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Virtual Reality Simulated Augmented Reality Display on Windshields: Improving the Spatial Awareness of Autonomous Car Drivers

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Virtual reality simulated augmented reality display on windshields: Improving the spatial awareness of autonomous car drivers

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Abstract:

The emergence of autonomous driving technology gradually facilitates the shift towards self-driving vehicles, altering the role of drivers and transitioning them from active operators to passive observers, which may impact their spatial cognition and decision-making abilities. This study leverages virtual reality (VR) to create a simulated autonomous driving experience, integrating augmented reality (AR) displays that present spatial information through distant and local landmarks. The objective is to assess how drivers interact with and process AR-enhanced spatial cues in a virtual autonomous driving context. Building upon R. Li's research (2023), this study employs a two-by-two experimental design to investigate the effects of road type and AR landmark conditions on spatial knowledge acquisition. Eye-tracking data collected via the VR headset is analysed to examine variations in gaze behaviour under different experimental conditions in five windshield areas. Additionally, the study compares immersive VR-based results with those from R. Li's original online video-based research (2023) to evaluate the consistency and reliability of findings. The results indicate that the AR display with landmark information enhances spatial knowledge acquisition. Regarding road type, participants on the highway took more time to comprehend spatial layouts but achieved higher accuracy compared to those on the local road AR landmarks displayed on the top and bottom areas of the windshield attracted more attention than the right edge windshield area during VR experiments, as evidenced by increased average fixation duration, fixation count, and dwell time (which are eye-tracking metrics). Conversely, compared to the AR absent condition, adding AR landmarks reduced the frequency of gaze focus on the right edge of the windshield with less dwell time and lower fixation count. The route and configurational knowledge task accuracies produced consistent results in in-person VR and video-based online research. For directional knowledge, the VR experiment revealed higher accuracy than the online video experiment. The research findings guide future research in enhancing the integration of AR in autonomous driving, with a focus on improving safety, spatial awareness, and the overall user experience.

Acknowledgement:

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1 Introduction

1.1 Background

The emergence of autonomous driving technology is transforming the transportation industry. It promises to fundamentally change how we view and interact with our vehicles, providing unmatched convenience, safety, and efficiency during our daily commutes. However, as we go towards the world of self-driving vehicles, we find ourselves at a crossroads where technical innovation can transform not just the way we move but also our cognitive relationship with the act of driving itself.

Human drivers have depended on their intrinsic spatial knowledge, perceptual ability, and intuition for decades to manage the complex and dynamic road environment. However, the introduction of GPS navigation systems to driving activities has shown a decline in spatial learning and awareness as drivers become more reliant on technology and less on their cognitive mapping abilities (Aporta & Higgs, 2005; Burnett & Lee, 2005). As we further transition to fully autonomous vehicles, this concern intensifies. There is a growing concern that the reliance on technology may induce a gradual degradation in human competence when it comes to spatial decision-making (Fleetwood, 2017). With autonomous systems taking over control, drivers become passive passengers, increasingly detached from the once-critical task of piloting a vehicle (Janssen et al., 2019).

Autonomous driving has challenged our traditional understanding of spatial awareness and decision-making (Parekh et al., 2022). Spatial awareness is the ability to understand, reason, and remember the visual and spatial relations among objects or space (Bolton & Bass, 2009; Endsley, 1995; Wickens, 2002). Spatial awareness and learning are pivotal as they aid in navigation and enhance cognitive abilities, problem-solving, and memory. A robust spatial understanding allows individuals to relate to their environment, make informed decisions, and anticipate potential challenges (McCunn & Gifford, 2018; Spence & Feng, 2010). As we lean more toward technology while driving, it is crucial to recognize and address the potential cognitive impacts and maintain a balance between convenience and cognitive development.

This transformation prompts us to examine how we can empower individuals within autonomous vehicles to regain their spatial awareness, stay engaged, and enhance their overall driving experience. One compelling solution lies in adapting the windshield as an information display canvas and using Augmented Reality (AR) visualization as an efficient means for augmenting the travel experience (Keil et al., 2020). AR, a technology that overlays digital information in the real world, offers a unique way to enhance visual data without detaching passengers from their surroundings (Çöltekin et al., 2020; Flavián et al., 2019). This integration of AR visualization provides a context-rich environment, making autonomous driving more informative and immersive (Dwivedi et al., 2022; Riegler et al., 2022).

This thesis explores the intersection of autonomous driving technology, human cognition, and future AR technology. The experiment will create a virtual reality (VR) self-driving simulation, where the AR display will be presented through the windshield. Specifically, the windshield will add landmark cues and auxiliary driving information to enhance the acquisition of spatial knowledge for experimenters. The spatial knowledge is divided into three specific categories: route knowledge, directional knowledge, and configurational knowledge. Route knowledge involves the ability to recall and navigate the sequences of the landmarks of different locations (Hirtle & Hudson, 1991; Siegel & White, 1975). Directional knowledge requests the ability to form a mental framework for understanding the orientations in spaces (Burte & Montello, 2017). And the configurational knowledge involves understanding the spatial layout and relationships between different locations (Golledge et al., 1992; Ishikawa & Montello, 2006).

Furthermore, the study extends beyond mere task performance; it incorporates eye-tracking data alongside other metrics to scrutinize how drivers process the information presented on the AR windshield. One of the groundbreaking applications of VR is the integration of eye-tracking technology, which captures the gaze patterns and eye movements of users in real-time within the virtual environment (Clay et al., 2019). This convergence of technologies provides a unique opportunity to study human spatial knowledgeability. By analysing where, how long, and in what sequence users look at specific objects or landmarks in a virtual space, researchers can gain insights into how individuals navigate, recognize spatial patterns, and process spatial information (Walter et al., 2022).

It is important to note that, although eye-tracking data is pivotal in interpreting the findings, integrating this data with statistical analyses of individuals' task performance is essential for understanding the stimulus effectiveness. This comprehensive approach aims to shed light on the potential of AR technology in enhancing spatial awareness in the realm of autonomous vehicles.

1.2 Related work

1.2.1 GPS effects on spatial knowledge acquisition

Over the years, numerous studies have consistently indicated a concerning trend: using GPS in traditional vehicle navigation and pedestrian wayfinding appears to be associated with a diminished capacity for spatial learning.

Burnett and Lee (2005) explored the difference in spatial awareness and memory between users of traditional navigation methods (like paper maps) and those relying on modern vehicle navigation systems. The research suggested that the use of navigation systems might lead to a decreased ability to form detailed cognitive maps, as these systems often provide turn-by-turn instructions that require less active engagement from the user. Münzer et al. (2006) explored how computer-assisted navigation systems affect the route knowledge and survey knowledge. The results found that while navigation systems can aid in efficiently learning route, however, reliance on navigation hinder the development of a deeper, more integrated understanding of spatial environments. Parush et al. (2007) discussed the negative impact of reliance on automatic navigation systems on the acquisition of spatial knowledge. The key argument presented is that over-reliance on these systems may lead to a "mindless" approach to navigation, where users pay less attention to their environment and fail to develop necessary spatial knowledge.

Later on, several empirical studies collectively examined the impact of different navigation tools on spatial knowledge acquisition and cognitive workload. Ishikawa et al. (2008) compared the efficacy and impact of GPS navigation with traditional paper maps and direct experiential navigation. This study reported while GPS-based systems are highly efficient in guiding users to their destinations, they tend to lead to less engagement with the environment and poorer spatial knowledge acquisition compared to traditional maps and direct experience. Willis et al. (2009) explored the differences in how traditional maps and mobile map applications affect understanding and memory of spatial environments for users. In this research, users of mobile maps tended to perform worse in terms of estimating route distances and understanding the overall spatial layout compared to those who use traditional maps, which implied that mobile maps are not as effective as traditional maps in developing a comprehensive and integrated understanding of spatial environments (Willis et al., 2009).

In recent years, studies have increasingly tested the aforementioned effects using virtual environments. For instance, Gardony et al. (2015) delved into how the use of navigational aids (like GPS) impacts spatial memory, particularly focusing on the concept of divided attention. The results of these experiments generally revealed that the reliance on navigational aids, combined with divided attention, can impair the formation of robust spatial memory. Participants using navigational aids under divided attention conditions often showed a lesser ability to recall spatial details or navigate effectively without aids, compared to those who navigated without such aids or without divided attention (Gardony et al., 2015). Hejtmánek et al. (2018) involved participants navigating a virtual town using a GPS-like map, with their eye movements being tracked to assess spatial awareness and memory. In this study, participants who spent more time using the GPS-like map exhibited less accurate spatial knowledge, suggesting a negative correlation between GPS reliance and spatial awareness. Most recently, Ruginski et al. (2019) examined how reliance on GPS navigation impacts an individual's ability to learn and understand their environment. The study suggested that GPS use can negatively affect the overall process of environmental learning. Participants who heavily relied on GPS for navigation showed a decrease in their spatial transformation abilities.

Taken together, the trend observed from previous studies on navigation assistance suggests that as autonomous vehicles become more prevalent, drivers may experience similar reductions in spatial cognition. The introduction of autonomous driving systems has the potential to transition individuals from active drivers, who rely on keen spatial awareness and navigation skills, to passive passengers (Brishtel et al., 2021; Mondschein et al., 2010; Parekh et al., 2022). During autonomous driving, many driver behaviours have nothing to do with paying attention to road information and driving behaviour itself (Riegler et al., 2022). The shift from active navigation to passive travel could further diminish the need for spatial awareness and cognitive map formation. In line with this prediction, Brishtel et al. (2021) investigated the effects of various navigation aids, including autonomous driving, on spatial knowledge acquisition and found out that with autonomous vehicles handling the complexities of the road, individuals may become less reliant on these skills in everyday travel which leads to poorer spatial knowledge and suggests a disadvantage to the long-term development of spatial memory. Notwithstanding, in transportation technology the convergence of self-driving capabilities and spatial cognition is a nascent area of study. It remains a relatively uncharted domain with limited researchers delving into its intricacies.

1.2.2 Head-up displays (HUD)

Existing research in autonomous driving primarily concentrates on the development and refinement of self-driving technologies, with a predominant focus on vehicular control, navigation, and safety (Mora et al., 2020). Drivers are physically and cognitively passive while sitting in autonomous cars because they do not need to pay any attention to or intervene in the driving environment during the entire driving process. Previous study has proven that reducing the driver's mental load using autonomous driving mode comes at the expense of spatial learning (Brishtel et al., 2021).

Therefore, the goal of modern autonomous driving technology should be to enhance the driving experience and avoid adverse effects on the driver's acquisition of spatial knowledge (Brishtel et al., 2021). The primary interface for human interaction in both autonomous and traditional manual vehicles is the windshield, a crucial element for acquiring spatial knowledge and forming spatial cognition of the driving environment (Riegler et al., 2022). This interface allows drivers to perceive spatial information from the surrounding environment, especially when no GPS is available in autonomous driving vehicles.

A head-up display (HUD) is a technology used in vehicles to project essential driving information as visual cues onto the car's windshield (Ablassmeier et al., 2005; Charissis & Papanastasiou, 2010; Stojmenova Pečečnik et al., 2023). Conventional 2D HUDs project straightforward, two-dimensional information such as speed or basic navigation onto the windshield (Feierle et al., 2019). Previous research indicates that 2D HUDs in manual vehicles efficiently enhance driving performance and contribute to comprehensive situational awareness for drivers. Situational awareness allows individuals to assess what is happening around them, understand how information, events, and their own actions will impact their goals and objectives, and foresee potential dangers or opportunities (Endsley, 1995).

For traditional vehicles, Ablassmeier et al. (2005) evaluated the integration of HUDs into a multimodal interaction concept, considering factors like driver attention and information processing. In this research, results indicated that HUDs could significantly enhance driving performance by providing critical information in the driver's line of sight, thus improving situational awareness and reducing distractions (Ablassmeier et al., 2005). Charissis and Papanastasious (2010) assessed how this HUD interface impacts driving performance and cognition. The HUD interface revealed the potential in enhancing driver awareness, safety, and interaction with vehicle controls, thus improving overall human-machine collaboration in the automotive environment. Jakus et al. (2015) evaluated different types of information displays within vehicles to determine which of these display methods is more efficient and effective for drivers. The findings suggested that interactions with visual and audio-visual HUDs are generally faster and more effective than with audio-only displays.

Traditional HUDs use simple projection technologies to display non-interactive, static information that does not change based on the viewer's perspective or the external environment (Ablassmeier et al., 2005; Charissis & Papanastasiou, 2010; Jakus et al., 2015). Compared to traditional HUDs, AR HUDs demonstrate enhanced effectiveness in driving performance. They offer a more engaging experience by projecting dynamic, interactive three-dimensional information onto the real-world view for drivers, significantly enriching environmental perception with detailed contextual cues (Feierle et al., 2019; Pauzie, 2015). As autonomous driving technology advances, AR HUDs are increasingly incorporated into studies focusing on autonomous vehicles, illustrating their potential in this emerging field. Langlois and Soualmi (2016) compared the effectiveness of AR HUDs with traditional HUDs during the transition from automated to manual driving. The experiment showed the advantages of AR HUDs in enhancing driver response and maneuver anticipation, suggesting their potential superiority over classical HUDs in rebuilding situation awareness to take over driving. Feierle et al. (2019) assessed how AR technology influences driver behavior, situational awareness, and interaction with the vehicle's automated systems. The results indicated that AR HUDs potentially offer significant benefits in enhancing driver awareness and response in complex urban driving scenarios. More recently, X. Li et al. (2023) explored the role of HUDs in enhancing the driving experience in automated vehicles. The experiment design involved participants in a driving simulator, assessing their response to taking over control from automated driving while engaged in tasks via the HUD. The results indicate that AR HUDs enhance readiness and efficiency in transitioning back to manual control for drivers in autonomous vehicles (X. Li et al., 2023).

1.2.3 HUD for spatial awareness

The relationship between situational and spatial awareness is foundational to navigating and making decisions in complex environments. Situational awareness provides the contextual understanding necessary to assess the current state of the environment, including potential hazards and opportunities (Endsley, 1995). Spatial awareness builds on this understanding, enabling an individual to navigate through or interact with the environment based on spatial relationships and orientations of objects and features (Bolton & Bass, 2009; Endsley, 1995; Wickens, 2002).

Based on research reviewed above, there is potential for incorporating AR landmarks on the windshield due to the usefulness of HUDs in enhancing situational awareness. AR HUDs present interactively environmental information directly within the driver's field of view, which is beneficial for immediately understanding the environment and its potential changes (Feierle et al., 2019; Langlois & Soualmi, 2016; X. Li et al., 2023). Given the close relationship between situational and spatial awareness, it is reasonable to anticipate that the benefits observed in situational awareness could also extend to spatial awareness. Therefore, by displaying significant spatial signals and instructions onto the actual environment, AR landmarks have the potential to improve spatial awareness and make navigating safer and more accessible in autonomous driving.

In a study conducted by R. Li (2023), the author delved into the varying capabilities of acquiring spatial knowledge through AR landmarks displayed on the windshield (R. Li, 2023). This experiment delves into the application of AR for visualizing distant landmarks, transitioning from mobile phones to vehicle windshields, to enhance spatial learning. It uses simulated autonomous driving videos to explore the influence of AR landmarks and varying road conditions—highway and local road—on spatial knowledge acquisition. Participants are allocated randomly to two distinct scenarios and undertake tasks to evaluate their spatial knowledge. In R. Li’s experiment, the participants joined the research online by watching the video. While online and video research methods are advantageous in many respects, they have inherent limitations. Generally, online researchers have limited control over the participant’s environment, and it is hard to verify the identity of participants or ensure they are not distracted during the study. Moreover, video only provides a fixed viewpoint and static perspective, leading to a low immersion level for participants.

The current study adopts VR technology to overcome the limitations. Using a computer-generated 3D virtual world that one can interact with, resulting in immersive real-time simulation, is characterized as VR. Firstly, VR provides a highly immersive and realistic experience (S. Kim & Dey, 2009; Riegler et al., 2019). Zhao et al. (2023) utilized an immersive VR experimental setup to investigate the advantages of AR cues in enhancing spatial learning and navigation, demonstrating the effectiveness of VR technology in facilitating the acquisition of spatial knowledge. Instead of passive observation, participants in VR feel like they are within the environment, allowing for a more authentic representation of the impact of autonomous driving on individuals (Nezami et al., 2020; Riegler et al., 2021). Moreover, VR allows for detailed behavioural analysis by utilizing eye-tracking technology (Clay et al., 2019). Researchers can track participants’ movements, gazes, and reactions in real time, providing valuable data on their responses to different autonomous driving situations (Clay et al., 2019; Walter et al., 2022). Also, the experimental environments can be precisely controlled, ensuring that all participants are exposed to the same conditions and stimuli. This control enhances the scientific rigour of experiments and minimizes confounding variables.

2 Research Objective

This study seeks to replicate the findings of a previous video-based online study conducted by R. Li (2023), but with a twist: it utilizes VR to recreate two autonomous driving scenarios (highway and local road). A significant objective of this study is to compare the results derived from the video-based online method with those from the VR approach. This comparison serves a dual purpose: to cross-validate the findings (using results from video participants to validate those from VR participants and vice versa) and to explore the joint effects of the experimentation method (VR + in-person vs. video + online) on spatial learning.

To begin, a virtual driving environment based on VR implementation is required to simulate the AR display showing distant landmarks along with directional cues to evaluate the effectiveness of this innovative display in spatial learning in local road and highway environments.

Using this VR environment, the influence of the AR display on the spatial learning of autonomous vehicle drivers in two specific contexts, highway and local road, will be investigated. Furthermore, by analysing and visualizing gaze-behaviour patterns, this research aims to understand the cognitive processing of visual-spatial information presented on the windshield.

2.1 Research Questions and hypotheses

Several research questions (RQs) can be generated to explore the impact of different factors on the results of the immersive driving simulation. These RQs can help guide the investigation:

RQ1. How do road types and AR landmarks affect task completion times and spatial knowledge formation during the immersive driving simulation?

RQ2. Which changes in eye-tracking data significantly differ across road types and landmark types, and does this affect spatial knowledge accuracy?

RQ3. What are the differences between the experiment results from online video and in-person VR participants?

These RQs address the between-subject factors (landmark conditions and road types) and dependent variables (task completion times, route knowledge accuracy, directional knowledge accuracy, and configuration knowledge accuracy) which will be given more details in the experiment design section.

Analysing these aspects with the two-way analysis of variance can provide valuable insights into the immersive driving simulation and its effects on participants' performance for studying RQ1. Additionally, eye-tracking data such as average fixation duration, dwell time, and fixation count will be used to investigate the experiment's outcomes to answer RQ2. In this study, the windshield is segmented into five areas, each depicting diverse environmental details of landmarks. And the cumulative link mixed model is conducted to interpret the interaction effects that involve the experimental methods to answer RQ3.

For RQ1, based on the synthesis of existing literature on AR applications in driving conditions, our hypothesis posits that different road types combined with AR landmarks will significantly influence drivers' task completion times and spatial knowledge acquisition (Charissis & Papanastasiou, 2010; Feierle et al., 2019; R. Li, 2023). Specifically, we hypothesize that complex road types, when augmented with strategically placed AR landmarks, will facilitate quicker task completion and enhance spatial knowledge.

Regarding RQ2, we predict that participants will participate in more proactive information processing and higher eye-tracking metrics when traversing complicated road situations, such as highways and AR landmarks. Moreover, different kinds of landmarks are expected to improve the accuracy of spatial information at various levels. Increased cognitive interaction with environmental features aids in improving memory encoding and retrieval processes, thereby fostering the development of spatial awareness.

Regarding the comparison between online video and VR (RQ3), we predict consistent outcomes across both in-person VR sessions and research utilising online videos. This consistency supports the hypothesis that AR landmarks displayed on the windshield can enhance spatial awareness in autonomous driving scenarios across varied road conditions. The inherent ecological validity of VR and the effectiveness of video as a research tool validate their application in simulating autonomous driving environments. Moreover, VR can perform head movement simulation, more accurately reflecting real-world experiences than traditional video research.

3 Methodology

A schematic description of the workflow is shown in Figure 1. The VR development prepares and establishes the experiment environment. The experiment procedure analysis aims to get the experimental findings and answer all RQs.

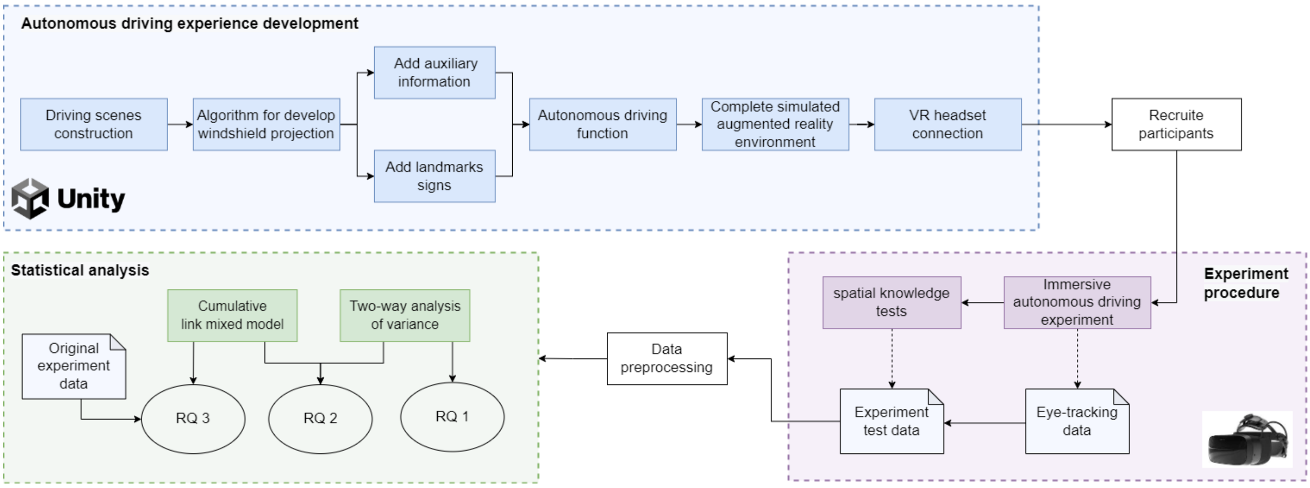

Figure 1: Workflow of the research

3.1 Autonomous driving experience

Unity, a renowned game engine, has shown its versatility beyond gaming, making strides in VR applications (Riegler et al., 2019). This research crafts immersive VR environments that closely replicate real-world driving conditions through Unity, allowing for comprehensive autonomous driving simulations, AR landmark displays, and eye-tracking functions (see the development window in Figure 2).

Figure 2: Unity development window

Four scenarios are developed within the Unity project to simulate autonomous driving experiences. These scenarios are differentiated by the presence or absence of an AR display on the windshield and the type of driving environment, either highway or local roads. The first scenario involves driving on a highway without the AR display, while the second scenario introduces the AR display in the same environment. Similarly, for local roads, one scenario is designed without the AR display, and another incorporates it, allowing experiencers to engage with both environments under varying conditions.

Upon completion of the game project, relevant VR plugins are integrated into the Unity project. The Varjo Aero Headset is then connected to the VR headset host computer. This setup provides individuals with a VR view and includes built-in capabilities for eye tracking data detection and collection.

3.1.1 Virtual environments

In developing VR driving scenes within a Unity project, the methodology begins with modelling scenarios based on real-world driving videos to ensure realism. Assets and models from the Unity Asset Store are utilized to build these scenes, enhancing the visualization of 3D road infrastructures.

During the environment development phase, special attention is given to differentiating highways from local roads (two environments showed in Figure 3). This differentiation is achieved by varying the route lengths, speed limits, and specific characteristics unique to each road type, thereby creating a more authentic driving experience (two routes displayed in Figure 4).

Figure 3: Driving scenes and autonomous navigation system (left: highway, right: local road)

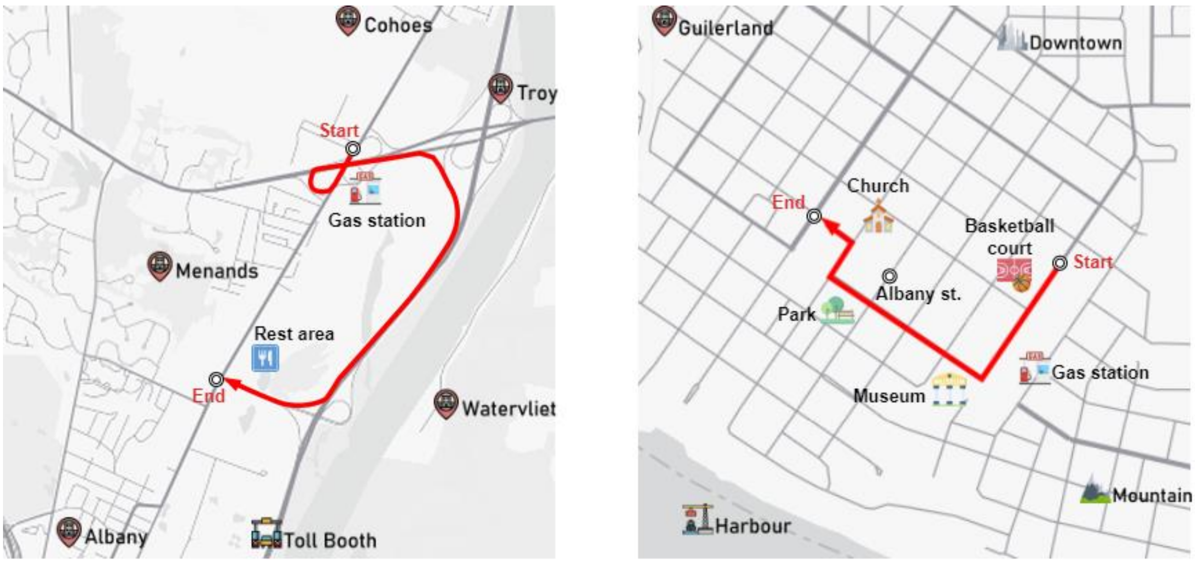

Figure 4: A top down view of the two routes (left: highway, right: local road)

Landmark placement is crucial in these scenes for fostering spatial awareness and environmental understanding. The number and location of landmarks are strategically chosen, focusing on global landmarks like traffic signs for spatial learning and local landmarks like custom building signs for contextual information.

The Unity model used in this project is equipped with innovative autonomous driving features. These include newly developed windshield functions that project landscapes and AR information, enhancing the immersion and interactivity of the simulation. Autonomous navigation is facilitated by using waypoints and navigation meshes, which guide the vehicle along pre-defined paths. However, this system intentionally limits user control over specific driving dynamics like vehicle speed and turning behaviour to maintain a consistent and controlled simulation environment.

3.1.2 AR windshield

The windshield is divided into five distinct portions, as seen in Figure 5 and described below, to display different types of information for enhancing driver safety and awareness (R. Li, 2023). This setup also provides distinct areas of interest for eye-tracking data collection.

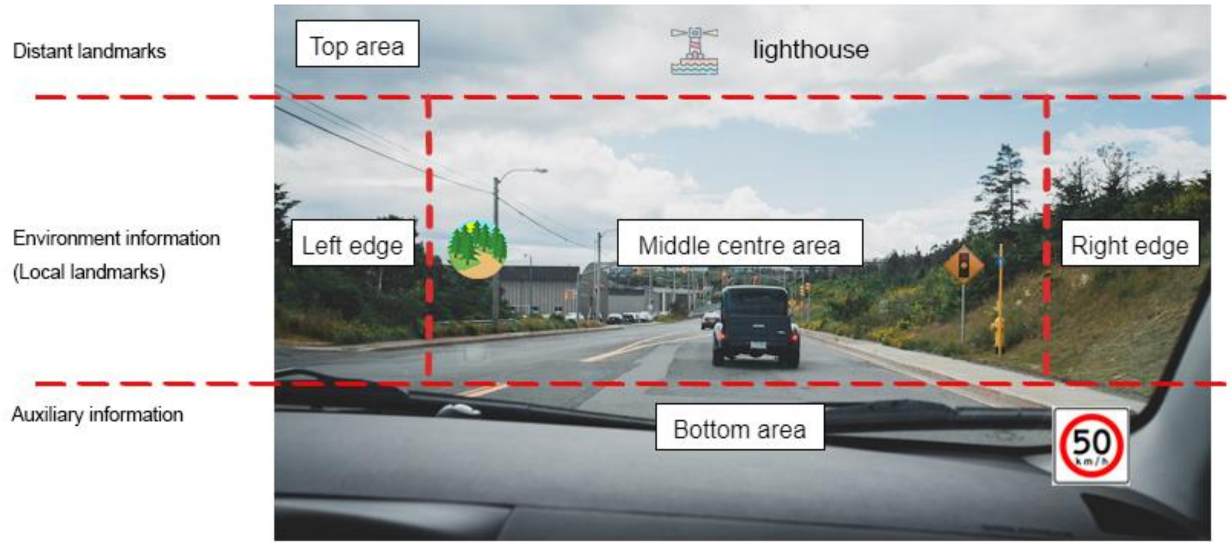

Figure 5: AR visualization of different portions on the windshield (modified from R. Li, 2023)

1) Top area - distant landmarks: Displaying distant landmarks in the top portion of the windshield aids drivers in long-range navigation. This view helps in identifying major landmarks for orientation, and understanding the broader context of the driving environment (Yesiltepe et al., 2021).

2) Middle centre area – local landmarks: Displaying the location of local landmarks on central part of the windshield, which offers the most comprehensive view of the immediate surroundings. Local landmarks play a crucial role in spatial learning by serving as reference points that aid in constructing cognitive map and formatting spatial awareness (Bruns & Chamberlain, 2019; Steck & Mallot, 2000).

3) Left edge - local landmarks: Reporting the position changes of local landmarks from the central projection area of the windshield to the left outside area when local landmarks are still in front of the observers. These off-screen local landmarks enable users to better orient themselves and understand the layout of the surrounding area (R. Li & Zhao, 2017).

4) Right edge - local landmarks: Same as the left side, the right edge also indicates the relative location of the local landmarks, which moved to the right side of the off-screen area.

5) Bottom area - auxiliary Information: Presenting auxiliary information, such as speed limitations, at the bottom portion ensures drivers don't have to divert their eyes far from the road. Having this information within the periphery of their primary view allows drivers to quickly check essential data without losing focus on the central environment or the road ahead.

In the top area of the windshield, the transparency of the distant landmarks will gradually change to indicate the distance of the landmarks. As the car and distant landmarks become closer, the transparency gradually decreases. When people are presented with such transparency changes, they may generate better spatial insights from the visualization (Ananny & Crawford, 2018). For off-screen local landmarks (the left and right edges of the windshield), as shown in Figure 6, transparency increases as the angle between the line connecting the landmark to the observer's eye and the observer's body level decreases. Once the direction of the landmark is opposite to the vehicle's heading, it completely vanishes from view. A local landmark loses visibility and becomes a distant landmark once it is farther away than 1 km. Likewise, when a distant landmark is within the immediately visible range (1 km), it transforms into a local landmark and becomes visible in the middle of the windshield.

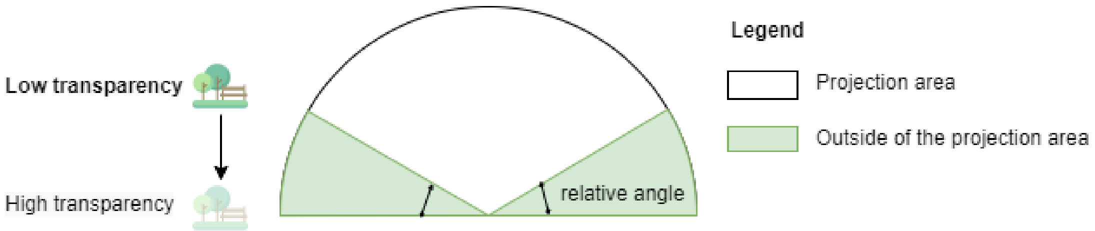

Figure 6: Transparency changes for off-screen local landmarks as they move away from the projection area (where users can directly see the physical surroundings through windshield).

To achieve the AR display functionality in Unity for replicating reference research, a flexible approach to landmark projection on the vehicle's windshield is employed (see in Figure 7). Unity models feature windshields that are often curved rather than flat. To address this, a flat, transparent canvas is strategically positioned at the windshield's location. This addition simplifies the task of transforming coordinates from the real-world system to the local screen system for landmark anchors, ensuring accurate projection and orientation representation of the landmarks.

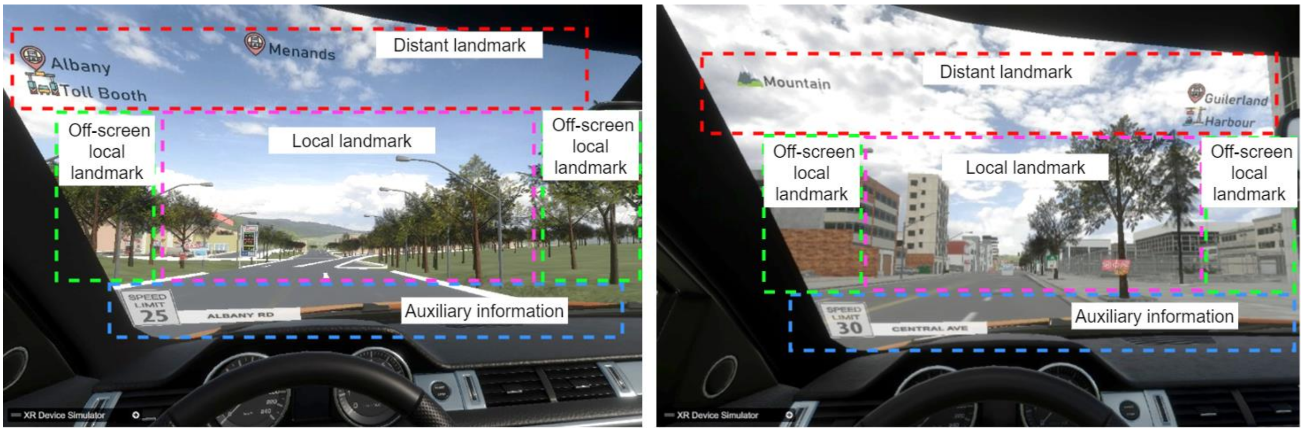

Figure 7: AR displays on the windshield (left: highway, right: local road)

In the AR system designed for immersive autonomous driving simulations, distant landmarks receive a more comprehensive representation on the top portion of the windshield. This area features both an icon and the name of the landmark, strategically placed in a section generally clear of crucial environmental data. This placement not only efficiently uses the available space but also supports spatial learning by using the upper part of the windshield to display global information (Steck & Mallot, 2000).

Conversely, local landmarks in the AR system are depicted in a more simplified manner. Only the icons of these landmarks appear on an image layer, which is centrally located in the middle of the canvas. This design approach effectively reduces visual clutter and avoids overwhelming the driver with excessive information in their immediate field of view, thereby reducing the risk of distraction.

Additionally, the system thoughtfully displays auxiliary information at the bottom of the windshield, such as the road name and speed limit. This information is dynamically updated based on the vehicle’s location and the characteristics of different roads, ensuring that drivers receive critical information without being overwhelmed. This sophisticated integration of various AR elements not only enhances the overall driving simulation experience but also contributes significantly to the learning process within this simulated environment.

3.1.3 Eye-tracking and VR setup

In this research, eye-tracking data was cooperated to enhance our understanding of learning performance. Eye-tracking technology offers several benefits over traditional questionnaires and tests. It provides real-time, objective data on where and how long subjects focus their attention, which is particularly valuable in understanding the cognitive processes involved in learning (Adhanom et al., 2023). In this research, eye-tracking data collected by Varjo Aero includes information on pupil situations, fixation count, and dwell time, offering insights into the visual attention patterns of subjects.

However, relying solely on eye-tracking data for interpreting VR experimental results has its limitation. While eye-tracking offers valuable insights, it primarily focuses on visual attention and may not capture the complete cognitive processing involved (Shadiev & Li, 2023). To address this, eye-tracking data is integrated with questionnaires. This approach allowed us to gain a more comprehensive understanding of spatial knowledge learning performance, especially in the context of evaluating cognitive processing in simulated AR windshields for drivers (Jeong et al., 2022).

In a practical application, the Varjo Aero VR headset is combined with its software development kit (SDK) in Unity to collect data. Varjo SDK for Unity includes pre-made scripts for eye-tracking data collection, which are instrumental in efficiently gathering and exporting eye-tracking data for subsequent statistical analysis. This setup was chosen for its robustness and convenience for research needs in autonomous driving simulation.

3.2 Participants and experimental design

This research project initially aimed to recruit 40 volunteers. Ultimately, 34 individuals enrolled and participated in the VR experiments. The experiment received approval from Wageningen University & Research and the Laboratory of Geo-Information Science and Remote Sensing, adhering to all necessary legal and ethical guidelines.

The two-by-two design for this study includes two variables: road type (highway vs. local road; see Figure 4) and AR landmark condition (AR present (Figure 5) vs. AR absent). In the experiment, volunteers were divided into two groups. Each participant was assigned to one of two conditions: either 1) a highway without an AR landmark and a local road with an AR landmark, or 2) a local road without an AR landmark and a highway with an AR landmark. The road types are arranged in reverse order for each condition to counterbalance the order effect. For each condition, the spatial knowledge task survey varied in its settings. Participants were required to complete only one survey, corresponding to their assigned group, as detailed in Appendix 1.

In total, 60 participants participated in this experiment, with 17 in each condition: seven men and ten women in condition one and three men and 14 women in condition two (Figure 8). In general, 30 participants are full-time students (28 with bachelor's degrees and two with graduate degrees) in Wageningen University, and four are full-time employees (three work in Wageningen University & Research and one in another company). In condition one, volunteers were first assigned to the highway without an AR landmark and followed the local road environment with an AR landmark. In condition two, volunteers are on the local road without an AR landmark display environment and on the highway with an AR landmark environment.

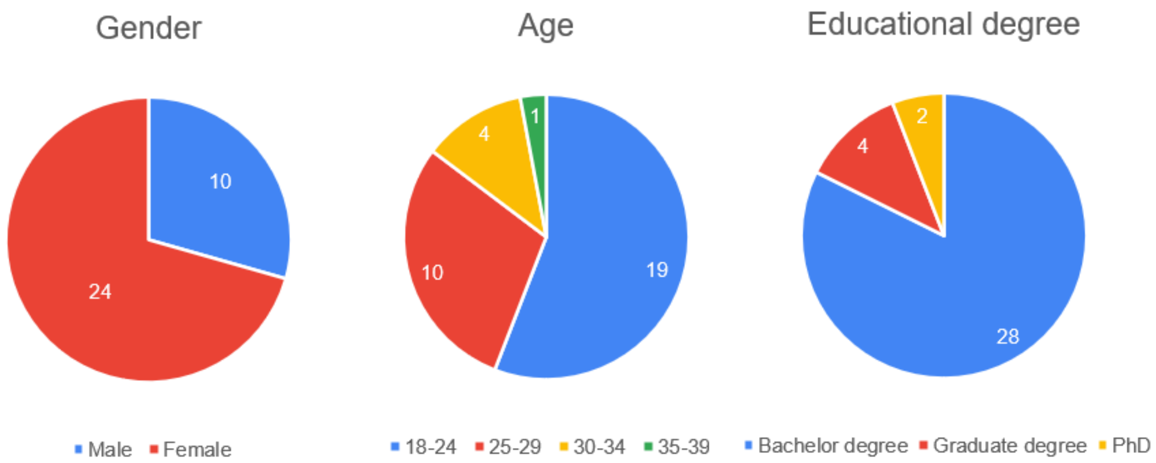

Figure 8: The gender, age and educational degree of the participants

Out of all, 19 participants are within the age range of 18–24, ten are within the age range of 25–29, four are within the age range of 30–34, and one is within the age range of 35–39. Regarding education level, only four participants have less than a high school diploma, 14 have bachelor's degrees, 13 have graduate degrees, and one finished a PhD degree.

3.3 Procedure and Measures

The experimental procedure was conducted in a laboratory room, where participants completed the survey and engaged in an immersive autonomous driving experience using the Varjo Aero headset. In immersive experiment, each participant spent 20 minutes on average completing an autonomous driving simulation using the Varjo Aero headset. The VR headset was crucial for capturing eye-tracking data, which was then saved in .csv format for thorough data analysis.

The experimenter had each participant peruse the consent form and give verbal consent as soon as they arrived at the lab. Every participant gave their implicit agreement to take part in the survey and experiment (experimental procedure indicated in Figure 9). Prior to the VR experience, volunteers are required to complete a pre-experiment questionnaire evaluating their self-assessed spatial knowledge and directional abilities, which were based on the Santa Barbara Sense of Direction Scale (SBSOD) questionnaire (Hegarty, 2002). Upon completing a scenario within the VR environment, each participant was expected to undertake three specific tasks. As the study involved two distinct self-driving scenarios, a total of six tasks were undertaken by each volunteer, the results of which contributed to the analysis of spatial knowledge acquisition.

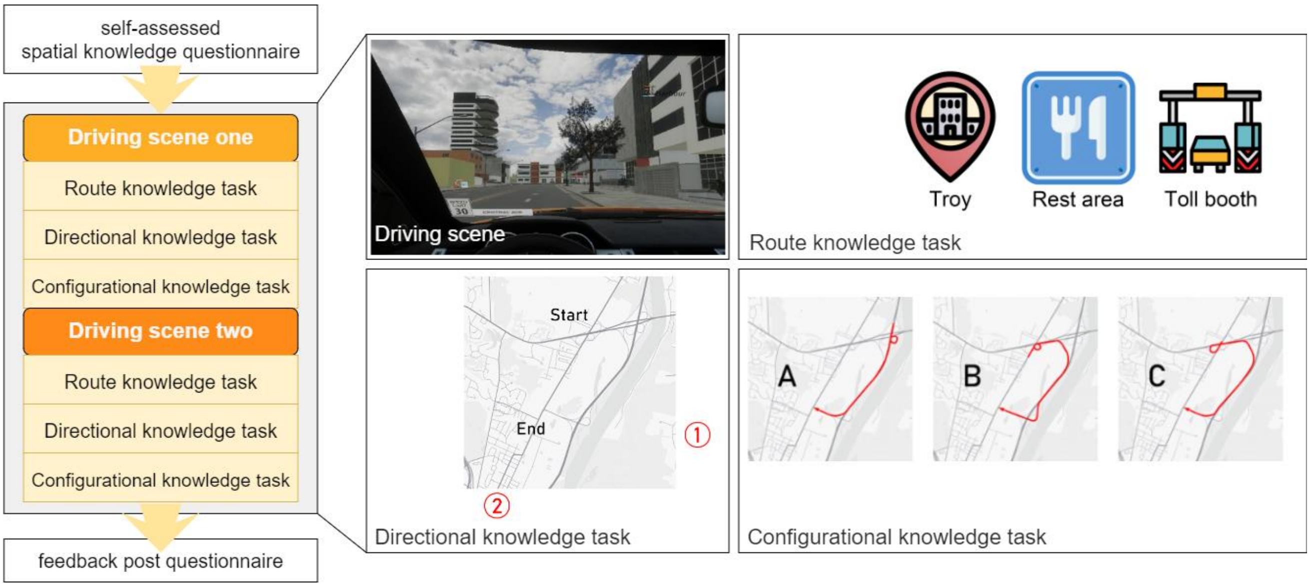

Figure 9: Experimental procedure schematic diagram

The research specifically includes three varieties of tasks to evaluate the spatial knowledge acquisition of the participants by processing distant and local landmark information: route knowledge, directional knowledge, and configurational knowledge (example tasks are shown in Figure 10). Upon conclusion of the trials, two key metrics are recorded: the accuracy of responses to the spatial knowledge questions and the time taken to answer each question. These metrics provide valuable insights into the effectiveness of the VR simulation in enhancing spatial understanding and wayfinding abilities.

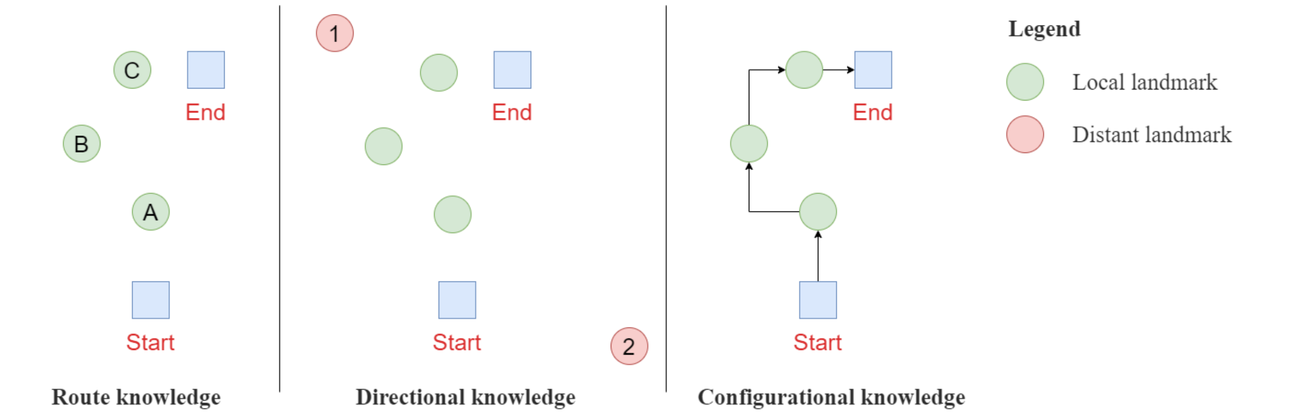

Figure 10: Example tasks for three level of spatial knowledge

Three spatial knowledge formation tasks are set as multiple-choice questions (details in Appendix 1). Task one asks participants to select the correct sequence of the appearance of landmarks with a focus on representing the route knowledge learning performance (e.g., from landmark A to B to C; see the left side of Figure 10). Participants need to recall the order of the landmarks along the travelled route. In the highway environment, both the local and distant landmarks are used for route knowledge testing, while only local landmarks are used on local roads. To enhance the comparability between AR and AR absence conditions, in virtual environments the information of local landmarks is indicated by the buildings along with custom-building signs, and distant landmarks are indicated with traffic signs along the road. Furthermore, in the spatial knowledge testing phase, for the AR absence condition only landmarks names are displayed in multiple choice questions, while both landmark names and icons are presented for the AR condition.

The second task is to test the directional knowledge learning ability. Two distant locations need an accurate name displayed in a figure (middle task in the Figure 10). Participants are asked to match the names of the distant landmarks they encountered in the autonomous driving scene. Depending on the conditions, the distant locations are indicated by AR landmarks or the environment's traffic signs.

For the configurational spatial knowledge testing, as shown by the right of Figure 10, the task (third) asks participants to choose the correct route configuration out of three options with a similar topology. Individuals need to memorize the significant features of the traffic roads and attempt to recall the directions of turning points that contribute to the topological shapes.

Specifically, there are three output eye-tracking metrics to assist the experiment and understand how individuals navigate and process spatial information:

1) Average fixation duration: this metric measures the time span for which the eyes remain steadily focused on a specific point, offering insights into which landmarks or road types capture the most attention or require extensive cognitive processing (Negi & Mitra, 2020);

2) Fixation count: this refers to the number of times the eyes fixate on a specific point or area (Mahanama et al., 2022). A higher fixation count might indicate either confusion or interest in the observed element (Kwon & Kim, 2021);

3) Dwell time: this quantifies the duration spent looking at a particular area of interest (AOI) (Holmqvist et al., 2011). Longer dwell times can suggest a high level of interest in a region, whereas shorter durations may imply that other areas are more engaging or relevant.

These three metrics are specifically selected and calculated based on fixation object names to offer insights into user behaviour and performance.

Additionally, participants are asked to provide their insights through a post-experiment questionnaire (Appendix 2). Their responses, crucial for refining the experimental design and VR simulation experience, encompass their overall impressions and reactions as well as motion sickness (how uncomfortable they felt after finishing the VR experiment). This feedback was used to provide guidelines that other relative research could consider on how to improve the usability of VR simulations as a research tool in assessing spatial knowledge.

3.4 Data analysis

3.4.1 Data preprocessing

Upon gathering all necessary data, it is crucial to manually convert the responses from multiple-choice format into a scale of relative accuracy for a detailed analysis of spatial knowledge (original results in Appendix 3 and pre-processing data in Appendix 4).

In the first task, which involves ordering three landmarks, the accuracy scale is defined as follows: 0 indicates that none of the landmark orders is correct, whereas a score of 1 signifies that the sequence of landmarks is accurately identified. To align with pre-processing data in original experiment by R. Li (2023), a partial score of 0.2 is allocated for a partially correct order, considering that three landmarks are evaluated in this task. Specifically, if participants correctly identify the sequence of two adjacent landmarks, they are awarded a 0.2 score.

The scoring is slightly different for the second task, which assesses the positioning of two distant landmarks. Each landmark position is assigned a value of 0.5. Therefore, a total score of 0 is given for completely incorrect positions and a score of 1 for entirely correct positions of the two distant landmarks. A score of 0.5 is designated for partially correct answers, applicable when the participant accurately identifies the position of one out of the two landmarks.

The scoring system is straightforward in the third task, with only two possible scores: 0 or 1. The participant receives a score of 0 if they select an incorrect topological shape and a score of 1 for a correct selection. This binary scoring system simplifies assessing the participant's understanding of topological relationships.

For eye-tracking data pre-processing, the Velocity-Threshold Identification (I-VT) fixation classification algorithm is employed (Hartridge & Thomson, 1948; Olsen, 2012). This algorithm, based on velocity threshold of 130 degrees/ second, distinguishes between fixations and saccades by categorizing eye movement data points as either stationary fixations or rapid saccades (Andersson et al., 2017; Birawo & Kasprowski, 2022). In the detailed process of classifying the eye-tracking data, each data point is meticulously evaluated based on its velocity. When the velocity of a particular point falls below a predefined threshold, it is identified as a fixation (Orsi & Geneletti, 2010). Conversely, should the velocity surpass this threshold, the movement is categorized as a saccade (Orsi & Geneletti, 2010).

Within the context of this study, there is a need to filter out the saccades to hold the more relevant fixation data through I-VT filter (Olsen, 2012). To optimize this fixation data, the algorithm undertakes maximum time between fixations of 75ms and maximum angle between fixations of 0.5 degrees for merging adjacent fixations while simultaneously discarding any fixations of brief duration less than a minimum fixation duration threshold of 150ms (Chen & Hou, 2022; Olsen, 2012). Thereby enhancing the quality and efficiency of the data for subsequent analysis.

To address the variation in eye-tracking metrics (dwell time and fixation count) influenced by the duration of the experiment, a normalization procedure has been applied to the data collected from the highway environment experiments. The dwell duration and fixation count in the highway setting are multiplied by 0.75 since the local road scenarios take around three minutes to complete, but the highway scenarios usually last four minutes. The adjustment aims to mitigate data discrepancies arising from the different experiment lengths, thereby ensuring a more meaningful comparison between the two environments.

3.4.2 Statistical analysis

The first research question (RQ1) is about to research the impact of AR landmarks and road types for task completion times and spatial knowledge task accuracies during the immersive driving simulation. To answer this question, six two-way analysis of variance (ANOVA) tests are applied (Table 1).

Table 1: Statistical analysis methodologies and data components for three research questions

Method	Description	Research target	Balanced design
two-way analysis of variance (two-way ANOVA)	examine the interaction effects between the two independent variables on the dependent variable	RQ1, RQ2	yes
cumulative link mixed model (CLMM)	evaluate the significance of fixed effects and random effects, focusing on the ordinal dependent variable	RQ2, RQ3	no

For the second research question (RQ2), the eye-tracking data, such as average fixation duration, dwell time, and fixation count, are the additional variances to explain the performance differences across road types and landmark types according to the results of two-way ANOVA tests (eye-tracking metrics attached in Appendix 5). The cumulative link mixed models (CLMMs) are conducted to explore the impact from individual eye movement behaviour to spatial knowledge accuracy (treated as the ordinal scale) in immersive autonomous driving experiments (Table 1).

Also, for the third research question (RQ3), the CLMMs are conducted to cross-validate results in video and VR experiments. Specifically, the differences between the two experiments should be compared by using several generalized linear mixed models to examine the joint effects of the experimentation method (VR + in-person vs. video + online) on spatial learning.

After conducting the statistical analysis methods, two-way ANOVA and CLMM, the pairwise post hoc test is conducted to examine all possible pairwise comparisons between groups to pinpoint exactly which differences are statistically significant. Thereby it could provide a clear understanding of how the factors interact with each other. Also, in multiple comparisons, the likelihood of a Type I error (false positive) increases (McHugh, 2011). Post hoc tests are designed to control the familywise error rate, ensuring that the probability of making one or more Type I errors is kept within a desired level, thus maintaining the integrity of the statistical analysis (McHugh, 2011).

3.4.3 Research question one

A statistical technique called the two-way ANOVA, which tests how two between-subjects independent variables affect the dependent variable in combination, is expected to be utilized in RQ1 (Frude, 1987). The categorical variables, road types (highway vs. local road) and AR landmark conditions (AR absent vs. AR present), are set as between-subject factors. In this instance, six dependent variables are route knowledge examining task completion time, directional knowledge examining task completion time, configurational knowledge examining task completion time, route knowledge task accuracy, directional knowledge task accuracy, and configuration knowledge task accuracy.

ANOVA is a statistical method used for comparing the means across three or more groups (Frude, 1987; Gelman, 2005). Specifically, two-way ANOVA can analyse the interaction effects of variables, such as road type and AR landmark condition, on performance characteristics. However, it is important to note that if the interaction effects of the independent variables are not significant, two-way ANOVA primarily indicates the overall differences attributable to one independent variable alone (Alin & Kurt, 2006; H.-Y. Kim, 2014). In the post hoc comparisons, the Bonferroni correction was applied with interaction effects, which adjusts the significance level when performing multiple comparisons (McHugh, 2011).

3.4.4 Research question two

Two comprehensive statistical analysis models are conducted to study RQ2 in five separating gaze areas, two-way ANOVA models with post hoc comparisons and CLMM in logit function.

The two-way ANOVA models examined the influence of road type (highway vs. local road) and AR landmark condition (AR present vs. AR absent) on participant's eye movement performances. The interaction between these two factors was also a critical aspect of the analysis. The results from two-way ANOVA tests provided a clear understanding of whether the differences observed in the means were statistically significant, which is crucial in determining the effect of road type and AR landmark condition on eye movement. To further validate and elucidate the findings from the two-way ANOVA tests, post hoc Bonferroni comparisons are conducted.

In addition to the ANOVA models, CLMMs play a significant role in tracing the effects of eye-tracking metrics on spatial knowledge task accuracy. In CLMM, ordinal logistic regression is commonly employed to evaluate the significance of fixed effects and random effects, focusing on the ordinal nature of the dependent variables (Christensen, n.d.; McCullagh, 1980).This statistical approach is particularly useful for understanding complex relationships between ordinal dependent variables and independent variables. In this research, the dependent variables for spatial knowledge task accuracies are three-level or two-level ordinal categories.

These CLMMs are applied to five separate gaze areas, providing a detailed understanding of how different aspects of eye movement relate to task performance. The results are instrumental in identifying significant eye-tracking metrics that acted as factors influencing the dependent variables, and it improve understanding the relationship between eye movements (independent variables) and spatial knowledge task accuracy (dependent variables).

3.4.5 Research question three

CLMM is particularly suitable for data with ordinal categories and unbalanced samples. In Li's reference research, 60 volunteers donated 120 samples for three types of spatial knowledge accuracy assessment. In contrast, this research only includes 34 volunteers and 68 samples. To adjust for the unbalanced sample sizes between the two studies and to account for random effects, the CLMM is chosen for its robustness in handling ordinal data and mixed effects, compared to models like the generalized linear model or linear mixed model (Taylor et al., 2023).

CLMM examines the differences in experimental findings and explore the interaction effects of the experimentation method (VR + in-person vs. video + online) to address RQ3, and post hoc Bonferroni comparisons are conducted to reveal the value of the means in different groups. Specifically, the dependent variables in CLMM are road type, AR landmark condition, and the experimentation method. This approach is crucial for identifying disparities between experiment results from online video participants and in-person VR participants. Focusing on interaction effects in CLMM provides detailed insights, especially in understanding the differences in experimental outcomes based on the various methods of experimentation.

Additionally, since the data comes from multiple participants, we include a random intercept for subjects to capture individual variability. Along with the fixed effects, selecting appropriate link functions is essential in CLMM. For ordinal outcomes like accuracy levels, appropriate ordinal link functions, such as logit, is used to model the ordinal nature of the responses.

4 Results

The results of this study are present in three sections (aligned with three research questions): First, we examine the impacts of road type (highway vs. local road) and AR landmark condition (AR absent vs. AR present) on accuracy and time performance; then, we observe the differs in the eye-tracking metrics and examine the patterns of metrics in spatial knowledge accuracy; finally, we examine the joint effects of the experimentation method (VR + in-person vs. video + online), road type, and AR landmark condition. Additionally, the discomfort and motion sickness conditions after experiencing VR equipment collected from the post-questionnaire are revealed in the last subsection.

In interpreting the p-value, which displays the significant differences between the groups selected for the null hypothesis, distinct p-value ranges are substituted to offer a relative gauge of the persuasiveness of the evidence (Ganesh & Cave, 2018). $P < 0.001$ in this study denotes extremely strong support for the null hypothesis, $p < 0.01$ for strong effect, $p < 0.05$ for moderate effect, and $p < 0.1$ for possible effect (Ganesh & Cave, 2018). The asterisks next to the p-values denote the level of significance, with more asterisks indicating higher statistical significance.

4.1 Accuracy and time performances

The study methodically evaluated the accuracy and time performance of two independent variables: road type and AR landmark condition. This evaluation included six two-way ANOVAs (Table 2) supplemented with pairwise post hoc analyses (Figure 11 and Figure 12). These statistical tests sought to determine the significance of observed discrepancies in the data.

Table 2: Two-way ANOVA between subjects (road type and AR landmark condition) in accuracy and time performance of spatial knowledge tasks

Two-way ANOVA						
Dependent variable	**Factor**	**DF**	**MS**	**F-value**	**p-value**	**η2**
Route knowledge task accuracy	Road type (R)	1	0.038	0.231	0.632	0.003
	AR landmark condition (A)	1	2.562	15.733	**0.0002*** **	0.196
	R * A	1	0.021	0.130	0.720	0.002
Directional knowledge task accuracy	Road type (R)	1	0.033	0.186	0.668	0.003
	AR landmark condition (A)	1	0.827	4.639	**0.0350***	0.066
	R * A	1	0.298	1.670	0.201	0.024
Configurational knowledge task accuracy	Road type (R)	1	2.118	9.846	**0.0026****	0.125
	AR landmark condition (A)	1	0.529	2.462	0.122	0.031
	R * A	1	0.529	2.462	0.122	0.031
Route knowledge task time	Road type (R)	1	168.368	1.029	0.314	0.013
	AR landmark condition (A)	1	2460.015	15.033	**0.0002*** **	0.187
	R * A	1	66.015	0.403	0.528	0.005
Directional knowledge task time	Road type (R)	1	2046.015	2.863	0.096	0.042
	AR landmark condition (A)	1	181.191	0.254	0.616	0.004
	R * A	1	371.779	0.520	0.473	0.008
Configurational knowledge task time	Road type (R)	1	1980.721	6.576	**0.012***	0.087
	AR landmark condition (A)	1	1496.485	4.968	**0.0293***	0.066
	R * A	1	41.309	0.137	0.712	0.002

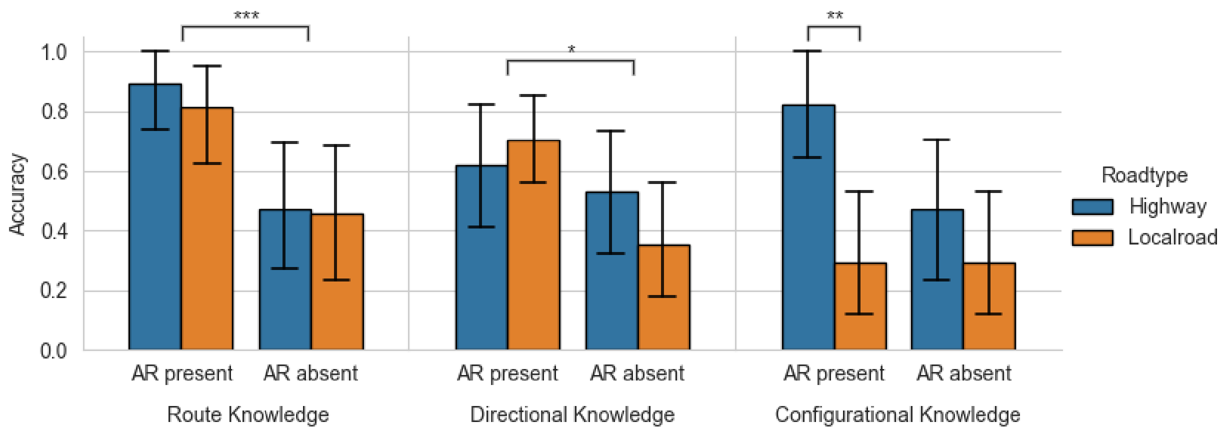

Figure 11: Pairwise post hoc comparisons between subjects (road type and AR landmark condition) by significant differences in accuracy of spatial knowledge tasks

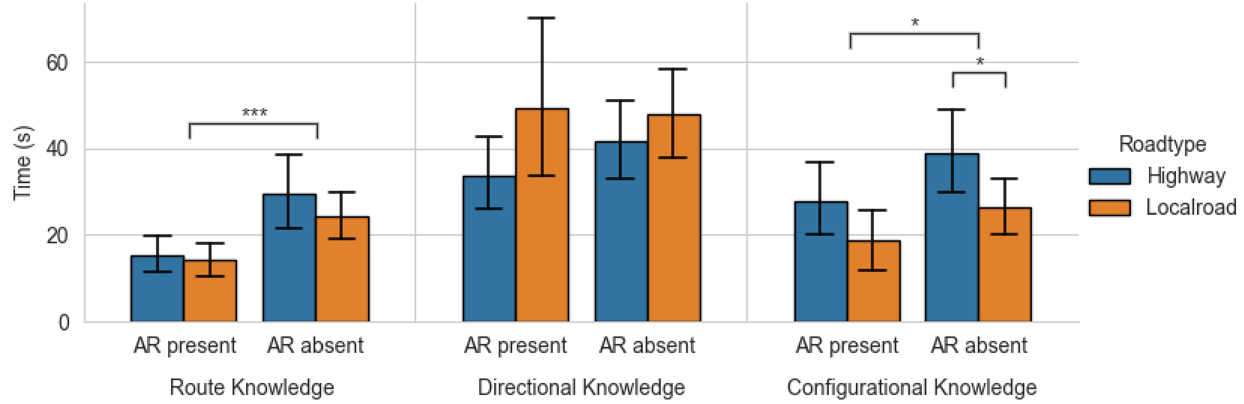

Figure 12: Pairwise post hoc comparisons between subjects (road type and AR landmark condition) by significant differences in time performance of spatial knowledge tasks

Initially, there are no significant interactive effects for two independent variables (road type and AR landmark condition) in two-way ANOVA, and only the overall differences indicated to one independent variable alone, shown in Table 2: Two-way ANOVA between subjects (road type and AR landmark condition) in accuracy and time performance of spatial knowledge tasks. For route knowledge, revealed from recalling the appearance order of landmarks, the accuracy is strongly influenced by the AR landmark condition [F (1, 68) = 15.73, p = 0.0002, η^2 = 0.196]. From pairwise post hoc comparison (details revealed in Figure 11 and Figure 12), the participants revealed better performance in route-level accuracy with AR landmark display on the windshield (M = 0.85, SE = 0.06) for all road types of driving environments. Without AR display, route accuracy in all driving environments is lower (M = 0.47, SE = 0.08). Also, the AR landmark display condition reveals significant differences for the time spent recalling the landmarks' order [F (1, 68) = 15.03, p = 0.0002, $\eta 2$ = 0.187]. With AR landmarks, time spent on route-level knowledge tasks is shorter (M = 14.82, SE = 1.47), and participants took longer time on the same task without the AR landmarks (M = 26.85, SE =2.72).

For Directional knowledge of distant locations, the sole effect of task accuracy, which reveals a moderate difference, is the AR landmark condition [F (1, 68) = 4.64, p = 0.035, η^2 = 0.066]. As shown in Table 2: Two-way ANOVA between subjects (road type and AR landmark condition) in accuracy and time performance of spatial knowledge tasks, participants with AR landmarks had a significant advantage in visualizing the correct locations of distant landmarks (*M* = 0.66, *SE* = 0.07), which leads to higher accuracy in directional knowledge tasks and a better understanding of spatial orientation in VR experiences. For participants with the conditions without AR landmarks displayed on the windshield, lower accuracy for directional knowledge (*M* = 0.44, *SE* = 0.08) revealed a poorer memory of the orientation of distant landmarks. Additionally, the differences in road type and AR landmark condition for directional knowledge examination time in this study are not significant.

The two-way ANOVA analysis results, shown in Table 2: Two-way ANOVA between subjects (road type and AR landmark condition) in accuracy and time performance of spatial knowledge tasks, revealed a very strong significant difference on configurational accuracy between road types [F (1, 68) = 9.85, p = 0.0026, η^2 = 0.125]. Based on the pairwise post hoc comparison, participants who travelled on the highway had better accuracy in configurational-level tasks (*M* = 0.65, *SE* = 0.08) than those who travelled on the local road (*M* = 0.29, *SE* = 0.08). For the time to recall the topology of the travelled route, both road type [F (1, 68) = 6.58, p = 0.012, $\eta 2$ = 0.087] and AR landmarks condition [F (1, 68) = 4.97, p = 0.0293, $\eta 2$ = 0.066] have moderately significant differences on time to answer the configurational-level task. With AR landmarks, participants in the highway environment spent longer time (*M* = 33.41, *SE* = 3.46) than those in the local road environment (*M* = 22.62, *SE* = 2.57). Regardless of the road type, participants with AR landmarks presented on the windshield spent shorter time (*M* = 23.32, *SE* = 2.94) than those without AR landmarks (*M* = 32.71, *SE* = 3.22).

4.2 Eye-tracking metrics

Fifteen two-way ANOVA models were utilized to determine whether there are any statistically significant differences between the means of road type (highway vs. local road) and AR landmark condition (AR present vs. AR absent) and their interaction on participants' eye movement performances in the VR experiments. The results from two-way ANOVA tests were supported by post hoc Bonferroni comparisons, revealed the value of the means in different groups.

For the top portion of the windshield (which displays distant landmarks in the AR present condition), see in Table 3, a statistically moderate significant difference was shown in average fixation duration between road types [F (1, 68) = 4.449, p = 0.037, η^2 = 0.062]. The Bonferroni post hoc comparison, revealed in Figure 13, indicates that average fixation duration is significantly greater for highways (*M* = 644.81, *SE* = 25.88) compared to local roads (*M* = 567.05, *SE* = 26.66). Dwell time is significantly influenced by two main factors: Road type [F (1, 68) =5.656, p = 0.020, η^2 = 0.065] and AR landmark condition [F (1, 68) =4.155, p = 0.045, η^2 = 0.048], and the interaction between road type and AR landmark condition [F (1, 68) = 10.324, p = 0.002, η^2 = 0.118]. Dwell time is significantly longer when AR landmarks are present (*M* = 49283, *SE* = 3735.13) compared to absent on highways (*M* = 27804.00, *SE* = 3494.40), and for AR absent on highways (*M* = 27804.00, *SE* = 14407.8) dwell time is less than for AR absent on local roads (*M* =51070.00, *SE* = 4716.71). For Fixation count, there were statistically significant effects of the road type [F (1, 68) = 14.034, $p < 0.001$, η^2 = 0.150]. This indicates that participants had more fixations on local roads (*M* = 89.943, *SE* = 6.74) compared to highway environments (*M* = 60.98, *SE* = 5.10). The interaction between road type and AR landmark condition was also significant [F (1, 68) = 9.955, p = 0.002, η^2 = 0.106]. This suggests a differential effect of the AR landmark condition on fixation counts depending on the road type. Specifically, there were more fixations on highways when the AR landmark was present (*M* = 79.33, *SE* = 5.82) than absent (*M* = 42.63, *SE* = 5.59), and this effect was greater on local roads (*M* = 96.00, *SE* = 10.68) compared to highways (*M* = 42.63, *SE* = 5.59) in AR absent conditions.

Table 3: Two-way ANOVA results for top area with eye-tracking metrics

Two-way ANOVA						
Gaze Area	**Dependent Variable**	**Factor**	**DF**	**F-value**	**p-value**	**η2**
Top	Average fixation duration	Road type (R)	1	4.449	**0.039***	0.062
		AR landmark condition (A)	1	0.330	0.567	0.005
		R * A	1	0.315	0.577	0.004
	Dwell time	Road type (R)	1	5.656	**0.020***	0.065
		AR landmark condition (A)	1	4.155	**0.045***	0.048
		R * A	1	10.324	**0.002****	0.118
	Fixation count	Road type (R)	1	14.034	**0.000*****	0.150
		AR landmark condition (A)	1	2.783	0.100	0.030
		R * A	1	9.955	**0.002****	0.106

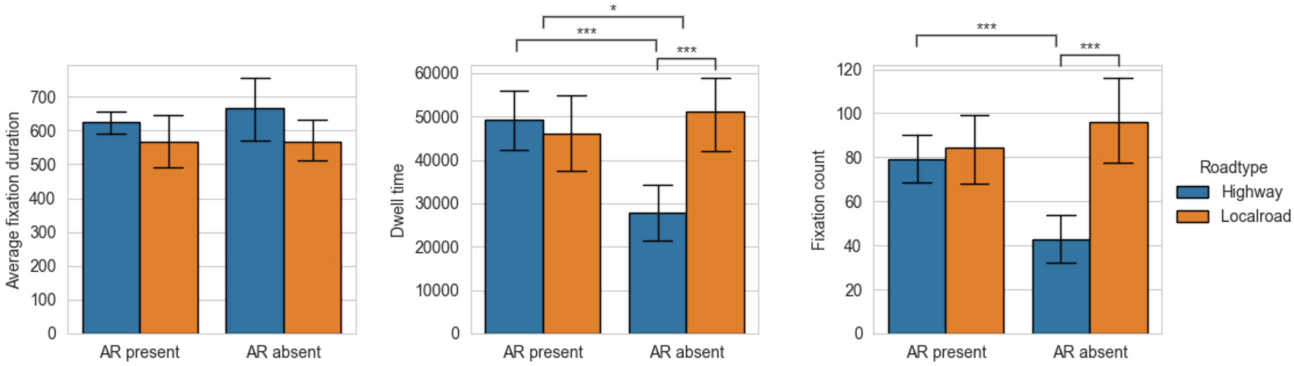

Figure 13: Pairwise post-hoc comparisons for top area with eye-tracking metrics

For the gaze area in the middle centre (displaying local landmarks in the AR present condition), a distinct difference in attention allocation based on the type of road observed in Table 4 and Figure 14. The variable average fixation duration is significantly affected by the road type [F (1, 68) = 30.393, $p < 0.001$, $\eta^2 = 0.309$], indicating a strong effect where gazes are more focused on highways (*M* = 743.64, *SE* = 22.82) compared to local roads (*M* = 575.68, *SE* = 20.71). Dwell time, which represents the duration of gaze, also shows a significant effect of road type [F (1, 68) = 7.454, p = 0.008, $\eta^2 = 0.100$], with longer dwell times on highways (*M* = 132788.00, *SE* = 7001.73) than on local roads (*M* = 110010.00, *SE* = 4585.49).

Table 4: Two-way ANOVA results for middle centre area with eye-tracking metrics

Two-way ANOVA						
Gaze Area	**Dependent Variable**	**Factor**	**DF**	**F-value**	**p-value**	**η2**
Middle centre	Average fixation duration	Road type (R)	1	30.393	**0.000*****	0.309
		AR landmark condition (A)	1	0.569	0.453	0.006
		R * A	1	0.431	0.514	0.004
	Dwell time	Road type (R)	1	7.454	**0.008****	0.100
		AR landmark condition (A)	1	0.024	0.878	0.000
		R * A	1	0.000	0.997	0.000
	Fixation count	Road type (R)	1	1.521	0.222	0.022
		AR landmark condition (A)	1	0.090	0.766	0.001
		R * A	1	0.036	0.849	0.001

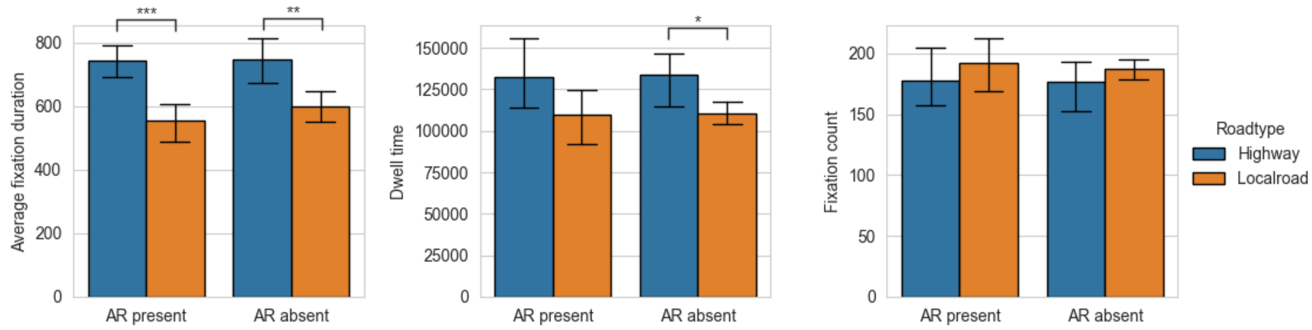

Figure 14: Pairwise post-hoc comparisons for middle centre area with eye-tracking metrics

The analysis indicated a significant main effect of road type on several gaze variables at the left edge (see in Table 5 and Figure 15). For the average fixation duration, participants had a significantly higher value when observing highways (*M* = 646.00, *SE* = 36.90) compared to local roads (*M* = 524.95, *SE* = 31.18). This suggests a moderate effect size, indicating that road type accounts for 8.7% of the variance in average fixation duration [F (1, 68) = 6.425, p = 0.014, η^2 = 0.087]. The dwell time was significantly different between road types [F (1, 68) = 17.413, p < 0.001, η^2 = 0.193], with more time spent on local roads (*M* = 27931.50, *SE* = 1733.93) than highways (*M* = 19583.01, *SE* = 1213.68). For the fixation count, the results were significant [F (1, 68) = 25.161, p < 0.001, η^2 = 0.257]. But in this case, participants had a lower fixation count for highways (*M* =32.44, *SE* = 2.72) compared to local roads (*M* = 55.46, *SE* = 4.01), suggesting that participants may have had fewer but more focused fixations on highways.

Table 5: Two-way ANOVA results for left edge area with eye-tracking metrics

Two-way ANOVA						
Gaze Area	**Dependent Variable**	**Factor**	**DF**	**F-value**	**p-value**	**η2**
Left edge	Average fixation duration	Road type (R)	1	6.425	**0.014***	0.087
		AR landmark condition (A)	1	0.188	0.666	0.003
		R * A	1	0.287	0.594	0.004
	Dwell time	Road type (R)	1	17.413	**0.000*****	0.193
		AR landmark condition (A)	1	1.992	0.163	0.022
		R * A	1	3.920	0.052	0.043
	Fixation count	Road type (R)	1	25.161	**0.000*****	0.257
		AR landmark condition (A)	1	2.025	0.159	0.021
		R * A	1	3.726	0.058	0.038

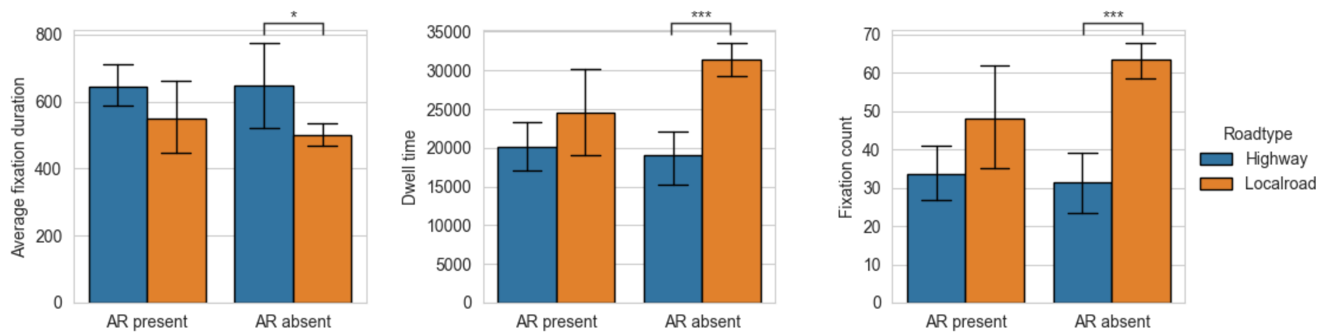

Figure 15: Pairwise post-hoc comparisons for left edge area with eye-tracking metrics

In the right edge area, the effect of road type on average fixation duration was statistically significant [F (1, 68) = 4.661, p = 0.034, η^2 = 0.062], see in Table 6 and Figure 16, which is higher for highway (*M* = 788.60, *SE* = 42.43) compared to local road (*M* = 673.32, *SE* = 34.48). There was a highly significant effect of road type on dwell time [F (1, 68) = 17.978, p < 0.001, $\eta^2 = 0.160$]. This indicates that road type has a substantial impact on dwell time, with significantly longer durations on highways (*M* = 22028.25, *SE* = 1279.98) than on local roads (*M* = 15329.9, *SE* = 1351.35). The presence of AR landmarks significantly affected dwell time [F (1, 68) = 15.034, p < 0.001, $\eta^2 = 0.108$]. Participants had shorter dwell time when AR landmarks were present (*M* = 18697.63, *SE* = 1978.14) compared to when they were absent (*M* = 26308.30, *SE* = 1712.81). There was a significant interaction between road type and AR landmark condition on dwell time [*F* (1, 68) = 19.937, $p < 0.001$, $\eta^2 = 0.177$]. This suggested a specific condition where the combination of local road and AR present (*M* = 9847.46, *SE* = 1275.43) leads to shorter dwell times compared to local road and AR absent condition (*M* = 21134.90, *SE* = 1391.94). And highways in general had longer dwell times with AR landmarks than local roads (*M* = 20660.85, *SE* = 1630.95). The road type also significantly influenced fixation count [*F* (1, 68) = 4.428, $p = 0.039$, $\eta^2 = 0.050$]. This signified that the road type is strongly associated with the number of fixations, with more fixations occurring on highways (*M* = 28.85, *SE* = 2.07) compared to local roads (*M* = 23.11, *SE* = 2.20). The presence of AR landmarks significantly affected the fixation count [*F* (1, 68) = 13.095, $p < 0.001$, $\eta^2 = 0.147$]. Participants had fewer fixations when AR landmarks were present (*M* = 21.24, *SE* = 1.94) compared to when they were absent (*M* = 30.95, *SE* = 2.11). The interaction effect was significant [*F* (1, 68) = 4.817, $p = 0.032$, $\eta^2 = 0.054$], exhibiting that fixation count decreased with the AR on local road environments (*M* = 15.56, *SE* = 1.99) compared to without AR conditions (*M* = 31.12, *SE* = 2.92), and participants gazed at the right edge more frequently on the highways in AR present conditions (*M* = 26.92, *SE* = 2.73) than on local roads.

Table 6: Two-way ANOVA results for right edge area with eye-tracking metrics

Two-way ANOVA						
Gaze Area	**Dependent Variable**	**Factor**	**DF**	**F-value**	**p-value**	**η2**
Right edge	Average fixation duration	Road type (R)	1	4.661	**0.034***	0.062
		AR landmark condition (A)	1	0.247	0.621	0.003
		R * A	1	2.719	0.104	0.036
	Dwell time	Road type (R)	1	17.978	**0.000*****	0.160
		AR landmark condition (A)	1	19.937	**0.000*****	0.177
		R * A	1	7.548	**0.007****	0.067
	Fixation count	Road type (R)	1	4.428	**0.039***	0.050
		AR landmark condition (A)	1	13.095	**0.000****	0.147
		R * A	1	4.817	**0.032***	0.054

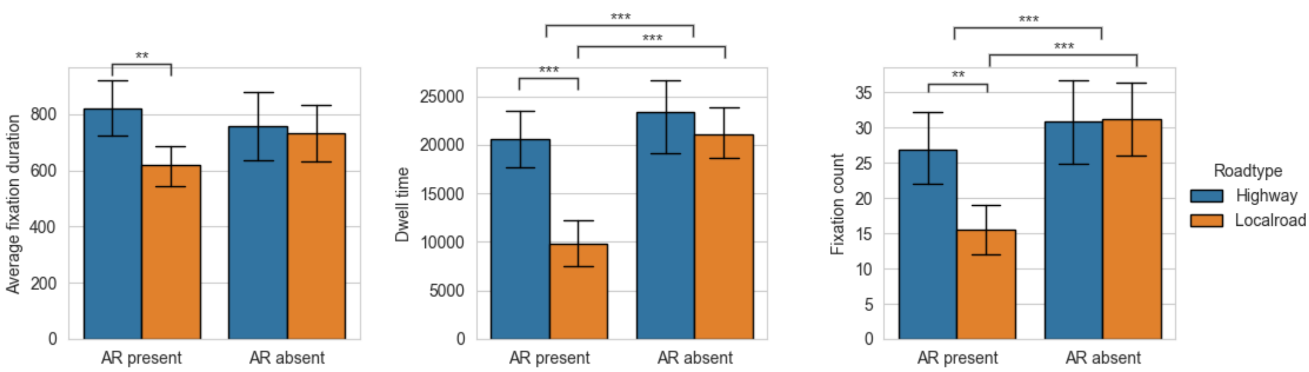

Figure 16: Pairwise post-hoc comparisons for right edge area with eye-tracking metrics

In the bottom area of the windshield (displaying auxiliary information in the AR present condition), the two-way ANOVA results in Table 7 for the variable average fixation duration with respect to the road type were highly significant [F (1, 68) = 27.167, p < 0.001, η^2 = 0.276], indicating a strong effect where the average fixation duration was significantly greater for highways (M = 940.70, SE = 67.43) compared to local roads (M = 534.52, SE = 43.54). This suggested that traffic signs in highways require longer fixation times for processing (details in Figure 17). For dwell time, the impact of road type [F (1, 68) = 14.431, p < 0.001, η^2 = 0.163] was also highly significant, showing that participants spent more time dwelling on highways (M = 19269.00, SE = 3367.48) than on local roads (M = 6638.08, SE = 1071.18). The AR landmark condition [F (1, 68) = 6.926, p = 0.011, η^2 = 0.078] had a significant effect, indicating that dwell time was longer when AR landmarks were present (M = 17310.00, SE = 3275.55) compared to when they were absent (M = 8653.63, SE = 1753.61). The fixation count showed a significant main effect of road type [F (1, 68) = 4.499, p = 0.003, η^2 = 0.051], with participants counting more fixations on highways (M = 20.92, SE = 3.75) than on local roads (M = 12.97, SE = 2.12). The effect of AR landmark condition [F (1, 68) = 16.265, p < 0.001, η^2 = 0.185] was highly significant, suggesting that the presence of AR landmarks significantly increased the number of fixations when on highways and local roads (AR present: M = 24.60, SE = 3.67; AR absent: M = 9.19, SE = 1.56).

Table 7: Two-way ANOVA results for bottom area with eye-tracking metrics

Two-way ANOVA						
Gaze Area	**Dependent Variable**	**Factor**	**DF**	**F-value**	**p-value**	**η2**
Bottom	Average fixation duration	Road type (R)	1	27.167	**0.000*** **	0.276
		AR landmark condition (A)	1	2.127	0.149	0.022
		R * A	1	1.990	0.163	0.020
	Dwell time	Road type (R)	1	14.431	**0.000*** **	0.163
		AR landmark condition (A)	1	6.926	**0.011***	0.078
		R * A	1	0.140	0.710	0.002
	Fixation count	Road type (R)	1	4.499	**0.003****	0.051
		AR landmark condition (A)	1	16.265	**0.000*** **	0.185
		R * A	1	0.003	0.959	0.000

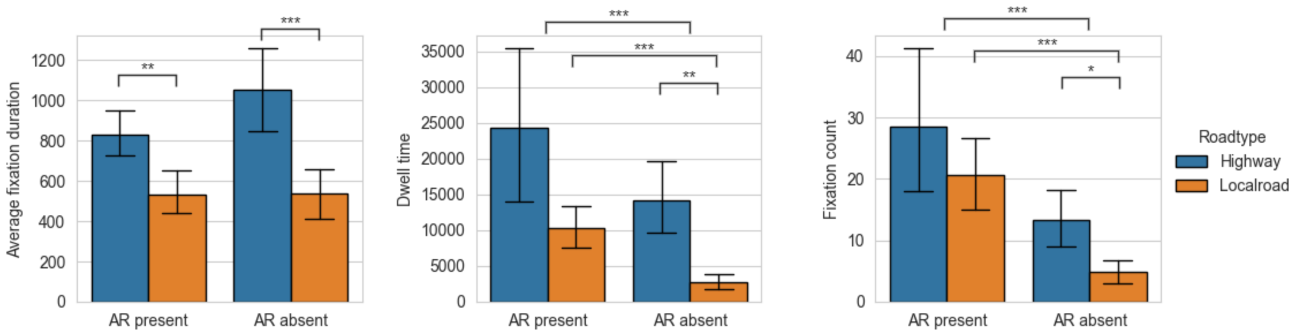

Figure 17: Pairwise post-hoc comparisons for bottom area with eye-tracking metrics

Fifteen CLMMs were used to trace the effect of eye-tracking metrics, in five separately gaze areas, on spatial knowledge task accuracy. The results listed in Table 8 indicated the significant eye-tracking metrics as factors, and the dependent variables affected by the independent factors.

Table 8: CLMM results for gaze areas with spatial knowledge task accuracy dependent variables and eye-tracking metric factors

Cumulative link mixed model					
Gaze area	**Variable**	**Factor**	**coef**	**z**	**p-value**
Top	Route knowledge task accuracy	Average fixation duration	-0.003	-1.094	0.274
		Dwell time	0.000	1.336	0.182
		Fixation count	-0.024	-1.130	0.259
	Directional knowledge task accuracy	Average fixation duration	-0.003	-1.361	0.173
		Dwell time	0.000	0.275	0.784
		Fixation count	-0.013	-0.730	0.466
	Configurational knowledge task accuracy	Average fixation duration	0.001	0.390	0.696
		Dwell time	0.000	-0.572	0.567
		Fixation count	0.002	0.083	0.934
Middle centre	Route knowledge task accuracy	Average fixation duration	-0.003	-1.349	0.177
		Dwell time	0.000	1.242	0.214
		Fixation count	-0.008	-0.812	0.417
	Directional knowledge task accuracy	Average fixation duration	-0.008	-3.852	**0.000*** **
		Dwell time	0.000	4.265	**0.000*** **
		Fixation count	-0.025	-3.152	**0.002** **
	Configurational knowledge task accuracy	Average fixation duration	-0.002	-0.991	0.322
		Dwell time	0.000	3.076	**0.002** **
		Fixation count	-0.015	-1.993	**0.046* **
Left edge	Route knowledge task accuracy	Average fixation duration	0.000	-0.190	0.849
		Dwell time	0.000	0.235	0.815
		Fixation count	-0.014	-0.401	0.688
	Directional knowledge task accuracy	Average fixation duration	0.000	0.021	0.983
		Dwell time	0.000	-0.515	0.606
		Fixation count	0.009	0.268	0.789
	Configurational knowledge task accuracy	Average fixation duration	0.003	1.348	0.178
		Dwell time	0.000	-1.117	0.264
		Fixation count	0.033	0.965	0.334
Right edge	Route knowledge task accuracy	Average fixation duration	0.000	-0.033	0.974
		Dwell time	0.000	-0.393	0.694
		Fixation count	0.014	0.216	0.829
	Directional knowledge task accuracy	Average fixation duration	0.001	0.352	0.725
		Dwell time	0.000	-0.310	0.756
		Fixation count	-0.021	-0.365	0.715
	Configurational knowledge task accuracy	Average fixation duration	0.002	0.891	0.373
		Dwell time	0.000	0.293	0.770
		Fixation count	-0.023	-0.322	0.748
Bottom	Route knowledge task accuracy	Average fixation duration	0.001	1.191	0.234
		Dwell time	0.000	-1.695	0.090
		Fixation count	0.140	2.230	**0.026* **
	Directional knowledge task accuracy	Average fixation duration	0.001	0.631	0.528
		Dwell time	0.000	-0.873	0.383
		Fixation count	0.075	1.692	0.091
	Configurational knowledge task accuracy	Average fixation duration	0.001	0.859	0.390
		Dwell time	0.000	0.190	0.849
		Fixation count	0.047	0.895	0.371

In the middle centre gaze area, a significant negative effect showed up between average fixation duration and directional knowledge task accuracy (z = -3.852, p < 0.001). This suggests that longer attentional focus duration is associated with lower directional knowledge task accuracy. There was a very strong significant effect of dwell time on directional knowledge task accuracy in middle centre area (z = 4.265, p < 0.001). This means longer dwell times are strongly associated with higher directional knowledge task accuracy. The significant effect of fixation counts on directional knowledge task accuracy indicated that an increase in fixation count is associated with better directional knowledge task accuracy (z = -3.152, p = 0.002).

There was a highly significant positive effect of dwell time on configurational knowledge task accuracy (z = 3.076, p = 0.002). Longer dwell times are strongly associated with better configurational knowledge task accuracy. The significant effect depicted on the fixation count number to configurational knowledge task accuracy (z = -1.993, p = 0.046). The increase in fixation count is associated with better configurational knowledge task accuracy.

The results of fixation count in bottom area suggests a marginally significant positive effect of fixation count on route knowledge task accuracy (z = 2.230, p = 0.026). This implies that as fixation count increases, there was a slight tendency for route knowledge accuracy to improve.

4.3 Experimentation method

Experimentation method expressed differences between original research by R. Li (2023) and this research. Three CLMMs were applied to examine the joint effects of the experimentation method (VR + in-person vs. video + online), road type, and AR landmark condition as the statistical analysis model. The medium and experimentation method, road type, and AR landmark condition were modelled as fixed effects of the test accuracies, and participants were the random effect. The CLMM results in Table 9 showed significant differences between the experimentation method, and the significant interaction effects on the experimentation method and road type or AR landmark condition are in light grey backgrounds. In the post hoc results, details shown in Figure 18, asterisk annotates the accuracy value differences in the experimentation method groups are significant.

Table 9: Cumulative link mixed model analysis of independent variables (experimentation method, road type and AR landmark condition)

Cumulative link mixed model					
Dependent variable	**Factor**	**DF**	**coef**	**z**	**p-values**
Route knowledge task accuracy	Road type (R)	1	0.530	0.532	0.595
	AR landmark condition (A)	1	2.145	2.296	0.022*
	Method of experimentation (M)	1	1.688	1.232	0.218
	R * A	1	-0.234	-0.177	0.859
	R * M	1	-1.230	-1.084	0.278
	A * M	1	-1.768	-1.677	0.094-
	R * A * M	1	1.259	0.853	0.394
Directional knowledge task accuracy	Road type (R)	1	-0.785	-1.067	0.286
	AR landmark condition (A)	1	-0.110	-0.15	0.881
	Method of experimentation (M)	1	4.339	3.219	0.001***
	R * A	1	2.020	1.755	0.079
	R * M	1	-2.759	-2.839	0.005**
	A * M	1	-2.983	-3.116	0.002**
	R * A * M	1	3.565	2.586	0.01**
Configurational knowledge task accuracy	Road type (R)	1	2.632	2.923	0.003**
	AR landmark condition (A)	1	1.874	2.147	0.032*
	Method of experimentation (M)	1	1.419	1.093	0.274
	R * A	1	-2.088	-1.609	0.108
	R * M	1	-3.073	-3.029	0.002**
	A * M	1	-2.179	-2.199	0.028*
	R * A * M	1	1.591	1.115	0.265

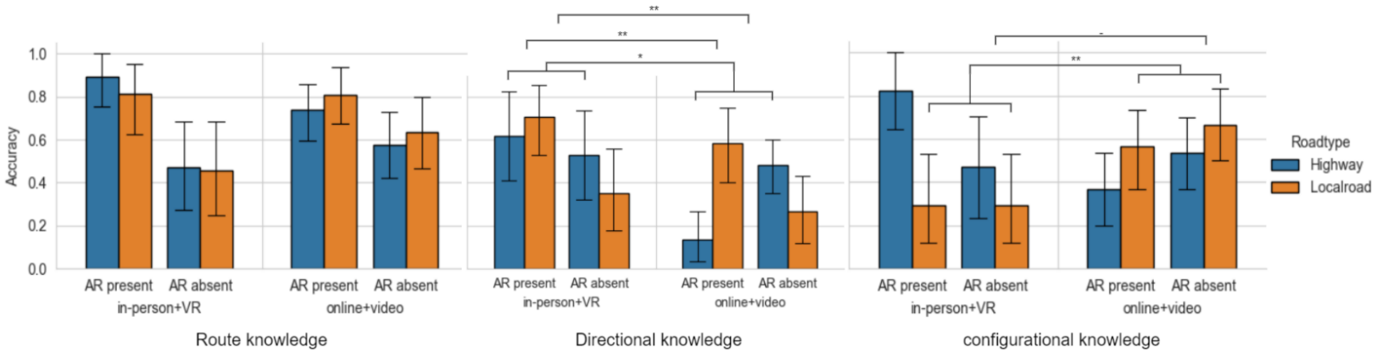

Figure 18: Pairwise post hoc comparisons between variables (experimentation method, road type and AR landmark condition)

For route knowledge accuracy, shown in Table 9, there are no sole effects from experimentation method in the task of recalling the landmark orders (z = 1.232, p = 0.218), but AR landmark condition and experimentation method indicated the moderate interaction effect (z = -1.677, p = 0.094). As suspected from the post hoc comparison result table, there are no significant differences in the route knowledge accuracy for different AR measurements in both the in-person VR experiment and the online video experiment.

There was a powerful significant effect of the experimentation method on directional knowledge accuracy (z = 3.219, p = 0.001), and a strong interaction effect of the experimentation method and the road type or AR landmark condition (road type * experimentation method: z = -2.819, p = 0.005; AR landmark condition * experimentation method: z = -3.116, p = 0.002). Pairwise comparisons indicated that participants in the in-person VR experimental approach made significantly larger directional accuracy (M = 0.55, SE = 0.05) in task-related directional knowledge than the online video experimental approach (M = 0.37, SE = 0.05). For participants who were assigned to the highway condition or AR present condition, the average directional knowledge accuracy detected in the in-person VR research is higher (highway: M = 0.57, SE = 0.07; AR present: M = 0.66, SE = 0.06) than in online video research (highway: M = 0.30, SE = 0.06; AR present: M = 0.36, SD = 0.07).

There is no significant difference between the experimentation method on configurational knowledge accuracy in the task (z = 1.093, p = 0.274). For both road type and AR landmark condition, the two-way interaction effects of each above and the experimentation method on directional task accuracy are significant (road type * experimentation method: z = -3.029, p = 0.002; AR landmark condition * experimentation method: z = -2.199, p = 0.028). The differences between the two studies affected by the interaction effect of road type and medium and experimentation method in highway and local road environments are opposite. On the local road, configurational knowledge task accuracy is higher in online video compared to in-person VR research (in-person + VR: M = 0.29, SE = 0.07; online + video: M = 0.62, SE = 0.07). For the joint effect of AR landmark condition and experimentation method, when there was no AR landmark, online video participants had higher configurational knowledge accuracy than VR participants (in-person + VR: M = 0.38, SE = 0.07; online + video: M = 0.60, SE = 0.07).

4.4 Discomfort and motion sickness

The Figure 19 presents data on the frequency of reported discomfort and motion sickness among participants, with scores ranging from 1 to 5. These scores likely represent increasing levels of discomfort and motion sickness, where 1 indicates the lowest level and 5 the highest level of experienced discomfort or motion sickness.

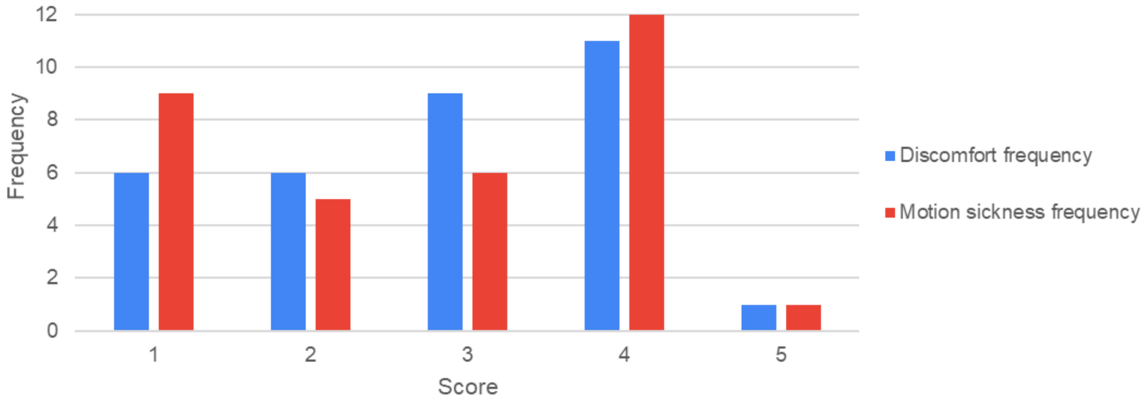

Figure 19: Frequency of discomfort and motion sickness scores

In this study, the distribution of scores indicates that participants experienced a broad range of discomfort and motion sickness levels, spanning from low to high (scores 1 to 4). The highest level of discomfort and motion sickness (score 5) was relatively rare, reported by only one participant in each category. On average, the data suggest that the 34 participants experienced moderate levels of discomfort and motion sickness while engaging with the immersive experiences (M = 2.79, SE = 0.15).

5 Discussion

The research's analysis delivers insights into three main questions related to research. The following discussion goes into the findings and then focuses on the study's limitations.

5.1 Accuracy and time performances

The study's findings provide valuable insights into how road types and AR landmarks influence task completion times and spatial knowledge formation during immersive driving simulations. In general, the enhancement in accuracy with AR landmarks suggests that AR provides effective visual cues, aiding spatial orientation and memory. The faster task completion with AR assistance across both environments indicates that AR landmarks streamline navigation, reducing the cognitive load on participants. These results align with previous research indicating the benefits of AR in spatial knowledge tasks and that AR can enhance spatial understanding and reduce the time taken for navigational tasks (Gabbard et al., 2019; Jabbari et al., 2022).

Consistent with the order of the experimental tasks, the discussion below explores three aspects of spatial awareness, explicitly concentrating on spatial learning in the context of realistic simulations for self-driving cars: route knowledge, directional knowledge, and configurational knowledge.

5.1.1 Route knowledge

Route knowledge is a fundamental aspect of spatial learning, involving the ability to recall and navigate through a series of locations using landmarks as key reference points (Hirtle & Hudson, 1991; Siegel & White, 1975). Recent research has underscored the significant role of AR landmarks in supporting the acquisition of route knowledge in autonomous driving scenarios (R. Li, 2023). In this research, local AR landmarks reveals markedly benefits in enhancing the accuracy of route knowledge learning and facilitating the recall of landmark sequences encountered during travel. Ruddle et al. (2011) demonstrated that local landmarks significantly benefit route knowledge by reducing errors and enhancing the accuracy of navigation decisions, which supports the idea that drivers using AR displays exhibit a more precise memory of landmark sequences, leading to more effective recall and enhanced memorisation efficiency (Ruddle et al., 2011).

The application of AR technology on highways and local roads greatly assists drivers in memorizing sequences of local landmarks. These landmarks, frequently incorporated into traffic signs or represented by local features like buildings, become more memorable through AR displays. Unlike brief glimpses of landmarks seen through a car windshield, AR displays maintain a constant presence, ensuring continuous visibility for the driver. This is typically accomplished using a HUD technique, which projects AR imagery, such as navigational cues and landmarks, onto the windshield of the car (Feierle et al., 2019; Pauzie, 2015; Stojmenova Pečečnik et al., 2023). The HUD allows for prolonged interaction with the AR landmarks, enabling a more thorough and accurate mental construction of their sequence along a route.

5.1.2 Directional knowledge

Directional knowledge, essential for spatial orientation, involves navigating an environment using various cues and is key to forming a mental framework for understanding and navigating spaces (Burte & Montello, 2017). This research has shown that the inclusion of distant AR landmarks significantly improves the accuracy of directional knowledge tasks. These distant AR landmarks serve as beneficial markers, especially over larger distances, aiding drivers in navigation and enhancing their understanding of spatial orientation (Jabbari et al., 2022). Distant landmarks assist in the subconscious acquisition of directional knowledge, enabling individuals to perceive and interpret spatial information more effectively, thereby improving spatial awareness. Studies examining the impact of virtual global landmarks and the visualization of distant landmarks on mobile devices have shown a parallel effect that distant landmarks enhance incidental spatial learning, facilitating the processing of spatial orientation (R. Li et al., 2014; Liu et al., 2022).

In this research, distant AR landmarks significantly impact directional knowledge acquisition in urban environments, but their effectiveness appears to be less pronounced on highways. Urban landscapes, characterized by their complexity with numerous intersections, streets, and landmarks, present more significant navigational challenges. Here, distant AR landmarks provide clear and visible cues that help individuals orient themselves and navigate the intricate city layout effectively. They serve as essential reference points where buildings and other structures obstruct natural orientation cues. In contrast, highways offer a more open and straightforward environment with fewer obstructions and more traffic signs, making the role of AR landmarks less critical.

However, the research also found no significant differences in the time performance of directional knowledge tasks based on road type or AR landmark condition. This suggests that while AR landmarks may improve accuracy, they do not necessarily reduce the time required to complete these tasks.

5.1.3 Configurational knowledge

According to this research, AR displays have a significant impact on configurational knowledge, especially in highway environments. Configurational knowledge involves understanding the spatial layout and relationships between different locations (Golledge et al., 1992; Ishikawa & Montello, 2006). AR enhances this by superimposing relevant information directly onto the driver's field of view, aiding in route configuration and spatial understanding.

In highway settings, AR displays improve accuracy and efficiency in configurational tasks. They provide clear, contextually relevant cues that align with the driver's visual perspective, making it easier to process spatial information and make quick, accurate decisions. This is particularly useful in the more predictable and linear layout of highways, where AR can effectively guide drivers at crucial decision points like exits or lane changes.

Highways typically have a more straightforward layout than urban areas, making AR cues easier to follow and more directly applicable to the task of navigating the route. They present fewer distractions and less complex decision-making scenarios than urban settings. AR displays can provide just the right amount of information needed for highways to understand the spatial layout and evaluate relative distance without overwhelming the driver. In urban environments, the abundance of visual stimuli can compete with AR cues, potentially reducing their effectiveness. In contrast, the open environment of highways allows AR displays to be more visible and impactful.

5.2 Eye-tracking metrics

5.2.1 Gaze areas

Across all gaze areas, there is a consistent pattern where highways attract longer, and more focused attention compared to local roads. This is evidenced by higher average fixation duration, dwell time, and fixation count on highways.

The presence of AR landmarks generally increases the fixation count, indicating that these landmarks draw more attention and cause participants to return their gaze to these points more frequently. However, the impact of AR landmarks varies by road type and gaze area. For instance, on highways, AR landmarks tend to increase dwell time and fixation count, whereas on local roads, they can reduce these metrics. Eye-tracking metrics exhibit significant differences in gaze areas not aligned with the drivers' direct line of sight, such as the windshield's top, right edge, and bottom regions. However, such significant differences in eye-tracking metrics are not observed in areas typically aligned with the drivers' direct line of sight (the middle centre and left edge). The following discussion is structured into five sections, corresponding to the windshield's five regions: top area, middle area, left edge, right edge and bottom area.

5.2.1.1 Top area

In the top gaze area, highways show greater average fixation duration than local roads. The presence of distant AR landmarks also led to an increase in dwell time, and this increase was more pronounced on highways. Dwell time and fixation count were significantly longer on local roads than on highways, especially when distant AR landmarks were absent.

Highways typically have more traffic signs with contextual information about distant landmarks than local roads. While driving near highway traffic signs, distant landmark information is located in the top portion of the windshield, resulting in a more significant average fixation duration as drivers need more time to process the information. Introducing distant AR landmarks on the windshield likely provides additional spatial cues, aiding global orientation and directional spatial knowledge (Jabbari et al., 2022; R. Li et al., 2014; Liu et al., 2022). Additional indicators can increase dwell time, and fixation count as drivers focus more on these new visual elements to integrate them into their navigation strategy. When distant AR landmarks are absent, increasing dwell time and fixation count on local roads might be compensatory for drivers. Drivers could put more effort into proactively seeking additional spatial cues in the environment to compensate for the lack of augmented guidance, leading to more frequent and prolonged fixations (Kwon & Kim, 2021).

5.2.1.2 Middle centre area

In the middle centre gaze area, there was a strong effect of road type on average fixation duration and dwell time with highways consistently showing higher values than local roads.

The middle centre of the windshield is the primary observation zone for drivers. On both highways and local roads, the primary focus of drivers is likely on the driving environment itself, which requires monitoring the road, traffic, and navigation cues through the middle portion of the windshield. The local AR landmarks, while informative, do not significantly impact eye-tracking metrics in the middle centre. Moreover, due to the less complex traffic environments on highways compared to local roads, drivers experienced fewer distractions during the simulation. The higher average fixation duration and dwell time on highways indicate more focused and sustained attention than the more complex local road scenarios.

5.2.1.3 Left edge

For the left edge gaze area, average fixation duration was higher for highways, but interestingly, dwell time and fixation count were lower on highways compared to local roads, indicating fewer but more focused fixations on highways.

Like the middle centre area, the left edge is a driver's primary observation zone. In this area, local AR landmarks do not significantly impact eye-tracking metrics. This lack of change indicates that the AR landmarks do not alter the drivers' natural gaze patterns. The observed combination of longer fixation duration with fewer fixations time and frequency on highways suggests a pattern of more focused attention. This is likely because highway drivers concentrate on specific, crucial elements like signs or distant vehicles. Consequently, they do not need to shift their gaze as frequently as on local roads, where immediate navigational challenges are more prevalent and require frequent gaze adjustments.

5.2.1.4 Right edge

In the right edge area, all metrics were significantly higher for highways. The presence of AR landmarks generally reduced the value of metrics. For dwell time and fixation count, decrease effect of local AR landmarks is more noticeable on local roads.

In highway driving scenarios, the abundance of traffic signs on the right side increases the likelihood of drivers focusing their gaze on the right edge. As a result, eye-tracking metric are generally higher for highway drivers. However, introducing AR landmarks on the right edge tends to decrease these metrics. This reduction implies that AR landmarks provide more efficient visual cues (similar to AR HUDs), enabling drivers to process information more quickly (Feierle et al., 2019; Langlois & Soualmi, 2016; X. Li et al., 2023). Consequently, this efficiency lessens the requirement for extended or multiple fixations, streamlining the visual attention process.

5.2.1.5 Bottom area

In the bottom gaze area, average fixation duration, dwell time, and fixation count were all significantly higher for highways. The presence of AR landmarks increased fixation count number.

On highways, traffic signs display speed limits, and road names are more frequent. Meanwhile, the AR elements of auxiliary information like speed limits and road names are superimposed onto the driving view. This AR technology aids drivers in merging AR information with standard driving data, leading to an increased gaze towards the bottom area of the windshield.

5.2.2 Effect on spatial knowledge accuracy

A marginally significant positive correlation was observed between fixation count and route knowledge task accuracy in the bottom gaze area. However, this area primarily displays auxiliary information unrelated to route knowledge, suggesting the need for further investigation into how fixation count influences route knowledge accuracy in this context.

Local landmark indicators are projected onto the windshield in the middle centre gaze area. These indicators generally have minimal direct impact on directional knowledge. However, the statistical analysis revealed that dwell time positively correlates with configurational knowledge, while fixation count demonstrated a negative relationship. Research results suggest that prolonged focus on specific environmental elements enhances the depth of spatial information processing. The extended focus aids in connecting individual local landmarks into a unified spatial understanding, facilitating a more precise grasp of the interrelations among various locations. In contrast, a high fixation count, which is a sign of frequent attentional shifts, hinders the acquisition of spatial knowledge.

5.3 Experimentation method

In this research, the experimentation method represented significant differences in accuracy in directional tasks. For route and configurational knowledge, the participants in the two types of research behaved consistently in accuracy tasks. Interestingly, when considering the interaction effect for configurational knowledge, significant two-way interaction effects were observed for road type and AR landmark condition with the experimentation method.

5.3.1 Route knowledge

There was no significant main effect of experimentation method on route knowledge accuracy. Route knowledge, which focuses on understanding sequence landmarks, is not influenced by the medium (VR vs. video) or experimentation method (in-person vs. online), probably because it primarily relies on sequential memory rather than immersive spatial experience. The simplicity and straightforward nature of acquiring route knowledge mean that different mediums or methods may not significantly affect the learning outcome. The cognitive process of memorising sequences of landmarks is consistent across various mediums and methods, leading to similar levels of accuracy in route knowledge acquisition, regardless of the medium or method employed.

5.3.2 Directional knowledge

A significant effect of the experimentation method was found on directional knowledge accuracy. Strong interaction effects were also noted between experimentation method and road type, and between experimentation method and AR landmark. In the in-person VR approach, participants showed significantly higher accuracy in directional knowledge tasks than those in the online video approach. In highway environments or with distant AR display conditions, there was a significant increase of accuracy in directional knowledge with in-person VR approach.

In-person VR, offering a more immersive spatial experience than online videos, significantly enhances understanding of global orientations and distances. Its realistic space representation supports better focusing and memorising locations and directions, with shorter experimental times in VR settings potentially boosting learning efficiency and retention of directional knowledge.

In highway environments, in-person VR experiments show higher directional spatial accuracy. The simplicity of highways, compared to urban areas, allows for clearer spatial cues, making VR more effective in conveying directional information and reducing cognitive load. This focused environment enables users to concentrate more on VR's directional cues, leading to improved directional knowledge accuracy.

Furthermore, a previous study indicates that AR cues in immersive VR environments, particularly with screen-fixed conditions, greatly enhance spatial learning and navigation (Zhao et al., 2023). AR landmarks in VR, being contextually relevant and integrated into the user's field of view, simplify understanding and memorising spatial relationships and locations, which are crucial for directional knowledge.

5.3.3 Configurational knowledge

The lack of significant difference between the medium (VR vs. video) and experimentation method (in-person vs. online) on configurational knowledge accuracy suggests that these factors do not independently influence the ability to understand spatial layouts and relationships. This could imply that configurational knowledge, which involves understanding the spatial arrangement and connections between different locations, may be robust across various mediums and methods of learning.

However, the two-way interaction effects identified for road type and AR landmark condition with the experimentation method reveals some intriguing details. Specifically, compared to VR experiment, the online video research yielded significantly higher configurational knowledge accuracy in local road environments or scenarios without AR landmarks.

In complex environments like local roads, where navigation may be more challenging, the online video medium might be ideal for individuals to stay undistracted for the acquisition of good configurational knowledge. However, it is important to note that while this medium may result in better performance due to less distraction, it does not necessarily equate to high ecological validity. One of the principal advantages of VR over video is its ecological validity. In fact, VR simulations are designed to simulate the distractions present in real-world driving environments (S. Kim & Dey, 2009; Nezami et al., 2020; Riegler et al., 2019). Therefore, a VR simulation that is as distracting as an actual driving scenario is desirable, as it more accurately represents the real-world conditions and challenges that drivers face.

6 Limitations and future study suggestions

Based on the feedback gathered from participants in the post-questionnaire and the analysis of experimental results, as detailed in Appendix 2, the study identified several vital limitations and proposed actionable suggestions for future research.

6.1 Variability in Experimental Length

In this research, experiments in highway and local road conditions have different time lengths. The variation in experimental duration significantly impacts participant engagement and data reliability. Longer durations might yield more detailed responses but risk participant fatigue. Standardizing the duration across experiments is essential to address these challenges. This approach will ensure uniform conditions for all participants, minimizing data variability and enhancing the consistency and comparability of results.

6.2 Lack of representativeness of statistics

The study's focus on young adults and the disproportionate number of female participants presents notable limitations in terms of demographic representation. This concentration on a specific age group and gender imbalance restricts the study's applicability and may introduce biases in the results. To address these limitations and improve the generalizability of future research findings, it is essential to include a more diverse age range and a balanced gender representation.

Moreover, the recruitment of participants from the Netherlands presents additional constraints. This lack of demographic variability limits the study's ability to reflect broader population dynamics accurately. Future studies should aim for a more diverse participant pool to mitigate these limitations, improve the representativeness of research findings and encompass a more comprehensive range of nationalities and cultural backgrounds.

6.3 Confounding effect

Given the limitations identified in the current research, where participants were divided into two groups rather than four, future studies should adopt a more balanced design that aligns with the ideal two-by-two experimental framework for two-way ANOVA. This design divides the experimental sample into four distinct groups, each randomly assigned to one level of both independent variables. Such a structure ensures that all combinations of the experiment's conditions are fully explored, covering road types and AR landmark conditions across the groups.

While the current design may have offered advantages regarding participant economy and mitigating order effects associated with experiencing different road types and AR conditions, it potentially introduces complications. Specifically, the design might lead to confounding within-subject effects for variables to be analysed between subjects, which obscures the clarity of the interaction effects between road types and AR landmark conditions, making it challenging to isolate the impact of each independent variable.

6.4 Intrusive AR elements

Integrating AR landmarks into drivers' natural viewing patterns presents an intriguing area for further research. Potential distractions in this research, caused by abruptly intrusive AR elements, can divert drivers' attention away from the road elements (H. Kim & Gabbard, 2022). Attention reduction on the windshield in driving could disrupts the process of spatial learning and slows the formation of spatial knowledge.

Future investigations could improve designing non-intrusive AR elements that blend seamlessly with the driving environment. The goal is to incorporate AR technology in a way that does not disrupt the attention of travellers, ensuring that these advancements support rather than detract from the overall driving experience.

6.5 Simultaneous generation of spatial knowledge

In this research, spatial knowledge encompasses route, directional, and configurational knowledge. Local landmarks assess the route and configurational knowledge, while distant landmarks focus on directional and configurational aspects. Previous studies reveal that different levels of spatial knowledge may not develop sequentially but can emerge simultaneously (Bruns & Chamberlain, 2019; Kelly & McNamara, 2010; Montello, 1998; Stites et al., 2020). This simultaneous generation of spatial knowledge layers presents a complex interplay that warrants deeper exploration. Future studies should consider more comprehensive task designs that intricately test these overlapping elements of spatial knowledge to dissect the nuanced ways more effectively in which individuals navigate and understand spatial environments.

6.6 Distance indication beyond transparency changes

In the study, altering the transparency of AR indicators were employed as a method to signal distance to drivers. However, it was observed that drivers often did not effectively perceive these transparency changes, especially when their attention was focused on other environmental elements. The lack of sensitivity to transparency shifts in AR displays suggests a need for alternative approaches to convey distance information, such as changing the size of the indicators.

6.7 Simulation environment

One limitation is the environment of a driving simulator, which may not fully replicate real-world conditions. The simulated environment for this research ignores the dynamic elements of live traffic and pedestrians, which are essential aspects of daily driving, potentially omitting challenges and distractions in developing spatial knowledge during autonomous driving. The simulation scenarios are also based on the eastern United States, a region unfamiliar to the Dutch-recruited participants. This geographical unfamiliarity may influence their navigation strategies, spatial awareness development, and overall simulation performance. Given the distinct differences between immersive simulation and actual driving situations, further research is necessary to explore the effectiveness of AR interfaces and the applicability of eye-tracking metrics in actual driving conditions.

6.8 Discomfort and motion sickness

Based on participant feedback from the post-questionnaire (see Figure 19), many participants experienced moderate discomfort and motion sickness with a mean score of 2.79, primarily attributed to the jerky car turning function in the VR simulation. Additionally, prolonged exposure to the VR scenarios exacerbated discomfort among participants. To enhance user experience in future studies, it is essential to refine the VR driving simulation, focusing on creating smoother car movements. This improvement aims to reduce motion sickness and provide a more comfortable and realistic driving experience for participants.

7 Conclusion

This research employs VR and AR technologies to illuminate the dynamics of spatial knowledge processing in a simulated autonomous driving context. The study underscores the efficacy of AR displays in enhancing spatial knowledge acquisition, with both distant and local landmarks playing pivotal roles. Local AR landmarks significantly improve route knowledge accuracy and facilitate the recall of landmark sequences, while distant landmarks offer crucial orientation cues in complex urban environments.

A notable discovery is the influence of AR landmarks on gaze behaviour. The study finds that AR landmarks in areas of the windshield that typically receive less attention draw increased focus (top and bottom areas), as evidenced by eye-tracking metrics. Conversely, the introduction of AR landmarks in frequently observed windshield areas (right edge) leads to reduced gaze focus, indicating AR's potential to direct attention and bolster spatial awareness strategically. Additionally, the results indicate that greater attention in the middle centre area assists in understanding the spatial layout and relationships of different locations, emphasising the significance of this gaze area for spatial understanding.

Spatial knowledge performances generally report consistency between VR research and online video research in spatial knowledge tasks. The consistency across the results of both experiments mutually validates their findings, further substantiating VR's credibility as a research methodology. VR has a great deal of potential as a research tool because of its ability to accurately replicate real-world settings, which emphasises its relevance, ecological validity, and potential for use in upcoming studies.

Historical research findings suggest that as autonomous vehicles become more prevalent, there is a risk of exacerbating the decline in spatial cognition observed with GPS-reliant navigation (Brishtel et al., 2021; Gardony et al., 2015; Hejtmánek et al., 2018; Ishikawa et al., 2008; Münzer et al., 2006; Parush et al., 2007; Ruginski et al., 2019). Existing research also posits that integrating AR technology can mitigate these effects by enhancing situational awareness and engaging drivers more actively in navigation (Feierle et al., 2019; Langlois & Soualmi, 2016; X. Li et al., 2023; Pauzie, 2015). This research addresses the identified research needs and sets a foundation for future studies to optimize AR integration in autonomous vehicles, ensuring that advancements in self-driving technology do not come at the expense of essential cognitive skills and spatial awareness. Also, it paves the way for future investigations to optimize AR integration in autonomous vehicles, focusing on safety and enhancing the driving experience. Furthermore, the work emphasises the feasibility of in-lab VR experiments in spatial cognition research, indicating an optimistic outlook for immersive techniques in spatial learning studies.

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Appendix 1: Spatial knowledge tasks

Experiment condition one: highway without AR+ local road with AR

Scenario one: highway without AR

Q1: From the start to end, you have passed a few traffic signs in the environment, they are:

Troy, Rest area, Toll booth

Please use your best judgement to choose which is the correct order of seeing the three locations, from the start to end?

A. Troy -> Toll booth -> Rest area
B. Toll Booth -> Rest area -> Troy
C. Toll Booth -> Troy -> Rest area
D. Rest area-> Troy -> Toll booth

Q2: The following figure shows the start and end of the travelled route and two distant locations that are indicated by exit signs in the environment.

Please try to recall the "travel" experience" and use your best judgement to choose the correct names for the two distant locations.

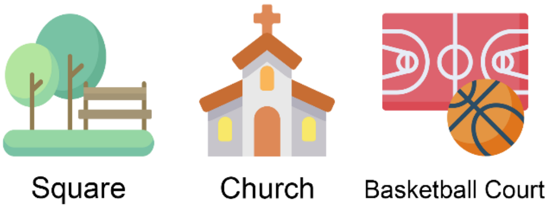
A. 1: Albany, 2: Watervliet
B. 1: Cohoes, 2: Watervliet
C. 1: Watervliet, 2: Albany
D. 1: Cohoes, 2: Albany

Q3: One of the following figures shows the correct route that you "travelled" in the simulated driving experience. Please try to recall the experience and use your best judgement to choose one route that you have just "travelled".

A. Route A
B. Route B
C. Route C

Scenario two: local road with AR

Q5: From the start to end, you have passed a few locations marked by the icons on the windshield, they are:



A. Church -> Square -> Basketball court

B. Basketball court-> Square -> Church

C. Basketball court -> Church-> Square

D. Square -> Basketball court -> Church

Q6: The following figure shows the start and end of the travelled route and two distant locations that have been displayed on the windshield.

Please try to recall the "travel" experience" and use your best judgement to choose the correct names for the two distant locations.

A. 1: Guilderland, 2: Mountain

B. 1: Mountain, 2: Guilderland

C. 1: Guilderland, 2: Downtown

D. 1: Downtown, 2: Mountain

Q7: One of the following figures shows the correct route that you "travelled" in the simulated experience. Please try to recall the experience and use your best judgement to choose one route that you have just "travelled".

A. Route A

B. Route B

C. Route C

Experiment condition two: local road without AR+ highway with AR

Scenario two: local road without AR

Q1: From the start to end, you have passed a few landmarks in the environment, they are:

Square, Church, Basketball court

Please use your best judgement to choose which is the correct order of seeing the three locations, from the start to end?

A. Church -> Square -> Basketball court

B. Basketball court-> Square -> Church

C. Basketball court -> Church-> Square

D. Square -> Basketball court -> Church

Q2: The following figure shows the start and end of the travelled route and two distant locations that have been displayed on the windshield.

Please try to recall the "travel" experience" and use your best judgement to choose the correct names for the two distant locations.

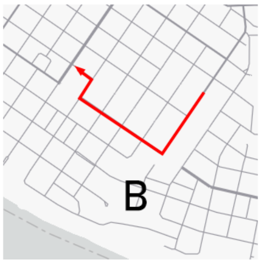
A. 1: Guilderland, 2: Mountain

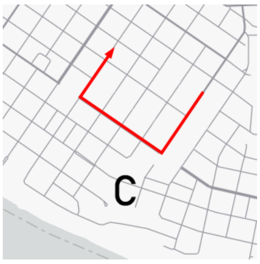
B. 1: Mountain, 2: Guilderland

C. 1: Guilderland, 2: Downtown

D. 1: Downtown, 2: Mountain

Q3: One of the following figures shows the correct route that you "travelled" in the simulated experience. Please try to recall the experience and use your best judgement to choose one route that you have just "travelled".





A. Route A

B. Route B

C. Route C

Scenario two: highway with AR

Q4: From the start to end, you have passed a few traffic signs in the environment, they are:

Please use your best judgement to choose which is the correct order of seeing the three locations, from the start to end?

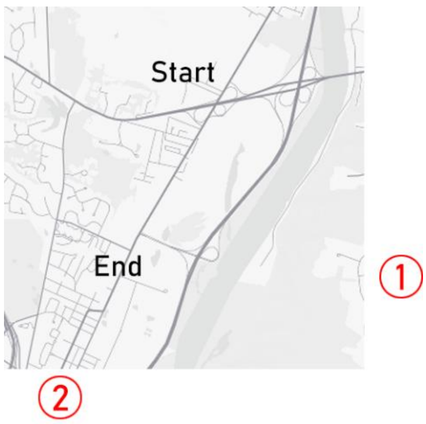
A. Troy -> Toll booth -> Rest area

B. Toll Booth -> Rest area -> Troy

C. Toll Booth -> Troy -> Rest area

D. Rest area-> Troy -> Toll booth

Q5: The following figure shows the start and end of the travelled route and two distant locations that are indicated by exit signs in the environment.



Please try to recall the "travel" experience" and use your best judgement to choose the correct names for the two distant locations.

A. 1: Albany, 2: Watervliet

B. 1: Cohoes, 2: Watervliet

C. 1: Watervliet, 2: Albany

D. 1: Cohoes, 2: Albany

Q6: One of the following figures shows the correct route that you "travelled" in the simulated driving experience. Please try to recall the experience and use your best judgement to choose one route that you have just "travelled".

A. Route A

B. Route B

C. Route C

Appendix 2: Post-questionnaire

While using VR, people always come into different levels of motion sickness. We want to know how you feel after experiencing all these "travel" scenarios. You should have different feedback for the fieldtrip enjoyment and the system usability scale. You should circle a number to indicate your level of the statements.

Circle "1" if you strongly agree that the statement applies to you, "5" if you strongly disagree, or some number in between if your agreement is intermediate. Circle "3" if you neither agree nor disagree.

Q1. How much you enjoyed the previous "travel experiments" in VR?

	1	2	3	4	5	
Very satisfied	○	○	○	○	○	Very disatisfied

Q2. How would you think the AR windshield displays are useful for improving the spatial learning.

	1	2	3	4	5	
Very useful	○	○	○	○	○	Very useless

Q3. Do you have any suggestions on the VR experiment?

____

Q4. How much general discomfort are you experiencing right now?

	1	2	3	4	5	
Not at all	○	○	○	○	○	Very discomfort

Q5. How much the motion sickness affects you are feeling right now?

	1	2	3	4	5	
Not at all	○	○	○	○	○	Very discomfort

Appendix 3: Original experiment results of spatial knowledge tasks

Experiment condition one: highway without AR+ local road with AR

Gender	Age	Educational degree	Current status	Q1	Time(s)	Q2	Time(s)	Q3	Time(s)	Q4	Time(s)	Q5	Time(s)	Q6	Time(s)
Female	18-24	Bachelor degree	Full-time student	Troy -> Toll booth -> Rest area	2	1: Albany, 2: Watervliet	30	Route B	20	Basketball court-> Square -> Church	2	1: Downtown, 2: Park	31	Route B	5
Female	30-34	Graduate degree	Full-time student	Troy -> Toll booth -> Rest area	30	1: Watervliet, 2: Albany	90	Route C	14	Basketball court-> Square -> Church	15	1: Guilderland, 2: Mountain	30	Route A	10
Male	30-34	PhD	Full-time employee	Toll Booth -> Rest area -> Troy	20	1: Watervliet, 2: Albany	15	Route A	8	Basketball court-> Square -> Church	30	1: Guilderland, 2: Mountain	20	Route B	2
Female	25-29	Bachelor degree	Full-time student	Rest area-> Troy -> Toll booth	20	1: Albany, 2: Watervliet	37	Route C	28	Basketball court -> Church-> Square	19	1: Mountain, 2: Guilderland	13	Route A	15
Female	25-29	Bachelor degree	Full-time student	Troy -> Toll booth -> Rest area	12	1: Watervliet, 2: Albany	29	Route B	30	Basketball court-> Square -> Church	8	1: Guilderland , 2: Downtown	21	Route B	20
Female	18-24	Bachelor degree	Full-time student	Toll Booth -> Troy -> Rest area	40	1: Cohoes, 2: Watervliet	27	Route B	54	Basketball court -> Church-> Square	10	1: Downtown, 2: Mountain	25	Route A	2
Female	18-24	Bachelor degree	Full-time student	Troy -> Toll booth -> Rest area	10	1: Albany, 2: Watervliet	14	Route B	18	Basketball court-> Square -> Church	3	1: Downtown, 2: Mountain	63	Route A	11
Female	18-24	Bachelor degree	Full-time student	Troy -> Toll booth -> Rest area	25	1: Watervliet, 2: Albany	50	Route C	40	Basketball court-> Square -> Church	12	1: Guilderland, 2: Mountain	58	Route A	40
Female	35-39	Bachelor degree	Full-time student	Rest area-> Troy -> Toll booth	30	1: Watervliet, 2: Albany	70	Route C	80	Basketball court-> Square -> Church	28	1: Guilderland, 2: Mountain	87	Route A	47
Female	30-34	Graduate degree	Full-time employee	Toll Booth -> Troy -> Rest area	42	1: Watervliet, 2: Albany	75	Route C	40	Basketball court-> Square -> Church	7	1: Guilderland, 2: Mountain	72	Route B	2
Female	18-24	Bachelor degree	Full-time student	Troy -> Toll booth -> Rest area	27	1: Watervliet, 2: Albany	35	Route C	46	Basketball court-> Square -> Church	12	1: Downtown, 2: Mountain	33	Route A	15
Female	25-29	Bachelor degree	Full-time student	Troy -> Toll booth -> Rest area	60	1: Watervliet, 2: Albany	41	Route C	71	Basketball court -> Church-> Square	14	1: Downtown, 2: Mountain	63	Route A	37
Male	18-24	Bachelor degree	Full-time student	Rest area-> Troy -> Toll booth	23	1: Watervliet, 2: Albany	37	Route B	20	Basketball court -> Church-> Square	19	1: Downtown, 2: Mountain	55	Route A	7
Female	18-24	Bachelor degree	Full-time student	Toll Booth -> Troy -> Rest area	80	1: Watervliet, 2: Albany	20	Route C	72	Basketball court-> Square -> Church	15	1: Downtown, 2: Mountain	24	Route A	12
Male	18-24	Bachelor degree	Full-time student	Troy -> Toll booth -> Rest area	37	1: Watervliet, 2: Albany	50	Route C	38	Basketball court-> Square -> Church	14	1: Downtown, 2: Mountain	30	Route A	39
Female	18-24	Bachelor degree	Full-time student	Troy -> Toll booth -> Rest area	24	1: Albany, 2: Watervliet	44	Route C	52	Basketball court-> Square -> Church	27	1: Guilderland, 2: Mountain	182	Route C	40
Female	18-24	Bachelor degree	Part-time employee/Freelancer	Troy -> Toll booth -> Rest area	18	1: Watervliet, 2: Albany	43	Route C	30	Basketball court-> Square -> Church	7	1: Downtown, 2: Mountain	31	Route B	14

Experiment condition two: local road without AR+ highway with AR

Gender	Age	Educational degree	Current status	Q1	Time(s)	Q2	Time(s)	Q3	Time(s)	Q4	Time(s)	Q5	Time(s)	Q6	Time(s)
Male	18-24	Bachelor degree	Full-time student	Basketball court-> Square -> Church	28	1: Mountain, 2: Guilderland	55	Route A	5	Troy -> Toll booth -> Rest area	20	1: Cohoes, 2: Watervliet	24	Route C	10
Male	18-24	Bachelor degree	Full-time student	Basketball court-> Square -> Church	10	1: Guilderland , 2: Downtown	15	Route A	20	Troy -> Toll booth -> Rest area	10	1: Cohoes, 2: Albany	18	Route C	15
Female	25-29	Bachelor degree	Full-time student	Basketball court -> Church-> Square	50	1: Guilderland , 2: Downtown	37	Route C	35	Toll Booth -> Troy -> Rest area	23	1: Watervliet, 2: Albany	33	Route B	60
Male	30-34	PhD	Full-time employee	Basketball court -> Church-> Square	18	1: Guilderland , 2: Downtown	53	Route A	12	Troy -> Toll booth -> Rest area	30	1: Albany, 2: Watervliet	34	Route C	19
Male	18-24	Bachelor degree	Full-time student	Basketball court-> Square -> Church	12	1: Guilderland, 2: Mountain	29	Route B	14	Troy -> Toll booth -> Rest area	9	1: Watervliet, 2: Albany	78	Route C	21
Female	18-24	Bachelor degree	Full-time student	Square -> Basketball court -> Church	39	1: Guilderland, 2: Mountain	37	Route B	51	Troy -> Toll booth -> Rest area	15	1: Watervliet, 2: Albany	35	Route C	50
Female	18-24	Bachelor degree	Full-time student	Basketball court -> Church-> Square	42	1: Downtown, 2: Mountain	59	Route A	29	Troy -> Toll booth -> Rest area	12	1: Cohoes, 2: Albany	50	Route C	50
Male	25-29	Bachelor degree	Full-time student	Basketball court-> Square -> Church	9	1: Mountain, 2: Guilderland	45	Route A	18	Troy -> Toll booth -> Rest area	5	1: Watervliet, 2: Albany	58	Route A	30
Female	18-24	Bachelor degree	Full-time student	Basketball court-> Square -> Church	13	1: Downtown, 2: Mountain	18	Route B	25	Troy -> Toll booth -> Rest area	6	1: Albany, 2: Watervliet	39	Route C	15
Male	25-29	Bachelor degree	Full-time student	Basketball court-> Square -> Church	16	1: Guilderland , 2: Downtown	35	Route A	24	Troy -> Toll booth -> Rest area	12	1: Watervliet, 2: Albany	15	Route C	5
Female	25-29	Bachelor degree	Full-time student	Basketball court -> Church-> Square	29	1: Downtown, 2: Mountain	94	Route B	46	Troy -> Toll booth -> Rest area	19	1: Watervliet, 2: Albany	33	Route C	27
Female	18-24	Bachelor degree	Full-time student	Basketball court-> Square -> Church	18	1: Mountain, 2: Guilderland	36	Route B	23	Troy -> Toll booth -> Rest area	5	1: Watervliet, 2: Albany	21	Route C	16
Female	25-29	Bachelor degree	Full-time student	Square -> Basketball court -> Church	27	1: Downtown, 2: Mountain	55	Route A	36	Troy -> Toll booth -> Rest area	26	1: Albany, 2: Watervliet	50	Route B	20
Female	25-29	Graduate degree	Currently not employed	Basketball court -> Church-> Square	25	1: Guilderland, 2: Mountain	57	Route A	43	Toll Booth -> Troy -> Rest area	36	1: Albany, 2: Watervliet	25	Route C	63
Female	18-24	Bachelor degree	Full-time student	Basketball court -> Church-> Square	20	1: Mountain, 2: Guilderland	50	Route B	43	Troy -> Toll booth -> Rest area	9	1: Watervliet, 2: Albany	12	Route C	24
Female	18-24	Bachelor degree	Currently not employed	Basketball court -> Church-> Square	40	1: Guilderland , 2: Downtown	100	Route A	18	Troy -> Toll booth -> Rest area	14	1: Cohoes, 2: Albany	26	Route C	38
Male	25-29	Graduate degree	Full-time employee	Basketball court -> Church-> Square	17	1: Downtown, 2: Mountain	39	Route A	9	Troy -> Toll booth -> Rest area	11	1: Watervliet, 2: Albany	21	Route C	12

Appendix 4: Statistical table after data preprocessing

Experiment condition one: highway without AR+ local road with AR

Gender	Age	Degree	Status	H_Rt_Acc	H_Rt_Time	H_Dir_Acc	H_Dir_Time	H_Con_Acc	H_Con_Time	LAR_Rt_Acc	LAR_Rt_Time	LAR_Dir_Acc	LAR_Dir_Time	LAR_Con_Acc	LAR_Con_Time
Female	18-24	Bachelor degree	Full-time student	1	2	0	30	0	20	1	2	1	31	1	5
Female	30-34	Graduate degree	Full-time student	1	30	0	90	1	14	1	15	0.5	30	0	10
Male	30-34	PhD	Full-time employee	0	20	1	15	0	8	1	30	0.5	20	1	2
Female	25-29	Bachelor degree	Full-time student	0	20	0	37	1	28	0.2	19	0	13	0	15
Female	25-29	Bachelor degree	Full-time student	0.2	12	0.5	29	0	30	1	8	0	21	1	20
Female	18-24	Bachelor degree	Full-time student	0	40	0	27	0	54	0.2	10	1	25	0	2
Female	18-24	Bachelor degree	Full-time student	1	10	0	14	0	18	1	3	1	63	0	11
Female	18-24	Bachelor degree	Full-time student	1	25	0.5	50	1	40	1	12	0.5	58	0	40
Female	35-39	Bachelor degree	Full-time student	0	30	1	70	0	80	1	28	0.5	87	0	47
Female	30-34	Graduate degree	Full-time employee	0.2	42	1	75	1	40	1	7	0.5	72	1	2
Female	18-24	Bachelor degree	Full-time student	0.2	27	0.5	35	0	46	1	12	1	33	0	15
Female	25-29	Bachelor degree	Full-time student	1	60	1	41	1	71	0.2	14	1	63	0	37
Male	18-24	Bachelor degree	Full-time student	0	23	1	37	0	20	0.2	19	1	55	0	7
Female	18-24	Bachelor degree	Full-time student	0.2	80	1	20	1	72	1	15	1	24	0	12
Male	18-24	Bachelor degree	Full-time student	0.2	37	0.5	50	0	38	1	14	1	30	0	39
Female	18-24	Bachelor degree	Full-time student	1	24	0	44	1	52	1	27	0.5	182	0	40
Female	18-24	Bachelor degree	Part-time employee /Freelancer	1	18	1	43	1	30	1	7	1	31	1	14

Experiment condition two: local road without AR+ highway with AR

Gender	Age	Degree	Status	L_Rt_Acc	L_Rt_Time	L_Dir_Acc	L_Dir_Time	L_Con_Acc	L_Con_Time	HAR_Rt_Acc	HAR_Rt_Time	HAR_Dir_Acc	HAR_Dir_Time	HAR_Con_Acc	HAR_Con_Time
Male	18-24	Bachelor degree	Full-time student	1	28	0	55	0	5	1	20	0	24	1	10
Male	18-24	Bachelor degree	Full-time student	1	10	0	15	0	20	1	10	0.5	18	1	15
Female	25-29	Bachelor degree	Full-time student	0	50	0	37	0	35	0.2	23	1	33	0	60
Male	30-34	PhD	Full-time employee	0.2	18	0	53	0	12	1	30	0	34	1	19
Male	18-24	Bachelor degree	Full-time student	1	12	0.5	29	1	14	1	9	1	78	1	21
Female	18-24	Bachelor degree	Full-time student	0	39	0.5	37	1	51	1	15	1	35	1	50
Female	18-24	Bachelor degree	Full-time student	0.2	42	1	59	0	29	1	12	0.5	50	1	50
Male	25-29	Bachelor degree	Full-time student	1	9	0	45	0	18	1	5	1	58	0	30
Female	18-24	Bachelor degree	Full-time student	1	13	1	18	1	25	1	6	0	39	1	15
Male	25-29	Bachelor degree	Full-time student	1	16	0	35	0	24	1	12	1	15	1	5
Female	25-29	Bachelor degree	Full-time student	0	29	0.5	94	0	46	1	19	1	33	1	27
Female	18-24	Bachelor degree	Full-time student	1	18	0	36	1	23	1	5	1	21	1	16
Female	25-29	Bachelor degree	Full-time student	0.2	27	1	55	0	36	1	26	0	50	0	20
Female	25-29	Graduate degree	Currently not employed	0.2	25	0.5	57	0	43	0	36	0	25	1	63
Female	18-24	Bachelor degree	Full-time student	0	20	0	50	1	43	1	9	1	12	1	24
Female	18-24	Bachelor degree	Currently not employed	0	40	0	100	0	18	1	14	0.5	26	1	1
Male	25-29	Graduate degree	Full-time employee	0	17	1	39	0	9	1	11	1	21	1	12

Appendix 5: Eye-tracking metrics filtered by I-VT algorithm

Gaze area: Top

Subject	Gender	Age	Degree	Status	afd	dwell_time	fixation_count	revisits
1	Female	18-24	Bachelor degree	Full-time student	503.6351	56407.12691	112	111
1	Female	30-34	Graduate degree	Full-time student	911.3943	47392.5024	52	51
3	Male	30-34	PhD	Full-time employee	588.2237	55881.25312	95	94
5	Female	25-29	Bachelor degree	Full-time student	851.4808	73227.35206	86	85
7	Female	25-29	Bachelor degree	Full-time student	1079.164	8633.315712	8	7
9	Female	18-24	Bachelor degree	Full-time student	213.8536	855.414272	4	3
11	Female	18-24	Bachelor degree	Full-time student	649.9332	51344.72576	79	78
13	Female	18-24	Bachelor degree	Full-time student	747.3976	29895.90298	40	39
15	Female	35-39	Bachelor degree	Full-time student	635.2554	12705.10848	20	19
17	Female	30-34	Graduate degree	Full-time employee	479.7067	40775.06765	85	84
19	Female	18-24	Bachelor degree	Full-time student	515.1928	15970.97638	31	30
21	Female	25-29	Bachelor degree	Full-time student	800.9614	30436.5321	38	37
23	Male	18-24	Bachelor degree	Full-time student	657.9291	52634.32934	80	79
25	Female	18-24	Bachelor degree	Full-time student	764.6212	28290.98304	37	36
27	Male	18-24	Bachelor degree	Full-time student	909.9971	50959.83744	56	55
29	Female	18-24	Bachelor degree	Full-time student	536.7974	30060.65421	56	55
31	Female	18-24	Bachelor degree	Part-time employee/Freelancer	556.0779	35032.91085	63	62
33	Female	18-24	Bachelor degree	Full-time student	577.6795	46792.03712	81	80
2	Female	30-34	Graduate degree	Full-time student	684.043	56091.52333	82	81
4	Male	30-34	PhD	Full-time employee	456.5873	80815.95443	177	176
6	Female	25-29	Bachelor degree	Full-time student	640.389	64679.28563	101	100
8	Female	25-29	Bachelor degree	Full-time student	608.0146	63233.52077	104	103
10	Female	18-24	Bachelor degree	Full-time student	653.5375	63393.14163	97	96
12	Female	18-24	Bachelor degree	Full-time student	890.97	20492.31002	23	22
14	Female	18-24	Bachelor degree	Full-time student	492.229	19196.93133	39	38
16	Female	35-39	Bachelor degree	Full-time student	746.5431	38073.69882	51	50
18	Female	30-34	Graduate degree	Full-time employee	385.144	34662.96154	90	89
20	Female	18-24	Bachelor degree	Full-time student	566.738	20402.56845	36	35
22	Female	25-29	Bachelor degree	Full-time student	491.658	66865.48365	136	135
24	Male	18-24	Bachelor degree	Full-time student	563.3016	36614.60698	65	64
26	Female	18-24	Bachelor degree	Full-time student	407.6966	65639.14534	161	160
28	Male	18-24	Bachelor degree	Full-time student	574.8082	50583.11808	88	87
30	Female	18-24	Bachelor degree	Full-time student	429.688	59296.9417	138	137
32	Female	18-24	Bachelor degree	Part-time employee/Freelancer	433.5254	52890.09728	122	121
34	Male	18-24	Bachelor degree	Full-time student	616.8264	75252.82419	122	121
2	Male	18-24	Bachelor degree	Full-time student	676.3637	94690.91251	140	139
2	Female	25-29	Bachelor degree	Full-time student	568.7611	80764.07411	142	141
4	Male	30-34	PhD	Full-time employee	633.5966	40550.18509	64	63
6	Male	18-24	Bachelor degree	Full-time student	503.7009	71021.82886	141	140
8	Female	18-24	Bachelor degree	Full-time student	672.1108	99472.39488	148	147
10	Female	18-24	Bachelor degree	Full-time student	578.3706	64199.13114	111	110
12	Male	25-29	Bachelor degree	Full-time student	573.1195	57311.94547	100	99
14	Female	18-24	Bachelor degree	Full-time student	616.6837	57351.58016	93	92
16	Male	25-29	Bachelor degree	Full-time student	639.4785	63308.37427	99	98
18	Female	25-29	Bachelor degree	Full-time student	519.8124	41065.17734	79	78
20	Female	18-24	Bachelor degree	Full-time student	506.5211	70406.43507	139	138
22	Female	25-29	Bachelor degree	Full-time student	597.4706	30471.0007	51	50
24	Female	25-29	Graduate degree	Currently not employed	719.3732	92799.14317	129	128
26	Female	18-24	Bachelor degree	Full-time student	651.4302	93154.51174	143	142
28	Female	18-24	Bachelor degree	Currently not employed	728.789	69234.95245	95	94
30	Male	25-29	Graduate degree	Full-time employee	624.8781	43741.46982	70	69
32	Male	18-24	Bachelor degree	Full-time student	734.212	48457.99002	66	65
34	Male	18-24	Bachelor degree	Full-time student	689.3505	64798.94874	94	93
1	Female	25-29	Bachelor degree	Full-time student	266.4124	15185.50502	57	56
1	Male	30-34	PhD	Full-time employee	445.4502	46326.82496	104	103
3	Male	18-24	Bachelor degree	Full-time student	695.0215	60466.86758	87	86
5	Female	18-24	Bachelor degree	Full-time student	516.2125	55234.73856	107	106
7	Female	18-24	Bachelor degree	Full-time student	667.1493	68049.23238	102	101
9	Male	25-29	Bachelor degree	Full-time student	824.4762	24734.28621	30	29
11	Female	18-24	Bachelor degree	Full-time student	460.1674	12424.51866	27	26
13	Male	25-29	Bachelor degree	Full-time student	450.2083	54925.40877	122	121
15	Female	25-29	Bachelor degree	Full-time student	660.4662	71990.81318	109	108
17	Female	18-24	Bachelor degree	Full-time student	301.7591	44056.82765	146	145
19	Female	25-29	Bachelor degree	Full-time student	447.7806	38509.13446	86	85
21	Female	25-29	Graduate degree	Currently not employed	811.9379	42220.77338	52	51
23	Female	18-24	Bachelor degree	Full-time student	421.9486	31646.14592	75	74
25	Female	18-24	Bachelor degree	Currently not employed	502.6017	29150.89907	58	57
27	Male	25-29	Graduate degree	Full-time employee	721.3324	78625.22931	109	108
29	Female	18-24	Less than bachelor degr	Full-time student	894.2134	48287.52346	54	53
31	Female	18-24	Less than bachelor degr	Full-time student	557.8602	73637.55123	132	131
33	Male	18-24	Bachelor degree	Full-time employee	560.126	33047.43526	59	58

Gaze area: middle centre

Subject	Gender	Age	Degree	Status	afd	dwell_time	fixation_count	revisits
1	Female	18-24	Bachelor degree	Full-time student	579.5892	170399.239	294	293
1	Female	30-34	Graduate degree	Full-time student	816.772	205826.5536	252	251
3	Male	30-34	PhD	Full-time employee	711.4964	170759.1341	240	239
5	Female	25-29	Bachelor degree	Full-time student	761.2411	186504.0617	245	244
7	Female	25-29	Bachelor degree	Full-time student	925.4948	217491.274	235	234
9	Female	18-24	Bachelor degree	Full-time student	354.2485	2125.4912	6	5
11	Female	18-24	Bachelor degree	Full-time student	749.3869	192592.4224	257	256
13	Female	18-24	Bachelor degree	Full-time student	860.433	185853.5246	216	215
15	Female	35-39	Bachelor degree	Full-time student	818.5212	185804.3212	227	226
17	Female	30-34	Graduate degree	Full-time employee	566.2711	144399.1281	255	254
19	Female	18-24	Bachelor degree	Full-time student	876.0496	192730.9119	220	219
21	Female	25-29	Bachelor degree	Full-time student	871.9603	191831.2586	220	219
23	Male	18-24	Bachelor degree	Full-time student	641.0766	180142.5236	281	280
25	Female	18-24	Bachelor degree	Full-time student	805.2801	201320.0265	250	249
27	Male	18-24	Bachelor degree	Full-time student	1058.552	224413.0175	212	211
29	Female	18-24	Bachelor degree	Full-time student	693.4221	179596.3283	259	258
31	Female	18-24	Bachelor degree	Part-time employee/Freelancer	651.8501	188384.6792	289	288
33	Female	18-24	Bachelor degree	Full-time student	673.0835	181732.5366	270	269
2	Female	30-34	Graduate degree	Full-time student	703.9945	127422.9988	181	180
4	Male	30-34	PhD	Full-time employee	515.4938	94850.85619	184	183
6	Female	25-29	Bachelor degree	Full-time student	679.5692	129118.1549	190	189
8	Female	25-29	Bachelor degree	Full-time student	614.0279	107454.8902	175	174
10	Female	18-24	Bachelor degree	Full-time student	637.047	119764.8429	188	187
12	Female	18-24	Bachelor degree	Full-time student	833.5273	126696.1457	152	151
14	Female	18-24	Bachelor degree	Full-time student	630.4013	96451.392	153	152
16	Female	35-39	Bachelor degree	Full-time student	734.0213	123315.578	168	167
18	Female	30-34	Graduate degree	Full-time employee	484.7469	101312.1124	209	208
20	Female	18-24	Bachelor degree	Full-time student	625.8844	120795.6805	193	192
22	Female	25-29	Bachelor degree	Full-time student	521.8393	101236.8183	194	193
24	Male	18-24	Bachelor degree	Full-time student	588.2466	112943.3524	192	191
26	Female	18-24	Bachelor degree	Full-time student	466.3221	91399.13843	196	195
28	Male	18-24	Bachelor degree	Full-time student	625.2617	118799.7249	190	189
30	Female	18-24	Bachelor degree	Full-time student	463.9837	85372.9984	184	183
32	Female	18-24	Bachelor degree	Part-time employee/Freelancer	490.865	100627.3349	205	204
34	Male	18-24	Bachelor degree	Full-time student	548.9856	124070.7432	226	225
2	Male	18-24	Bachelor degree	Full-time student	774.644	169647.0254	219	218
2	Female	25-29	Bachelor degree	Full-time student	569.7233	133884.9665	235	234
4	Male	30-34	PhD	Full-time employee	788.5976	202669.5711	257	256
6	Male	18-24	Bachelor degree	Full-time student	651.7501	144688.5192	222	221
8	Female	18-24	Bachelor degree	Full-time student	598.9382	121584.4575	203	202
10	Female	18-24	Bachelor degree	Full-time student	771.1682	157318.3155	204	203
12	Male	25-29	Bachelor degree	Full-time student	697.4335	150645.6338	216	215
14	Female	18-24	Bachelor degree	Full-time student	844.8683	163904.441	194	193
16	Male	25-29	Bachelor degree	Full-time student	763.0157	141157.8984	185	184
18	Female	25-29	Bachelor degree	Full-time student	577.9459	128303.9965	222	221
20	Female	18-24	Bachelor degree	Full-time student	697.5554	336919.2558	483	482
22	Female	25-29	Bachelor degree	Full-time student	965.3341	331109.5981	343	342
24	Female	25-29	Graduate degree	Currently not employed	811.2514	159005.2788	196	195
26	Female	18-24	Bachelor degree	Full-time student	730.5041	142448.299	195	194
28	Female	18-24	Bachelor degree	Currently not employed	863.9603	174519.9736	202	201
30	Male	25-29	Graduate degree	Full-time employee	831.235	201990.1006	243	242
32	Male	18-24	Bachelor degree	Full-time student	668.6828	127718.4132	191	190
34	Male	18-24	Bachelor degree	Full-time student	749.6047	184402.7535	246	245
1	Female	25-29	Bachelor degree	Full-time student	253.277	13930.23731	55	54
1	Male	30-34	PhD	Full-time employee	461.064	100973.0241	219	218
3	Male	18-24	Bachelor degree	Full-time student	746.3188	118664.6821	159	158
5	Female	18-24	Bachelor degree	Full-time student	528.8026	112106.1578	212	211
7	Female	18-24	Bachelor degree	Full-time student	563.617	118359.5745	210	209
9	Male	25-29	Bachelor degree	Full-time student	630.1104	151226.5078	240	239
11	Female	18-24	Bachelor degree	Full-time student	600.8543	152616.993	254	253
13	Male	25-29	Bachelor degree	Full-time student	532.9208	96991.5799	182	181
15	Female	25-29	Bachelor degree	Full-time student	654.5822	113897.2961	174	173
17	Female	18-24	Bachelor degree	Full-time student	293.0942	32533.45101	111	110
19	Female	25-29	Bachelor degree	Full-time student	472.1624	103403.5752	219	218
21	Female	25-29	Graduate degree	Currently not employed	773.4851	126851.559	164	163
23	Female	18-24	Bachelor degree	Full-time student	506.5956	115503.7948	228	227
25	Female	18-24	Bachelor degree	Currently not employed	572.7126	117978.7958	206	205
27	Male	25-29	Graduate degree	Full-time employee	678.3375	139737.5178	206	205
29	Female	18-24	Less than bachelor degr	Full-time student	611.7897	113181.0939	185	184
31	Female	18-24	Less than bachelor degr	Full-time student	486.6404	106574.2566	219	218
33	Male	18-24	Bachelor degree	Full-time employee	618.3162	134174.6115	217	216

Gaze area: left edge

Subject	Gender	Age	Degree	Status	afd	dwell_time	fixation_count	revisits
1	Female	18-24	Bachelor degree	Full-time student	479.9850	37438.8338	78	77
1	Female	30-34	Graduate degree	Full-time student	846.8617	33027.6064	39	38
3	Male	30-34	PhD	Full-time employee	564.1974	36108.6362	64	63
5	Female	25-29	Bachelor degree	Full-time student	710.8161	19192.0356	27	26
7	Female	25-29	Bachelor degree	Full-time student	966.4184	13529.8572	14	13
9	Female	18-24	Bachelor degree	Full-time student	0.0000	0.0000	0	0
11	Female	18-24	Bachelor degree	Full-time student	573.2388	30381.6581	53	52
13	Female	18-24	Bachelor degree	Full-time student	721.3593	33182.5279	46	45
15	Female	35-39	Bachelor degree	Full-time student	968.3939	17431.0911	18	17
17	Female	30-34	Graduate degree	Full-time employee	418.1567	22998.6203	55	54
19	Female	18-24	Bachelor degree	Full-time student	718.8278	20127.1773	28	27
21	Female	25-29	Bachelor degree	Full-time student	1031.0271	23713.6228	23	22
23	Male	18-24	Bachelor degree	Full-time student	424.3630	28856.6852	68	67
25	Female	18-24	Bachelor degree	Full-time student	469.2258	15015.2260	32	31
27	Male	18-24	Bachelor degree	Full-time student	1144.8048	28620.1204	25	24
29	Female	18-24	Bachelor degree	Full-time student	508.5803	31531.9800	62	61
31	Female	18-24	Bachelor degree	Part-time employee/Freelancer	625.2337	30011.2182	48	47
33	Female	18-24	Bachelor degree	Full-time student	497.1261	35793.0765	72	71
2	Female	30-34	Graduate degree	Full-time student	490.5615	25999.7615	53	52
4	Male	30-34	PhD	Full-time employee	398.9081	25929.0253	65	64
6	Female	25-29	Bachelor degree	Full-time student	588.7402	37679.3733	64	63
8	Female	25-29	Bachelor degree	Full-time student	504.1044	34783.2035	69	68
10	Female	18-24	Bachelor degree	Full-time student	562.8492	39399.4419	70	69
12	Female	18-24	Bachelor degree	Full-time student	600.3166	30616.1485	51	50
14	Female	18-24	Bachelor degree	Full-time student	460.0229	29901.4865	65	64
16	Female	35-39	Bachelor degree	Full-time student	549.5240	28025.7244	51	50
18	Female	30-34	Graduate degree	Full-time employee	402.2013	20512.2647	51	50
20	Female	18-24	Bachelor degree	Full-time student	630.8872	29651.6961	47	46
22	Female	25-29	Bachelor degree	Full-time student	424.9393	29320.8124	69	68
24	Male	18-24	Bachelor degree	Full-time student	564.1226	33847.3577	60	59
26	Female	18-24	Bachelor degree	Full-time student	416.7019	32502.7488	78	77
28	Male	18-24	Bachelor degree	Full-time student	525.5744	35213.4861	67	66
30	Female	18-24	Bachelor degree	Full-time student	429.1552	34332.4191	80	79
32	Female	18-24	Bachelor degree	Part-time employee/Freelancer	471.9967	31151.7846	66	65
34	Male	18-24	Bachelor degree	Full-time student	494.2869	36082.9459	73	72
2	Male	18-24	Bachelor degree	Full-time student	873.6325	20967.1794	24	23
2	Female	25-29	Bachelor degree	Full-time student	464.7522	39039.1812	84	83
4	Male	30-34	PhD	Full-time employee	647.8887	34338.1024	53	52
6	Male	18-24	Bachelor degree	Full-time student	491.7264	33437.3919	68	67
8	Female	18-24	Bachelor degree	Full-time student	525.1851	33611.8479	64	63
10	Female	18-24	Bachelor degree	Full-time student	844.7614	15205.7048	18	17
12	Male	25-29	Bachelor degree	Full-time student	668.5888	16046.1321	24	23
14	Female	18-24	Bachelor degree	Full-time student	771.0896	14650.7026	19	18
16	Male	25-29	Bachelor degree	Full-time student	582.3239	18052.0398	31	30
18	Female	25-29	Bachelor degree	Full-time student	407.8880	26104.8303	64	63
20	Female	18-24	Bachelor degree	Full-time student	581.9578	36663.3436	63	62
22	Female	25-29	Bachelor degree	Full-time student	625.2267	16881.1200	27	26
24	Female	25-29	Graduate degree	Currently not employed	589.1345	35348.0687	60	59
26	Female	18-24	Bachelor degree	Full-time student	606.9580	15780.9079	26	25
28	Female	18-24	Bachelor degree	Currently not employed	903.0871	26189.5247	29	28
30	Male	25-29	Graduate degree	Full-time employee	746.1132	31336.7532	42	41
32	Male	18-24	Bachelor degree	Full-time student	577.8396	26580.6235	46	45
34	Male	18-24	Bachelor degree	Full-time student	679.2261	42791.2461	63	62
1	Female	25-29	Bachelor degree	Full-time student	180.0383	180.0383	1	0
1	Male	30-34	PhD	Full-time employee	379.8185	52414.9517	138	137
3	Male	18-24	Bachelor degree	Full-time student	588.1641	19997.5785	34	33
5	Female	18-24	Bachelor degree	Full-time student	435.2358	29596.0317	68	67
7	Female	18-24	Bachelor degree	Full-time student	821.4847	20537.1172	25	24
9	Male	25-29	Bachelor degree	Full-time student	611.2888	23228.9756	38	37
11	Female	18-24	Bachelor degree	Full-time student	534.1330	27774.9166	52	51
13	Male	25-29	Bachelor degree	Full-time student	519.6480	33777.1232	65	64
15	Female	25-29	Bachelor degree	Full-time student	393.1831	12975.0412	33	32
17	Female	18-24	Bachelor degree	Full-time student	242.3789	5817.0945	24	23
19	Female	25-29	Bachelor degree	Full-time student	368.5882	21378.1156	58	57
21	Female	25-29	Graduate degree	Currently not employed	739.0984	31781.2293	43	42
23	Female	18-24	Bachelor degree	Full-time student	464.9295	29290.5573	63	62
25	Female	18-24	Bachelor degree	Currently not employed	522.9188	28760.5318	55	54
27	Male	25-29	Graduate degree	Full-time employee	1156.4353	11564.3533	10	9
29	Female	18-24	Less than bachelor degree	Full-time student	966.1070	44440.9225	46	45
31	Female	18-24	Less than bachelor degree	Full-time student	400.4363	27229.6667	68	67
33	Male	18-24	Bachelor degree	Full-time employee	534.3482	21908.2746	41	40

Gaze area: right edge

Subject	Gender	Age	Degree	Status	afd	dwell_time	fixation_count	revisits
1	Female	18-24	Bachelor degree	Full-time student	497.1691	29830.1436	60	59
1	Female	30-34	Graduate degree	Full-time student	632.1406	34767.7352	55	54
3	Male	30-34	PhD	Full-time employee	613.7701	29460.9660	48	47
5	Female	25-29	Bachelor degree	Full-time student	835.1527	25054.5815	30	29
7	Female	25-29	Bachelor degree	Full-time student	1178.7775	42435.9905	36	35
9	Female	18-24	Bachelor degree	Full-time student	0.0000	0.0000	0	0
11	Female	18-24	Bachelor degree	Full-time student	907.2075	24494.6019	27	26
13	Female	18-24	Bachelor degree	Full-time student	854.2747	36733.8117	43	42
15	Female	35-39	Bachelor degree	Full-time student	861.5002	40490.5085	47	46
17	Female	30-34	Graduate degree	Full-time employee	566.5131	39655.9155	70	69
19	Female	18-24	Bachelor degree	Full-time student	983.8080	28530.4323	29	28
21	Female	25-29	Bachelor degree	Full-time student	742.2114	28946.2460	39	38
23	Male	18-24	Bachelor degree	Full-time student	560.5176	26344.3265	47	46
25	Female	18-24	Bachelor degree	Full-time student	730.2611	24098.6173	33	32
27	Male	18-24	Bachelor degree	Full-time student	1271.2318	33052.0268	26	25
29	Female	18-24	Bachelor degree	Full-time student	740.8404	53340.5055	72	71
31	Female	18-24	Bachelor degree	Part-time employee/Freelancer	880.4754	29936.1627	34	33
33	Female	18-24	Bachelor degree	Full-time student	798.2109	34323.0670	43	42
2	Female	30-34	Graduate degree	Full-time student	887.5615	15976.1074	18	17
4	Male	30-34	PhD	Full-time employee	495.7182	23298.7564	47	46
6	Female	25-29	Bachelor degree	Full-time student	984.4968	16736.4460	17	16
8	Female	25-29	Bachelor degree	Full-time student	593.5848	27304.9025	46	45
10	Female	18-24	Bachelor degree	Full-time student	783.7017	14890.3314	19	18
12	Female	18-24	Bachelor degree	Full-time student	1237.4022	22273.2392	18	17
14	Female	18-24	Bachelor degree	Full-time student	715.4941	32197.2358	45	44
16	Female	35-39	Bachelor degree	Full-time student	1071.1254	28920.3862	27	26
18	Female	30-34	Graduate degree	Full-time employee	514.5224	23153.5071	45	44
20	Female	18-24	Bachelor degree	Full-time student	743.8206	23058.4396	31	30
22	Female	25-29	Bachelor degree	Full-time student	796.3124	19907.8111	25	24
24	Male	18-24	Bachelor degree	Full-time student	716.5789	16481.3156	23	22
26	Female	18-24	Bachelor degree	Full-time student	438.8591	13604.6321	31	30
28	Male	18-24	Bachelor degree	Full-time student	757.1984	19687.1579	26	25
30	Female	18-24	Bachelor degree	Full-time student	476.9163	15261.3201	32	31
32	Female	18-24	Bachelor degree	Part-time employee/Freelancer	539.2775	29660.2620	55	54
34	Male	18-24	Bachelor degree	Full-time student	703.3963	16881.5113	24	23
2	Male	18-24	Bachelor degree	Full-time student	729.1539	22603.7696	31	30
2	Female	25-29	Bachelor degree	Full-time student	532.4847	24494.2949	46	45
4	Male	30-34	PhD	Full-time employee	850.0717	34002.8682	40	39
6	Male	18-24	Bachelor degree	Full-time student	617.3471	36423.4812	59	58
8	Female	18-24	Bachelor degree	Full-time student	599.8480	16195.8964	27	26
10	Female	18-24	Bachelor degree	Full-time student	882.0362	38809.5935	44	43
12	Male	25-29	Bachelor degree	Full-time student	775.4642	23263.9264	30	29
14	Female	18-24	Bachelor degree	Full-time student	970.5160	28144.9637	29	28
16	Male	25-29	Bachelor degree	Full-time student	1032.1289	23738.9646	23	22
18	Female	25-29	Bachelor degree	Full-time student	610.8914	36653.4833	60	59
20	Female	18-24	Bachelor degree	Full-time student	1357.4295	17646.5829	13	12
22	Female	25-29	Bachelor degree	Full-time student	636.9154	9553.7312	15	14
24	Female	25-29	Graduate degree	Currently not employed	1045.5950	27185.4711	26	25
26	Female	18-24	Bachelor degree	Full-time student	742.4551	28955.7482	39	38
28	Female	18-24	Bachelor degree	Currently not employed	1124.0470	20232.8463	18	17
30	Male	25-29	Graduate degree	Full-time employee	745.4239	26089.8377	35	34
32	Male	18-24	Bachelor degree	Full-time student	673.8861	39759.2828	59	58
34	Male	18-24	Bachelor degree	Full-time student	809.7237	42105.6325	52	51
1	Female	25-29	Bachelor degree	Full-time student	390.1038	390.1038	1	0
1	Male	30-34	PhD	Full-time employee	803.1273	11243.7827	14	13
3	Male	18-24	Bachelor degree	Full-time student	978.4740	7827.7920	8	7
5	Female	18-24	Bachelor degree	Full-time student	706.8707	17671.7687	25	24
7	Female	18-24	Bachelor degree	Full-time student	530.1867	6892.4270	13	12
9	Male	25-29	Bachelor degree	Full-time student	625.2333	14380.3649	23	22
11	Female	18-24	Bachelor degree	Full-time student	628.7614	6287.6141	10	9
13	Male	25-29	Bachelor degree	Full-time student	583.8755	17516.2647	30	29
15	Female	25-29	Bachelor degree	Full-time student	580.5888	8128.2437	14	13
17	Female	18-24	Bachelor degree	Full-time student	233.4019	700.2056	3	2
19	Female	25-29	Bachelor degree	Full-time student	683.6783	10938.8530	16	15
21	Female	25-29	Graduate degree	Currently not employed	621.9936	8707.9105	14	13
23	Female	18-24	Bachelor degree	Full-time student	544.0828	4896.7455	9	8
25	Female	18-24	Bachelor degree	Currently not employed	706.1987	18361.1654	26	25
27	Male	25-29	Graduate degree	Full-time employee	821.3946	7392.5516	9	8
29	Female	18-24	Less than bachelor degree	Full-time student	498.5118	11964.2842	24	23
31	Female	18-24	Less than bachelor degree	Full-time student	481.3755	10108.8860	21	20
33	Male	18-24	Bachelor degree	Full-time employee	692.2641	13845.2814	20	19

Gaze area: bottom

Subject	Gender	Age	Degree	Status	afd	dwell_time	fixation_count	revisits
1	Female	18-24	Bachelor degree	Full-time student	761.7892	7617.8920	10	9
1	Female	30-34	Graduate degree	Full-time student	1224.8881	9799.1050	8	7
3	Male	30-34	PhD	Full-time employee	494.4638	6922.4929	14	13
5	Female	25-29	Bachelor degree	Full-time student	1159.8239	10438.4147	9	8
7	Female	25-29	Bachelor degree	Full-time student	1380.0408	60721.7961	44	43
9	Female	18-24	Bachelor degree	Full-time student	0.0000	0.0000	0	0
11	Female	18-24	Bachelor degree	Full-time student	1034.9741	24839.3791	24	23
13	Female	18-24	Bachelor degree	Full-time student	1227.4258	22093.6641	18	17
15	Female	35-39	Bachelor degree	Full-time student	889.9897	51619.4025	58	57
17	Female	30-34	Graduate degree	Full-time employee	565.0108	14125.2692	25	24
19	Female	18-24	Bachelor degree	Full-time student	998.4983	23963.9597	24	23
21	Female	25-29	Bachelor degree	Full-time student	1505.5829	15055.8294	10	9
23	Male	18-24	Bachelor degree	Full-time student	992.8876	3971.5506	4	3
25	Female	18-24	Bachelor degree	Full-time student	1365.7648	27315.2959	20	19
27	Male	18-24	Bachelor degree	Full-time student	2188.3161	21883.1612	10	9
29	Female	18-24	Bachelor degree	Full-time student	884.4318	15035.3402	17	16
31	Female	18-24	Bachelor degree	Part-time employee/Freelancer	1414.6741	16976.0895	12	11
33	Female	18-24	Bachelor degree	Full-time student	833.9258	9173.1843	11	10
2	Female	30-34	Graduate degree	Full-time student	696.9777	4181.8661	6	5
4	Male	30-34	PhD	Full-time employee	444.8223	6672.3341	15	14
6	Female	25-29	Bachelor degree	Full-time student	312.6492	625.2984	2	1
8	Female	25-29	Bachelor degree	Full-time student	782.8612	1565.7225	2	1
10	Female	18-24	Bachelor degree	Full-time student	615.0403	615.0403	1	0
12	Female	18-24	Bachelor degree	Full-time student	622.9622	6852.5847	11	10
14	Female	18-24	Bachelor degree	Full-time student	623.8120	4366.6840	7	6
16	Female	35-39	Bachelor degree	Full-time student	315.1789	315.1789	1	0
18	Female	30-34	Graduate degree	Full-time employee	277.4015	3051.4168	11	10
20	Female	18-24	Bachelor degree	Full-time student	580.2244	4061.5707	7	6
22	Female	25-29	Bachelor degree	Full-time student	210.0870	210.0870	1	0
24	Male	18-24	Bachelor degree	Full-time student	1048.3680	5241.8401	5	4
26	Female	18-24	Bachelor degree	Full-time student	513.9388	2055.7554	4	3
28	Male	18-24	Bachelor degree	Full-time student	796.3162	3981.5812	5	4
30	Female	18-24	Bachelor degree	Full-time student	386.8468	1160.5403	3	2
32	Female	18-24	Bachelor degree	Part-time employee/Freelancer	0.0000	0.0000	0	0
34	Male	18-24	Bachelor degree	Full-time student	877.9060	1755.8120	2	1
2	Male	18-24	Bachelor degree	Full-time student	1289.8132	20637.0116	16	15
2	Female	25-29	Bachelor degree	Full-time student	867.9407	16490.8726	19	18
4	Male	30-34	PhD	Full-time employee	1072.7886	28965.2928	27	26
6	Male	18-24	Bachelor degree	Full-time student	666.5681	19997.0444	30	29
8	Female	18-24	Bachelor degree	Full-time student	549.1725	13180.1399	24	23
10	Female	18-24	Bachelor degree	Full-time student	855.0502	33346.9571	39	38
12	Male	25-29	Bachelor degree	Full-time student	713.2694	17831.7352	25	24
14	Female	18-24	Bachelor degree	Full-time student	901.0570	49558.1357	55	54
16	Male	25-29	Bachelor degree	Full-time student	516.4441	8263.1057	16	15
18	Female	25-29	Bachelor degree	Full-time student	669.1982	19406.7474	29	28
20	Female	18-24	Bachelor degree	Full-time student	773.9728	94424.6829	122	121
22	Female	25-29	Bachelor degree	Full-time student	1323.2681	100568.3727	76	75
24	Female	25-29	Graduate degree	Currently not employed	652.9384	15670.5219	24	23
26	Female	18-24	Bachelor degree	Full-time student	587.0918	9393.4688	16	15
28	Female	18-24	Bachelor degree	Currently not employed	736.9470	6632.5231	9	8
30	Male	25-29	Graduate degree	Full-time employee	788.0754	104814.0339	133	132
32	Male	18-24	Bachelor degree	Full-time student	603.9111	9058.6669	15	14
34	Male	18-24	Bachelor degree	Full-time student	1375.0609	15125.6700	11	10
1	Female	25-29	Bachelor degree	Full-time student	244.6420	2691.0624	11	10
1	Male	30-34	PhD	Full-time employee	488.6416	6352.3406	13	12
3	Male	18-24	Bachelor degree	Full-time student	593.2299	8898.4483	15	14
5	Female	18-24	Bachelor degree	Full-time student	304.2523	10648.8310	35	34
7	Female	18-24	Bachelor degree	Full-time student	568.1722	8522.5828	15	14
9	Male	25-29	Bachelor degree	Full-time student	652.4808	11744.6545	18	17
11	Female	18-24	Bachelor degree	Full-time student	565.2016	14695.2412	26	25
13	Male	25-29	Bachelor degree	Full-time student	342.6404	8223.3706	24	23
15	Female	25-29	Bachelor degree	Full-time student	505.2462	3536.7235	7	6
17	Female	18-24	Bachelor degree	Full-time student	364.1853	1820.9265	5	4
19	Female	25-29	Bachelor degree	Full-time student	363.6577	18546.5441	51	50
21	Female	25-29	Graduate degree	Currently not employed	584.1665	22198.3258	38	37
23	Female	18-24	Bachelor degree	Full-time student	547.3595	16420.7840	30	29
25	Female	18-24	Bachelor degree	Currently not employed	369.0552	5166.7725	14	13
27	Male	25-29	Graduate degree	Full-time employee	1346.7829	5387.1315	4	3
29	Female	18-24	Less than bachelor degree	Full-time student	833.4195	24169.1657	29	28
31	Female	18-24	Less than bachelor degree	Full-time student	473.6840	4736.8398	10	9
33	Male	18-24	Bachelor degree	Full-time employee	456.1431	11859.7194	26	25

Appendix 6: Table of Content of the zip file

This thesis report is accompanied by a zip file. The table provides an overview of what this zip file includes.

Index	Content
1. Documentation of what is where in the file	- Documentation .txt file explaining the content of the zip file
2. Report (word, pdf)	- Thesis report (word) - Thesis report (pdf)
3. Midterm & final presentation (pptx)	- Midterm presentation (pptx) - Final presentation (pptx)
4. Animations	
5. Datasets used and created	- VR: Unity project - Eye-tracking data: .csv files - Outputs: .xlsx excel tables
6. Figures/ maps/ tables	- All figures and tables used in the report
7. Scripts/ code/ exe	- Statistical analysis scripts: .py files
8. Questionnaires	- Experiment questionnaires (Google forms)
9. Literature (pdfs of used articles)	- References in the report