signs [93]. In addition, the traditional exit sign icon (i.e., a running person) may be oriented and located towards the direction of the optimal exit route in order to facilitate evacuations [329]. Here, various designs for indicating incorrect or inefficient directions have also been tested. Signs with a red "X" symbol were found to be the most dissuasive [330], and ground installations tend to be more effective than overhead suspensions for guiding evacuees [325]. Finally, some researchers have introduced novel computational methods to optimize the locations of signs [98, 133].

However, such intelligent systems are usually built using a centralized processing and communication entity, which undermines the systems' abilities to handle loss or damage of their components [331]. A decentralized system can avoid situations in which a failed central entity causes a system to collapse by distributing the resource or introducing independent management [332]. Towards this end, de Farias and colleagues [316] created a decentralized control and decision-making system for smart buildings in which wireless sensor and actuator network nodes share the sensed data and make cooperative decisions. Similarly, Sarkar and colleagues [333] proposed a distributed layered architecture for Internet of Things applications. While various frameworks have been proposed to facilitate the establishment of such distributed systems [334–336], none of these decentralized systems were designed for wayfinding or evacuation situations.

Fire evacuations can be difficult and unethical to investigate with real participants because of their dangerous nature. Here, VR [337–340] and agent-based simulations [341–343] may offer safe and cost-effective alternatives in controlled environments [261, 344–346]. In addition, VR experiments allow researchers to gain insight regarding the level of stress experienced during an evacuation [347]. Stress and mass panic could severely reduce the efficiency of the evacuation [348], causing arching and clogging at the exit [38]. At the same time, agent-based simulations allow for the testing of large numbers of different evacuation scenarios in a short amount of time. The combination of VR experiments and agent simulations can be used to connect individual behaviors to the state of a larger crowd.

In the present study, we combine a VR experiment with agent simulations to test the efficiency and effectiveness of adaptive and non-adaptive signage (see Figure 5.2) in order to guide people/agents towards the safest and most efficient route during a simulated fire evacuation. To anticipate, in the VR experiment, we found that such a system can improve evacuation efficiency, decrease damage caused by the fire, and reduce participants' level of stress. The agent simulations also demonstrate that adaptive systems can substantially increase the survival rate of agents during a fire evacuation. We also compared the performance of centralized and decentralized signage systems for computing and communicating the optimal evacuation route. Although the decentralized system propagated signage information slightly slower than the centralized system (by approximately one second), the decentralized system is more resilient to system malfunctions. These findings may contribute to the development of intelligent systems for human-building interaction and crowd management in public spaces. In the following sections, we describe the VR experiment used to test the adaptive system, the centralized and decentralized versions of the computational framework for these adaptive systems, and the agent-based model used to validate these frameworks for multiple scenarios.

5.3 VR EXPERIMENT

In this experiment, we tested the utility of an adaptive signage system compared to traditional exit signs for fire evacuation from a virtual museum.

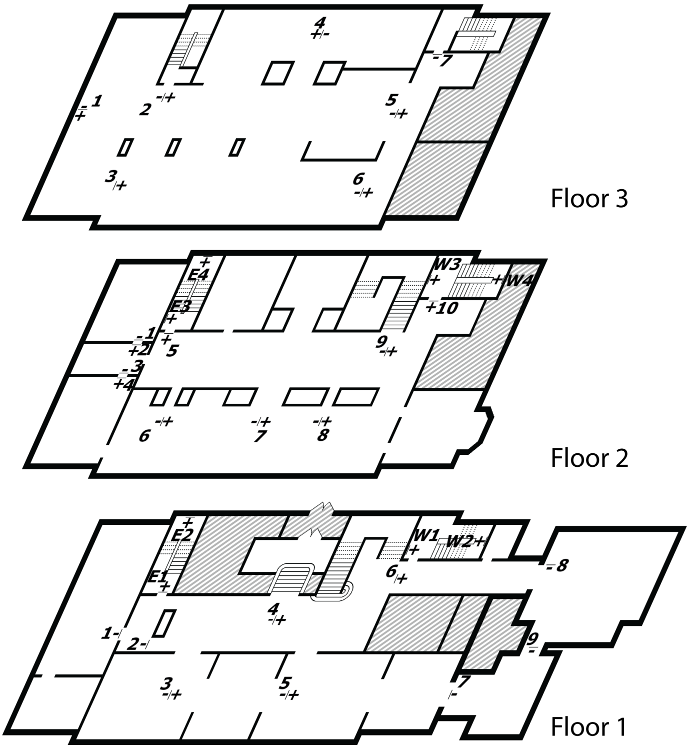

FIGURE 5.1: Museum floor plan. Each number corresponds to one evacuation sign. Depending on the placement location, each sign has either one or two sides (+/-) and the stairwell signs are indicated with East (E) or West (W). Three floors are connected via two side stairwells and a main stairway between the first and second floor. The main entrance and only exit are located on the first floor next to the main stairway. Gray areas were not accessible by participants during the experiment.

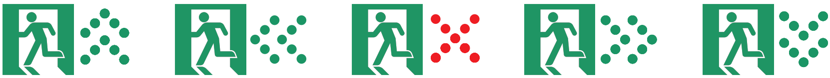

FIGURE 5.2: Evacuation sign design. The four arrow designs were applied and animated with scrolling motion in both the non-adaptive and adaptive sign conditions. The blinking red "X" only appeared in the adaptive sign group.

We expected participants using adaptive signage to evacuate more efficiently, more safely, and with lower stress levels. This experiment was approved by the ethics committee of the university.

5.3.1 *Participants*

Participants were recruited via the university experiment registration system. In total, 94 participants (average age of 23 years and a range of 18 to 33 years; 46 women) participated in the study. Nine participants were excluded from the experiment due to simulator sickness or software failures. In addition, two participants were excluded from the behavioral data analysis due to incomplete database recording. Because of motion artifacts, an additional three participants were excluded from the heart rate variability (HRV) analysis, and three participants were excluded from the electrodermal activity (EDA) analysis. Participants were compensated 30 CHF regardless of their performance.

5.3.2 *Materials*

5.3.2.1 *Virtual museum*

For this study, we adapted a 3D model of the Cooper Hewitt Smithsonian Design Museum in New York (used with permission) [349]. This 3D model was chosen due to its complexity and detail. Specifically, the model contains three floors that are connected by one main stairway between the first and second floor and two side stairwells that traverse all three floors (see Figure 5.1). The virtual museum was altered using the Unity game engine (https://unity.com) by placing physical barriers to block specific areas and by adding art installations (e.g., paintings and sculptures). Materials for these installations were obtained online and from the Unity Asset Store.

5.3.2.2 *Software and hardware*

We used the *Experiment in Virtual Environments (EVE) framework* [61, 299] to implement and control the VR experiment. The experiment was conducted using a high-performance gaming computer (Dell Alienware Area 51 Base; i7-5820K processor at 3.8 GHz overclocked; dual NVIDIA GeForce GTX 1080 video cards; 32 GB of SDRAM; Windows 10 operating system) with a 55″ ultra-high-definition television (Samsung UE55JU6470, 3840X2160 pixels).

In addition to the behavior data collected during the experiment, we also collected electrodermal activity (EDA) and heart rate data in order to measure participants' physiological responses [290, 299, 350]. These data were collected using a Powerlab 8/35 recording device with FE116 GSR Amp and FE132 Bio Amp signal amplifiers and LabChart 8.14 software (https://www.adinstruments.com/). For EDA, two electrodes were placed on participants' right shoulders so that they could operate the mouse and keyboard with both hands. Two heart rate electrodes were placed on the second intercostal space below the middle of the right and left clavicles. In addition, another electrode was attached below the ninth left rib.

5.3.2.3 *Sign systems*

Five types of signs were designed by combining the traditional running person symbol [329] with animated arrows (see Figure 5.2). For both adaptive and non-adaptive sign groups, the arrow signs were animated with a scrolling motion [314]. In the non-adaptive sign group, the signs always directed participants along the shortest path towards the exit of the building without considering paths blocked by fire. In the adaptive sign group, the signs indicated safe directions towards the exit based on the distribution of fire in the building. A red blinking "X" [330] indicated that the route was blocked and that participants should turn around and seek an alternative path. Left and right arrows indicated that the participant should turn left or right, respectively. In the stairwells, the up arrow indicated that participants should move upstairs, and the down arrow indicated that participants should move downstairs. Outside of the stairwells, the down arrow indicated that the participant should keep moving in the same direction. For the VR experiment only, all sign directions, sign locations, and fire locations were manually placed for both groups. Signs were placed where a navigation decision was needed.

FIGURE 5.3: (a) Training tutorial. The instructions were for participants to collect the gems by walking towards them one by one using the mouse and keyboard. (b) Learning route with a floating green arrow that guided participants towards the gems. (c) Virtual environment with fire illustration. (d) An evacuation route from the adaptive sign group. The red "X" indicates to participants not to enter the area, and the down arrow indicates to participants to pass through the doorway on the right.

5.3.2.4 *Fire mechanism*

Fire in the virtual environment consisted of visual flames, smoke effects (see Figure 5.3c), and physical barriers to prevent passage. Fire locations were designed to block particular routes that would have been safe in normal circumstances. All of these fire locations are listed in the Appendix A.2. The harmful effects of smoke and burns depended on the time spent in the building and collisions with the fire during the entire evacuation. Towards this end, we defined a health score in the range from 0 to 1. The health score decreased linearly (ranging from 0 to 1) for five minutes to represent the harmful effects of toxic fumes to approximate real-life survival expectancy [351]. In addition, if participants were within approximately 0.5 meters from the physical obstacle representing the fire, their health decreased rapidly at the rate of 5% per second and a red screen flashed as a warning message. Otherwise, this health score was not visible to participants during the experiment.

5.3.3 *Procedure*

Before the experiment, participants read and signed an information sheet and consent form. The experimenter then helped the participant to attach the physiological electrodes for measuring the heart rate and electrodermal activity and provided them with a mouse and keyboard. The experiment began with a demographics questionnaire, a video game experience questionnaire, and the first part of the Short Stress State Questionnaire (SSSQ) [293]. Next, participants were trained to navigate with a mouse and keyboard through the virtual environment by completing a tutorial in a multi-floor virtual hotel (see Figure 5.3a). During training, participants were asked to move through the environment and collect gems placed at different locations and elevations. After training, participants watched a seven-minute nature video in order to obtain a baseline of physiological activity.

Participants then navigated through the virtual museum on three different trials. Each trial consisted of a learning route and an evacuation route. To simulate the natural behavior of people visiting a museum, participants were asked to follow a learning route by collecting a series of gems. The location of each successive gem was indicated by a moving arrow in the middle of the participant's viewpoint (see Figure 5.3b). Each learning route ensured that participants moved through all three floors of the virtual museum, albeit in different orders for different trials. At the end of each

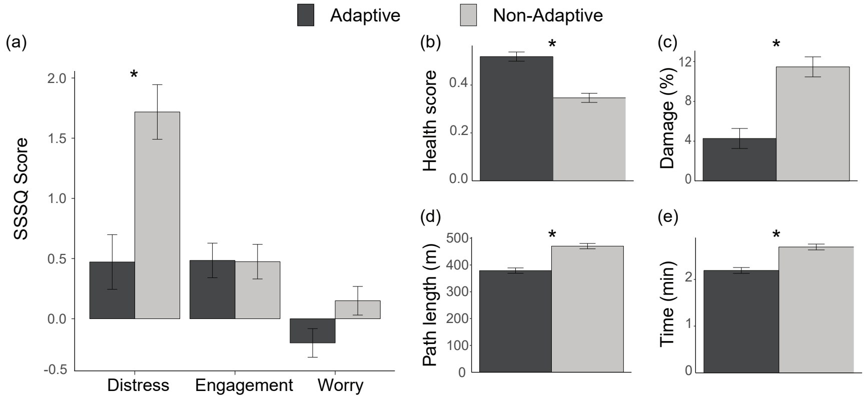

FIGURE 5.4: Results of the VR evacuation experiment. (a) SSSQ scores, (b) health score, (c) damage caused by the fire, (d) path length, and (e) evacuation time. The error bars represent the standard error of the difference between the two groups. Asterisks denote significant differences between adaptive and non-adaptive sign groups.

learning route, the evacuation route was immediately triggered. During the evacuation route, participants were instructed to locate the main entrance, where they started their first learning route in the first trial. For every trial, the end of the learning route and beginning of the evacuation route was on a different floor. After each trial, participants were asked to rate their level of stress during the evacuation on a scale from 1 to 9. After the third trial, participants completed the second part of the SSSQ.

5.3.4 *Design and analyses*

We created six learning routes with different floor visiting orders. The order of learning routes across trials was constrained for each participant so that the first trial always started on the first floor, each of the three trials started on a different floor, and each of the three trials ended on a different floor. These constraints resulted in four different orders of learning routes that were the same for adaptive and non-adaptive sign groups. We also devised six evacuation routes with different fire distributions that were also the same for adaptive and non-adaptive sign groups. Thus, the only difference between adaptive and non-adaptive sign groups of participants was the direction indicated by the signage system.

Participants were randomly assigned to one of the four possible trial orders and one of the two sign groups (between-subjects). The two sign types were the only independent variable. The dependent variables consisted of responses to the stress level questionnaires, video game questionnaire, health score, evacuation path length, evacuation time, damage (percentage of health score resulting from direct fire harm), and physiological responses (EDA and HRV) [293, 303, 352]. These dependent measures were compared between adaptive and non-adaptive sign groups using two-tailed, independent-samples t-tests.

For physiological responses, we exported both EDA and electrocardiogram data from LabChart, imported the EDA data into LedaLab (http://www.ledalab.de), and imported the electrocardiogram data into Kubios (https://www. kubios. com). All physiological data were visually inspected for artifacts. In LedaLab, we downsampled the EDA data from 1000 Hz to 10 Hz and extracted the number of non-specific skin conductance responses (nSCR) using Continuous Decomposition Analysis with a minimum amplitude threshold of 0.01 μS [301]. In Kubios, we first applied low threshold (0.45 sec) and smoothness prior filters (λ = 500, cut-off frequency = 0.035 Hz) to the electrocardiogram data. In order to calculate HRV as a measure of stress or worry (Log(HF)), we then selected and natural log-transformed the absolute values of power in the high-frequency range between 0.15Hz to 0.4 Hz [305, 306]. We subtracted EDA and HRV during the baseline nature video from EDA and HRV during the evacuation routes in order to derive a measures of reactivity towards the evacuation scenario.

5.3.5 *Results*

In the adaptive sign group, participants successfully evacuated from the building in 111 of 126(88%) trials. In comparison, participants from the non-adaptive sign group escaped in only 83 of 123(67%) trials. A two-proportion Z-test confirmed that these survival rates are significantly different (Z=3.921, p<.001, d=0.817). The following results represent all of trials, including those in which the participants were not able to evacuate from the building until the time out (5mins). We found a significant difference between the adaptive and non-adaptive sign groups in terms of SSQ Distress (t(83)=-2.743, se=0.580, p=.008, d=-0.607), health score (t(83)=4.503, se=0.038, p<.001, d=0.991), damage (t(83)=-3.689, se=0.019, p<0.001, d=-0.812), path length

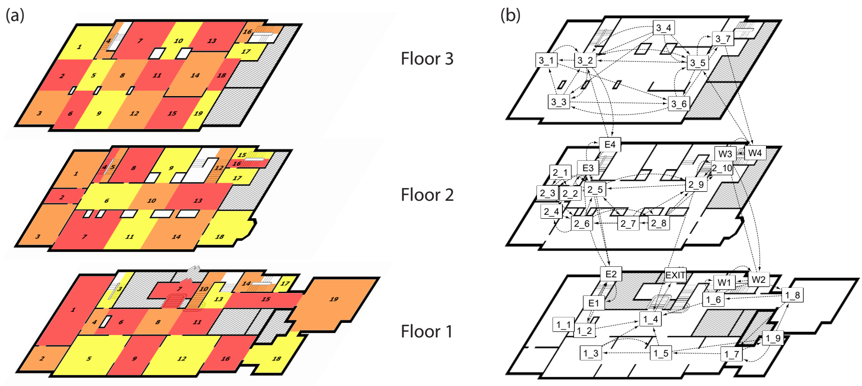

FIGURE 5.5: (a) Illustration of sensor areas for each floor of the building. Different colors represent the coverage areas of different sensors. (b) Connection graph of all exit signs in the museum.

($t(83)$=-4.571, se=19.968, p<.001, d=-1.006), and time ($t(83)$=-4.008, se=0.130, p<.001, d=-0.881) (see Figure 5.4). These results demonstrate that participants in adaptive sign group experienced less distress, obtained a higher health score, suffered less damage, and exited the building with shorter path lengths in less time. We did not find significant differences in terms of SSSQ Engagement ($t(83)$=0.037, se=0.287, p=.972, d=0.008), SSSQ Worry ($t(83)$=-1.474, se=0.238 p=.145, d=-0.325), and self-reported stress level immediately after each trial ($t(83)$=-1.233, se=0.344, p=.221, d=-0.271). There was also no significant difference between the sign groups in terms of video game experience ($t(83)$=0.885, se=0.126, p=.129, d=0.334). For the physiological measures, we did not find significant differences between the adaptive and non-adaptive sign groups in terms of nSCR ($t(82)$=-0.596, se=0.032, p=0.553, d=-0.131) or in terms of Log(HF) ($t(82)$=-1.232, se=0.180, p=.221, d=-0.273). However, there were significant differences between the baseline and the evacuation routes in terms of nSCR ($t(82)$=-2.183, se=0.027 p=.031, d=-0.341) and Log(HF) ($t(82)$=3.970, se=0.173, p<.001, d=0.623).

5.3.6 *Discussion*

Overall, the results of the VR experiment supported our hypothesis that adaptive signs can be more effective and efficient during an evacuation in terms of survival rate, self-reported distress, health score, fire damage, path length, and time to evacuate. Contrary to our expectations, we did not find significant differences between the two sign conditions in terms of physiological arousal (i.e., EDA and HRV). This may indicate that the evacuation task was stressful in general, as supported by the significant physiological differences between the baseline and evacuation phases. We also found no significant differences in self-reported stress level immediately after each trial. Although this short question allowed us to measure self-reported stress after each trial, this measure may not have been sufficiently sensitive (consistent with [51]).

Together, these findings demonstrate that this adaptive signage prototype may be developed further to produce a viable system. For the VR experiment, we manually determined the directions indicated by the signs, but for a real application, these signs would need to adapt to the locations of the fire automatically. In order to achieve this, we developed a computational framework for automatically directing evacuees during a fire.

5.4 COMPUTATIONAL FRAMEWORK FOR ADAPTIVE SIGNS

In this section, we present a computational framework that uses either a centralized or decentralized approach to automate the control of sign direction. The main difference between the centralized and decentralized versions of the system is that the optimal path is automatically and explicitly computed in the centralized system but emerges from the relay of information among different nodes in the decentralized system. This computational framework was implemented within the Unity game engine. We define four requirements for such a framework, including universality, adaptability, autonomy, and robustness. Universality refers to the principle that it should be possible to apply the sign system to any existing building based on the blueprint or 3D model. Adaptability refers to the ability of the framework to quickly respond to detected fire locations by automatically changing the directions of the evacuation signs accordingly. The system should be autonomous so that it is resilient and reliable in the absence of a building supervisor. The system should also be robust so that it is prepared to respond to unpredictable events (e.g., the malfunction of a sensor or sign).

5.4.1 *Room segmentation*

To achieve the above goals, we developed a virtual sensor system to simulate the detection of fire incidents across the virtual museum. In our sensor system, each sensor monitors a specific area of the building. The area covered by each sensor was manually defined. In a real application, the building manager would have assigned the location and density of these sensors during installation of the system. Figure 5.5a illustrates the coverage area of our virtual sensor system. Once the heat or smoke of the room reaches a certain level, the sensor judges that this area is no longer suitable for an evacuation route.

5.4.2 *Sign network graph*

To calculate the evacuation paths, a sign network graph was generated based on the topological connections of the fire sensors and their corresponding areas. A directed graph $G(V, E)$ is defined, where the set of nodes V represents all the evacuation signs, and the set of edges E represents navigational routes between two nodes (see Figure 5.5b). Each edge is weighted to represent cost, defined as the length of the walking distance in this case. Due to the complex structure of the building, each node may have multiple edges which connect multiple nodes. Each edge corresponds to one of the five possible sign types, depending on the relative positions of the two nodes. Without any fire, the directions of the edges in the graph naturally converge to the optimal evacuation route leading to the exit node on Floor 1. Each node of the graph has access to all the sensors of its neighboring areas. Once a fire breaks out, the graph recalculates sign directions based on the distribution of the fire. For signs that contains two sides (+/-), the indicated directions are altered based on the relative position between two nodes. If one edge of the node is considered unsafe (i.e., passing through the fire area), this edge is removed from the graph and the system regenerates the optimal route without this edge. Detailed network graph can be found in the Appendix A.2.

5.4.3 *Centralized and Decentralized systems*

In case of fire, the network system needs to be robust and resilient to withstand unexpected damage. To study the trade-off between security and efficiency, we implemented and compared two kinds of structures for the sign system.

5.4.3.1 *Centralized system*

The centralized approach includes a central entity which has access to the information from every sensor and can communicate directly to every sign in the building (see Figure 5.6a). Here, each of the signs displays routing information without having any computational ability (see Algorithm 1). Computations in the central entity include the following three functions :

- gatherInfo(): The central entity gathers all the information from the sensors regarding the current locations of different fires in the building and updates the graph accordingly. When a new fire occurs, the sensors immediately notify the corresponding entity with an object that checks whether outgoing edges are safe or not. If the locations of the fire remains unchanged, the central entity sleeps for a predefined amount of time (120*ms*) until new fire information arrives. Disconnection between any sensor and the central entity is treated as a fire situation in the corresponding area.
- calculate(): Once all fire information has been gathered and updated in the previous step, this function calculates the optimal evacuation route based on the new graph.
- update(): After the optimal route is generated, the central entity assigns different directions to each sign, so that all the signs display the shortest and safest route to the exit.

Algorithm 1 Centralized sign computation

```
Route safeRoute ← DEFAULT
if gatherInfo().notify then
    sensorData ← gatherInfo()
    safeRoute ← calculate(sensorData)
    update(safeRoute)
end if
```

5.4.3.2 *Decentralized system*

The decentralized system differs from the centralized system in that there exists no central entity which controls communication among all of the

Algorithm 2 Decentralized sign computation

```
Route safeRoute ← DEFAULT
Messages[] messages
if last_update_time > wait_time then
    sensorData ← gatherInfo()
    messages ← receive()  ▷ Retrieve information from all neighboring nodes
    UPDATE()
    if last_send_update > send_time or safeRoute.isUpdated then
        for all e ∈ Edge_in do
            SendMsg(UpdateMessage(safeRoute), e)
        end for
    end if
end if
```

```
function UPDATE( )
    if safeRoute.last_update > invalidation_time or ¬ sensorData.isSafe(safeRoute.edge) then
        safeRoute ← INVALID
    end if
    for all msg ∈ messages where msg.edge = safeRoute.edge do
        if msg.path.contains(this) then
            safeRoute ← INVALID
        else
            UpdateRoute(safeRoute,msg)
        end if
    end for
    for all msg ∈ messages where sensorData.isSafe(msg.edge) ∧ ¬ msg.path.contains(this) do
        if msg.cost < safeRoute.cost then
            UpdateRoute(safeRoute,msg)
        end if
    end for
end function
```

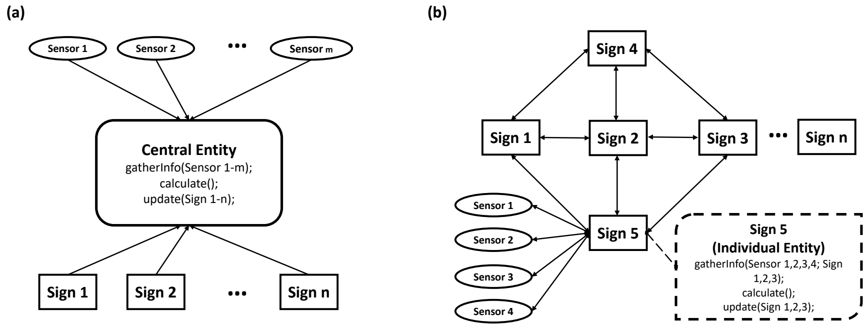

FIGURE 5.6: Visualization of the centralized and decentralized sign system. (a) Centralized system. The Central Entity is in charge of gathering sensor information and then calculating the optimal route and corresponding sign directions. The Central Entity then regularly broadcasts the sign directions to all the signs. (b) Decentralized system. The decentralized system functions without a Central Entity. Each sign gathers information from its corresponding sensors and then constantly sends and receives information from its connected neighbor signs.

sensors and signs and computes the optimal path (see Figure 5.6b). Here, each sign is equipped with its own computational power that can be used to store the network graph and calculate the new optimal route based on up-to-date information. As shown in Algorithm 2, during a fire, each sign individually updates (with function $Update()$) its path based on information collected from the sensors and communicates the updated path to its neighbors. Each node in the decentralized system constantly queries the fire situation from its corresponding sensors and detects its neighbors' status. Once the neighbor does not update information for a certain time period ($1300ms$ in our scenario), this node is considered by the neighboring nodes as unsafe, and the optimal route is recalculated. This information is then passed on to other nodes, one by one through the entire network with the function $SendMsg()$. The communication over these edges occurs in exactly the opposite direction of the graph (i.e., the node receives messages over the outgoing edges and sends messages over the incoming edges). This is due to the reason that the nodes closest to an exit are informed first about the existence of a path, after which they propagate this information backwards through the graph until it reaches all the rerouted nodes.

Compared to a decentralized system, the centralized approach can be easier to implement and cheaper to install in the real world since the only required communication is from the sensors to the central entity and from the central entity to the signs. However, a potential danger of the centralized system is that, if the central entity is damaged or malfunctioning, communication throughout the sign system breaks down. In contrast, the decentralized system should be more robust to system failure because the information communicated among the signs is redundant and distributed. However, decentralized systems may be more difficult to implement and more expensive.

5.4.4 *Results*

The performance of the centralized and decentralized systems were compared in terms of the generated optimal routes and computational time for the same fire distributions. Computational time was defined as the time elapsed between the initial event (e.g., detection of a fire, failure of a node) and the last event that occurred in any sign direction. Computational time for both systems included the amount of time required for communication to the sensors. While computational time for the centralized system was based on computations in the central entity, computational time for the decentralized system included the time required for the individual entities to converge on an optimal route. Because both systems generated the same optimal routes, we focus here on computational time. All of the measurements were conducted on a PC running Windows 8.1 with an Intel Core i7-5500U CPU at 2.4 GHz, 15.9 GB RAM, and a NVIDIA GeForce GTX 850M graphics card. For these simulations, we used Unity 2018.2.18f1 Personal (64 bit). In order to compare the performance of centralized and decentralized systems statistically, we conducted these simulations in 100 different fire scenarios. For each fire scenario, we pseudorandomly generated the fire with the constraints that between one and eight fire locations were placed on each floor. A two-tailed, paired-samples t-test revealed that computational time for the centralized system (*mean*=0.001s, *max*=0.003s, *SD*=0.001) was significantly lower than computational time for the decentralized system (*mean*=0.838s, *max*=1.788s, *SD*=0.439), $t(99)$=-19.087, *se*=0.044, $p<.001$, d=2.69 (see Figure 5.7a). Despite this significant difference, the maximum computational time for either system was below two seconds.

We next compared the performance of the decentralized system to the theoretical worst case given the detection of a fire. The theoretical worst case

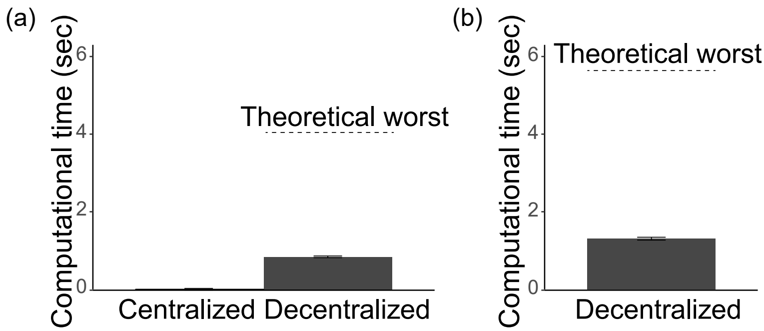

FIGURE 5.7: (a) Mean computational time for functioning centralized and decentralized systems after a fire event. (b) Mean computational time for the decentralized system after a node malfunction.

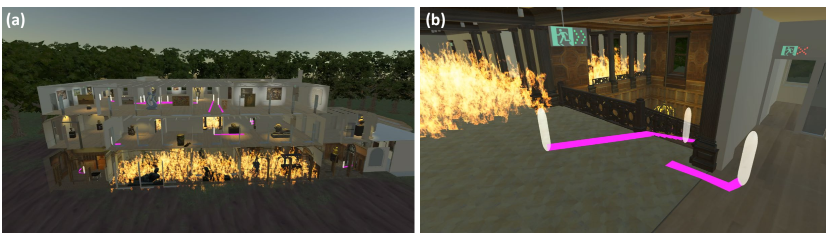

FIGURE 5.8: (a) Overview visualization of the agent simulation. Each agent is represented by a white cylinder. The pink lines represent the projected trajectories. (b) A closer view of the agent simulation on the second floor of the building.

of computational time for the detection of a fire was $n * wait\_time$. Here, $wait\_time$ (120ms) represented the maximum time between two update functions, and n was the number of nodes (34 in this case) in the graph. We included an additional $(n-1) * wait\_time$ because this process could have continued until the fire information propagated through all nodes in the graph. The theoretical worst-case computational time for fire detection was 4.1s. A two-tailed, one-sample t-test revealed that the mean computational time for 100 simulations of the decentralized system was significantly lower than this theoretical worse case, $t(99)$=-74.353, se=0.044, p<.001, d=7.431 (see Figure 5.7a).

Another event that could activate the decentralized system is the failure of one or more nodes. Here, we simulated the failure of between one and five randomly selected nodes for the same fire locations as in the previous simulations. These node failure simulations were repeated 100 times ($mean$=1.306s, max=2.823s, SD=0.739). The theoretical worst case (5.3s) for this scenario was computed as $invalidation\_time + (n-1) * wait\_time$. $invalidation\_time (= 1.3s)$. Here, $invalidation\_time$ (1.3s) is the maximum time required for the neighbor nodes to treat the current node as invalid, and n excludes the deactivated nodes because they were not used in the active graph. A two-tailed, one-sample t-test revealed that the 100 simulations of node failure in the decentralized system resulted in significantly lower computational time than the theoretical worst case, $t(99)$=-54.064, se=0.074, p<.001, d=5.405 (see Figure 5.7b).

5.4.5 *Discussion*

Together, our simulation results demonstrate the advantages and disadvantages of the decentralized adaptive signage system. Compared to the centralized system, the decentralized system was inherently slower because of the communication between individual entities. Nonetheless, in our simulations, computational time for the decentralized system was always below 2s and much faster than the theoretical worst case for computing the optimal route after both the detection of a fire and node failure. In contrast, the centralized system could not have adapted the optimal route based on the failure of only one node. These results clearly show the utility of the decentralized adaptive signage system over the centralized system for fire evacuation.

5.5 AGENT VALIDATION

In order to validate the decentralized adaptive framework, we describe an agent model that is grounded in spatial decision-making and considers the signage system. The agent simulations were implemented in Unity with C#, and the signs indicated directions as generated by the decentralized system (see Figure 5.8). During a wayfinding task, these agents search and interpret signs to help them find the exit during an evacuation. For all of these simulations, agents were initialized in open spaces (i.e., outside of areas with fires) with at least one agent per room. Each agent kept track of the areas visited by itself and recorded them as "memory points" so that it could backtrack to the last decision point in case it reached a dead-end. Each agent also checked whether it was near the building exit. If the agent was near the exit, the agent went to the exit directly. If the agent was not near the exit, the agent could enter either *Exploration* or *Signage following* mode.

In our model, signs were detected by rays cast from within a simulated vision cone that had a field of view of 120 degrees (accounting for head rotation). During the exploration mode, the agent classified every detected sign as indicating either "Enter" (i.e., display arrows) or "Do Not Enter" (i.e., display red "X"). If a sign was not detected, the agent set a temporary destination point and walked towards it. This destination point could not be near a previously visited point, outside of the walkable area of the environment, or in the direction of a sign indicating "Do Not Enter." If there was not a point that satisfied these criteria, the agent randomly selected whether to turn left, turn right, or return to a previously visited point. Once the agent reached a temporary destination point, the agent repeated *Exploration* mode until it reached the exit. If the exit was on a different level, the agent cleared its memory of all the destination points from the previous floor and started a new *Exploration* mode on the current floor. If a sign was detected and indicated "Enter", the agent transitioned into *Signage following* mode.

In *Signage following* mode, the agent walked into the direction of a chosen sign. If multiple visible signs indicated "Enter", the agent moved towards the closest visible sign and followed its indicated direction. After reaching the chosen sign, the agent transitioned back into *Exploration* mode. The agent continued to switch between *Exploration* and *Signage following* modes until the agent reached the exit or died from exposure to the fire (see Algorithm 3).

Algorithm 3 Agent model

```
VisitedPoints ← null
DoNotEnterPoints ← null
while not reached the exit do
    VisitedPoints ← NewVisitedAreas;
    if close to exit then
        Go to exit;
    else
        EXPLORATION MODE();
    end if
    if Change of floor then
        VisitedPoints ← null;
    end if
end while
```

```
function EXPLORATION MODE( )
    if detected sign ≠ null then
        if detected sign = Enter then
            SIGNAGE FOLLOWING MODE(AllDetectedSigns);
        else
            DoNotEnterPoints ← detected sign;
        end if
    else
        Go to random direction or back to a visited point;
    end if
end function
```

```
function SIGNAGE FOLLOWING MODE(AllDetectedSigns S)
    if S>1 then
        Go to closest sign and follow sign direction;
    else
        Move towards the direction of sign;
    end if
    if Reached the sign location then
        EXPLORATION MODE();
    end if
end function
```

5.5.1 *Results*

We simulated six fire scenarios that were the same for adaptive and non-adaptive conditions. Multiple agents moved through the environment in each scenario (between 14 and 41) but could not interact or interfere with each other's trajectories. One agent began in each room without a fire. Each fire scenario was conducted twice to obtain between 100 and 200 agents that survived the non-adaptive condition in total. These simulations revealed that 45% of agents in the non-adaptive condition survived and that 94% of agents in the adaptive condition survived. A two-proportion Z-test confirmed that the difference between conditions was significant, Z=15.977, p<.001.

We then matched the agents that survived the non-adaptive condition with the agents with the same starting location and fire scenario from the adaptive condition. This approach is important because surviving agents from the non-adaptive condition were more likely to have started near the exit. Two-tailed, paired-samples t-tests were used to compare these agents from the non-adaptive and adaptive conditions in terms of distance and time. As expected, these agents were comparable in terms of both distance, $t(194)$=0.254, se=2.735, p=.800, and time, $t(194)$=-1.361, se=1.345, p=.175.

5.5.2 *Discussion*

These agent simulations demonstrate the benefits of adaptive over non-adaptive signs for a decentralized signage system. This is evident in the large difference in survival rate of agents between the adaptive and non-adaptive conditions. The surviving agents in the two conditions evacuated in a similar amount of time and traveled a similar distance. This may be attributable to the agents' perfect memory for nodes already traveled and perfect interpretation of the directions indicated by signs. In general, these agent simulations allowed us to test the advantages of adaptive signs over non-adaptive signs for the decentralized system more efficiently and over a larger number of replications and scenarios than another VR experiment would provide.

5.6 CONCLUSION

In this paper, we have presented a decentralized adaptive signage system that may facilitate evacuations by computing the safest and most efficient routes towards an exit given the locations of fire hazards. We also showed the advantages of adaptive signs over non-adaptive signs using both VR and agent-based modeling. In the VR experiment, we demonstrated that adaptive signs allowed human participants to evacuate with less self-reported distress, higher health scores, lower fire damage, shorter path lengths, and less evacuation times compared to participants using non-adaptive signs. Using a graph-based approach, we then developed and compared centralized and decentralized systems for detecting hazards and communicating the safest route to evacuees via directional signs. Specifically, we propose a system in which the optimal evacuation route is computed locally and communicated by individual signs. This redundancy allows the system to easily recover in the event of a sign malfunction [332]. Using agent simulations, we then demonstrated that adaptive signs can lead to a higher survival rate than non-adaptive signs for a large variety starting locations and fire scenarios.

For our validation of the decentralized adaptive signage system, we considered the principles of universality, adaptability, autonomy, and robustness. For the present study, we tested the system using a virtual replica of an existing museum (i.e., the Cooper Hewitt) in New York City. However, the system may be universal in that future studies can easily deploy the system in any building with similar design features. The system is also adaptable because we show that its utility generalizes over a wide range of fire scenarios using our agent simulations. The system is also autonomous because the directions indicated by signs can be automatically updated without the intervention of a building manager. In our comparison of centralized and decentralized systems, we also show that the decentralized system is robust to malfunctioning sensors/nodes.

Previously, researchers have developed signage displays [97, 325, 329, 330, 353, 354], routing algorithms [322, 323], and wireless sensor networks [321, 324] for evacuation. Signage designs that incorporate ground installations [325], directional information [329], and/or animations (e.g., a red blinking "X") [330] have been found to positively affect wayfinding decisions and efficiency during evacuation. In real buildings, such designs may benefit from directions from an intelligent routing mechanism and connections to wireless sensor networks. Routing mechanisms can adapt to the emergency situation (e.g., fire hazard) using dynamic graphs [322] without information regarding the exact location of each sensor and without synchronization among sensors [323]. Researchers have also simulated [324] and prototyped [321] wireless sensor networks for informing and testing routing algorithms. Some researchers have designed similar systems in which a central computing entity determines the safest route and coordinates different displays given a network of integrated wireless sensors (e.g., radio-frequency identification devices) [97, 354].

In the present paper, we extended this approach by decentralizing computations and coordination among the sensors and by validating the system with human participants in VR and agent simulations. VR allowed us to measure human behavior in situations that would be otherwise too difficult and dangerous to create. Similarly, previous research has successfully used VR to investigate evacuations from tunnel fires [337] and office buildings [347]. While we captured several behavioral differences between the adaptive and non-adaptive conditions in our VR study, our physiological measures were not sufficiently sensitive to reflect these potential differences. In the future, more immersive systems may be employed in order to provide multisensory cues such as heat and smell [347] that typically accompany fire hazards. In contrast, agent simulations allow us to efficiently and artificially generate responses to a wider range of evacuation scenarios [261].

This research also paves the way for future work on multi-user frameworks that can account for crowd dynamics in public spaces during large-scale disasters [39, 355]. Crowds may increase the amount of time required for route computations as each individual agent attempts to optimize their own escape. If these agents are directed along the same route, congestion can further complicate the evacuation. Here, it may be useful to connect mobile devices to the building system in order to personalize evacuation instructions [328]. Decentralization may be an especially robust approach in such a scenario because of the larger number and diversity of connected nodes.

6

RESPONSIVE ENVIRONMENT FOR COLLECTIVE INTELLIGENCE

6.1 INTRODUCTION

Collective intelligence and altruistic behaviors are often associated with our social systems. With the rapid development of information technologies, people increasingly volunteer to share intelligence and data with each other over the Internet. The shared information often assists the activities in daily life, such as the use of Wikipedia [356] or open-sourced map [357]. Social media [358] and online platform [40] start to show their potential and utility in emergency evacuation and crowd disasters. However, the role of such altruistic behavior in emergencies still remain unknown. The collective intelligence that emerged during the emergency could be a key to study the crowd behaviors and facilitate the evacuations. With emerging technologies such as virtual reality [63] and human digitalizations [359], it becomes urgent to understand the social influence of collective intelligence in the virtual world.

In this research, we investigated the social influence of altruistic behavior in a spatial information exchange scenario. Conducted in a virtual environment while having participants presented simultaneously in a real-world lab, we facilitated an experiment design that allows participants to share spatial information about hazards and exits with each other. We intended to identify the factors that can enhance the frequency of altruistic behavior and whether such behavior can improve the group's performance during evacuations. Two multi-user studies were conducted to observe altruistic behavior in a collective intelligence situation. In the first study, the participants are given different incentives across the trials about their individual performance or public group's performance. In the second study, we used the sharing activities and crowd movement from the first study as controlled stimulus, and replayed their behavior to another group of participants. The results revealed that sharing behavior happened significantly more often when the group's performance was incentivized, compared with that when individual performance was incentivized. We have also found that when no specific incentives were given regarding individual or public performance, participants were more altruistic when there was less information in the public knowledge pool. By deploying the experiment design in a networked virtual environment, we provided some of the first indications of how collective intelligence can be observed and enhanced in a multi-player virtual world. These findings of dynamics in the group activities can also help policymakers and event organizers to better understand altruistic behavior during disaster evacuations.

6.2 PRIOR WORKS

What we know about altruistic behavior comes largely from observational studies in longstanding domains such as psychology and social economics. Altruistic behaviors include actions that people frequently choose even though such behavior cannot maximize their monetary reward [360]. Fehr and Fischbacher [361] observed that a typical altruistic behavior involves strong motivation to cooperate without any reciprocal gains even in non-repeated interaction. Such voluntary actions can actually reduce the actors' own assets or rewards [362]. Authentic altruistic behavior can benefit not only the economy of human society [363] but also animals' sociobiological systems [364]. The topic's importance has led to socioeconomics and psychology researchers to try to decode the reasons and motivations for selfishness and altruism. People are more likely to behave altruistically when their altruism is made public [365]. Andreoni and Rao [366] suggested that interaction between subjects could be key to stimulating greater altruism through the power of empathy and external communication. Klimecki and colleagues [367] have also found that inducing empathy specifically through the suffering of the recipient can enhance altruism. Institutional incentives are found to be vital to induce cooperation behaviors [368, 369].

The studies of altruistic behavior have inspired many new types of research. However, the conclusions that can be drawn from such studies are somewhat limited. Hoffman and colleagues [370] have suggested that altruistic behavior in research studies may result from the experimenter effect: the presence of the experimenter encouraged the participants to behave altruistically. In addition, most altruistic behavior studies use either questionnaires [371, 372] or behavioral games [373, 374] and thus lack a context in which participants can be realistically immersed and engaged during the interaction. Altruism requires interaction based on the relationships of the group members. Many past studies remain inconclusive about the social factors that cause altruistic behavior.

Social influence, which operates through social norms, conformity, and compliance [375], is one of the principles on which relationships are built with others. Reciprocation is the behavior of paying others back for what we have received [376] and is one of the affiliation-oriented goals that establish a relationship with others. It is common to observe reciprocal behaviors in commercial activities [377] and sharing economics [378]. Reciprocation may influence decision-making and resource allocation [379]. It also requires mutual evaluation and judgment, from which trust and distrust can be propagated [380]. Judgment propagation involves adopting a judgment from a sender before spreading it to others [217]. Several key aspects of the behavior define how far a judgment can be propagated. In a visual perception experiment, Moussaid and colleagues [217] revealed various influencing factors through a chain of social distance. They found that a social distance of three to four degrees of separation limited the spread of judgment propagation. In addition, the variety of sources of a unified behavior [381], the social structure between senders and recipients [382], and subjective perceptions of information [383] can largely define the probability of judgment propagation.

A few applications that use the theory of altruistic behavior and social influence have been developed and deployed in the real world [384, 385]. Among these, crowdsourced mapping services provide maps that contain location information that is generated and shared by users voluntarily [386]. The shared information includes navigation-assistive information [387], route choices [388], real-time traffic conditions [389], and hazard information [390, 391]. Such information can be shared offline [392, 393] or online through internet networks [80]. The warnings shared by users increase the level of safety and navigational capabilities [387]. Facilitated route planning reduces the cognitive load while driving [388]. The value of shared information can extend further than the interests of individuals. Philipp and colleagues [394] used crowdsourced trajectories from pedestrians to automate the generation of indoor structures. Similar approaches have generated indoor structures with crowdsourced sensor-rich videos [395]. Routes shared by travelers can also facilitate map information update, which is often challenged by constant large changes in road networks [396]. However, contributing to a common information pool requires individuals to help others [390], which is potentially cumbersome and time-consuming. Recently, social media and personal smart devices [80] have facilitated individuals' helping behavior during hazardous events [358].

As a qualified proxy for reflecting real-life dynamics, the virtual environment provides a systematic exploration of participants' behavior without violating safety and ethical rules [63]. Dangerous and stressful stimuli can be simulated and presented to the participants without actually threatening their physical or mental health. Previous research has successfully used virtual environments to investigate safety education [397], emergency evacuation [198], and hazardous working environments [398]. Social behavior studies can also be conducted in virtual environments. Gillath and colleagues [399] found similarities between people's reactions to a virtual person in needs and their reactions in a real-world environment. The costly altruistic behavior observed in a virtual environment was found to be correlated with greater empathic concern reported in a questionnaire [400].

Virtual environments can also provide another layer of convenience for the researchers of hazardous events. The complexity of wayfinding behavior limits the possibilities of conducting multiplayer experiments that require rapid changes of stimulus between trials in the real world. However, conducting experiments in a virtual environment enables such fast variations [64]. In addition, multiplayer experiments provide researchers with an overview of the interactions of a group of participants [65]. Predefined protocols [241] and frameworks [151] support the often-complex implementation of the experiment stimulus. Wayfinding researchers can use existing frameworks to conduct experiments that require interaction and collaboration in virtual environments [401]. Moussaid and colleagues [63] used a virtual experiment to study crowd-herding behaviors during a stressful evacuation. Zhao and colleagues [402] extended such an experimental framework to study the effect of map complexity and crowds on group wayfinding.

6.3 RESEARCH OVERVIEW

To date, much uncertainty about the possibility of identifying altruistic behavior and collective intelligence in a multiplayer virtual environment still needs investigation. This study attempts to explore social influences on altruistic behavior with a multiplayer experiment that enables collective intelligence during evacuation. We designed a fire evacuation task in which the participants were required to locate an exit and evacuate a maze with help from a map application. Through this crowdsourced map application, participants can share the locations of hazards and the exit. Sharing actions required the participants to stop moving for a certain amount of time, thus delaying their own evacuation. Thus, the act of sharing can be defined as *cooperative* behavior if the sharing is helpful to increase the incentives. On the contrary the act of sharing can be defined as *altruistic* when they are not incentivized by the group's performance. Two studies were implemented to inspect these two different kinds of behavior. In the first study, two types of trials with different incentive mechanism were designed: in trials with individual targets, participants were instructed to evacuate as fast as possible and they were incentivized if they were the fastest to evacuate; in trials with public targets, participants were encouraged to cooperate as they were incentivized if everyone from the group could evacuate in time. With two types of trials, we created two types of social context: selfish context (i.e. from individual trials) and cooperative context (i.e. from public trials). Next, the trajectories and behavior collected from the first study were used in the second one to create virtual computer agents that mimicked the participants. Throughout the second study, we used the previous participants' behavior to replicate the same social context that subjects experienced in the first study. Participants only encountered computer agents and were not given specific incentives regarding individual or public performance. The experiment setup is summarized in Table 6.1:

Study	Type of crowd	Incentives	Social context	Investigated behavior
1	Human	Individual or public	Selfish or Cooperative	Cooperative
2	Computer	Unspecified	Selfish or Cooperative	Altruistic

TABLE 6.1: Experiment design summary

With such a design, we seek to examine the following hypotheses:

Hypothesis 1 *When given specified incentives, participants are more cooperative in trials with a public target than participants with an individual target are.*

Hypothesis 2 *When given specified incentives, participants with a public target perform better than participants with an individual target, in terms of success rate, time, and path length.*

Hypothesis 3 *When given unspecified incentives, participants are more altruistic in trials with a cooperative social context than participants with a selfish social context are.*

Hypothesis 4 *When given unspecified incentives, participants with a cooperative social context perform better than participants with a selfish social context, in terms of success rate, time, and path length.*

6.4 STUDY 1 - EXPERIMENT ON COOPERATION

The first study was designed to examine the effect of different types of incentives on *cooperative* behaviors. Concurrently, two types of social contexts that correspond to the two types of incentives were collected in the form of map sharing activities and evacuation trajectories.

6.4.1 *Methods*

PARTICIPANTS Thirty participants (15 men and 15 women) were recruited via the University Registration Center for Study Participants (https://www.uast.uzh.ch). All participants were between 19 and 35 years old (mean = 23.67). Each participant was compensated with a basic reward of 35 CHF and a bonus between 0 to 10 CHF, depending on his or her performance during the experiment. There were 15 participants in one session and the same session was repeated once.

MATERIALS The experiment was conducted in the Decision Science Laboratory (DeSciL) at ETH Zurich. The DeSciL consists of up to 36 networked desktop computers in separate cubicles that are connected to a server in a control room, from where the experimenters can monitor and manage the procedure. The experiment software was implemented with Unity game engine, similar with previous research [241]. Photon Cloud, a real-time multi-player game development framework for Unity, was used to establish the networking mechanism among the server and the clients. Each participant performed the experiment on a Lenovo Idea Centre AIO 700 computer running Windows 10 Enterprise and connected a 24-inch diagonal monitor with a resolution of 1920 × 1080 pixels. The frame rate of the software on the participants' end was at least 60 frames per second. Participants uses a mouse-and-keyboard control setup to move an avatar through the virtual environment [64].

The virtual environments in the experiment consisted of a series of grid mazes. Five different mazes at field size of 40m x 40m were designed. The obstacles were represented as fires, due to their unpredictable nature of locations to match with the context and the time limitation of the task. In each maze, the location of the fires varied between the trials. Additionally, the locations of the exits also varied from being on the edge of the maze to being inside of the maze. This design prevents the participant from speculating the locations of the exits based on a pattern. It further encourages them

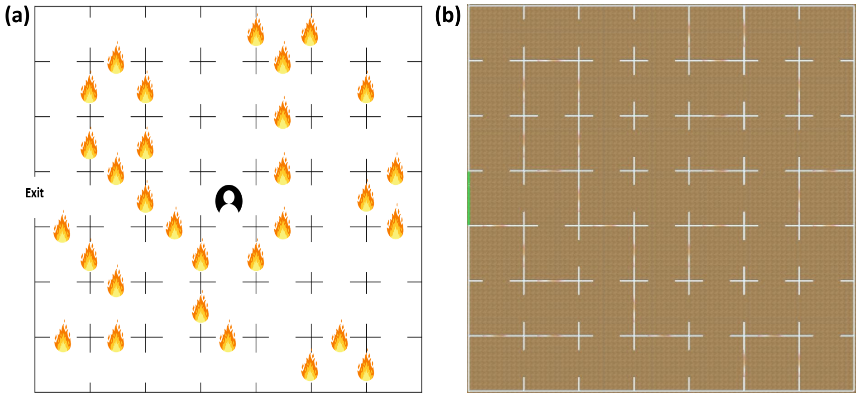

FIGURE 6.1: (a) Example maze from one of the five maze designs. Participants start from the middle of the maze where the user icon is located. The fire symbol represents obstacles. In this example, the exit is located on the left edge of the maze. (b) Top-down view of the example maze implemented in the virtual experiment.

to explore every corner of the maze by themselves. The starting location and the exit location were designed in the way that all of the five mazes have similar difficulties of evacuation. Figure 6.1 illustrated an example of one of the five designs.

Participants controlled an avatar from the first-person perspective and were able to move through the virtual environment by using the arrow or the WASD keys (e.g. the up arrow or 'W' for moving forward) on the keyboard. The maximum forward movement speed was the virtual equivalent of 1.3 m/s, and the maximum backward speed was 0.6 m/s. Participants also used the mouse to rotate their field of view up to a maximum angular velocity of 120°/s. A training tutorial was provided before the experiment to let the subjects to familiarize the control interface (see Figure 6.2a). The subjects were able see the other participants' avatars when presented within their fields of view (see Figure 6.2b).

There was a virtual map application for the participants to locate themselves by representing the participant's location and facing direction with a green arrow. The same application also allowed them to exchange information about the maze. As participants explored the map, they learned

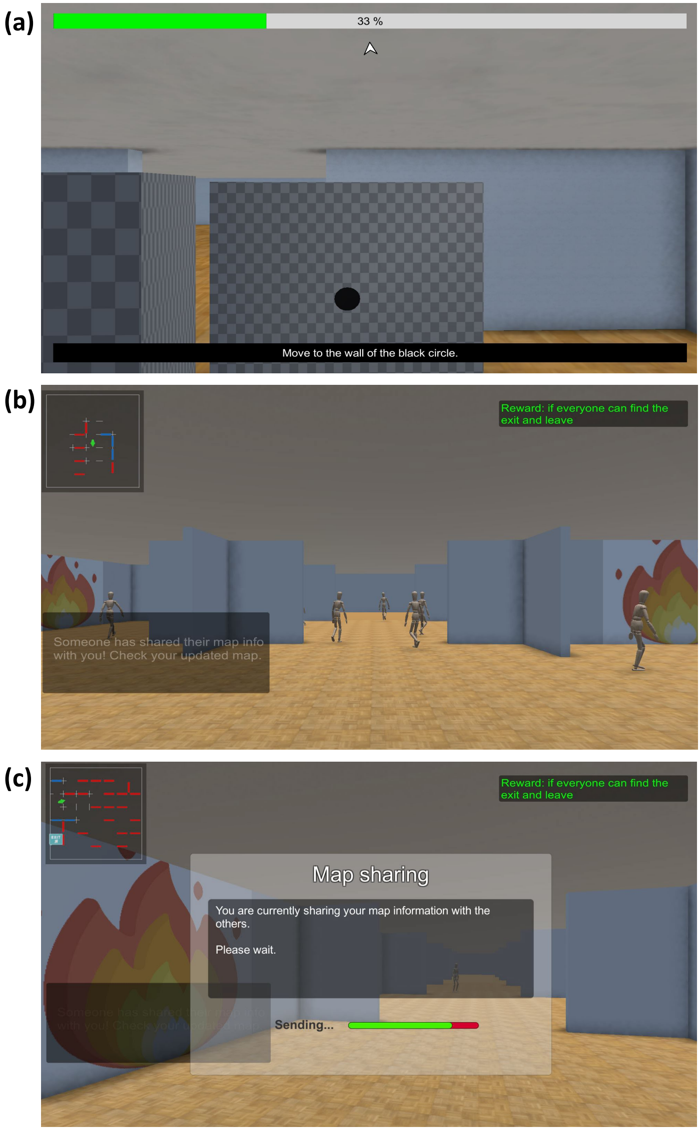

FIGURE 6.2: (a) The training tutorial for the control mechanism. (b) The user interfaces in Study 1. The virtual map is placed on the top left corner. Participants can get system message notifications from the message box in the bottom left corner. The incentive type is indicated constantly on the top right corner with colored text (e.g. in this case the type of incentive is public). (c) The system message during the sharing waiting time.

the locations of the fires and thus discovered the path. Once a fire obstacle appeared within the distance of visible area, its location was marked on the map to indicate that the participant has found an obstacle. Within this process, the participants were able to share their explored fire locations and exit with the others. By clicking the Space button, the participants can share the three most recent explored locations of fire with all the other participants. Once they were close to the exit (i.e., walked into the area from where the exit was visible), they can see a message telling them that they have found the location of the exit and they can choose to share it with the others now. When choosing to share the fire or the exit location, their actions were suspended for a period of 5 seconds to reflect the cost of sharing this information (see Figure 6.2c). The last three locations of fires that they have detected by themselves were highlighted with the color blue, while other obstacle locations that were discovered but not sharable were highlighted with the color red. The exit location was represented with a green exit symbol on the map. The system notifications (e.g., when other players had shared fire or exit information with the subject) were displayed on the screen if new information had been updated on the map, based on the suggestion from Burnham [365].

PROCEDURE After entering the lab, each participant first was randomly assigned to a seat number, corresponding to a unique desktop computer. Then the participants read and signed an informed consent form and were shown how to use the mouse-and-keyboard control interface with an interactive tutorial. There were 10 trials in total. In each of the experiment trials, participants were placed in a maze and instructed to evacuate through the hidden exit. The trial ended after a maximum of 5 minutes. Study 1 presented two types of incentives: individual incentive, in which participants were incentivized to be the fastest to evacuate; and public incentive, in which participants were incentivized if the whole group was able to evacuate in time. Each incentive type contained five different mazes, making ten trials in total (i.e., each maze design was repeated once in one session). The order of mazes was randomized and no maze was repeated without at least two trials' gaps in between. The orders of the maze were reversed in the two sessions, in order to eliminate the learning effect. All of the participants started from the same area of the maze, but the exact coordinates of the participants' position were pseudo-randomized between trials in order to avoid the identification among the subjects.

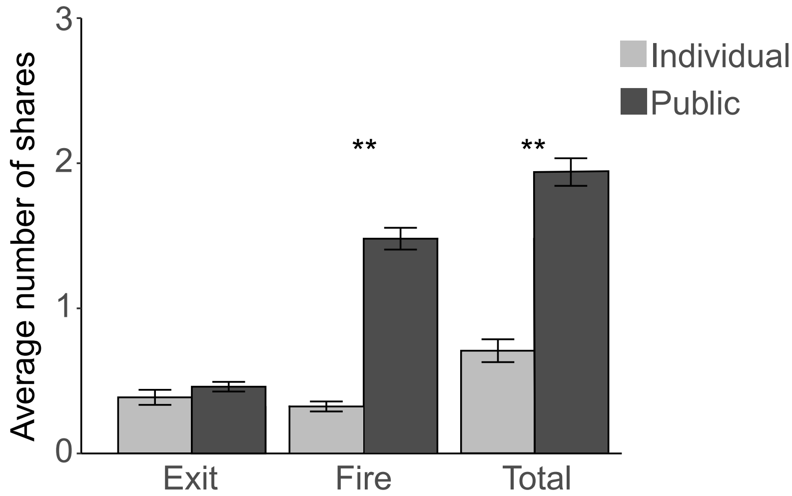

FIGURE 6.3: Average number of shares per participant in Study 1. The asterisks '**' denote a significant effect of p<0.001. For all graphs, the error bars represent standard error of the difference between means. The same applies for all of the following graphs.

DESIGN The independent variable of interest was the types of incentives: individual versus public. A within-subject design was applied. During each experiment session, we observed and collected the dependent variables of interests, including the map-sharing record, the evacuation success rate (i.e., whether they successfully evacuated through the exit), trajectories, and the evacuation time. The sharing activities were divided into two categories: the fire share represents the number of shares of fire locations and the exit share represents the number of shares of the exit locations. The total share was the sum of the fire share and exit share. Two-tailed, paired-sample t-tests were used to analyze the effect of incentive type on these dependent variables.

6.4.2 *Results*

The overall success rate of evacuation in study 1 was very high, with an average unfinished rate of 1% in trials with an individual incentive and an average unfinished rate of 1.33 % in trials with a public incentive (see

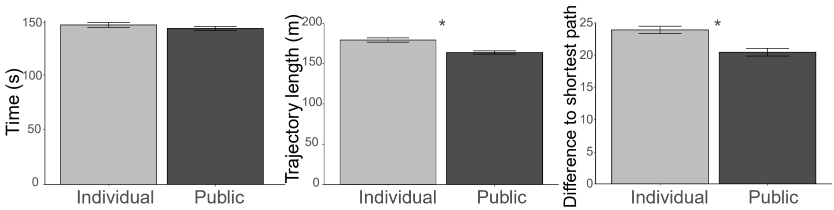

FIGURE 6.4: Average evacuation time and trajectories length in Study 1. The asterisks '*' denote a significant effect of $p<0.05$.

Figure 6.7). A two-proportion Z-test showed that these survival rates are not different (Z=0.010, p=0.992). The corresponding t-test revealed that participants in trials with individual incentives shared significantly less than in trials with public incentives, in terms of fire share, t_{29}=-9.153, s.e.=0.111, p<0.001, d=-1.805, and the total amount of share, t_{29}= -8.403, s.e.=0.146, p<0.001, d=-1.284 (see Figure 6.3). The share of exit was not significantly different (t_{29}= -0.721, s.e.=0.06, p=0.477, d=-0.153). When calculating the trajectory and time of the evacuation, we excluded the unfinished trials (7 out of 300), in order to focus on the behavior of successful evacuees. We didn't find significant differences of the evacuation time between the individual trials (mean=148.11s) and public trials (mean=144.83s), t_{29}=0.626, s.e.=2.867, p= 0.537, d=0.147. However, we found a significant difference of trajectories length between participants from trials with an individual incentive (mean=178.18m) and participants from trials with a public incentive (mean=162.80m), t_{29}=2.342, s.e.=3.445, p=0.026, d=0.597 (see Figure 6.4), and the difference to the shortest path between participants from trials with an individual incentive (mean=23.900) and participants from trials with a public incentive (mean=20.440), t_{29}=2.134, s.e.=0.854, p=0.041, d=0.537. This shows that experiment subjects performed better with information sharing. KDE analyses for density of the trajectories (see Figure 6.8) revealed no significant difference between the two types of incentives (p=0.557).

6.5 STUDY 2 - ALTRUISM IN EVACUATION

The results from study 1 showed that different incentive mechanisms successfully generated two types of social contexts. In the second study, we utilized these two types of social contexts from Study 1 to examine the altruism behavior. Trials with individual incentives provided the selfish social context in Study 2 and trials with public incentives provide the cooperative social context in Study 2. Different from Study 1, we focused on the influence of different social contexts by excluding the effect from specific incentives. Without the benefits of helping the other subjects, we can define the sharing behavior in Study 2 as *altruistic* behavior.

6.5.1 *Methods*

PARTICIPANTS Thirty different participants (16 men and 14 women) were recruited via the University Registration Center for Study Participants (https://www.uast.uzh.ch). All participants were between 18 and 31 years old (mean = 23.73). Each participant was compensated with a basic reward of 35 CHF and with a bonus between 0 to 10 CHF, depending on his or her performance during the experiment. There were 15 participants in one session and the same session was repeated once.

MATERIALS The same maze design and interaction mechanism from Study 1 were applied in Study 2. Differed from Study 1, each participant was only interacting with computer-controlled agents, which moved and shared the map autonomously. Each agent corresponds to one of the fifteen participants from the first session of Study 1 thus the agent behaved equivalently to the recorded behavior of real participants. The subjects' maps were updated simultaneously, based on the agent's sharing activity. Therefore, all of the participants in Study 2 experienced the same kind of stimulus throughout the whole experiment. The map information shared by real participants was only recorded but not broadcast to the other players. Unlike in Study 1, incentive type was not displayed on the first person perspective screen during the evacuations.

PROCEDURE The procedure in Study 2 was also similar to that in Study 1. Participants underwent the same training tutorial and completed ten trials of evacuation tasks. The orders of the trials in both of the sessions were same as the orders from Study 1. In contrast to Study 1, the participants were asked to simply evacuate and the incentives were only related to the success of evacuation. They can still choose to share the map information, but the group's performance did not influence their incentivize. Instead, two types of the stimulus were included, corresponding to the different types of incentives from Study 1: individual incentive corresponded to selfish social context, and public incentive corresponded to a cooperative social context.

DESIGN The independent variable of interest in Study 2 was the social context: selfish versus cooperative. A within-subject design was applied. During each experiment session, we observed and collected the dependent variables of interests, including the map-sharing record, the evacuation success rate (i.e., whether they successfully evacuated through the exit), trajectories, and the evacuation time. Two-tailed, paired-sample t-tests were used to analyze the effect of social contexts on these dependent variables.

6.5.2 *Results*

The success rate of evacuation in Study 2 was lower than in Study 1 but remained relatively high, with an average failure rate of 6.67% in trials with selfish context and an failure rate of 0% in trials with cooperative context (see Figure 6.7). A two-proportion Z-test revealed that these survival rates are significantly different (Z=4.398, p=<0.001). Figure 6.5 showed that the participants in trials with selfish context shared significantly more than participants in trials with cooperative context, in terms of fire share, t_{29}=6.462, s.e.=0.199, p<0.001, d=0.909, and total amount of share, t_{29}= 7.061, s.e.=0.218, p<0.001, d=0.591. The same difference was not found in terms of exit share, t_{29}= 0.907, s.e.=0.044, p=0.372, d=0.229. The same exclusion of unfinished trials was applied when calculating the time and trajectories. Regarding the evacuation time, it was significant higher in the selfish trials (mean=154.59s) than cooperative trials (mean=141.31s), t_{29}=2.400, s.e.=3.415, p= 0.023, d=0.514. Significant difference was also found in terms of difference to the shortest path between participants from trials with an individual incentive (mean=24.233) and participants from trials with a public incentive (mean=18.327), t_{29}=3.250, s.e.=0.981, p=0.003, d=0.837. No significant difference was found in terms of trajectory length, t_{29}=1.418, s.e.=3.289, p= 0.167, d=0.360. The aggregated values of the time and trajectories are illustrated in Figure 6.6. We have also compared the sum of the numbers of sharing event from both the agents and the participants in Study 2, and we found that there was no significant difference (p=0.510) between selfish trials (mean=3.95) and cooperative trials (mean=3.81). KDE analyses for density of the trajectories (see Figure 6.8) revealed no significant difference between the two types of contexts (p= 0.132).

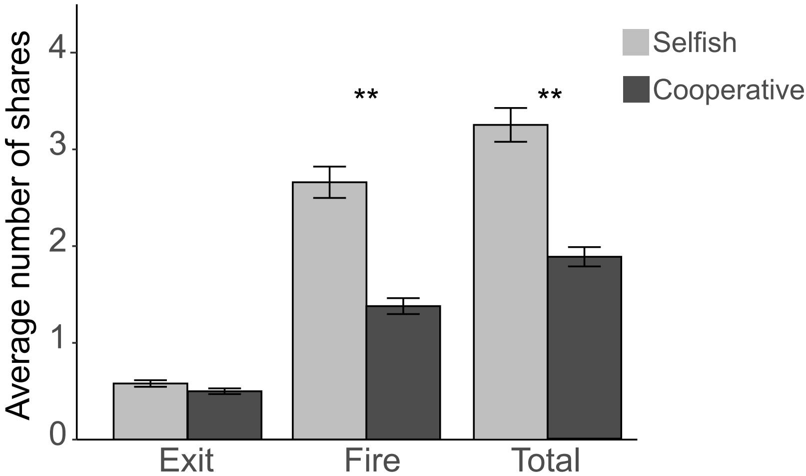

FIGURE 6.5: Average number of shares per participant in Study 2. The asterisks '*' denote a significant effect (p<0.001).

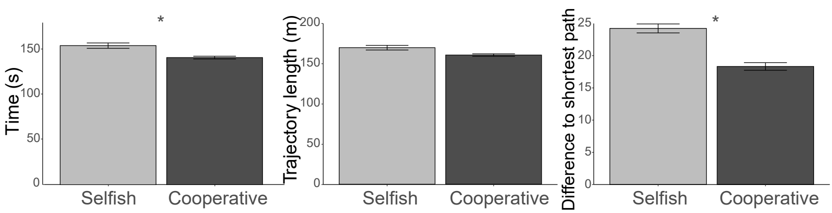

FIGURE 6.6: Average evacuation time and length of trajectories in Study 2. The asterisks '*' denote a significant effect (p<0.05).

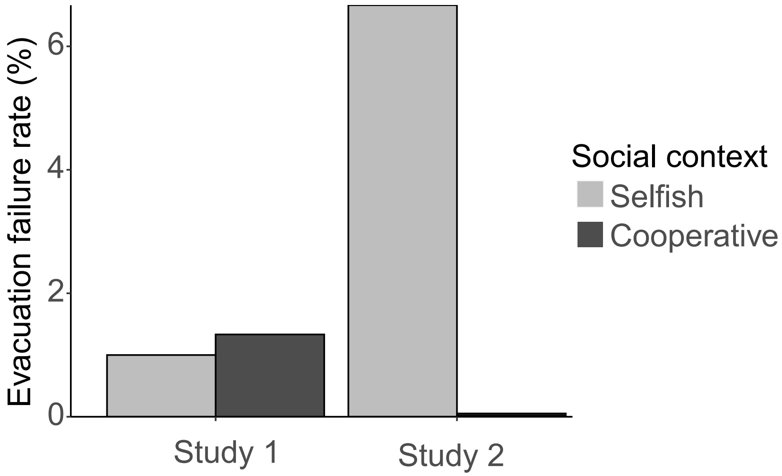

FIGURE 6.7: Percentage of failed evacuations in both Study 1 and Study 2.

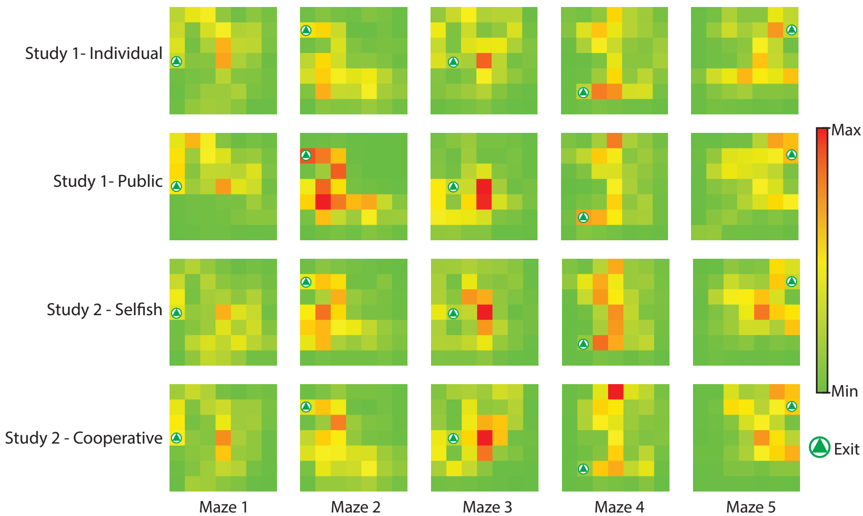

FIGURE 6.8: Density of the trajectories from both studies. The density unit is based on the room structure of the maze. Green triangle represents the exit in each of the maze design. Maximum density corresponds to 0.276 m^{-2}.

Measure	Contrast	F	MSE	p
Number of sharing event	2x2 interaction	114.563	50.181	<0.001*
	Effect of incentives	0.304	0.438	0.583
	Effect of social context	15.876	2.906	<0.001*
Time	2x2 interaction	1.721	750	0.195
	Effect of incentives	4.719	435.849	0.034*
	Effect of social context	0.090	729.538	0.766
Trajectory length	2x2 interaction	0.469	296.395	0.496
	Effect of incentives	7.112	632.031	0.01*
	Effect of social context	1.868	669.851	0.177
Difference to shortest path	2x2 interaction	1.009	44.896	0.319
	Effect of incentives	14.791	44.487	<0.001*
	Effect of social context	0.508	46.745	0.479

TABLE 6.2: Two-way ANOVA results for all four dependent variables from Study 1 and 2. The asterisks '*' denote a significant effect on the level $p<0.05$.

6.5.3 *Results of different incentives*

In order to compare the results of the different incentives between Study 1 and Study 2, a mixed model 2X2 ANOVAs was used to investigate the interaction of the effects of both the incentives (individual versus public) and social context (selfish versus cooperative). Their effects on the total number of sharing event, time and trajectory length are presented in Table 6.2. A significant main effect of incentives was found on time, trajectory length, and difference to shortest path. Effects of social context were found on the number of sharing event. In addition, there was a significant interaction between incentives and social context on the number of sharing event ($p<0.001$).

6.6 DISCUSSIONS

This investigation aims at assessing the social influence on spatial collective intelligence during evacuations. The results of this study demonstrate the effect of collective intelligence on evacuation behaviors and the impact of incentives and social context on sharing behavior. Study 1 sets out the aim of examining the influence of incentives on cooperation. The hypothesis that when given specified incentives, participants are more cooperative in trials with a public target than participants with an individual target has been supported. Specifically, the participants shared more map information when the incentives were related to other players' evacuation performance. This confirms with previous findings on the positive effects of incentives on cooperation behavior [368, 369]. A similar trend was not found in terms of the number of exit shares. It seems possible that this result is due to the exclusive character of individual incentives. Once the exit was revealed by one of the subjects, the participants might realize that they have lost their chance of winning the individual incentive since it was only rewarded to the fastest evacuee. Under such a circumstance, they tended to help others anyway in order to reduce their waiting time for the other participants to finish their trials. This finding is particularly interesting because it implies that if people's own interests become irrelevant, they become as cooperative as the subjects with a public incentive.

On the question of evacuation performance, Study 1 found that only the metric of trajectory length supported the hypothesis that participants with a public incentive performed better. This observation suggests that a group target and a cooperative social context in evacuation can help the evacuees to shorten their travel path to the safe exit. These results corroborate the findings from previous work of the beneficial role of grouping in facilitating emergency evacuation [160, 403]. Although the difference is not significant in terms of time, the direct metric of time used to evacuate does not reflect an interesting observation that has been made. We found that participants in trials with public incentives stayed longer to help other participants by walking around the exit to attract other participants' attention even after they have found the exit. This unexpected behavior implied the indifference of the evacuation time between the two types of incentives, due to the extended evacuation time from players who stayed in the trials with public incentive. The failure rates of evacuation were low in both types of trials, which indicated that the mazes were not very complicated for the participants when driven by time-sensitive incentives. In addition to the empirical data, Study 1 successfully provided two types of social contexts that were distinguishable enough to be used as stimulus in the next study.

Followed with a similar experimental setup from the first study, we excluded the effect of incentives and focused on the altruistic behavior under the impact of selfish and cooperative social contexts in Study 2. In contrast to earlier findings, the hypothesis that participants are more altruistic in trials with cooperative social contexts than in trials with selfish social contexts was rejected. There are several possible explanations for this result. First, the absence of information in the public information pool might actually encourage people to share more. Combined with the relatively higher failure rate of evacuation in the selfish context, it implies that the true altruistic behavior emerged in Study 2 since the participants were willing to share more despite experiencing less sharing from the others. In fact, the most frequent sharing put themselves in danger occasionally, with the highest failure rate of 6.67% across the studies. Second, the scale of the maze and the amount of shareable information were confined. Each maze contains 28 fire obstacles on average, thus if every sharing consists of uniquely new information, ten shares would reveal all of the fire obstacles. Participants' willingness to share have been possibly suppressed by the limited needs of sharing when the public information pool is already full. The indifference of the sum of the shares from both agents and participants across the social contexts also supports this assumption. Such a finding implies that the overall willingness to fulfill an empty public information pool remained a constant value for a group. This rejected hypothesis is contrary to previous studies that emphasize the role of propagation of trust [380] and judgment [217] in social scenarios. However, with drastic differences in the experimental design, this comparison between our findings and the results from previous studies need to be interpreted with caution. This inconsistency may be due to the necessity of sharing instead of the willingness.

The hypothesis that participants performed better with cooperative social context was supported in terms of evacuation time. When given more information about the fire obstacles, the participants took less time to find the exit. The assistance from optimal routes provided by the obstacle location information cannot be ruled out, yet the significant more shares in the selfish trials can be another reason. Because of the observed difference of trajectory lengths in this study was not significant, the differences of time can be contributed by another factor. In our experimental design, each share cost 5 seconds of freezing time, during which the participants can not move. Thus, the more frequently the participants share, the more time they will "waste" in the maze. This result may be explained by the fact that being altruistic actually reduced the personal efficiency of the evacuation task. Another important finding was that all of the failed players in Study 2 were from the trials with a selfish social context. The difference in the failure rate also implies that participants perform better with a cooperative social context. This combination of findings provides support for the conceptual premise that the social context of sharing behavior has an influence on the altruistic behavior of the individuals.

When comparing the results from both Study 1 and Study 2, it was found that there exists an interaction between the incentive and the social context for the number of shares. This is an indicator that the sharing behaviors were indeed driven by the participants' personal interest and the observed behavior of the group. These findings support previous studies on the notion that social dynamics can be captured and observed even in a virtual environment [63, 400, 402]. It can further be suggested that the feelings of empathy can be transferred through virtual avatars. In the digitalized society where users commonly interact with each other remotely, this research opens one of the first questions on the effect of the virtual appearance of a real human on their social behavior. Another interesting finding is the difference in the success rates between Study 1 and Study 2. The failure rate of selfish trial in Study 2 was higher than that in Study 1 (see Figure 6.7). This result can be explained in part by the time-sensitive nature of the incentives. In addition, the bonus of escaping is not very strong thus could lead the participants to favor cooperation rather than saving themselves. In Study 1, both types of incentives introduced a certain level of time pressure. Whereas in Study 2, the incentives were less time-sensitive despite the same evacuation time limit. Such a loosened time pressure can contribute to the higher frequency of map shares, but it may result in a higher failure rate. The nature of fire evacuation also has another feature that was not introduced here, which is the fact that the longer that evacuees stayed in the scene, the more dangerous it becomes. Thus, the help behavior could have been encouraged when early offered. Previous researchers suggest that costly pro-social behaviors serve as a signal of pro-social identity and such behavior leads to consistent future behaviors [404]. Our results further complement their findings by extending the costly behavior from monetary cost to (virtual) danger to life. The impact of collective intelligence also varied in both studies. The participants who were exposed to more collective intelligent information (i.e. more map information in the cooperative social context) traveled less in Study 1, whereas the participants who were exposed to more collective intelligence used a shorter time to evacuate in Study 2. Considering the difference in failure rates, it can be inferred that the collective intelligence of the spatial information is helpful for evacuees when the incentive is unspecified. The findings agree with previous research on the effect of crowdsourced geographic information on improving the work performance [386, 388, 390, 391]. However, its impact is less explicit in terms of failure rate when the incentives are time-sensitive. The anxiety of losing incentives can play a bigger role in influencing the task performance and thus drive the participants to successfully evacuate.

Overall, the study was successful as we were able to identify the impact of incentives and social context on the sharing behavior. These findings raise a series of intriguing questions regarding the mechanism and utility of collective intelligence during hazardous events. These findings help us to understand the role of cooperation and altruism in an emergency evacuation. The cooperation behavior of exchanging spatial information was found to be beneficial for shortening the evacuation path length, yet the altruism behavior of exchanging spatial intelligence was found to be less effective regarding improving the evacuation success rate when the incentives were not time-sensitive. This information can be used to develop future collaborative applications for emergency evacuations. Such an application can contain the necessary mechanism to balance between the safety of the users and their willingness to contribute to the public information pool.

6.7 CONCLUSION

The present investigation provides a first step towards establishing the protocol of exchanging collective intelligence in emergency evacuations based on behavioral science. In essence, we used a series of virtual mazes and an interactive map application to study the participants' willingness to share the evacuation information with each other. Study 1 revealed that participants tended to share more when given a public incentive than when given an individual incentive. In Study 2, we excluded the effect of incentives and focused on altruistic behavior using data collected from Study 1. The most obvious finding to emerge is that the selfish social context urged the participants to share more than the cooperative social context, even though the sharing activities endangered their evacuation success rate. The results revealed the existence of real altruistic behavior in a selfish social context. The willingness to fulfill the information gap in the public pool plays a vital role as the motivation to share. The importance of collective intelligence is clearly supported by the trajectory length in Study 1 and the time used to evacuate in Study 2, which both demonstrate that the more people contributed to the collective intelligence information pool, the better they performed during the evacuation. The findings of this research provide valuable insights into the mechanism of spatial collective intelligence. They suggested that altruistic can also be achieved and promoted with the absence of information in the public resource pool. This findings can help interaction designers to better understand the motivation of promoting encouraging user-generated content. Showing users the absence of the current knowledge will help them to realize the necessity of information sharing. This investigation complements those of earlier studies on the influence of social behavior, by contributing in the understanding of collective intelligence and altruistic behavior in emergency evacuations. The approach of a multiplayer networked environment will prove useful in expanding our understanding of how to conduct behavioral science studies under dangerous situations (e.g. fire evacuation, crowd disaster, etc.) which are impossible to implement in real life. The insights gained from this study can be of assistance to establish a standard for the next generation of crowdsourced information applications for emergency evacuations.

In spite of the insights gained from this study, the conclusion was limited by the absence of feelings of real danger. We applied a fire scenario and used time as an incentive to replicate the urgency and danger of the evacuations in the experimental design. However, the comfortable lab environment in the real world neutralize the stressful context of the virtual emergency evacuation. Since it was not possible or ethical to place the participants in a real fire scenario, therefore, it is unknown if the panic and time-sensitive nature of the real fire could hinder the altruistic behavior. The virtual environment set up makes these findings less generalizable to the altruistic behavior in the real world. Further work needs to be done to investigate the effect of panicking and stress caused by the threat of danger in reality. For example, a future approach can make the firing areas expand as time goes by, similar to the fires in the real world. Such a change could make the emergency more realistic and putting on more time pressure on the evacuees.

Another limitation of this study is that the complexity of the environments. We designed a series of grid mazes and the variations between the mazes were limited to the exit and fire locations. The overall high success rate (>90%) in the studies implies that the participants did not find the evacuation task challenging, which is usually not the case in the real world fire evacuations [348]. More broadly, future research is also needed to determine the effect of the complexity of environments on the sharing behavior. Replacing the grid mazes with several real-world building layouts can bring another level of sophistication and realness to the evacuation task. A real building environment can also stimulate the use of crowdsourced maps by allowing the participants to share the layout of explored areas.

Such an extension can help crowdsourced application designers to better understand the users' needs and motivation under emergency evacuations.

Notwithstanding the limitations, this work offers valuable insights into the social influence of cooperative and altruistic behaviors. Collective intelligence will play an increasingly more important role in the age of digital disruption and sharing economy. Very little is currently known about when and why people choose to share their own information with others. To our knowledge, this research is the first comprehensive investigation of collective intelligence in virtual emergency evacuations. Continued efforts are needed to make collective intelligence more accessible via digital technologies, especially in emergencies.

7 CONCLUSION

I seldom end up where I wanted to go, but almost always end up where I need to be.

— Douglas Adams

7.1 RESEARCH PURPOSE

The safety and comfort of users should be prioritized for public environment managers. The effective control and management of the environment features are especially critical for high dense venues. Because of the danger of a large volume of pedestrians, planners must account for the presence and movement of the crowd. To date, harmful accidents occurred frequently in public environments where emergency reaction systems that are supposed to function in such situations often fail. Crowd disasters and unsuccessful evacuation systems are still one of the greatest challenges that public space managers need to confront nowadays. There is an urgent need to address the safety problems caused by traditional built environments, which often did not take their users' behavior and needs into consideration. With the help of computer technologies, an environment that responses to the user's needs can prevent potential risks and improve the user experience within the public environments. Such a responsive environment can prioritize the users' behavior and need and adapt to various hazardous situations. In the dangerous occasions, the valuable time that a responsive environment can help to save will potentially rescue valuable life. Decision-makers (e.g., designers of the public transport stations) can also benefit from the concept of a responsive environment in order to answer their users' needs before the execution of the construction. The pre-occupancy evaluation can help them to ameliorate their blueprints and examine the current design plan before the real constructions work starts. It can potentially save a large amount of financial and time costs for the project managers.

7.2 CONCLUDING SUMMARY

This dissertation has investigated the impacts and applications of responsive environments through virtual reality experiments and simulations. By studying the impact of environmental variations on individual and group behavior, I want to set future standards for computer-aided design tools in shared public environments. Empirical experiments with human participants were conducted to collect pattern data and inform systematic variations of environmental features. The utilization of a networked multiplayer platform was employed as a novel approach to data collection. The case studies of these responsive environments highlight the importance of establishing a standard for the next generation of artificial systems embedded in the public environment. Multiple empirical studies reveal that responsive environments are able to improve user experience and prevent hazardous events. These approaches to explore responsive environments can help researchers to understand the strengths of the simulation and virtual environment. To my knowledge, this is the first attempt to systematically address the responsive environment concept in hazardous events that combines expertise from both computer science and cognitive science.

This dissertation explored the classification of responsive environments and used a clustering method to disentangle static and dynamic time characteristics from passive and active measures in responsive environments. This classification concentrates on the functions of the environments rather than their utility. The concrete frameworks and state-of-the-art engineer technologies are implemented in applied cases. First, an experimental prototype was established for conducting multi-user experiments in a networked virtual reality laboratory. The protocol details the hardware and software components of the system and the procedures for recruiting and supervising a large number of human participants simultaneously. This protocol was used for the subsequent studies of social behavior and navigation in a controlled laboratory environment, which were designed to investigate the interactive effects of map complexity and crowd movement on wayfinding performance within a static and passive responsive environment. Furthermore, to analyze the strengths of static and active responsive environments, I conducted a series of simulations that investigate the effects of various crowd management strategies, such as opening an additional exit, that could have been implemented during the 2010 Love Parade disaster to relieve congestion and reduce casualties. A VR experiment that compared participants' physiological responses to replays of simulated scenarios was also demonstrated. Two additional pieces of research were then performed to investigate the power of a dynamic/passive responsive environment. This section began by demonstrating the efficiency and effectiveness of adaptive signs, which indicate different directions depending on the location of a hazard, using a virtual 3D model of the Cooper Hewitt museum in New York. In addition, I investigated the use of personal smart devices to explore collective intelligence in the context of a social wayfinding experiment. Collectively, these studies provide a deep insight into the benefits of applying responsive technology to ordinary and emergency scenarios in the environment as a means of improving the user experience and reducing risk. They further extend the concepts of a responsive environment defined by previous researchers [87–89]. The relevance and significance of responsive environments are clearly supported by the methods and experimental evidence from the studies: advanced engineering techniques such as virtual reality display, crowd behavior simulation, and decentralized system architectures have been applied in the next generation of the responsive environment; empirical studies demonstrated the effects of the responsive environment on individual and group's decision-making behaviors. The combination of methods and findings provides answers to the premises raised in the introduction section.

7.3 ANSWERS TO RESEARCH QUESTIONS

This dissertation presents answers to the three questions raises in the introduction:

1. **How can the social dynamic in hazardous accidents be investigated through simulation and virtual reality?**

   An initial objective of the dissertation was to explore the possibilities of studying social dynamics through simulation and virtual reality. Virtual environments have been commonly used as media to study individual behavior in a number of cross-sectional studies [149, 161–163]. However, the generalizability of the virtual platform from the single-player studies to multiple players remains contradictory. With respect to the first research question, I examined the possibility of using virtual environments to capture and characterize the interaction between users within a responsive environment.

   This question has been addressed with the series of experiments reported in Chapters 2, 3, and 6. To study the social dynamics between the participants, I first built a networked experimental protocol. The use of such a protocol has shown that in social wayfinding scenarios, both the behavior of the other participants and the geographic information have an intersected effect on individual behavior. This protocol can complement existed supportive frameworks for single [151, 299] and multiple players [164] experiments. Such findings may encourage other researchers to use responsive environment elements such as dynamic digital maps to adjust the group dynamics when necessary. These studies can also help behavioral scientists, computer scientists, and geographers gain a better understanding of map design and collective intelligence. Specifically, the findings suggest that crowds may be used as a wayfinding cue, even in VR, and that simple signs may facilitate spatial decision-making in social environments by reducing hesitation. Despite previous concerns on using a virtual platform to conduct behavioral studies [162, 166, 167], it can be seen that the investigation of social dynamics in a virtual environment is feasible. Placing the participants together physically in the same lab but then represented them with avatars in a virtual environment enables the social dynamic to be clearly revealed.

2. **How can a responsive environment help to improve the safety of crowds in hazardous accidents?**

   The second objective of this dissertation was to identify the opportunities for improving the safety in hazardous accidents through various engineering methods in a responsive environment. This question has been addressed with two different hazardous scenarios.

   First, the most prominent finding to emerge from Chapter 4 is the significance of the effect of crowd simulation on preventing crowd disasters. I investigated the effects of various crowd management strategies on simulated casualties and individuals' physiological responses in VR. In addition to VR, other main engineering methods used in the responsive environment to prevent a crowd disaster consist of a 3D game engine, physiological response monitoring, and a computational simulation. Altogether, this study found that opening an additional exit and removing the police cordons in the venue during the festival would have led to lower crowd densities, less congestion, higher throughput, and fewer simulated casualties. Vast majorities of the conclusion agree with the suggestions from previous assessments of the organization and operation of this event [3, 269]. Because of the differences between the implementations and the platforms, the simulated results are not completely consistent with other studies [4]. It is hard to identify the exact reason behind it, but it inspires the investigation of the different simulation platforms and their strengthens and weaknesses.

Second, through Chapter 5, two implemented and validated computational frameworks, one centralized and the other decentralized have been shown to be capable of identifying the optimal evacuation route and directing users along this route to the exit. Furthermore, I used agent-based modeling to reproduce differences between adaptive and non-adaptive signs within these frameworks in a variety of hazard scenarios. I extended previous research on adaptive evacuation signage [329, 330] by applying a decentralized approach to make the system more robust and resilient. The decentralized structure enables the system to easily recover if an event of malfunction occurs [332]. In summary, these studies have shown that agent-based simulation, adaptive display systems, virtual reality technologies, and computational modeling support the responsive environments with a considerable degree of intelligence and awareness of the users' behaviors.

3. **How can the responsive environment design influence the individual and group behavior?**

The final question focuses on the validation of the responsive environment design. Throughout the dissertation, multiple findings have supported the effectiveness of responsive environments. In Chapter 2, I have demonstrated that simple map designs led to shorter decision time and higher accuracy than complex map designs. This finding has important implications for developing environments that have simplified visual guidance. In Chapter 3, I found that the interaction between map design and crowd movement significantly affected the decision time and the distribution of hesitation locations. This combination of findings shows that crowd behavior and the responsive environment features have an interactive effect on individuals. In Chapter 4, I demonstrated that the optimized crowd management strategy causes the participants to have a higher emotional arousal level. This finding raises intriguing questions regarding the extent of the influence of a responsive environment to users' physiological reactions. Chapter 5 presents that evacuees using adaptive signs are quicker, use shorter routes, suffer less harm from fire, and report less distress than participants using non-adaptive signs. It further confirms the association between the optimized wayfinding strategies suggested by the responsive environment and the users' behavior.

In total, these studies confirm that variations in the virtual environment are associated with behavioral changes, which accords with observations from other researchers [337, 347]. The effect of environmental variation has also been extended from real environments [31] into virtual environments. The analytical procedures and the results obtained from them provide evidence that a responsive environment is able to influence both individual and group behavior. Therefore, the combination of findings provides support for the conceptual premise that these responsive environments can influence individual and group behavior. In future investigations and in real-world applications, the responsive environment methods applied here can be considered to have been verified as effective for their specific purposes.

7.4 IMPLICATIONS

This dissertation bridges knowledge between computer science and behavioral science. Prior to this study, advanced technologies from engineering disciplines [113, 147, 171, 322, 323] had rarely been combined with psychological research; conversely, the application of computer science knowledge has not been fully investigated in the traditional behavioral and cognitive science research [21, 22, 24, 31, 50]. The interdisciplinary nature of this dissertation expands our understanding of how responsive environments can be useful in various scenarios. The present study lays the groundwork for future research into human-environment interaction.

For the scientific community, the findings of this investigation complement and extend those of earlier studies. Consistent with the suggestions presented by Normal and Draper [24], the empirical data highlights the possibility and importance of integrating user feedback into a responsive environment design. The application of a virtual environment makes it possible to easily implement variations in the environment and then conduct usability studies with each of these variations. Despite the importance of applying virtual design before the real execution of the construction, there remains a paucity of evidence on whether such virtual environments can indeed reveal the design flaws from the behavioral analysis of their users. Spatial cognition plays a key role throughout the investigation, and a number of insights have been gained from the empirical experiments. This dissertation expands our understanding of how subjects perceive spatial information from virtual environments. It adds to the growing body of research [18, 22, 23, 25–27, 55–58] that investigates the relationship between public space and its users.

Although many findings here focus on experimental data, they may also have a bearing on the use of technologies in a responsive environment design. In Chapter 5, I established a decentralized computing system that can provide robustness and reliability against systematic failure and malfunction, based on previous suggestions from researchers of distributed systems [332]. The social dynamic between users in a shared virtual environment is another facet of the dissertation. In Chapters 3 and 6, the networked information-sharing mechanism facilitates and encourages collective intelligence and altruistic behaviors. In both scenarios, the environments intelligently responded to the users' needs with information generated by the crowd. The findings emphasize the value of the previous research [63] on networked crowd behavior, which has found that herding behavior and collective intelligence can be empowered even in virtual evacuation tasks.

For practitioners, this dissertation provides a comprehensive assessment of multiple responsive environment approaches. The tools developed during this research will provide the foundations for the next generation of supportive tools for responsive environment design. Furthermore, other decision-makers, such as designers and managers of the public transport terminals, can also benefit from such tools. Public space managers can use the tool to evaluate the crowd management strategies and oversee the crowds before a potential disaster is forming (see Chapter 4). It will not only reduce the potential risk of crowd disasters [3, 38, 39] but also improve users' experience of the environment. Advanced wayfinding assistance such as adaptive signage (see Chapter 5) and collaborative wayfinding (see Chapter 6) will radically improve the efficiency of evacuation during hazardous events, elevating public safety to another level of effectiveness. The investigation analyzed individual's and group's trajectories and movement patterns. Public space organizers can use these crowd-analyzing mechanisms within the virtual environment to better comprehend crowd behavior to optimize flow management or avoid disasters. Moreover, the output of this research is a sophisticated framework that can support design procedures for building engineers, urban designers, and architects. Practitioners can use it to scrutinize their current design plans and improve their blueprints even before the real construction work starts, which has shown the strengthen in automatic signage placement [32].

The concept of a responsive environment is not only valuable for the hazardous scenarios presented in this dissertation but can also be adapted to broader applications. The similarity between pedestrian management and vehicle traffic management makes the findings and methods used here effortlessly transferable to smart parking and traffic control. Hence, the methodologies here can surpass the disciplines of computer science and cognitive science. Traditional transportation system lacks real-time feedback and rapid reaction to emergency status and needs of the pedestrians, due to the difficulties of capturing the crowd's locomotion actively. Nowadays advanced computer vision techniques can enable such tasks that were used to be difficult if not impossible. Therefore, many aspects and concepts from the responsive environment can be applied further into the intelligent transportation systems with the smart city concept. Traffic control, pedestrians flow management, and even supply chain management can adopt the concept of a responsive environment, in order to answer the user's constantly changing needs. Sensible cities can redirect the vehicle flow based on the similar concept introduced in Chapter 5, in order to avoid traffic congestions; smart buildings can connect with each other and share valuable data in the hazardous event, just as the collaborative scenarios presented in Chapter 6. The findings here add to the growing body of research on intelligent transportation and the smart city.

7.5 LIMITATIONS

The generality of these results is subject to certain limitations. First, being limited to virtual environments, the findings and methods of these studies thus far lack validation from real-world scenarios. The main weakness with the generality of the virtual environment is that users' behavior differs from that in real-world scenarios. The control of navigation with mouse and keyboard and the lack of a feeling of physical proximity might contribute to unrealistic navigation behavior by either crowds or individuals. Even with immersive virtual reality equipment, the appearance of the environment and the elements inside of it are vastly different from the real world. Participants' decision-making may differ from that in experiments conducted in real environments. However, the dangerous nature of most of the scenarios that have been examined in this study, such as crowd disaster and fire evacuation, means that it is practically impossible to replicate these hazardous events or organize this type of study in the real world. The ethical concerns and the potential risks to the personal health of participants prevent researchers from investigating such behaviors in the real world. In addition, it was not possible to coordinate the scale of the environment in our study with that in the real world without an enormous monetary cost. Hence, constructing and making variations in the virtual environment is efficient and economical for studying such sensitive scenarios. Despite its drawbacks, the use of a virtual environment enables the study to offer sufficient insights into the responsive environment. The difference in the decision-making choices and the physiological reactions between the groups shows that the virtual environment can serve the role of providing significantly varied stimuli.

Second, thanks to the convenience of the virtual environment, data acquisition is exceptionally simplified. Users' behavioral data can be recorded directly in digital logging files. This data is highly precise and reliable, which is rarely the case when data acquisition is conducted in the real world. Tracking pedestrians' trajectories in the real world is a highly challenging research topic involving sensor technologies and computer vision methods. Such approaches were not fully studied and applied during this dissertation, which makes the performance of the system presented here in the real world difficult to predict. A natural progression of this work is to replicate some of the virtual systems into the real world (e.g. adaptive signage system from Chapter 5) and then design a series of studies to examine their performance. Considerably more work will need to be done to determine the effects of the responsive environments in the real world.

Third, most of the studies here focus on hazard scenarios. In spite of the necessity of preventing risk, these are not common circumstances in our daily lives. Although the current study is based on hazard scenarios, the questions raised within the investigation are broad. Researchers and practitioners from other domains may also benefit from the methods and findings in this dissertation. The simulation mechanism in Chapter 4 can be applied to traffic control and thus prevent congestion even at the city scale. The adaptive signage in Chapter 5 can be seamlessly converted into an intelligent parking system. The scope of this study was limited in its application scenarios, so further work is needed to fully understand the implications of the responsive environment in broader circumstances.

Finally, yet importantly, the design of these responsive environments was manual and subjective. The components and the presentation of these responsive elements within the environment were chosen and designed by the researchers. These include the design of the environment (i.e., level of detail, lighting and material resolution), the geographic information, the user interface, and the signage. The parameters of simulations were chosen based on those suggested by previous research studies, yet was manually tuned to adapt to the new context. Such a high level of predefined design limits the extensive possibilities of machine intelligence. Moreover, the design procedure can bring unconscious bias from the researchers themselves. This kind of bias can generate relatively better design among the available design choices created by the researcher, but better designs may exist that were not chosen here. Further investigation could focus on potential developments from computer-aided design, such as automated layout generation and data-driven design. Those investigations require collaboration with engineers and designers, which certainly increases the complexity of the research method. Continued efforts are needed to make responsive environments more creative and more generalized.

7.6 OUTLOOK

Further research should be undertaken to explore the value of the large quantity of data generated in the current responsive environments in this study. We collected rich amount of behavioral data yet fatigue is another interesting aspects that is worth investigation. Together, these data can benefit event organizers by providing them with another source of information about the users. A user management system could prevent potential health risks and improve users' performance within the environment. Furthermore, other key decision-makers, such as operators of risky machines and airplane pilots, can also benefit from such a management system. An abnormal behavior alerting mechanism can be developed through the user management system to reduce risk situations and create better work–relax balance in order to avoid damage to employees' health. Pilots and long-distance drivers can use the tool to avoid potential risks of distraction and thus work more safely. It will not only reduce their potential risk but also improve their user experience. The tools developed during such a future work could be foundational for the following generation of supporting tools for the intelligent working environment.

In addition to the user management system, another natural progression of this work is to predict the user's behavior. A user behavior prediction system, which serves the role of forecasting the users' emotional states and decision-making process, could be beneficial for practitioners. The prediction of user behavior is an interdisciplinary topic combining knowledge from such disciplines as behavioral science and artificial intelligence. The behavioral analysis provides insights for the next generation of smart environment design standards. Concurrently, artificial intelligence makes the prediction of behavior possible. Machine learning algorithms have been broadly applied in pattern recognition, prediction of behavior, images, and natural language processing. A potential future work could focus on using artificial intelligence and machine learning to develop such a user behavior forecast tool. Empirical experiments with human participants could be conducted to collect users' behavioral data that could inform systematic variations of environmental features. The utilization of environmental sensors such as motion capture and physiological measurements could also be employed as a novel approach to data collection.

Ultimately, various intervention methods could be investigated to reduce risks and improve users' experience in working environments. To serve those intervention purposes, technologies that enable the coexistence of a working environment and virtual objects are essential, for example, a mixed reality interface that combines the virtual and real environments simultaneously. Such immersive integration of the digital display makes it a suitable medium for human-machine interaction in the advanced responsive environment. A mixed reality interface could provide users with assistance and advice for better working habits in the future.

A

APPENDIX

A.1 SUPPLEMENTARY MATERIALS FOR CHAPTER 2

Experiment Protocol

All methods described here have been approved by Research Ethics Committee of ETH Zürich.

1. Recruit participants for the planned experimental session.

1.1 Sample participants within particular constraints (e.g., age, gender, educational background) using the participant recruitment system.
1.2 Send invitations by email to the randomly selected participants using the contact information provided by the recruitment system.
1.3 Wait for these participants to register via the online system. Make sure to register more participants than required (e.g., 4 overbooked participants for a session that requires 36 people). Overbooked participants help ensure that a session is viable in the event of no-shows.
1.4 A confirmation email will be sent to registered participants automatically.

2. Prepare the experimental session.

2.1 Prepare the laboratory environment.
2.1.1 Print the participant list from the recruitment system.
2.1.2 Turn on the server and lights in the control room of the DeSciL and organize the testing rooms according to the required number of participants.
2.1.3 Copy the executable experiment program and its corresponding configuration files on the network drive. This executable program deploys a custom-written software framework based on the Unity game engine to support client-server communication among different computers through a local area network. For navigation experiments, the framework provides a bird-eye observer server system for monitoring the client's behaviors during the experiment.
2.1.4 Open PowerShell Integrated Scripting environment on the Windows desktop. In the PowerShell console, specify an array of computer names (e.g.

$pool = "descil-w01", "descil-w02"...) to create a client pool object. Next, type "Start-Pool $pool" to start the client computers and "Register-Pool $pool" to connect the server to the client computers.
2.1.5 Prepare the computers on the client side before launching the program. Type "Invoke-Pool Mount-NetworkShare $path" to direct the computers to enter the right folder path.
2.1.6 Execute the prepared functions on the server (i.e., "Start-GameServer") and on the clients (i.e., "Invoke-Pool Start-GameClient "). Specify the IP address of the server as parameter of the function.
2.1.7 Wait for a message on the server's monitor that indicates a successful connection.
2.1.8 Distribute the consent forms and pens in each cubicle. The consent forms contains the information regarding the study (e.g., the purpose of the study, potential risks and benefits of the experiment), the contact information for the experimenter, and a legal disclaimer.
2.1.9 Shuffle the deck of seating cards that indicate the seating arrangement of the participants.
2.2 Welcome the participants.
2.2.1 Ask the participants to wait outside of the laboratory. Five minutes before the official start time, check participants' identity documents to ensure that they match the list of registered participants. At the same time, let participants pick a card that indicates their seat number. Participants may walk to the corresponding cubicle and wait for the experiment to begin.
2.2.2 Wait a few minutes for participants to read and sign the consent forms. Collect these forms before conducting the experiment.

3. Conduct the experiment.

3.1 Broadcast the experiment instructions with the microphone to all of the participants. Inform them of the basic rules, including no communication to other participants and no personal electronic devices permitted. Ask participants to raise their hands if they have any questions regarding the experiment.
3.2 Begin the experiment by presenting the demographic questionnaire (e.g., gender and age) on each client.
3.3 Deploy the training scene to teach the participants how to maneuver through the virtual environment. If the participants have trouble using the control interface (e.g, mouse and keyboard), walk towards their cubicle in order to assist them. Keep monitoring participants' progress by requesting

screenshots from all of the clients (i.e., type "Get-ScreenShots" on PowerShell console) until all of the participants have finished the training session.
3.4 After the training session, begin the testing phase of the experiment. Observe the participants' behaviors from the bird's-eye interface on the server computer. Send warning messages to participants through the program if they are doing something abnormal by clicking on their avatar. Otherwise, try not to interfere with the participants during the experiment.
3.5 There should be a short waiting period before each trial for loading the next scene and allowing the participants to read the instructions.

4. Finalize the experiment.

4.1 Close the server and client program by typing "Stop-GameClient" and "Stop-GameServer" in the PowerShell console.
4.2 Ask the participants to remain seated until their number is called over the microphone.
4.3 Extract participants' final scores from the file "Score.txt" in the project folder on the server computer and convert their scores into a monetary payment.
4.4 Call the cubicle numbers one at a time and meet each participant at the reception desk. Thank the participants and give them the corresponding payment.
4.5 Examine the cubicles and collect any remaining pens or forms.
4.6 Copy and save the experiment data from the server to an external disk for future analysis.

A.2 SUPPLEMENTARY MATERIALS FOR CHAPTER 5

A.2.1 *Fire routes with manually generated and framework generated signs*

Figures 1 to 12 illustrate the different fire areas (in red) used for each of six routes in the VR and agent-based simulations. For the VR experiment, sign directions were manually generated by the authors. For the agent simulations, sign directions were generated by the computational framework so that at least one of the existing exit routes was blocked by the fire. Fire areas for the VR experiment and agent simulations were slightly different, but the same paths were blocked by the fire.

A.2.2 *Floor plan with sign connections*

In Figure 13, for every sign $s_i \in Signs$, $Direction : s_i$ represents the set of all directions that s_i can display. Since each sign has both front and back sides (+/-, see Figure 13), when referring to the back side, the directions are mirrored to the front side accordingly. For every successor edge s_j, a directed edge $e = (s_i, s_j, dir, cost)$ from s_i to s_j is added to the vertex set E, where dir represents a set of possible directions $Directions_1 = \{R(right), L(left), D(down), C(cross)\}$. A $cost$ is added to each edge as a proportional value to the distance between s_i and s_j.

Figure 1. Manually generated signs for VR experiment of route 1

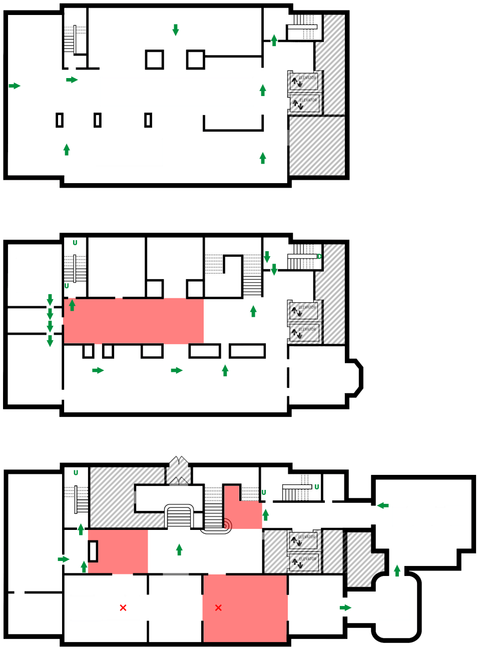

Figure 2. Framework generated signs of route 1

Figure 3. Manually generated signs for VR experiment of route 2

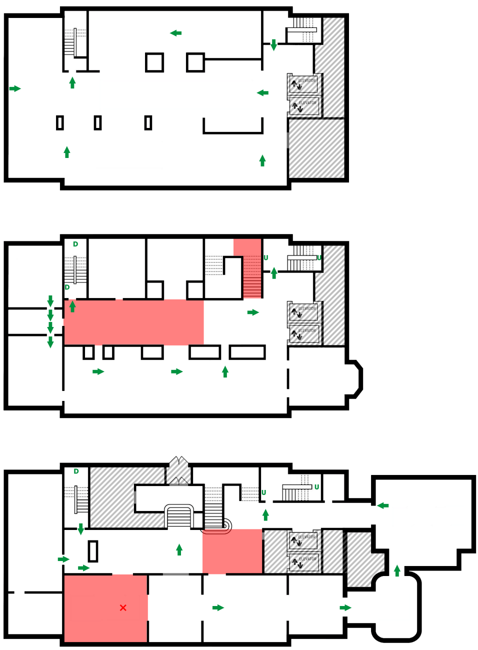

Figure 4. Framework generated signs of route 2

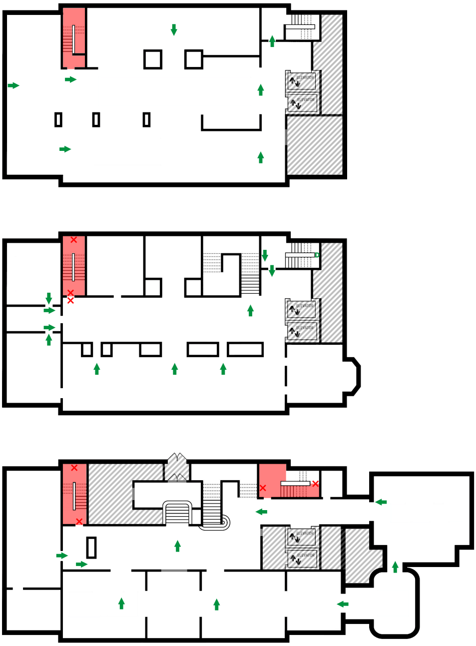

Figure 5. Manually generated signs for VR experiment of route 3

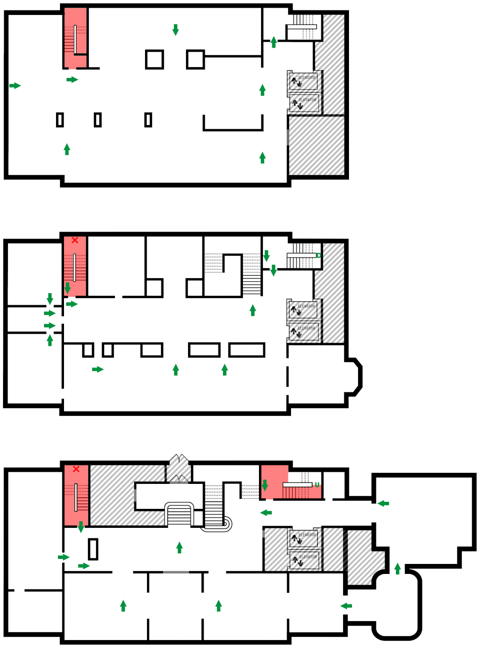

Figure 6. Framework generated signs of route 3

Figure 7. Manually generated signs for VR experiment of route 4

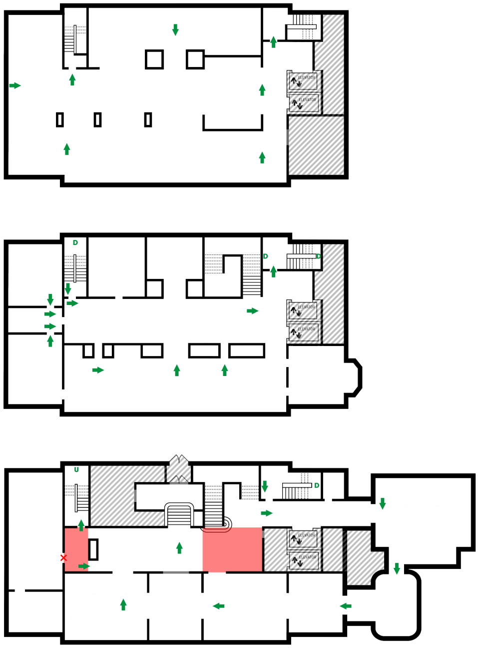

Figure 8. Framework generated signs of route 4

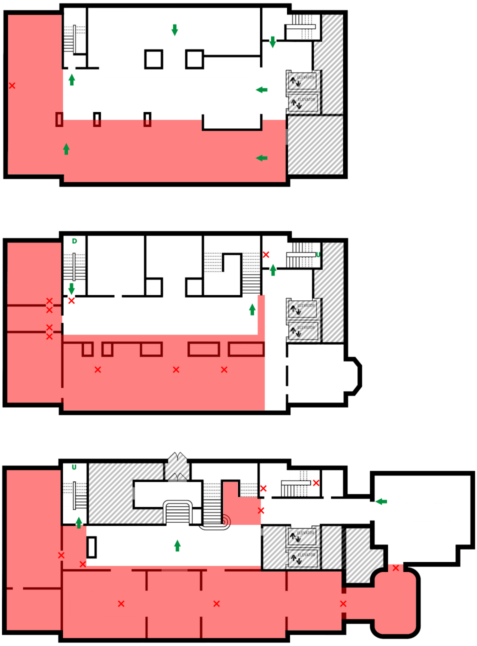

Figure 9. Manually generated signs for VR experiment of route 5

Figure 10. Framework generated signs of route 5

Figure 11. Manually generated signs for VR experiment of route 6

Figure 12. Framework generated signs of route 6

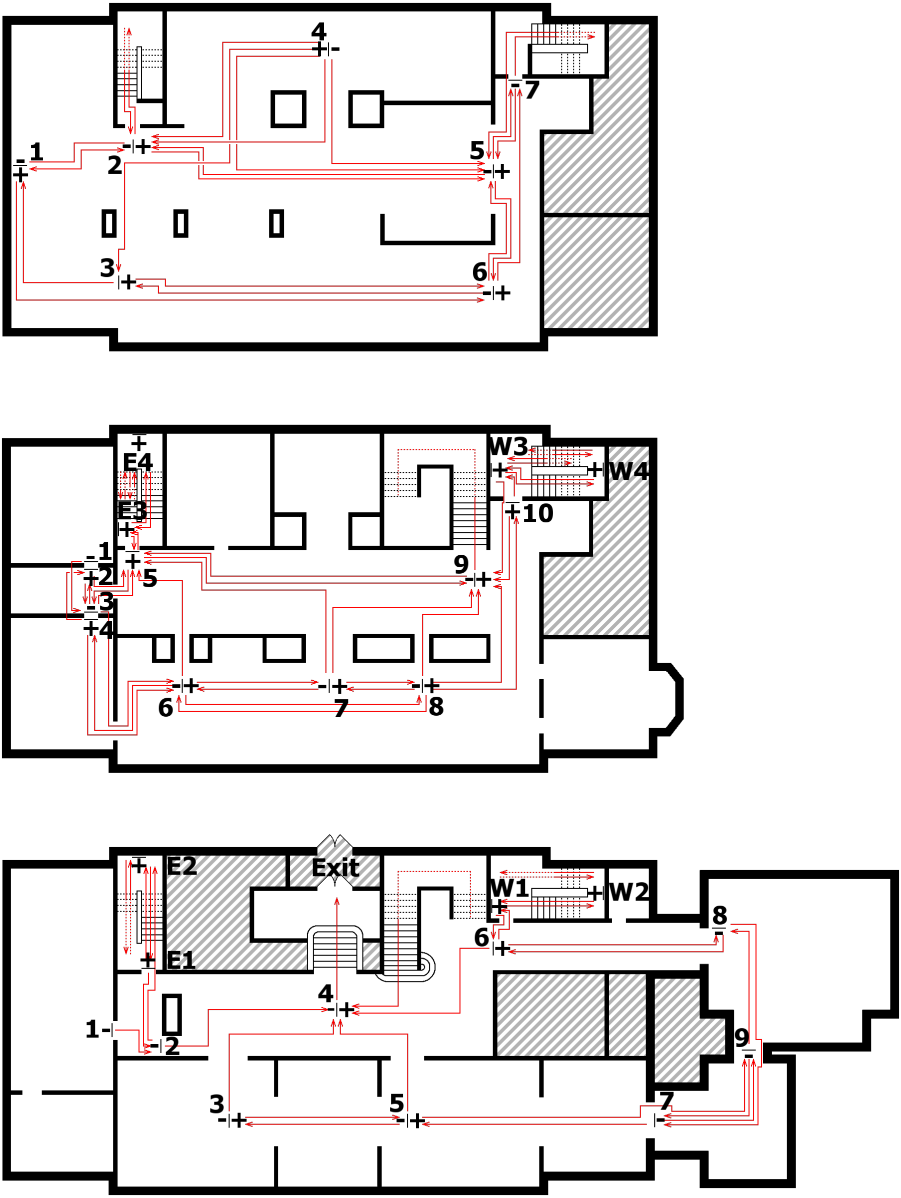

Figure 13. Paths and sign connections generated for the computational framework. Each number represents a sign here and each sign has two side (+/-). The red edges represent navigable path between signs.

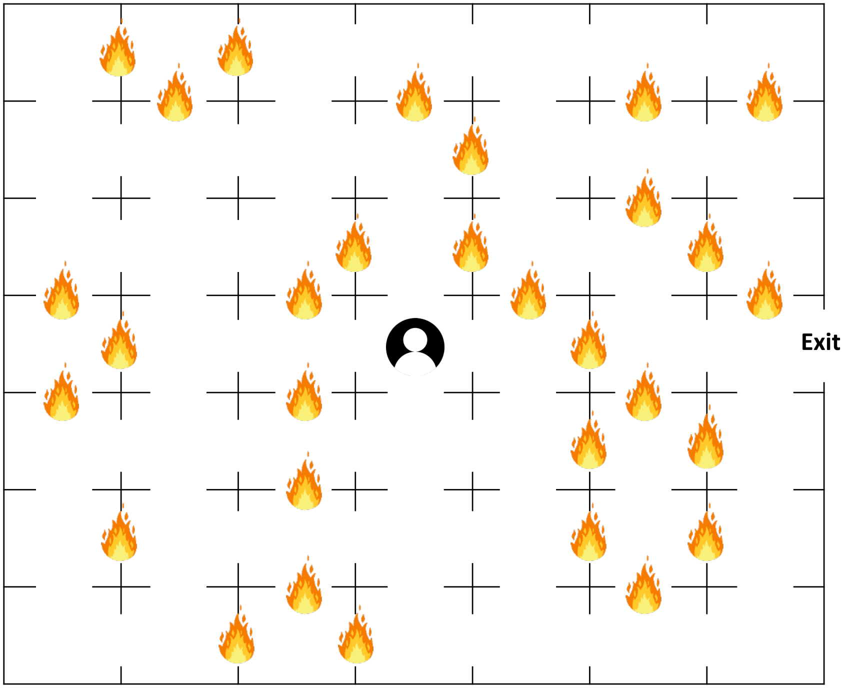

Figure A.1: Design of Maze 1.

A.3 SUPPLEMENTARY MATERIALS FOR CHAPTER 6

There are five different mazes used in both study 1 and 2, show in Figure A.1 to A.5. The user symbol represents the starting position and the "Exit" indicates the target of evacuation. Obstacles are presented with the fire symbols.

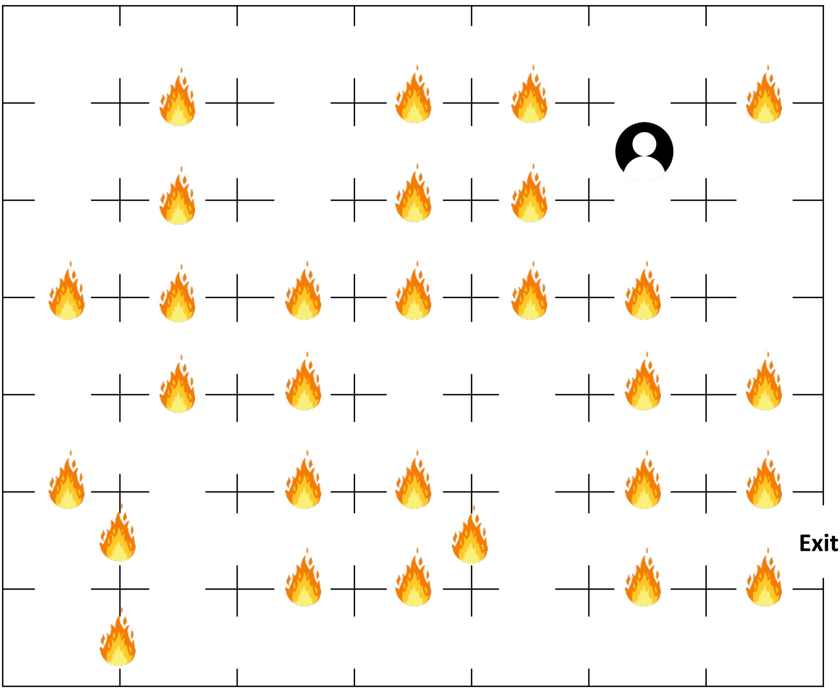

Figure A.2: Design of Maze 2.

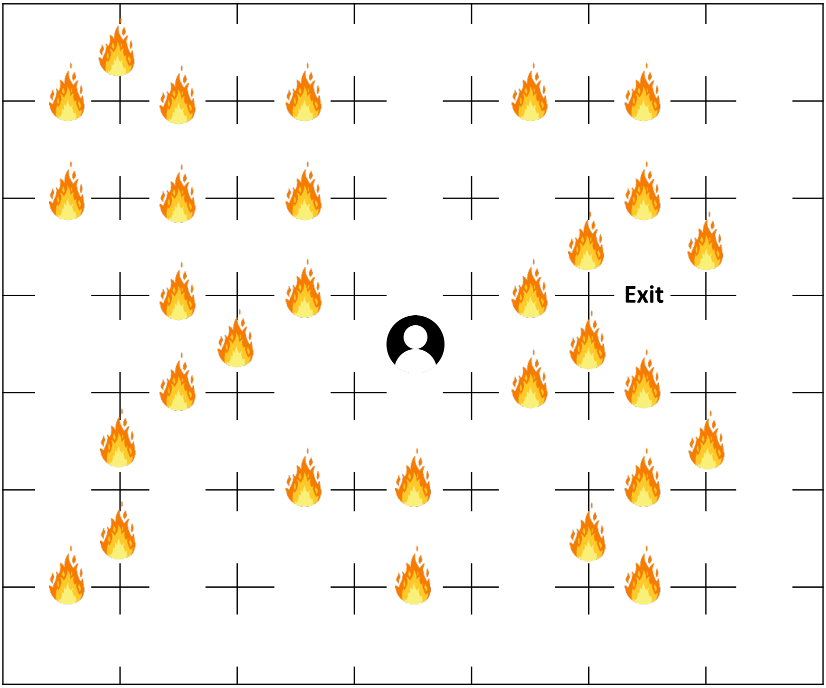

Figure A.3: Design of Maze 3.

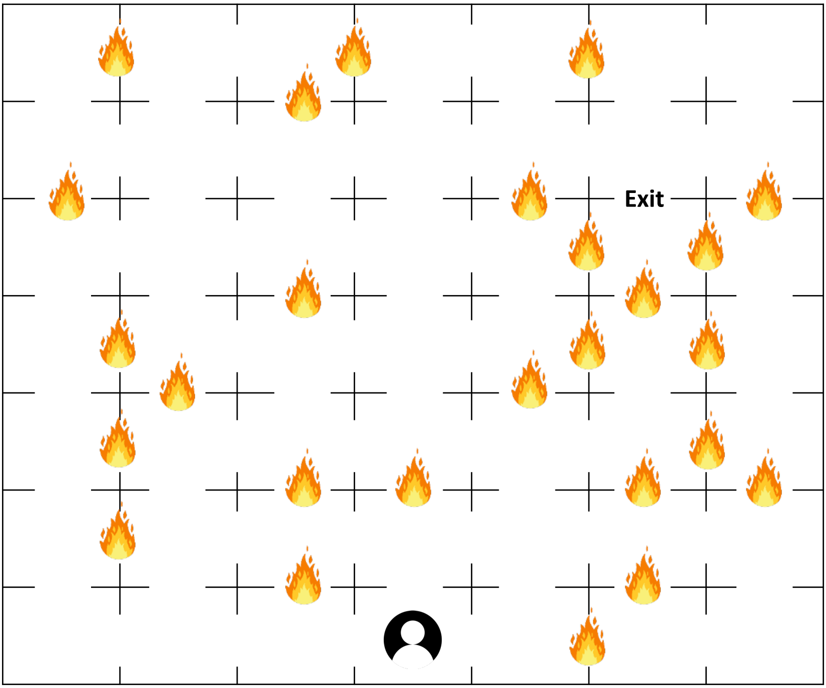

FIGURE A.4: Design of Maze 4.

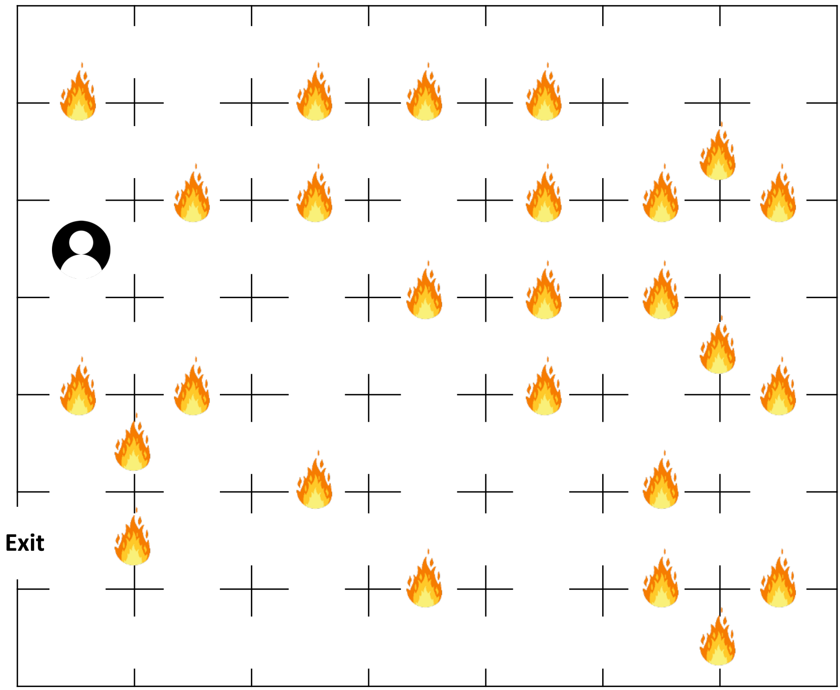

Figure A.5: Design of Maze 5.

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5. Zhao, H., Schwabe, A., Schläfli, F., Thrash, T., Aguilar, L., Dubey, R., Karjalainen, J., Hölscher, C., Helbing, D. & Schinazi, V. R. *A Decentralized Adaptive Sign System for Fire Evacuation with Human and Agent Validation*
6. Zhao, H. *The Social Influence of Spatial Collective Intelligence on Evacuees in a Mixed Human-Agent Experiment*