Beyond Constant Transparency: Evaluating a Pedestrian-Aware Transparency-Adaptive Interface for Mixed Reality Walking

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Abstract

Mixed Reality (MR) head-mounted displays are emerging as platforms for everyday personal computing, yet their use during walking raises critical safety concerns due to visual occlusion of the physical environment. While transparency-based interfaces have been proposed to address this issue, systematic comparisons of different UI rendering methods in realistic pedestrian scenarios remain limited. This study investigated how four UI rendering methods - Opaque, Always Transparent, Adaptive Transparent, and Depth-Aware - combined with two UI sizes (small and large) affect walking safety and UI legibility during pedestrian encounters. Twenty participants performed a dual-task paradigm involving continuous reading while walking and avoiding unpredictable pedestrians. Results revealed that transparency-based methods (Always Transparent and Adaptive Transparent) significantly outperformed occlusion-based methods (Opaque and Depth-Aware) across safety metrics, walking performance, subjective workload, and user preference. Specifically, transparency-based conditions yielded longer minimum time to collision, greater passing clearance, faster walking speeds, and lower NASA-TLX scores. In contrast, Depth-Aware method performed comparably to the Opaque condition, suggesting that depth-based occlusion alone is insufficient for dynamic pedestrian avoidance. A significant interaction between UI size and rendering method further indicated that transparency mitigates the negative effects of larger interfaces on user experience,

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whereas occlusion-based interfaces require size minimization to preserve safety and user experience. While Always Transparent achieved the highest subjective ratings for perceived safety and visual clarity, Adaptive Transparent offered a more balanced experience by preserving text legibility when no pedestrians were detected. Overall, these findings provide actionable design guidelines for developing mobile MR interfaces that balance content visibility with safety.

Keywords: Mixed reality, Augmented reality, Adaptive interface, Pedestrian safety, Mobile computing

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1. Introduction

Extended Reality (XR) technologies have evolved rapidly in recent years, with Mixed Reality (MR) head-mounted displays (HMDs) emerging as a promising platform for everyday personal computing. Advances in lightweight optics, wide field-of-view displays, and high-quality video pass-through now enable MR systems to seamlessly integrate persistent virtual content with the physical environment. A defining characteristic of MR interfaces is their ability to present floating virtual displays positioned in mid-air within users' forward field of view. While this enables heads-up, hands-free interaction, it also introduces new design challenges, particularly regarding user safety during mobile use.

Extensive research on pedestrian distraction reveals that smartphone use while walking alters stride patterns, reduces peripheral vision, and lowers situational awareness, thereby increasing the likelihood of near-collision events and mobility-related incidents [1, 2, 3, 4]. Although MR interfaces differ fundamentally from handheld devices, they introduce analogous challenges in attention division. By relocating digital content directly into users' forward field of view, MR interfaces can visually occlude critical environmental information, such as pedestrians, vehicles, and navigational hazards. As a result, MR does not inherently resolve the risks associated with mobile multitasking and may introduce new safety concerns if interface behavior is not carefully designed for walking contexts.

To mitigate such risks, commercial Augmented Reality (AR) devices are increasingly incorporating semi-transparent interface designs for everyday mobility. Smart glasses such as Meta Ray-Ban Display [5] exemplify this trend. However, transparent interfaces introduce a well-documented trade-off: while they preserve access to the physical environment, reduced opacity degrades text legibility and readability, particularly against complex backgrounds [6, 7]. This trade-off suggests that static transparency alone may be insufficient for balancing environmental awareness and content readability during walking.

Additionally, empirical understanding of how MR interface designs influence pedestrian safety and walking behavior remains limited. Prior studies have examined isolated parameters such as layout [8, 9], anchoring strategies [10], and presentation styles [11, 12, 13]. While these works reveal important effects on reading performance and divided attention, they primarily rely on static or predefined configurations that do not capture the dynamic and unpredictable nature of real-world walking. More recent context-aware adaptive interfaces demonstrate strong conceptual potential for on-the-go use, as they adjust transparency, placement, or depth based on environmental cues [14, 15]. However, these systems often rely on computationally intensive approaches, such as large language models, which introduce processing latency that may be unsuitable for situations requiring prompt user response to sudden hazards. Moreover, their effects on locomotion-level safety outcomes remain unexplored. Although interest in AR and MR interfaces for mobile use continues to grow, a systematic comparison of different interface methods within realistic pedestrian walking scenarios remains absent.

To address this gap, we conducted a realistic walking experiment that examines four MR user interface (UI) rendering methods across two interface sizes during unpredictable pedestrian encounters: (1) *Opaque*; (2) *Always Transparent* with constant transparency; (3) *Adaptive Transparent*, which dynamically transitions opacity based on real-time pedestrian detection, and (4) *Depth-Aware*, which leverages depth sensing to correctly layer pedestrians relative to virtual content. These UI rendering methods were crossed with two UI sizes to systematically investigate how interface behavior and UI size jointly influence the trade-off between UI legibility and walking safety during mobile MR use.

This work makes three primary contributions. First, we design and evaluate an adaptive MR UI that adjusts transparency in real time based on pedestrian detection. Second, we present the first systematic empirical comparison of multiple UI rendering methods in realistic pedestrian encounter scenarios, using both objective behavioral measures and subjective assessments. Third, we derive design recommendations for MR UI configurations during outdoor walking. Collectively, our findings demonstrate that a continuous transparency adaptive interface can enhance user safety while preserving task performance, thereby supporting the viability of MR devices for outdoor walking scenarios.

2. Related Work

2.1. Interface Design for Mobile Dual-Task Performance

Using AR and MR while walking inherently creates a dual-task condition in which users must divide attention between real-world locomotion and virtual information. Prior work consistently shows that interface design choices directly shape how well users maintain this balance. Text-related studies demonstrate that font characteristics, layout, and polarity can influence both reading performance and gait stability during treadmill or corridor walking [12, 16, 13].

Beyond text presentation, anchoring strategies also influence dual-task behavior. Comparing head-, hand-, and torso-anchored content, recent work shows that anchoring choice affects walking stability, attention switching, and workload during continuous navigation tasks [10]. Other studies propose presentation techniques for the consuming mobile media, such as Layered Serial Visual Presentation, which improves video learning on-the-go while preserving the pace of walking [11].

Studies conducted in real pedestrian settings report similar patterns. When participants design or adjust MR interfaces while walking outdoors, their preferred interface size, opacity, and placement systematically shift with traffic density and task demands, indicating that dual-task pressures directly shape interface preferences [9, 8]. Together, these findings highlight that AR presentation parameters and spatial layout decisions substantially influence how effectively users maintain walking performance while engaging with virtual content.

2.2. Environmental Awareness and Pedestrian Safety

Maintaining awareness of nearby people, obstacles, and moving hazards is essential when using AR and MR during mobility. A substantial body of work investigates how AR interfaces can support safer walking by reducing collisions or missed environmental cues. Pedestrian-warning and obstacle-alerting systems demonstrate that visual cues can help users detect approaching vehicles or hazards during mobile AR use, highlighting the importance of preventing virtual overlays from masking critical real-world information [17, 18].

Beyond direct collision prevention, several studies examine how AR can support safe coexistence with bystanders in shared spaces. Techniques such as projected shadows or ambient indicators increase the visibility of an AR user's presence and intentions, helping reduce accidental interference during navigation [19]. Related work on boundary-awareness cues, originally developed for VR settings, shows that lightweight spatial indicators can prevent unintended contact with nearby people or objects, underscoring the value of subtle environmental signaling [20].

Other research highlights the broader tension between immersion and environmental visibility. Highly opaque or visually dominant AR overlays can hinder users' ability to detect dynamic events in the surrounding environment, suggesting the need for careful management of visual complexity in mobile scenarios [21]. Together, these studies emphasize that AR-based systems must preserve access to real-world cues during walking to support safe movement through shared environments.

2.3. Adaptive User Interfaces

Adaptive interfaces represent a growing direction in AR and MR research aiming to adjust UI behavior in response to changing environmental or user states. Several systems demonstrate how dynamic interface adaptation can improve usability by reducing occlusion or highlighting relevant real-world elements. Occlusion-management techniques, for example, automatically reposition or modulate the transparency of virtual content to maintain visibility of important environmental features, supporting quick glance interactions without fully obscuring the physical scene [22].

Beyond spatial adjustments, recent work explores intelligent adaptation pipelines that use computer vision, attention modeling, or large language models to infer user intent or environmental risk. Context-aware AR frameworks propose methods for recognizing objects, estimating scene semantics, or detecting social cues to drive interface adaptation [23]. More specialized systems, such as AttentionAR, incorporate multi-modal attention estimation combined with reasoning from large language models to modify UI layouts or provide timely warnings based on the user's attentional state [14]. Similarly, SituationAdapt leverages scene understanding and high-level contextual inference to rearrange or simplify MR interfaces in response to environmental complexity or social interactions [15].

Collectively, this work shows strong conceptual support for adaptive AR and MR interfaces capable of responding to dynamic real-world conditions. However, existing systems primarily evaluate interface quality, occlusion handling, or hazard detection rather than mobility outcomes such as walking behavior or safety margins. Moreover, reliance on external compute resources or high-latency perception pipelines challenges their suitability for on-the-go use. These gaps motivate a systematic evaluation of adaptive interfaces within MR walking contexts, where virtual content persistently occupies the user's forward field of view.

3. Method

3.1. Participants

Twenty healthy young Korean adults participated in this study (see Table 1). All had normal or corrected-to-normal vision. While all had prior experience with MR headsets, the majority (n = 15) were classified as light users who engaged with MR applications no more than once per month. None reported a history of motion sickness during MR use. This study was approved by the University Institutional Review Board (KAISTIRB-2025-218), and all participants provided written informed consent before participation.

Table 1: Descriptive statistics of the participants: mean and standard deviation

Gender	Number of participants	Age (years)	Body height (cm)	Shoulder width (cm)
Female	10	22.6 (2.4)	162.1 (3.3)	39.2 (1.9)
Male	10	23.4 (3.1)	173.0 (4.6)	44.9 (2.7)
Total	20	23.0 (2.73)	167.5 (6.8)	42.1 (3.7)

3.2. UI Rendering Methods and Experimental Design

In this experiment, we employed four different UI rendering methods combined with two UI sizes, resulting in a total of eight experimental conditions (see Figure 1).

The first method, referred to as *Opaque*, maintained a constant opacity of 1.0 regardless of the external environment. In this condition, the virtual UI completely occluded any real-world objects occupying the same visual space, whether they were physically in front of the UI plane or behind it. The second method, *Always Transparent*, applied a fixed opacity of 0.7 to the UI. This transparency level was adopted based on findings from prior research [8], allowing users to perceive the external environment through the UI while still maintaining sufficient visibility of the interface content. The third method, *Adaptive Transparent*, dynamically adjusted the UI opacity based on real-time pedestrian detection. We used Unity's inference system with a YOLOv9 ONNX model [24] to detect pedestrians, running entirely on-device. The system achieved approximately 60 FPS while running real-time detection, and the participants reported no perceptible latency during use. When a person was detected within 5 m, the UI opacity automatically changed to 0.7, allowing users to see through the interface; otherwise, the UI remained fully opaque. The fourth method, *Depth-Aware*, leveraged Meta's Depth Shader to render the UI with depth-based occlusion [25]. In this condition, the UI maintained an opacity of 1.0; however, real-world objects positioned closer to the user than the UI were rendered in front of the interface, while objects located further away remained occluded.

Regarding UI size, two conditions were implemented: Small and Large. The Small condition featured a UI with a diagonal field of view of 52°, which corresponds to the full-screen display of the XREAL Air 1S [26], while the Large condition expanded this to 70°, reflecting the field of view of the Meta Orion glasses [27]. In all conditions, the UI was head-anchored and positioned at a distance of 1.1 m from the user's eyes [8].

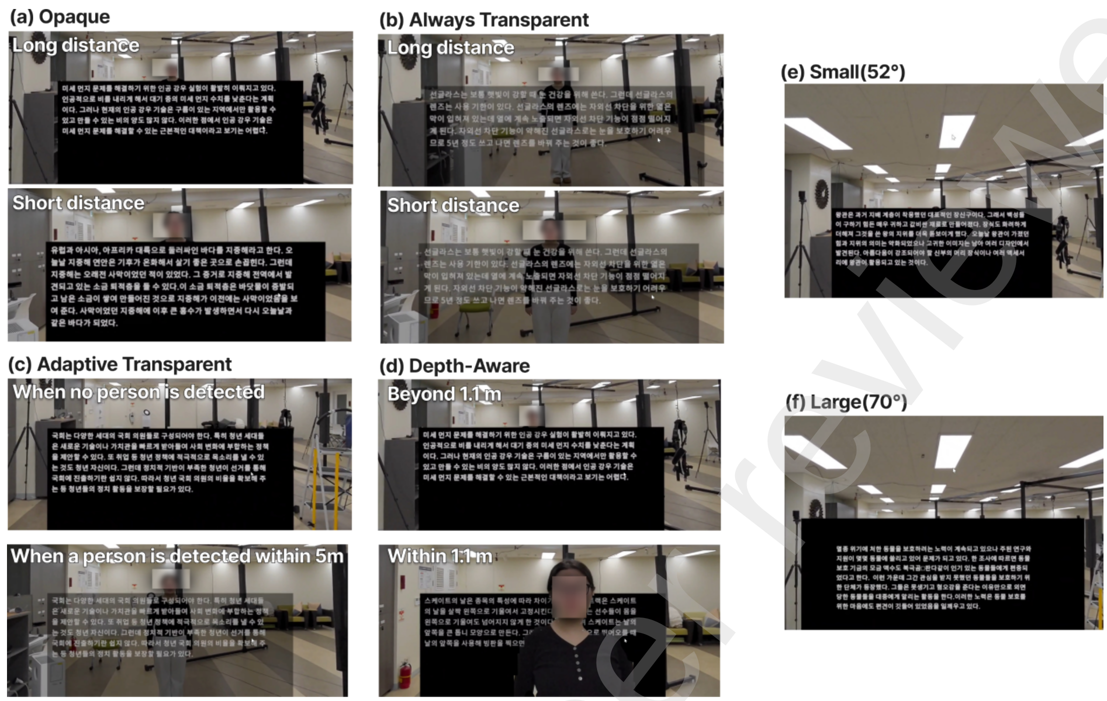

Figure 1: The eight experimental conditions: four UI rendering methods-(a) *Opaque*, (b) *Always Transparent*, (c) *Adaptive Transparent*, and (d) *Depth-Aware*-shown at short and long distances or different detection states, combined with two UI sizes-(e) Small (52°) and (f) Large (70°). Note that the user's actual field of view was wider than shown; images were cropped to highlight the UI effects.

3.3. Experimental Settings

Participants wore a Meta Quest 3 with camera passthrough enabled, allowing them to perceive the real-world environment while interacting with virtual UI elements. The experiment employed a dual-task paradigm designed to simulate a common real-world scenario in which pedestrians read text on a mobile device while walking and navigating around other people.

As illustrated in Figure 2, participants walked back and forth along a 9 m path for two minutes per condition. An auditory cue was provided each time participants reached either endpoint, signaling them to turn around and continue in the opposite direction. To replicate the real-world experience of pedestrians unexpectedly appearing from occluded areas - such as corners or building edges - four 2 m-tall walls were arranged diagonally around the midpoint of the path (Figure 2). This configuration obstructed participants' lateral lines of sight, preventing them from anticipating the direction from which another person might emerge.

During each traversal, an actor appeared from behind the walls. The actor was 1.6 m tall, with a shoulder width of 0.38 m, and wore black long-sleeved clothing and trousers throughout all sessions. The actor began walking from their starting point simultaneously with the participant departing from either endpoint, and exhibited one of two behaviors: passing through without stopping (Figure 2-c), or stopping partway along the path (Figure 2-b). In the latter case, the actor stopped at a position offset by 0.5 m randomly to either the left or right of the path's center while facing the participant. When the actor passed through, they always crossed the center before the participant arrived, so no collision risk existed, and participants could maintain their straight walking trajectory. When the actor stood stationary, participants were required to detour to the side opposite to the actor's position. This unpredictable variation prevented participants from anticipating the actor's behavior or position. Across each two-minute trial, the actor stopped five times randomly, with the remaining appearances consisting of pass throughs events. In total, across all eight experimental conditions, each participant encountered a total of 40 stopping events and an average of 34.5 (SD = 9.51) pass through events.

Concurrently, participants performed a reading task by continuously reading paragraphs aloud from the reading section of the Test of Proficiency in Korean (TOPIK). Text difficulty was calibrated to a high school proficiency level, and each paragraph consisted of three to four sentences. Upon completing a paragraph, participants performed a pinch gesture using their left index finger and thumb to advance to the next paragraph. The text was rendered in white against a black background with a character height of 2°. Both text size and position remained constant across the two UI size conditions.

Participants received the following instructions: "Walking is the primary task, and reading is the secondary task. Walk naturally, as you would in daily life, while reading clearly at a reasonable pace. If you perceive that a pedestrian has stopped in your path, detour around them safely; if you perceive that the pedestrian has simply passed by, continue straight along the black line."

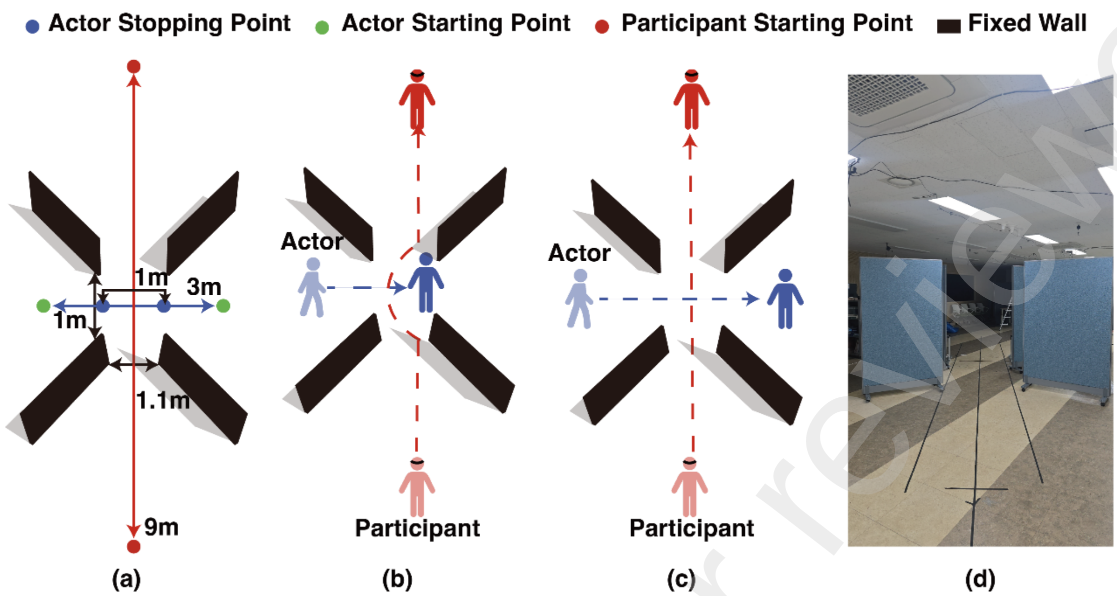

Figure 2: (a) Top-down view of the walking path with wall placement and dimensions. (b) Stopping condition: the actor stopped at one of two randomized positions. (c) Pass through condition: the actor crossed without stopping. Both conditions occurred bidirectionally as participants walked back and forth. (d) Actual experimental setup: the blue wall occluded the actor's actions, preventing participants from anticipating them. Participants were instructed to walk back and forth for 2 minutes along the central black line.

3.4. Experimental Procedure

The experimental protocol followed a systematic five-phase procedure designed to comprehensively assess the effects of UI rendering method and size on walking safety and UI legibility: (1) pretest questionnaire, (2) familiarization, (3) normalization, (4) main experimental trials with subjective evaluation, and (5) open-ended interview. Each participant completed all phases within a single session on the same day, lasting approximately 120 minutes.

During the pretest questionnaire phase, participants completed a standardized form documenting demographic characteristics, including age, gender, height, and shoulder width, as well as their prior experience with MR systems. This phase established baseline participant profiles and verified compliance with inclusion criteria. Subsequently, participants underwent a familiarization session in which they experienced all experimental conditions to minimize novelty effects and ensure familiarity with the experimental apparatus.

Table 2: Items of the subjective evaluation used in this study. Answers were given through 7-point Likert scales (Subjective evaluation: 1=strongly disagree, 7=strongly agree)

	Aspect	No.	Item
Custom Likert Questionnaire	Safety	1	I was able to easily identify the location of pedestrians.
		2	I rarely felt a risk of collision.
		3	I felt I had sufficient time to avoid obstacles.
	Visual Clarity	4	The UI did not obstruct my forward view.
		5	The UI did not interfere with my walking.
		6	I did not need to excessively move my gaze to check my surroundings.
	Reading Flow & Comprehension	7	I was able to read the text at a natural pace.
		8	The UI did not interfere with my ability to read the text.
		9	Switching gaze between the forward view and the text was smooth.

In the normalization phase, participants walked back and forth along the same 9 m path for two minutes without wearing the Meta Quest 3 and without the actor present. This baseline data collection enabled subsequent normalization of inter-participant variability in walking behavior. For the main experimental trials, we implemented a Balanced Latin Square design to mitigate potential order effects across conditions. After completing each condition, participants removed the MR headset and took a 5-minute break, during which they completed a subjective evaluation instrument consisting of nine custom 7-point Likert scale items (1=strongly disagree, 7=strongly agree) and the NASA Task Load Index rated on a 0–10 scale [28]. The custom Likert scale items are detailed in Table 2.

The session concluded with an open-ended interview to capture qualitative insights regarding participants' overall experiences, followed by a preference ranking across all eight conditions.

3.5. Data analysis

3.5.1. Reading performance

Oral reading performance was evaluated using two primary metrics: Syllable Per Minute (SPM) and Syllable Error Rate (SER). SPM was calculated as shown in Equation (1):

$$SPM = \frac{|S_{total}|}{Sec} \times 60 \tag{1}$$

where Sec represents the oral reading duration in seconds and $|S_{total}|$ denotes the total number of syllables read by the participant. The constant 60 converts the rate to a per-minute measure. Unlike the English-based Words Per Minute, SPM provides a more precise and consistent assessment for Korean [29], as each syllable block corresponds directly to a single syllable.

The reading accuracy was measured using the SER, as defined in Equation (2):

$$SER = \frac{E_{uncorrected}}{|S_{total}|} \times 100 \quad (2)$$

where $E_{uncorrected}$ denotes the number of uncorrected errors, such as substitutions, omissions, or additions. Following the standard scoring protocols for reading assessment [30], self-corrections - errors that the participant identified and corrected within a 3-second window - were excluded from $E_{uncorrected}$ and treated as correct syllables. This ensures that SER specifically reflects final reading accuracy.

3.5.2. Walking Performance

Walking performance was assessed using two primary metrics: Walking Speed and Lateral Deviation. Walking Speed was collected using the Xsens Awinda inertial motion capture system at a sampling rate of 100 Hz. It was derived from the inertial measurement unit attached to the pelvis, providing a reliable indicator of participants' walking velocity throughout each trial. Speed values were expressed as percentage change from each participant's baseline measurement obtained during the normalization session.

Lateral Deviation was calculated to quantify horizontal displacement from the designated straight-line path. A Vive Ultimate Tracker was attached to each participant's chest to capture positional data for this calculation at a sampling rate of approximately 90 Hz. Prior research has demonstrated that this tracker achieves positional accuracy within 1 mm when compared to Vicon motion capture systems [31]. To isolate natural walking variability from pedestrian avoidance behavior, Lateral Deviation was computed exclusively for pass through events. Additionally, data from the first and last 30 cm of each traversal were excluded to remove artifacts associated with turning behavior at the endpoints.

3.5.3. Safety metrics

Safety was evaluated using two metrics: Minimum Time to Collision and Passing Clearance. Figure 3 illustrates how both metrics were computed during actor stopping conditions. These metrics were computed exclusively for stopping conditions, as these instances required active collision avoidance maneuvers. To capture the spatial relationship between participants and the actor during such encounters, Vive Ultimate Trackers were attached to both the participant's and the actor's chests.

Both metrics were computed only when the actor stopped. Each individual was modeled as a circle on the horizontal plane with a diameter corresponding to their respective shoulder widths. Time to Collision was computed at each time step as the predicted time until the two circles would first make contact, assuming the participant maintained their velocity and the actor remained stationary (Figure 3a). For each actor stopping event, the lowest Time to Collision value was identified as the Minimum Time to Collision. Passing Clearance was defined as the minimum horizontal distance between the centers of the two circles at the moment the participant passed the stationary actor (Figure 3b). Consequently, five distinct values were derived for both metrics per condition, corresponding to the five stopping events in each trial. Together, these metrics provided quantitative indicators of collision risk and the spatial margin maintained during pedestrian avoidance.

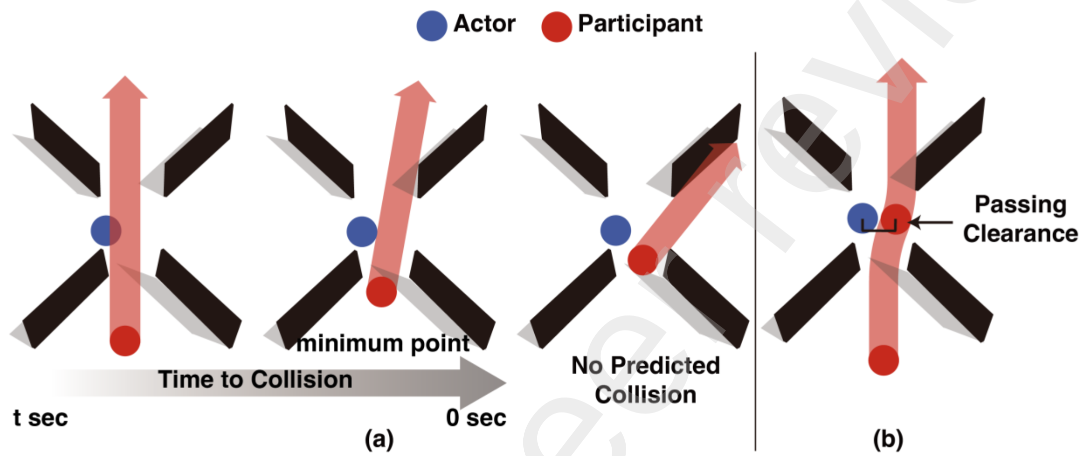

Figure 3: Illustration of safety metrics computed during actor stopping conditions. The participant (red) and actor (blue) were modeled as circles on the horizontal plane with diameters corresponding to their respective shoulder widths. (a) Minimum time to collision calculation: Left: The participant approaches the stationary actor on a collision course, with time to collision at t seconds. Middle: The time to collision decreases as the participant approaches the actor and reaches its minimum value immediately before the participant alters their trajectory to avoid a collision. Right: The participant's avoidance maneuver alters their trajectory such that no collision is predicted, and time to collision is no longer computed. (b) Passing clearance: the minimum horizontal distance between the centers of the two circles at the moment the participant passes the stationary actor.

3.5.4. Statistical analysis

We employed the Interquartile Range (IQR) method to screen for potential outliers, defined as SER values exceeding 1.5 × IQR. No outliers were detected, so the full dataset was retained for subsequent analyses. Ryan-Joiner normality tests were conducted to verify distributional assumptions of the collected data. Most dependent variables satisfied the normality criterion ($p > .05$) or exhibited minor deviations that were deemed acceptable given the robustness of analysis of variance (ANOVA) to moderate non-normality [32]. For these variables, we conducted repeated measures analysis of variance (RM-ANOVA) to assess statistical significance. For significant effects, pairwise comparisons were conducted using Bonferroni correction.

p

In cases where Mauchly's test indicated a violation of the sphericity assumption ($\varepsilon <$ .75), Greenhouse-Geisser corrections were applied to adjust the degrees of freedom. Effect sizes for all ANOVA results were reported as partial eta-squared ($\eta_p{}^2$).

For the preference ranking data, which did not meet parametric assumptions, we performed an Aligned Rank Transform as proposed by Wobbrock et al. [33] and applied the ART-C procedure introduced by Elkin et al. [34] for post-hoc analysis. Statistical analyses and data processing were conducted using R (version 4.4.1), with a predetermined significance threshold set at $\alpha = .05$.

4. Results

Table 3 summarizes the statistical test results for the effects of UI rendering method and UI size on all dependent variables. Detailed results are presented in the following sections.

4.1. Reading performance

Figure 4 presents the reading performance metrics across different UI rendering methods and UI sizes. As shown in Table 3, RM-ANOVA revealed no significant interaction effects between rendering method and UI size for either SPM or SER.

For main effects, UI rendering method significantly influenced both metrics. Specifically, *Adaptive Transparent* yielded significantly higher SPM than *Depth-Aware* (t = 3.24, p = .021), while no other pairwise differences reached significance. For SER, *Always Transparent* produced significantly higher error rates compared to both *Depth-Aware* (t = 3.01, p = .033) and *Opaque* (t = 3.77, p = .006). UI size, however, showed no significant main effect on either metric.

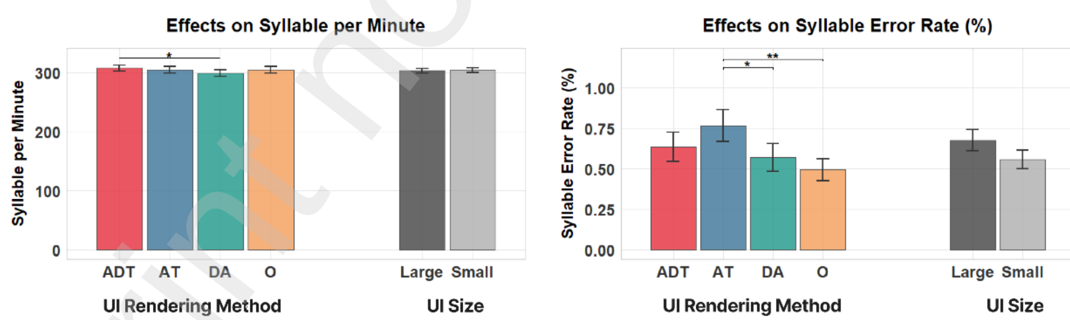

Figure 4: Mean (± SE) values of SPM and SER across UI rendering method and UI size. Abbreviations: ADT = Adaptive Transparent, AT = Always Transparent, DA = Depth-Aware, O = Opaque. These abbreviations apply to all subsequent figures and text. Asterisks denote statistically significant differences based on Bonferroni-corrected paired t-tests (*$p < .05$, **$p < .01$, ***$p < .001$; applies to all graphs).

Table 3: Summary of Repeated-Measures ANOVA results

Variables	UI Rendering Method			UI Size			UI Rendering Method × UI Size		
	F_{df}	p	η_p^2	F_{df}	p	η_p^2	F_{df}	p	η_p^2
Reading Performance									
Syllable Per Minute	$F_{2.94,55.81}$ =3.61	.019	.160	$F_{1,19}$ =0.42	.527	.021	$F_{2.63,49.88}$ =1.61	.204	.078
Syllable Error Rate	$F_{2.57,48.77}$ =5.71	.003	.231	$F_{1,19}$ =2.28	.147	.107	$F_{2.33,44.25}$ =1.51	.231	.074
Walking Performance									
Walking Speed	$F_{2.63,49.97}$ =21.68	<.001	.533	$F_{1,19}$ =3.00	.100	.136	$F_{2.46,46.83}$ =1.57	.216	.076
Lateral Deviation	$F_{2.85,54.15}$ =1.04	.381	.052	$F_{1,19}$ =0.01	.932	<.001	$F_{2.75,52.33}$ =2.39	.084	.112
Safety									
Minimum Time to Collision	$F_{2.21,40.47}$ =13.25	<.001	.411	$F_{1,19}$ =6.68	.018	.260	$F_{2.37,45.09}$ =1.68	.193	.081
Passing Clearance	$F_{2.70,51.24}$ =7.35	<.001	.279	$F_{1,19}$ =6.24	.022	.247	$F_{2.51,47.66}$ =1.10	.353	.055
Subjective Measure									
NASA-TLX	$F_{1.80,34.25}$ =22.60	<.001	.543	$F_{1,19}$ =3.22	.088	.145	$F_{2.84,53.87}$ =5.89	.002	.237
Safety	$F_{2.69,51.04}$ =68.84	<.001	.784	$F_{1,19}$ =17.68	<.001	.482	$F_{2.50,47.55}$ =3.31	.035	.149
Visual Clarity	$F_{2.66,50.53}$ =67.30	<.001	.780	$F_{1,19}$ =20.20	<.001	.515	$F_{2.68,50.85}$ =4.64	.008	.196
Reading Flow	$F_{1.99,37.90}$ =13.06	<.001	.407	$F_{1,19}$ =1.26	.276	.062	$F_{2.84,53.96}$ =1.88	.146	.090
Rank	$F_{3,133}$ =57.51	<.001	.560	$F_{1,133}$ =2.58	.111	.019	$F_{3,133}$ =0.15	.930	.003

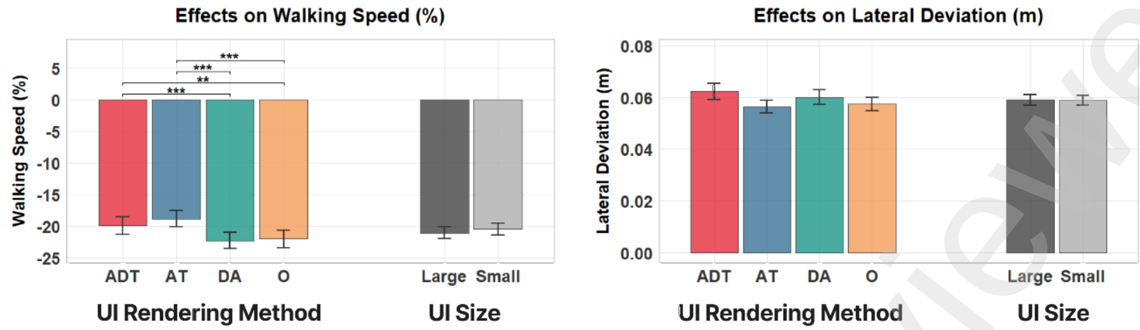

Figure 5: Mean (± SE) Walking Speed and Lateral Deviation by UI rendering method and UI size.

Figure 6: Mean (± SE) Passing Clearance and Minimum Time to Collision by UI rendering method and UI size.

4.2. Walking Performance

Figure 5 presents the walking performance metrics across different UI rendering methods and UI sizes. As shown in Table 3, RM-ANOVA revealed no significant interaction effects between rendering method and UI size for either metric.

For main effects, the rendering method significantly influenced Walking Speed. Specifically, both *Adaptive Transparent* and *Always Transparent* resulted in significantly faster speeds than *Depth-Aware* and *Opaque* (ADT vs. DA: $t = 5.02$, $p < .001$; ADT vs. O: $t = 4.41$, $p = .002$; AT vs. DA: $t = 5.92$, $p < .001$; AT vs. O: $t = 7.04$, $p < .001$). However, no significant differences were found between *Adaptive Transparent* and *Always Transparent*, nor between *Depth-Aware* and *Opaque*. For Lateral Deviation, the rendering method showed no significant main effect. Similarly, UI size did not significantly affect either metric.

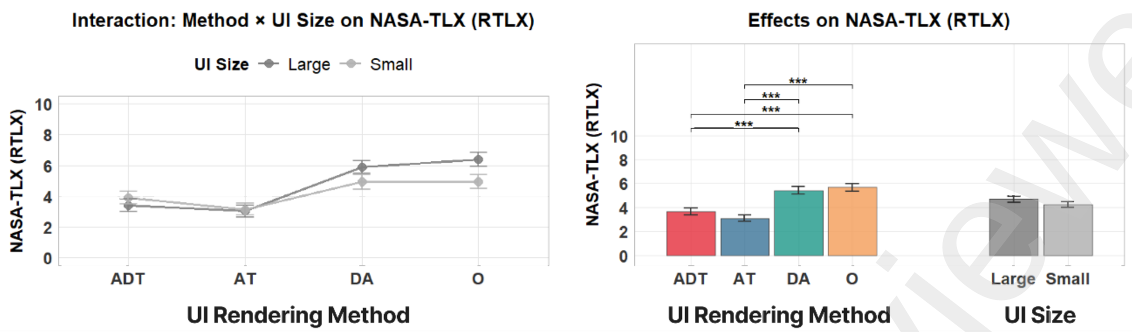

Figure 7: Interaction plot and Mean (± SE) NASA TLX by UI rendering method and UI size.

4.3. Safety Metrics

Figure 6 presents the safety metrics across different UI rendering methods and UI sizes. As shown in Table 3, RM-ANOVA revealed no significant interaction effects between rendering method and UI size for either metric.

For main effects, the rendering method significantly influenced both metrics. Regarding Minimum Time to Collision, *Adaptive Transparent* yielded significantly higher values than *Depth-Aware* ($t = 4.44$, $p = .001$) and *Opaque* ($t = 4.81$, $p < .001$). Similarly, *Always Transparent* produced higher values than *Depth-Aware* ($t = 3.37$, $p = .016$) and *Opaque* ($t = 3.68$, $p = .008$). However, no significant differences were found between *Adaptive Transparent* and *Always Transparent*, nor between *Depth-Aware* and *Opaque*. For Passing Clearance, *Adaptive Transparent* demonstrated significantly higher values than *Depth-Aware* ($t = 5.20$, $p < .001$) and *Opaque* ($t = 3.05$, $p = .031$), while *Always Transparent* showed significantly higher values only compared to *Depth-Aware* ($t = 2.87$, $p = .044$).

Unlike the previous metrics, UI size showed significant main effects on both safety measures. The Small UI size condition resulted in significantly higher Minimum Time to Collision and Passing Clearance compared to the Large condition.

4.4. NASA-TLX and subjective evaluation

Following Hart [28], we calculated the TLX score as an average of its six subscales. As shown in Table 3, a significant interaction effect between UI rendering method and UI size was observed for NASA-TLX. When participants used *Adaptive Transparent* and *Always Transparent*, differences between size conditions were minimal. In contrast, *Depth-Aware* and *Opaque* showed a tendency toward higher workload ratings in the Large condition compared to the Small condition (Figure 7). Similar interaction effects were observed for Safety and Visual Clarity: *Adaptive Transparent* and *Always Transparent* showed minimal influence from UI size, whereas *Depth-Aware* and *Opaque* resulted in lower scores for the Large condition (Figure 8). For Reading Flow, no significant interaction effect was observed.

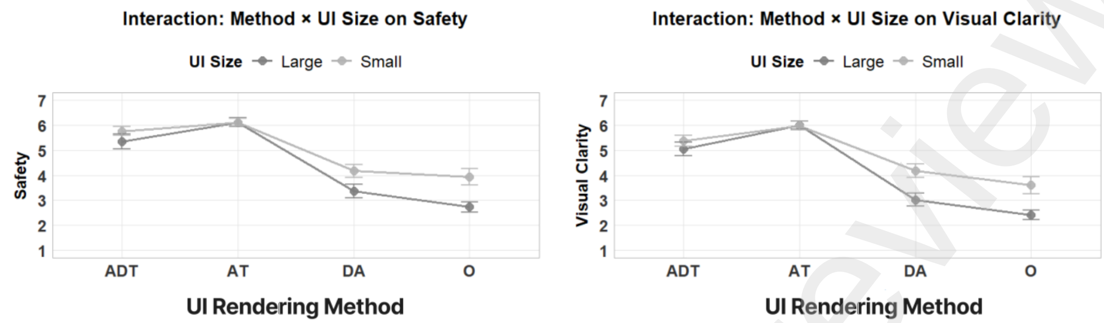

Figure 8: Interaction effects of UI rendering method × UI size on perceived Safety (left) and Visual Clarity (right). Error bars represent ± SE.

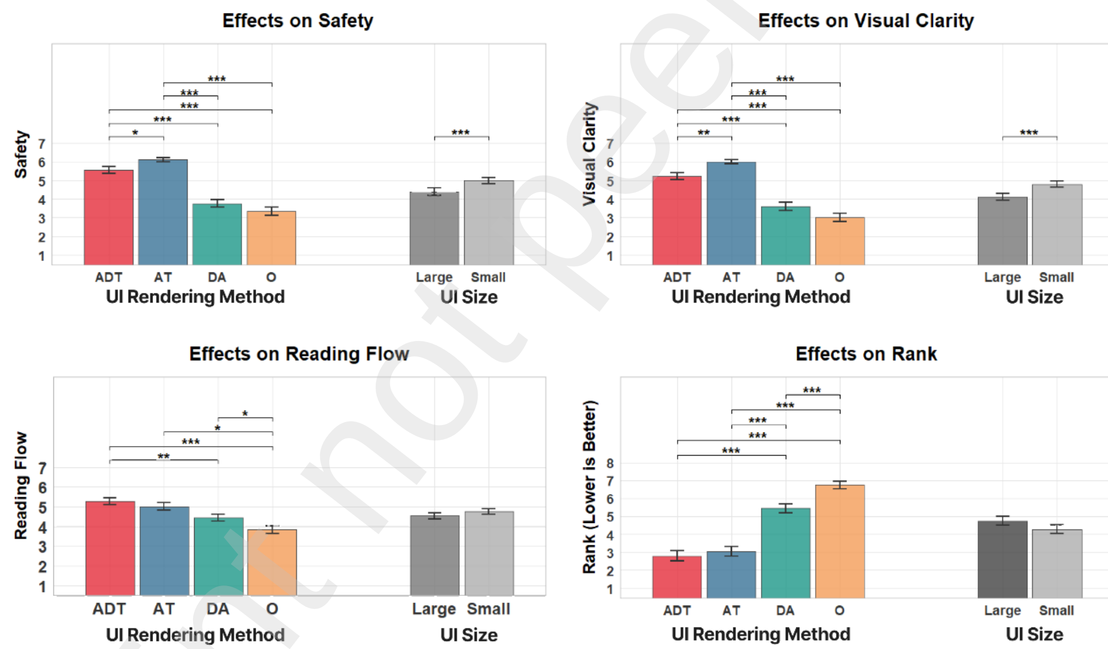

Figure 9: Mean ratings (± SE) for Safety, Visual Clarity, Reading Flow, and Rank by UI rendering method and UI size.

For main effects, UI rendering method significantly influenced NASA-TLX and all custom Likert scale items (Figure 7 and 9). Specifically, *Adaptive Transparent* and *Always Transparent* received significantly lower NASA-TLX ratings than *Depth-Aware* and *Opaque* (ADT vs. DA: t = 8.89, p < .001; ADT vs. O: t = 9.63, p <

.001; AT vs. DA: $t = 10.00$, $p < .001$; AT vs. O: $t = 11.55$, $p < .001$). However, no significant differences were found between *Adaptive Transparent* and *Always Transparent*, nor between *Depth-Aware* and *Opaque*.

For Safety, *Always Transparent* scored significantly higher than all other methods (AT vs. ADT: $t = 4.38$, $p = .002$; AT vs. DA: $t = 10.18$, $p < .001$; AT vs. O: $t = 11.48$, $p < .001$), and *Adaptive Transparent* also scored significantly higher than *Depth-Aware* and *Opaque* (ADT vs. DA: $t = 7.23$, $p < .001$; ADT vs. O: $t = 8.83$, $p < .001$). Visual Clarity followed the same pattern, with *Always Transparent* scoring highest (AT vs. ADT: $t = 4.38$, $p = .002$; AT vs. DA: $t = 10.18$, $p < .001$; AT vs. O: $t = 11.48$, $p < .001$), followed by *Adaptive Transparent* (ADT vs. DA: $t = 7.23$, $p < .001$; ADT vs. O: $t = 8.83$, $p < .001$). Reading Flow showed a similar pattern (ADT vs. DA: $t = 5.72$, $p < .001$; ADT vs. O: $t = 5.09$, $p < .001$; AT vs. DA: $t = 6.10$, $p < .001$; AT vs. O: $t = 4.78$, $p < .001$), with no significant difference between *Adaptive Transparent* and *Always Transparent*.

Regarding UI size, no significant main effect was observed for NASA-TLX or Reading Flow. However, for Safety and Visual Clarity, the Small condition resulted in significantly higher scores than the Large condition.

4.5. Qualitative feedback from open-ended responses and preference rank

After completing all experimental trials, participants ranked their preferences across all eight conditions (Figure 9). As shown in Table 3, no significant interaction effect between UI rendering method and UI size was observed for preference ranking.

For main effects, the rendering method significantly influenced preference ranking. Specifically, *Adaptive Transparent* and *Always Transparent* were ranked significantly higher (i.e., more preferred) than *Depth-Aware* and *Opaque* (ADT vs. DA: $t = -7.40$, $p < .001$; ADT vs. O: $t = -11.04$, $p < .001$; AT vs. DA: $t = -6.79$, $p < .001$; AT vs. O: $t = -10.43$, $p < .001$), with no significant difference between them ($t = -0.61$, $p = .545$). Additionally, *Depth-Aware* was ranked significantly higher than *Opaque* ($t = -3.64$, $p < .001$). UI size showed no significant main effect on preference ranking.

In addition to quantitative measures, participants provided open-ended feedback on their experiences with each condition. Representative comments are summarized in Table 4. For *Always Transparent*, several participants noted that it made pedestrians easiest to perceive, facilitating the walking task. However, they also reported discomfort due to fluctuating text readability depending on the background. For *Adaptive Transparent*, many participants expressed satisfaction with the balanced performance across both tasks and found that the transparency transition served as a helpful warning cue for safe walking. Nevertheless, some reported that excessive changes in transparency induced visual fatigue. For *Depth-Aware* and *Opaque*, participants primarily reported difficulty in detecting pedestrians.

Finally, many participants noted that the effect of UI size varied depending on the method used. These qualitative findings complement and contextualize the quantitative results reported above.

Table 4: Qualitative feedback on UI rendering methods

UI method	Participant No	Comments
Opaque	3,4,9,11,13,18,20	The UI and screen elements block too much of my field of view, making it uncomfortable.
	2,5,7,14,16,17,19	It detects pedestrians late or inaccurately, creating a risk of collision and a sense of fear.
	6,8,10,12,15	I need to put in a lot of effort and concentration to perceive pedestrians and obstacles.
Always Transparent	2,3,4,6,9,10,11,14,15	Perceiving pedestrians and obstacles is easiest in “Walking," so walking feels the most comfortable.
	1,8,12,13,15,18,20	My field of view is good, but text readability is poor.
	5,7,12,13	Being able to see both the external environment and the text allowed me to make my own judgments, but it demanded excessive concentration, which made me feel fatigued quickly.
	3,8,12,13,14,15,19,20	I’m equally satisfied with reading text and walking at the same time.
	5,7,17,18	It only becomes transparent when needed, so the “notification/warning" function works well.
Adaptive Transparent	1,2,6,9	The changes in transparency or flickering make it distracting and tiring.
	6,10,16	I did not fully trust the system to become transparent whenever a person was ahead, so I double-checked even when the UI remained opaque.
	1,2,5,7,19	It doesn’t feel much different from the Opaque, and the effect isn’t noticeable.
	4,8,9,10,11,12,13,18,20	I have to get too close before I can see things, leaving too little time to react before a collision.
Depth-Aware	14,15,16,17	Pedestrians/obstacles block the text, making it hard to perceive both text and walking simultaneously.
	2,4,10,13,14,15,16,17	A small screen is better for peripheral vision and walking; a large screen blocks too much of the view.
Size	1,8,9,11,12	The effect of screen size differed depending on the method.

5. Discussion

5.1. Main Findings

Our results revealed a clear pattern in which *Always Transparent* and *Adaptive Transparent* methods consistently outperformed the *Depth-Aware* and *Opaque* methods across walking performance, safety metrics, subjective evaluation, and user preference. For safety metrics, both *Always Transparent* and *Adaptive Transparent* resulted in significantly higher Minimum Time to Collision and Passing Clearance values, indicating that participants maintained safer distances from pedestrians when using these methods [35]. Walking Speed was also significantly faster under *Always Transparent* and *Adaptive Transparent* conditions, suggesting that participants felt more confident navigating the environment without sacrificing safety. Subjective evaluations further supported these objective findings: NASA-TLX scores were significantly lower for the transparency-based methods, and participants rated them higher on perceived Safety and Visual Clarity. Preference rankings reinforced this pattern, with *Always Transparent* and *Adaptive Transparent* ranked significantly higher than the other methods. Collectively, these findings suggest that providing visual access to the external environment through semi-transparency enables users to better anticipate and respond to pedestrian movements. In contrast, occlusion-based methods, whether fully *Opaque* or *Depth-Aware*, appear to impede situational awareness by obscuring critical visual information until pedestrians are in close proximity.

Although both transparency-based methods outperformed occlusion-based alternatives, they exhibited meaningful differences that warrant consideration for design decisions. *Always Transparent* achieved the highest scores on subjective Safety and Visual Clarity, and qualitative feedback indicated that participants found it easiest to perceive pedestrians under this condition. However, this method also yielded the highest Syllable Error Rate among all conditions and did not achieve highest scores for Reading Flow. This is consistent with prior research [36,37] and was supported in our qualitative findings, where participants frequently reported that text readability fluctuated depending on the visual complexity of the background. Additionally, while participants appreciated having continuous visual access to both the environment and the UI, some reported that the constant need to monitor and interpret the surroundings on their own led to increased fatigue. These findings suggest that constant transparency, while beneficial for situational awareness, may compromise reading performance and impose additional cognitive burden in visually cluttered environments [38].

Adaptive Transparent, by contrast, demonstrated a more balanced profile. Participants reported satisfaction with its ability to support both walking and reading tasks simultaneously, and the dynamic transparency transition was perceived as a helpful warning cue that enhanced safety without persistently degrading text visibility. However, some participants expressed limited trust in the detection system, indicating a preference for direct visual confirmation over reliance on automated cues. These trust-related concerns may have influenced their subjective assessments of both perceived Safety and Visual Clarity. Notably, such reduced trust in automated systems and the consequent undervaluation of their benefits is consistent with well-established findings in human-automation interaction studies regarding automation trust and calibration [39, 40].

Contrary to our initial expectations, the *Depth-Aware* method performed comparably to the *Opaque* condition across most performance and subjective metrics. This finding is noteworthy because depth-based occlusion intuitively appears to offer a natural solution for balancing virtual content visibility with real-world awareness [41]. The depth shader renders nearby objects in front of the UI, theoretically preserving access to critical environmental information. However, our results suggest that this approach may be insufficient for dynamic pedestrian avoidance scenarios. Previous research reports that pedestrian detection and avoidance behaviors occur at different spatial thresholds: individuals typically detect others at approximately 5 m and initiate avoidance maneuvers at around 2 m, although these distances may vary across contexts [42, 43, 44, 45]. In our experiment, the UI was positioned at a fixed distance of 1.1 m from the user to ensure consistent conditions across UI rendering methods, resulting in *Depth-Aware* rendering only revealed pedestrians after they had already entered a relatively close range. As shown in Figure 10, participants in the *Depth-Aware* condition behaved similarly to those in the *Opaque* condition, adjusting their walking direction only at close proximity to the actor. It should be noted that if the UI had been positioned at a greater distance, the effectiveness of *Depth-Aware* approach might have differed.

A notable interaction emerged between UI size and rendering method: under *Depth-Aware* and *Opaque*, the Large UI size significantly increased perceived workload and decreased Safety and Visual Clarity ratings, whereas *Always Transparent* and *Adaptive Transparent* showed minimal size-related differences. This interaction suggests that transparency-based rendering can effectively compensate for the increased visual occlusion caused by larger UI elements. When users are able to perceive the environment through the interface, the physical extent of the UI becomes less critical for perceived workload and Safety. Conversely, when the UI fully occludes the background, larger interfaces create proportionally greater blind spots that impair pedestrian detection, negatively affecting user experience.

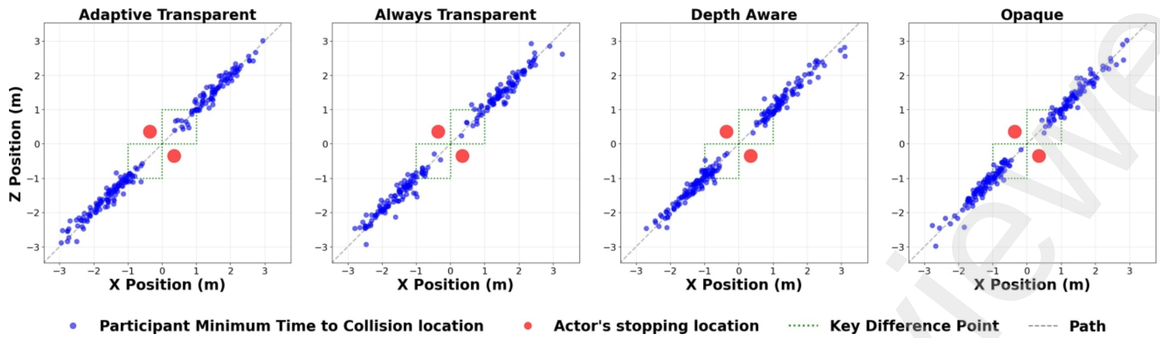

Figure 10: Spatial distribution of participant locations at the moment of Minimum Time to Collision across four UI rendering methods. Blue dots indicate the participant's location where Minimum Time to Collision was calculated, while red circles represent the actor's two stopping locations. The gray dashed line shows the movement path. The green dotted boxes highlight the Key Difference area, where notable differences in participant behavior were observed across conditions.

5.2. Design implications

Our findings offer several practical guidelines for designing MR interfaces intended for use during mobile activities. First, transparency-based rendering should be considered as a default approach when users are expected to navigate dynamic environments while engaging with virtual content. The consistent advantages observed for *Always Transparent* and *Adaptive Transparent* methods across safety, performance, and subjective measures suggest that maintaining visual access to the physical surroundings is more critical than preserving full UI legibility in mobile contexts.

Regarding the choice between always and adaptive transparency, our results suggest that adaptive transparency represent a more promising approach. However, user trust emerged as a critical determinant of its effectiveness. When users fully trust that the system will reliably detect hazard and alert them timely, adaptive transparency can offer the benefits of both safety and UI legibility. In contrast, insufficient trust may lead users remain overly cautious regardless of the system's transparency state, thereby negating its intended benefits. These findings highlight the importance of building user confidence through consistent, accurate and predictable detection before adaptive systems can achieve their full potential in mobile MR contexts.

Designers should exercise caution when relying on depth-based occlusion as a primary strategy for balancing virtual and physical visibility. Although this approach appears intuitive, our results indicate that it may not provide sufficient lead time for users to respond to approaching pedestrians. If *Depth-Aware* rendering is employed, it may be necessary to supplement it with additional warning mechanisms or to position the UI at a greater distance from the user to allow earlier detection of nearby individuals.

Finally, when transparency cannot be implemented due to content legibility requirements or technical constraints, UI size should be minimized to reduce visual occlusion. Our observed interaction effects demonstrate that larger opaque interfaces substantially impair safety outcomes, whereas transparency effectively mitigates the negative impact of increased UI size. This trade-off should inform decisions about interface scaling in safety-critical MR applications.

5.3. Limitations and future work

This study has several limitations that should be acknowledged when interpreting the findings. First, the *Adaptive Transparent* method employed a relatively simple detection mechanism that adjusted UI opacity solely based on the presence of pedestrians within a fixed distance threshold. In real-world scenarios, more sophisticated adaptation strategies may be beneficial. For instance, the system could modulate transparency based on pedestrian velocity, trajectory prediction, or the estimated likelihood of collision. Future work could explore multilevel or continuous adaptation algorithms that dynamically balance situational awareness and content legibility according to the complexity of the surrounding environment.

Second, the experimental apparatus used in this study was a Meta Quest 3 with a camera pass-through, which restricts the user's peripheral field of view to what the onboard cameras capture. In practical deployment scenarios, users are more likely to adopt optical see-through AR glasses, which do not constrain the natural field of view. With such devices, users retain full peripheral vision and can perceive approaching pedestrians outside the display area without relying on transparency-based rendering. Consequently, the benefits of transparency observed in our study may be diminished when using AR glasses, as the limited field of view imposed by the HMD may have amplified the negative effects of UI occlusion. Future research should therefore validate these findings using optical see-through devices to better understand how the preservation of peripheral vision influences the relative effectiveness of different rendering methods.

Finally, our experimental environment was a controlled indoor setting with a single actor and a somewhat predictable walking path. Real-world pedestrian environments involve multiple moving individuals, varying walking speeds, and more complex spatial layouts. Future studies could extend this work by examining how transparency-based methods perform in crowded outdoor environments with higher pedestrian density and greater unpredictability.

6. Conclusion

This study investigated how different UI rendering methods and sizes affect walking safety and UI legibility in MR pedestrian avoidance scenario. We compared four rendering approaches across two UI size conditions in a dual-task paradigm that required participants to read text while avoiding pedestrians. Our findings demonstrate that transparency-based methods consistently outperform occlusion-based methods across safety metrics, walking performance, subjective workload, and user preference. *Always Transparent* provided the highest situational awareness but introduced variability in text readability, whereas *Adaptive Transparent* offered a more balanced experience suitable for sustained use. Contrary to our initial expectations, *Depth-Aware* rendering did not yield meaningful advantages over the *Opaque* condition, suggesting that depth-based occlusion alone is insufficient for supporting pedestrian avoidance in dynamic environments. We also found that transparency-based rendering mitigates the negative impact of larger UI sizes, whereas occlusion-based interfaces require careful size minimization to preserve safety. Collectively, these findings provide empirical evidence and practical design guidelines for developing mobile MR interfaces that effectively balance virtual content visibility with user safety.

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Haejun Kim: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft

Qiuli Jin: Conceptualization, Investigation, Methodology, Visualization, Writing – original draft

Woojoo Kim: Conceptualization, Project administration, Resources, Supervision, Validation, Writing – review and editing

Shuping Xiong: Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Validation, Writing – review and editing

Declaration of Generative AI and AI-assisted technologies in the writing process

The author(s) employed Claude by Anthropic during manuscript preparation to assist with improving clarity and grammar. Following this assistance, the author(s) thoroughly reviewed and revised the manuscript and remain fully responsible for its content.

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