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How AR Guidance Shapes Behavioral Change in Walking: A Stage-Based Analysis of Gaze and Trajectories

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ABSTRACT

This study models behavioral change during real-world walking as a process rather than only an outcome. We propose three stages—Active Observation, Pre-action Behavior, and Active Behavior—quantified from gaze and walking trajectories. In a university corridor, 34 participants completed two sessions under either an augmented-reality (AR) guidance condition or a control condition; in the AR condition, a virtual object demonstrated the target action in real space. Successful execution was associated with a characteristic movement tendency toward the target. AR did not directly induce the target action, but was associated with earlier target recognition and reduced individual variability in exploration depth and trajectory straightness. Repeated exposure was also associated with changes in these characteristics, suggesting that AR information may facilitate progression from pre-action to active behavior.

Keywords: Augmented reality (AR), Behavioral analysis, Spatial design

INTRODUCTION

Behavior-change support that encourages desirable actions while respecting free will has attracted attention in urban and public spaces. Nudges support behavior through environmental and information design without coercion or monetary incentives (Thaler and Sunstein, 2008), while the Behaviour Change Wheel provides a systematic framework for interventions (Michie et al., 2011). Augmented reality (AR) can overlay action-relevant information on real environments (Azuma, 1997; Höllerer and Schmalstieg, 2016) and has been applied in tourism, education, and industry (Jung and tom Dieck, 2017; Wu et al., 2013; Masood and Egger, 2020), suggesting that it can influence perception and decision making as well as visualization.

Most studies of AR-based assistance evaluate performance indices or subjective workload (Dey et al., 2018; Kruijff et al., 2010). For continuous behaviors such as walking and exploration, however, a final outcome cannot distinguish whether a person failed to notice a target, noticed it without approaching, or approached without executing the action. Such distinctions matter because action comprises stages of perception, interpretation, and execution (Norman, 2013). Subjective reports are also limited by

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intention–behavior gaps (Sheeran, 2002), imperfect introspection (Nisbett and Wilson, 1977), and reconstructive memory (Schacter, 1999). Behavioral processes therefore need externally observable measures.

Accordingly, this study treats behavioral change as the observable process from target awareness to final action execution and models the behavior-generation process from gaze and walking trajectories. Extending our preliminary analysis of short-term AR-induced behavioral change (Matsui et al., 2026), we examine where differences between AR and no-AR conditions emerge. The contributions are to model the process in three stages, associate each stage with observable physical indicators, and evaluate AR effects stage by stage.

RELATED WORK AND POSITIONING OF THIS STUDY

Behavioral Analysis Using Gaze and Walking Trajectories

Gaze measurement and walking-trajectory analysis can quantify attention allocation and spatial decision making. Gaze indicates attention and information processing (Just and Carpenter, 1980; Duchowski, 2017), while trajectories reflect movement strategy, hesitation, and interaction with the environment (Wiener et al., 2009). Because visual search guides movement and movement changes the visual field, combining both measures can describe behavioral processes more fully. Existing work, however, rarely distinguishes whether an intervention affects awareness, the formation of an approach tendency, or action efficiency.

Spatial Behavior Guidance Using AR

AR can connect objects and actions to real space and thereby influence exploration and decision making (Azuma, 1997; Höllerer and Schmalstieg, 2016). Reviews report usability and assistance effects, including navigation and work support (Dey et al., 2018; Kruijff et al., 2010; Masood and Egger, 2020), but evaluation remains performance-focused. Novel AR presentations may also produce initial novelty or attention-capturing effects, so repeated measurement is needed to distinguish these from more persistent support effects (Koch et al., 2018).

Positioning of This Study

This study therefore treats behavioral change as a process rather than an outcome. Drawing on the theory of planned behavior (Ajzen, 1991) and situated action (Suchman, 1987), it uses gaze and walking trajectories to ask not simply whether AR causes behavior, but whether it affects target awareness, an intermediate approach tendency, or final action execution.

BEHAVIORAL-CHANGE PROCESS MODEL AND OBSERVATION INDICATORS

Behavioral change in real space is modeled as a continuous three-stage process: Active Observation, in which the target is noticed and environmental information is explored; Pre-action Behavior, in which bodily responses

appear before explicit action; and Active Behavior, in which goal-directed action is executed. The framework describes behavior as progressively generated through interaction with the environment rather than solely by internal intention (Ajzen, 1991; Suchman, 1987).

The observed variables are gaze, walking trajectory, and changes in body or face orientation. Pre-action Behavior is an operational category for bodily responses observed before explicit action; it does not imply that those responses are necessarily unconscious.

For Active Observation, the participant's first fixation on the target was defined as the First Fixation Point (FFP). The distance from the FFP to the target was calculated as maximum exploration depth, indicating how far from the target initial awareness occurred (Figure 1).

For Pre-action Behavior, the Deflection Turning Point (DTP) was the first point at which travel direction deviated by at least 19° from a hypothetical straight-ahead baseline (Figure 2). The threshold was selected empirically by comparing candidate thresholds with visually identified turning points so that natural walking fluctuations were not excessively detected while clear deflections were captured.

In Figure 2, Start is the participant's position when the target became visually available. Start is the origin; the baseline direction is the Y-axis and the orthogonal direction the X-axis. The deviation angle θt is the angle between the actual trajectory and this baseline. Body and face orientation were not used to determine the DTP.

Because DTP detection depends on the angular threshold, 19° should be regarded as an operational criterion for the present conditions and reconsidered for other environments or walking conditions.

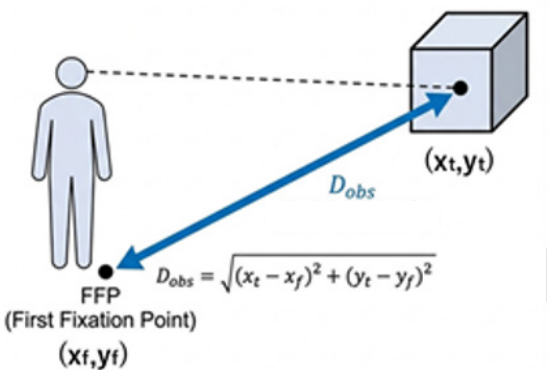


Figure 1: Geometric definition of maximum exploration depth.

The Orientation Turning Point (OTP) was defined separately as the point at which body or face orientation clearly changed from the baseline direction toward the target. Based on the occurrence of the DTP and OTP, Pre-action Behavior was classified descriptively as attraction (DTP followed by OTP), latent (OTP only), or no response (neither point detected).

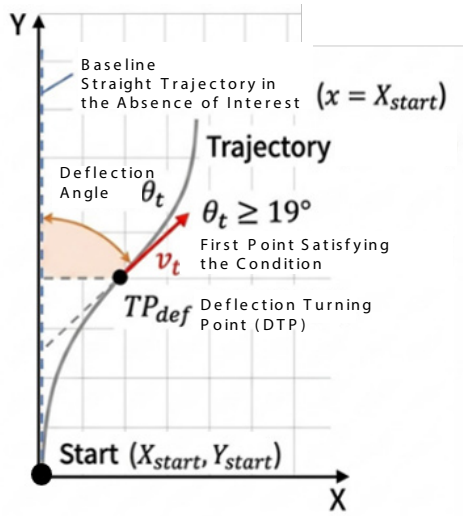


Figure 2: Definition of the deflection turning point and baseline.

For Active Behavior, approach efficiency after the OTP was quantified by the straightness index A_1 (Figure 3). Let Start be the OTP, End the target center, and Pi consecutive trajectory points after the OTP. A_1 is the shortest Start–End distance divided by the actual trajectory length:

$$A_1 = d(Start, End) / \Sigma d(P_i, P_{i+1}) \quad (1)$$

where d denotes the Euclidean distance between two points. A_1 ranges from 0 to 1, with values closer to 1 indicating a more direct approach trajectory.

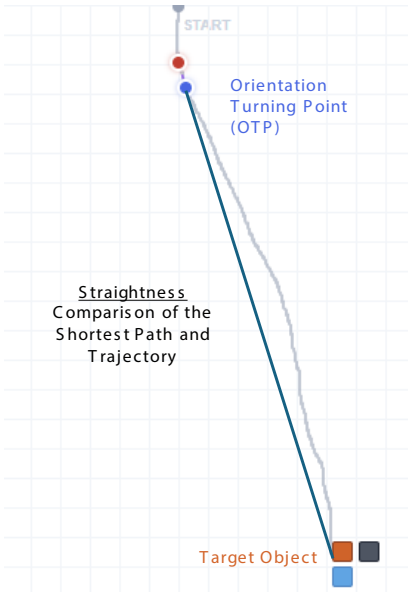


Figure 3: Definition of trajectory straightness.

EXPERIMENTAL METHOD

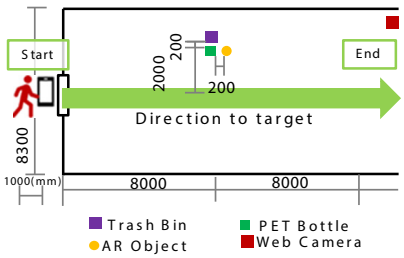
The experiment tested how AR presentation appears as differences in the observation indicators of the three-stage model. Participants assigned to either the AR or control condition completed two measurement sessions.

Participants were 34 university students (21 men, 13 women; mean age 20.8 years), randomly assigned to the AR group (n = 20; 10 men, 10 women) or control group (n = 14; 11 men, 3 women). All received explanations about behavioral, video, and gaze measurement, anonymization, study purpose, and data use, and provided written consent.

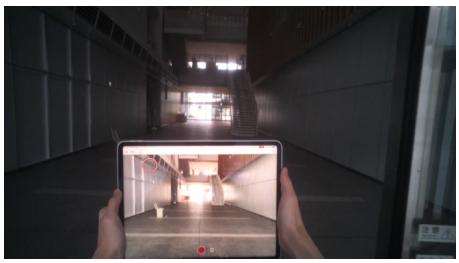
The AR-group size was based on our previous 20-participant street experiment, in which 11 participants disposed of a PET bottle whereas participants who did not view AR information almost never did so (Matsui et al., 2026). The smaller control group reflected the expectation of fewer disposal actions; larger samples would improve precision.

The same participants were measured in Session 1 (S1) and Session 2 (S2), with S2 conducted approximately three weeks later, generally on the same day of the week, to reduce day-dependent environmental differences while examining short-term repetition effects.

The experiment was conducted in the first-floor atrium corridor of Building No. 5 at Tokyo Denki University, Kitasenju Campus. The PET-bottle target was positioned to the side of the straight walking line, with a collection bin and AR presentation position nearby, so that awareness, route deflection, approach, and execution could occur without being forced (Figure 4).



(a) Experimental environment and analysis area.



(b) Overview photograph from near the starting point.

Figure 4: Experimental environment.

AR Presentation and Experimental Procedure

Participants in both groups were instructed to walk naturally from start to finish and received no explicit instruction to collect the PET bottle. The AR condition repeatedly overlaid a 2.5-s animation of an avatar picking up the bottle and placing it in the nearby bin; the avatar motion was generated with Adobe Mixamo (Adobe, 2026). Control participants carried the same tablet and viewed its camera image but received no AR content.

Thus, all participants walked under free-behavior conditions, allowing responses to emerge from interaction with environmental information rather than external commands. Figure 5 shows the AR action sequence. The study followed Tokyo Denki University ethical procedures for research involving human participants.

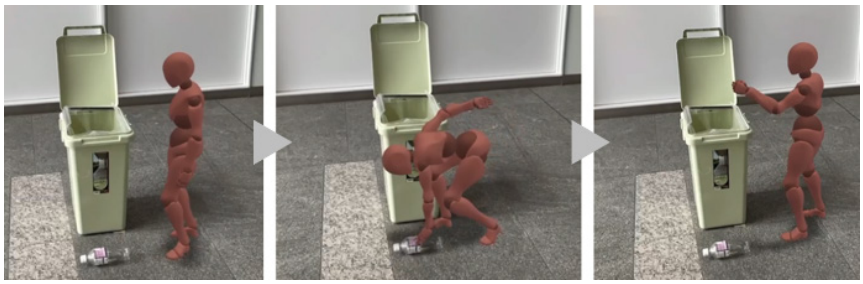


Figure 5: Action sequence of the AR object picking up and disposing of the PET bottle.

Data Acquisition and Analysis

A Tobii Pro Glasses 2 wearable eye-tracking system was used in both groups to record first-person-view video and gaze data. The first fixation on the target was identified from these data, and the participant's position at that moment was defined as the FFP.

The acquired data comprised gaze, walking trajectories, and target collection. Maximum exploration depth was calculated for Active Observation; DTP and OTP were extracted for Pre-action Behavior; and the post-OTP straightness index was calculated for Active Behavior. The final behavioral outcome was coded as a binary variable based on whether the participant contacted and lifted the target.

RESULTS

Results for the Active Observation Stage

Maximum exploration depth was used to compare the distance of initial target awareness. Participants who disposed of the PET bottle are termed performers and those who did not, non-performers.

Descriptive mean values are shown in Figure 6. Because performer status was determined after the experiment and participants were measured repeatedly, a linear mixed model with participant as a random effect tested performer status, AR/control condition, S1/S2, and the performer-status × AR interaction. Holm-adjusted pairwise AR–control comparisons were also conducted within performer strata (Table 1).

The model showed significant effects of performer status ($p < 0.001$), AR/control condition ($p = 0.0235$), and session ($p = 0.0016$), but not their specified interaction ($p = 0.195$; Table 1a). The Holm-adjusted AR–control difference was significant among non-performers ($p = 0.0048$) but not performers ($p = 0.441$; Table 1b).

AR presentation was therefore associated with recognition of the target from a greater distance, particularly among non-performers. S2 also tended to show greater exploration depth than S1, and overlaid trajectories showed reduced dispersion in S2, suggesting a possible repetition effect that requires further verification.

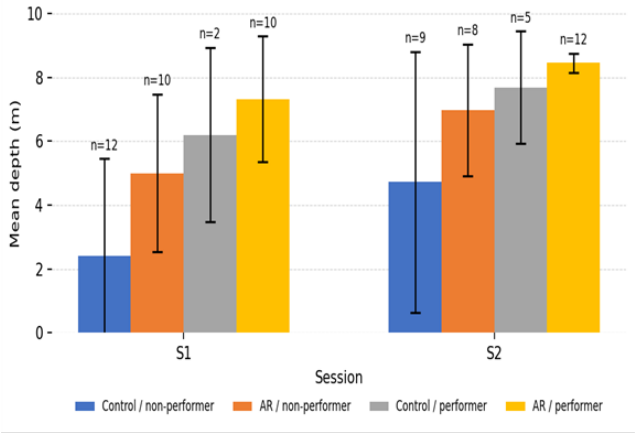


Figure 6: Descriptive statistics for means of maximum exploration depth.

Table 1: Tests of mean differences in maximum exploration depth.

(a) Tests of conditions using a linear mixed model

Condition	F Value	p Value
(1) Non-performer / performer	13.7	< 0.001
(2) Control / AR	5.61	0.0235
(3) S1 / S2	11.7	0.0016
(4) Performer status x AR	1.72	0.195

(b) AR-control differences by performer status after multiple-comparison adjustment

Status	Mean Difference	t Value	p Value
Non-performer	2.74	3.00	0.0048
Performer	0.917	0.777	0.441

Results for the Pre-Action Behavior Stage

Pre-action Behavior was classified from DTP/OTP patterns as attraction, latent, or no response. In S1, two control-group non-performers were latent, whereas no AR-group non-performer was latent; all performers in both groups were classified as the attraction type. Because the number of cases in each type was small, these differences are treated as descriptive. In S2, attraction increased in the control group, while latent or no-response cases remained among non-performers; larger samples are needed for quantitative testing.

Results for the Active Behavior Stage

For Active Behavior, the straightness index was compared between performers and non-performers and between AR and control groups within each session. Because the straightness data and the residuals of the linear mixed model did

not satisfy the assumption of normality, Wilcoxon rank-sum tests were used (Table 2).

Performer/non-performer differences were significant in both S1 and S2 ($p < 0.001$), with performers tending to have lower straightness indices. In S1, the AR group also had a significantly lower straightness index than the control group ($p = 0.0276$), whereas the AR–control difference was not significant in S2 ($p = 0.228$). Because performers necessarily reached the side-positioned target, the association between straightness and execution should not be interpreted causally; the curved trajectories can reflect the lateral movement required to approach the target.

Table 2: Comparison of straightness indices in each session.

Session	Condition	p Value (Holm)	Cohen Effect Size	95% CI Lower	95% CI Upper
S1	Non-performer / performer	6.93E-07	2.69	1.71	3.64
S1	Control / AR	0.0276	0.57	–0.13	1.26
S2	Non-performer / performer	3.43E-09	4.40	3.12	5.66
S2	Control / AR	0.228	0.41	–0.29	1.10

DISCUSSION

The results show that AR-related differences did not appear uniformly across the three-stage process. In Active Observation, maximum exploration depth was generally greater in the AR group, indicating that the target became an object of visual attention from farther away. Under the present conditions, AR therefore appears to exert its effect first at the early recognition stage rather than directly triggering the final action.

In Pre-action Behavior, attraction responses were more common with AR, whereas latent or no-response cases were relatively more evident in the control condition. In particular, the latent cases among S1 control non-performers were absent among AR non-performers. Although case counts were small, this supports treating route deflection and orientation change as an intermediate response stage between attention and execution.

For Active Behavior, straightness differed by performer status in both sessions and by AR/control condition in S1. Because reaching the side-positioned target is itself related to trajectory shape, these associations cannot establish that straightness caused action execution. Repetition also coincided with increased attraction responses in the control group and greater exploration depth; with only two measurements, however, random variation and other factors cannot be excluded, and AR effects cannot be fully separated from repetition effects.

The stage-based model is useful because cases that would otherwise share the same non-execution outcome can be distinguished by where the process stopped. It shifts evaluation from the outcome-centered question of whether AR increases behavior to the process-centered question of where in the process AR exerts its effects, using physical indicators from gaze and walking trajectories.

CONCLUSION

This study proposed a three-stage model of real-space behavioral change based on gaze and walking trajectories: Active Observation for target awareness, Pre-action Behavior for body deflection/orientation responses, and Active Behavior for the approach/execution trajectory. Each stage was linked to an observable physical indicator.

Maximum exploration depth was generally greater with AR across sessions, indicating earlier target awareness. Pre-action Behavior showed descriptive group differences, including latent responses among S1 control non-performers but not AR non-performers. Active Behavior showed session-specific differences in straightness; causal interpretation is limited because trajectory shape is related to reaching the side-positioned target. Overall, AR effects can be described by where differences arise in the behavior-generation process, not only by final outcomes.

This framework complements outcome-centered behavioral-change evaluation by making non-execution processes analyzable. The study is limited to short-term repetition, an imbalanced gender composition in the control group, and a modest sample. Future work should balance participant attributes, increase the sample size, broaden the range of environmental conditions, increase the number of measurements, and examine longer-term interactions between AR presentation and learning effects.

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