Information Presentation Strategies to Promote Pedestrian Behavior Change in Mixed Spaces with Automated Vehicle

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Abstract— **This paper introduces an information presentation strategy for pedestrians, aiming to enhance traffic efficiency in a mixed pedestrian-automated vehicle environment, such as a public road. While automated driving technology has made remarkable progress, interactions with pedestrians on regular roads have mostly been studied in virtual environments using virtual reality goggles. According to these studies, potential traffic efficiency and safety issues arise from pedestrians' limited understanding of automated vehicle behavior. To address this, we propose a human-machine interface employing a head-mounted display (HMD) to mitigate traffic efficiency degradation caused by pedestrians. The proposed system draws upon behavioral economics principles to encourage pedestrians to modify their behavior and develop better interactions with automated vehicles. Simulations were conducted to identify an information presentation strategy that strongly supports learning, and its effectiveness was further validated through experiments involving a real vehicle. Notably, the experimental results confirmed that the information presentation strategies proven effective in simulations also facilitated pedestrian learning during real-world interactions.**

I. INTRODUCTION

Interacting with pedestrians is crucial for Automated Vehicles (AVs) when navigating public roads, except for automobile-only roads. Typically, when an AV detects a pedestrian in its path, it will try to slow down and stop to ensure the pedestrian's safety. However, the behavior of pedestrians with a limited understanding of AVs during this protection process can potentially compromise traffic efficiency and safety[1]. Previous research on pedestrian-AV interactions has primarily taken place in virtual environments, utilizing a human-machine interface (HMI) called e-HMI attached to the vehicle. This approach has shown promising results, enhancing pedestrian trust in the AV and improving traffic efficiency[1][2]. Nevertheless, many of these studies have not thoroughly explored whether e-HMI actually facilitates pedestrian learning of AV behavior.

This study introduces an HMI system designed to aid pedestrians in comprehending the behavior of AVs and encourage them to adopt behaviors that enhance benefits for both vehicles and pedestrians. By facilitating pedestrians' understanding of AV behavior, the system aims to enhance traffic efficiency and reduce operational costs of e-HMI systems for vehicles. This study investigates the use of a behavioral economics framework to influence pedestrians' behavior positively, particularly in an open field setting where interactions between pedestrians and AVs take place.

The study presents the outcomes of a behavior change promotion system rooted in behavioral economics, enabling pedestrians to learn behaviors that optimize advantages for both vehicles and pedestrians.

II. RELATED WORK

According to [3], in critical traffic situations, such as road crossings, pedestrians decide whether to cross based on the speed and proximity of approaching vehicles. This holds true even when the vehicle has an external information display. However, in [4], an interview-style study conducted at an actual traffic scene, pedestrians mentioned that eye contact with the driver also influenced their crossing decisions.

Unlike interactions with human-driven vehicles, achieving eye contact may be challenging in interactions with AVs. Therefore, information presentation interfaces have been suggested to aid pedestrian-AV interactions.

According to [5], many studies have investigated visual and auditory HMI. And these proposed ideas have been mainly categorized by the physical triggers proposed in [6]. In this study, we attempted to design an HMI more based on pedestrian behavior change principles by further classifying them as psychological triggers.

In the case of [1], the focus is on a scenario where a pedestrian crosses an intersection simultaneously with an AV entering an intersection without a traffic signal. In this situation, visual and audio information presentation from the vehicle side enhanced the pedestrian's receptivity to the AV, both before and after exposure to the information presentation. Similarly, in [2][7], the authors share the outcomes of an experiment in which the vehicle was equipped with an information presentation interface using a display, while pedestrians were crossing an intersection without a traffic signal. The experimental results demonstrated that the information presentation significantly reduced the pedestrian's crossing decision time. Moreover, [2] reported an improvement in pedestrians' acceptance of AVs, similar to the findings in [1].

In [8], an attempt is made to convey information on pedestrians' recognition status by AVs using an eye-like device attached to the vehicle. This resulted in a reduction in the failure rate of pedestrian crossing decisions. Furthermore, [9] suggested that expressing "anger," "fear," "happiness,"

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and ”sadness” by eye-like interface can elicit empathy and increase agreement by pedestrians. This result suggests that emotional expression by HMIs may contribute to improving the benefits for both pedestrians and AVs. However, these studies[2][7][8][9] did not investigate how crossing decision time or safety changed after the experience of information presentation by the interface. Therefore, it is not possible to discuss whether pedestrians learned the behavior of the vehicles from these data alone.

Moreover, experiments conducted in virtual environments may not fully capture the same level of attentiveness from subjects as in real environments due to the absence of real danger [2]. To address these concerns, this study conducted experiments using actual AV to verify the effectiveness of the proposed HMI in real traffic situations.

III. Basic Concept of the Proposed HMI

This study introduces a system that provides information to pedestrians and helps them learn how to interact with AVs. The primary goal of the proposed system is to present information to pedestrians in a way that enables them to effectively interact with AVs when crossing the street, even without the information presentation. This chapter explains the interface hardware and the core concepts of behavioral economics that underpin the proposed information presentation.

A. Hardware

In this study, a head-mounted mixed reality device (Hololens2, Microsoft) was employed to provide information to pedestrians. Utilizing augmented reality (AR) technology, this device can overlay a virtual space onto the real world, allowing information to be presented without significant alterations to the environment, such as the need for a physical display installation.

B. Behavioral Economics

Our research focuses on pedestrian learning. Therefore, it is essential to modify the behavior of pedestrians who are unfamiliar with or have a limited understanding of the interaction. To achieve this goal, we proposed information–presenting ideas to create a synergistic effect that can bring about behavioral changes .

The triggers that induce behavioral changes are defined in the field of Shikakeology[6], a branch of behavioral economics. These behavior change triggers, as proposed in Shikakeology, are illustrated in Fig. 1. They are broadly categorized into ”physical triggers” and ”psychological triggers”. We assume that when these two types of triggers are combined, they produce a synergistic effect that can effectively modify a person’s behavior. As mentioned in the introduction section, by utilizing the idea generation framework proposed in Shikakeology to promote behavior change, we believed that we could devise an effective method of presenting information to assist pedestrians in their learning process.

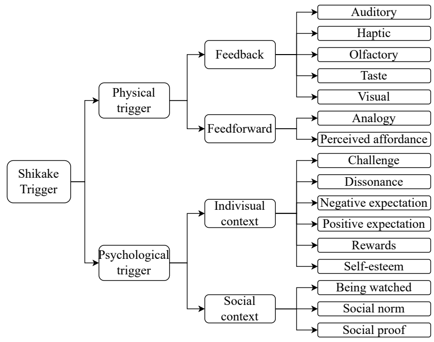

Fig. 1. Shikake triggers proposed in the Shikakeology[6].

IV. Information Presentation Prototype

In this study, we developed five behavior change ideas based on behavioral economics, as depicted in Fig. 2, along with the corresponding Shikake triggers..

Due to hardware limitations, we utilized only Visual and Perceived affordance as physical triggers in this study. Now, we will elaborate on the psychological triggers that were combined with these physical triggers and their intentions. First, in Idea 1, we combined Visual and Social Norm. Given that pedestrians face difficulties in communicating with AVs, such as through eye contact, we deemed it crucial for them to learn about the intentions and efficiency of the vehicle. To address this, we employed emotional icons as a communication medium. The utility of the AV is expressed through ”happy” and ”sad” values, indicating efficiency based on whether the AV can reach a pre-defined target arrival time. Our intention is to stimulate communication between the AV and pedestrians, leading to changes in social behavior, such as ”giving way to a vehicle.”

In Idea 2, we combine Visual and Being watched triggers to promote communication between vehicles and pedestrians using a virtual eye. The virtual eye is indicated when the vehicle is within a certain range from pedestrians, signifying that the AV is aware of their presence. This idea, like Idea 1, aims to facilitate communication between vehicles and pedestrians. However, it differs from Idea 1 in two aspects: first, it intends to deter selfish pedestrian behavior by evoking the sense of being watched; second, it does not display the AV’s efficiency to the pedestrian. These features allow us to respect the pedestrian’s intentions and make the crossing itself more challenging compared to Idea 1, thus enabling appropriate adjustments to the learning difficulty.

In Idea 3, we combine Visual and Negative expectation triggers. This method indicates the approaching AV’s direction using an arrow when it is within a certain range from pedestrians. We anticipate that this will implicitly give the driver an approximate distance to the AV and that the approach warning from the indicator will effectively restrain the driver’s behavior.

In Idea 4, we combine Perceived affordance and Negative expectation triggers. Idea 4 utilizes perceived affordance dynamically by displaying an arrow resembling a pedestrian crossing. It is expected that pedestrians will recognize that the system is presenting a crossing timing that does not collide with the AV. The indication of crossing timing is determined by an algorithm that calculates whether a pedestrian and AV will coincide at the vehicle's entry time based on the pedestrian's walking speed. If no collision is projected, a green arrow appears on the street, creating an easy problem setup to encourage pedestrians to proceed with the crossing task.

In Idea 5, we combine Visual and Negative expectation triggers. The concept involves displaying the level of danger at various locations on the road based on the AV's speed. The danger level is calculated from the AV's braking distance, and points within the AV's braking distance range are highlighted in red. Additionally, the AV's planned route is presented in yellow to indicate its intended direction. We believe that this information will provide pedestrians with more comprehensive safety details about the road, motivating them to optimize their behavior accordingly.

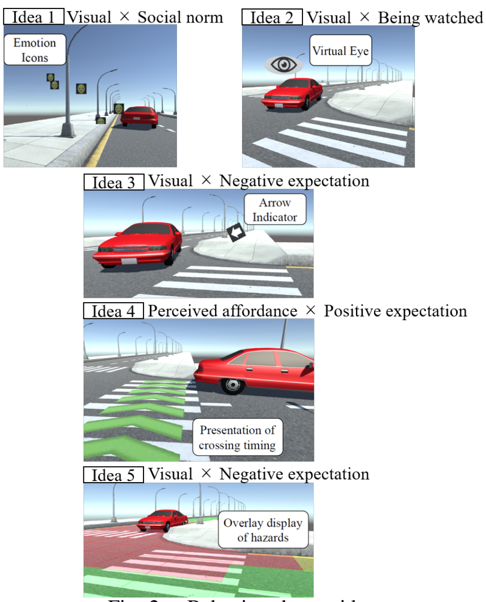

Fig. 2. Behavior change ideas.

V. Formulation of Interaction Evaluation Values

Since the objective of this study is to aid pedestrians in learning to interact with AV, it was essential to have an objective measure for evaluating the interaction. In this study, the interaction evaluation value, denoted as F-$value$, was defined as shown in Formula (1). Here, V_p represents the pedestrian's travel time when no vehicle is present and no interaction occurs, V_v is the AV's travel time when no pedestrian is present and no interaction occurs, T_p stands for the pedestrian's travel time when the AV is present, and T_v corresponds to the AV's travel time when the pedestrian is present. The calculation of V_p involved measuring the walking speed of each subject. Additionally, V_t was obtained by measuring the travel time again under the same experimental conditions in an environment where pedestrians were not present.

$$F = \frac{V_p}{T_p} + \frac{V_v}{T_v} \tag{1}$$

In both the preliminary experiment and the actual experiment using the actual device, a two-stage experiment consisting of a "learning process" and a "test process" was conducted to measure the subject's learning effect. In the "learning process," subjects used the HMI for a certain period to learn optimal interaction with the AV. Subsequently, a "test process" was conducted where subjects attempted to interact with the AVs on their own without using the HMI, to assess whether they had indeed learned the interaction. For both the preliminary and actual experiments, the learning process consisted of 10 trials, while the test process had 5 trials. The predicted learning effect of the subjects in advance (hypothesis) is illustrated in Fig. 3.

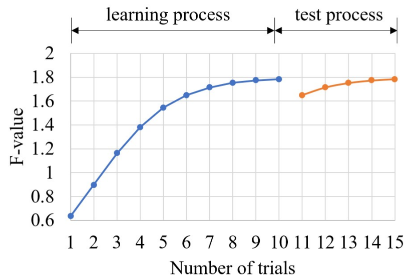

Fig. 3. Subject's learning hypothesis.

VI. Preliminary Experiment

As the ultimate goal of this study, we planned to conduct an open-field experiment (real scene experiment) using an actual AV. To ensure the experiment's practicality, we first conducted a preliminary experiment to further narrow down the five behavior change ideas shown in Fig. 2, which were implemented using an virtual AV in the preliminary phase. In this preliminary experiment, we created a virtual space simulating a real road on Hololens2. The configuration of the virtual space used in the pre-experiment is depicted in Fig. 4. We then evaluated the impact of these behavior change ideas in this virtual space and selected the ones that we expected to be effective in inducing behavior change when using the actual device.

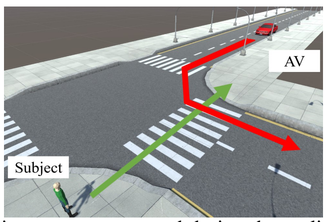

Fig. 4. Virtual environment constructed during the preliminary experiment (interaction between a subject crossing a T-intersection (green arrow) and an AV attempting to make a left turn (red arrow)).

A. Scenario

The preliminary experiment took place in the scenario depicted in Fig. 4, where a pedestrian (subject) crossed an intersection without a traffic light while an AV attempted to make a left turn into the same intersection. The subjects were given two instructions: first, that "the AV is in a hurry," and second, that "You should complete the crossing as quickly as possible within the range of not running." To ensure the subjects' learning of interactions, we recognized the importance of introducing randomness in the interactions they experienced. As a result, the speed of the AV was randomly selected for each experiment to incorporate this element of randomness.

B. Hypothesis in the Preliminary Experiment

During the preliminary experiment, three conditions were identified as having effective behavior change effects for the main experiment: Hypothesis I, Hypothesis II, and Hypothesis III.

Hypothesis I
: It is important for users to be able to understand and predict AV behavior.

Hypothesis II
: Learning occurs when the user is exposed to a large number of iterations of near-optimal behavior.

Hypothesis III
: It is important to learn that the learner can break free from HMI involvement.

Each of the subjects who experienced ideas most in line with each of these hypotheses would have the following properties:

Hypothesis I
: The results of the 5-point Likert scale subjective evaluation of the Understanding/Predictability item of the Trust in Automation questionnaire[10] will have the highest score.

Hypothesis II
: The sum of F-$values$ in the "learning process" will be the highest.

Hypothesis III
: The decrease in F-$value$ after the end of learning process will be minimized.

C. Experiment Result

In the preliminary experiment, data were collected from 15 subjects, aged between 21 and 30. Each behavior change idea was experienced by three subjects. The experiment's outcomes are presented in Fig. 5 and Table I. Idea 5 aligns most closely with Hypothesis I, while Idea 3 correlates well with both Hypothesis II and Hypothesis III.

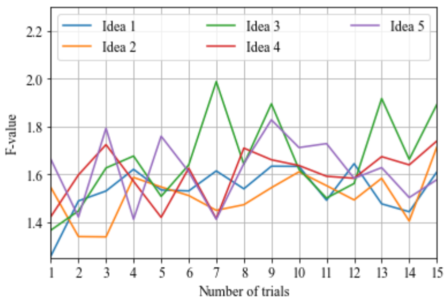

Fig. 5. Results of preliminary experiment (F-$value$ of each behavior change idea).

TABLE I
SUM OF F-$values$ IN THE LEARNING PROCESS.

Idea number	Results of Trust in Automation questionnaires.	Sum of F-$values$ in the learning process.	Displacement of F-$values$ after learning.
①	15.0	13.85	0.30
②	15.3	13.47	0.21
③	15.3	14.77	-0.26
④	14.7	14.07	-0.03
⑤	16.7	14.61	0.32

VII. EXPERIMENT IN REAL SCENE

Experiments were conducted to confirm the effectiveness of the behavior change ideas selected in the preliminary experiment in real scene.

A. Scenarios

In the experiment, conditions were randomly chosen for each trial from a pool of 18 possible combinations, comprising 6 AV starting positions and 3 pedestrian walking starting points. An overview of the placement of the vehicle starting position and the pedestrian starting position is depicted in Fig. 6. A scene of an experiment using actual AV is shown in Fig. 7.

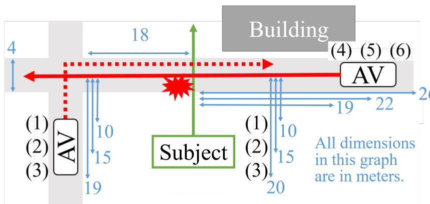

Fig. 6. Overview of AV start positions and subject start positions.

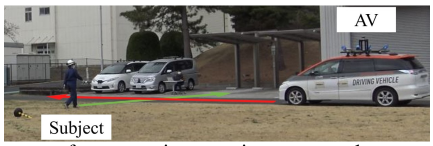

Fig. 7. Scenery of an experiment using an actual automated vehicle. (Example of a scenario in which the vehicle enters straight ahead).

B. Experiment Results

The experiment involved a total of five subjects. Each behavior change idea was experienced by two subjects using the HMI, while one subject participated in 15 interactions without any information presented. The experimental results are presented in Figs. 8, 9, and 10.

In right-hand member of Formula (1), the left term is referred to as the "Pedestrian term," denoting the efficiency of the pedestrian as $\frac{V_p}{T_p}$, while the right term is called the "AV term," representing the efficiency of the vehicle as $\frac{V_v}{T_v}$.

VIII. DISCUSSION

This study examined and investigated the following three points based on the results of the experiment in real scene:

- The impact of different experiment scenarios (vehicle turning right or going straight) on the F-$value$.
- Transitions of F-$value$ before and after the learning process.

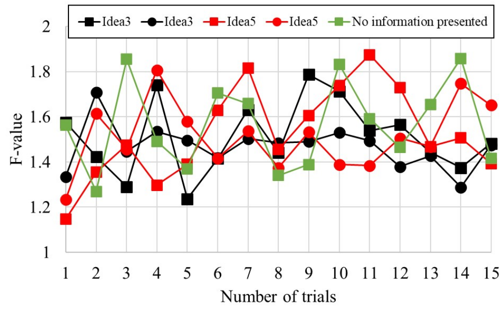

Fig. 8. Transitions of F-$value$ in experiments.

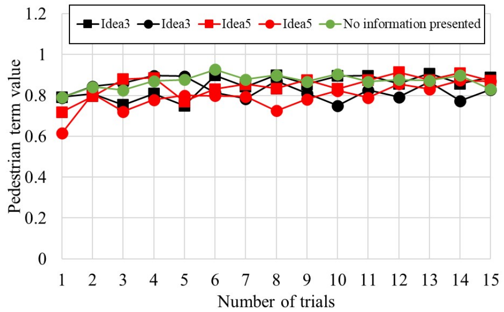

Fig. 9. Transitions of Pedestrian term value in experiments.

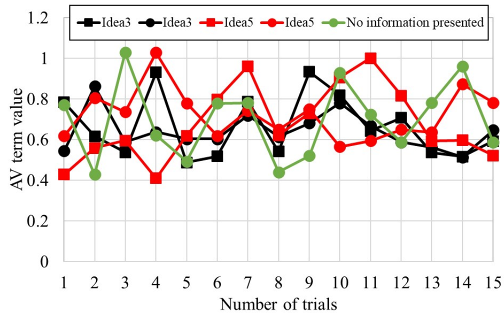

Fig. 10. Transitions of AV term value in experiment in real scene.

- The relationship between the two terms (Pedestrian term and AV term) that constitute the F-$value$.

A. The effect of the difference in the scenarios

The study verified the impact of variations in experiment scenarios (right-turn intrusion and going straight ahead for AVs) on the F-$value$, assuming that the F-$value$ can accurately assess the interaction's optimality. Hence, it was desirable to have a consistent distribution of F-$value$ across scenarios in the experiment. The 15 trials conducted by each subject were divided into two groups: one for AV start positions (1)-(3) and another for AV start positions (4)-(6).

First, the effect of differences in experiment scenarios (right-turn intrusion and going straight ahead) on F-$values$ was examined, assuming that F-$values$ could uniquely assess the interaction's optimality. Consequently, it was preferable for the distribution of F-values to remain consistent across the experiment scenarios. The 15 trials conducted by each subject were divided into two groups: a group for vehicle start positions (1)-(3) and a group for vehicle start positions (4)-(6). The results of the statistical test for the mean F-$values$ in each scenario are presented in Table II. The distribution of F-$values$ for each group is illustrated in Fig. 11. The significance level was set at 5%, and the results indicate that the F-$values$ exhibit different distributions under different scenarios.

To mitigate the differences among scenarios, an effort was made to normalize the F-$values$ for each scenario. The normality of the distribution of F-$values$ for each scenario was tested, and the results are displayed in Table III. According to Table III, the distribution of F-$values$ for each group may exhibit normality. Therefore, the F'-$values$, which are values with reduced bias due to scenarios, were determined using formula (2).

The F-$values$ after normalization are shown in Figs. 12 and 11. Additionally, the results of the t-test for the distribution of F-$values$ in each scenario group are presented again in Table IV. Table IV demonstrates that the bias of F-$values$ due to scenarios was reduced.

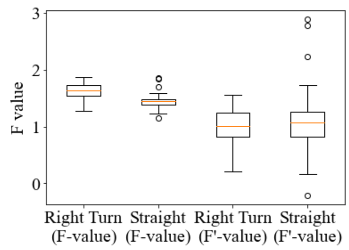

Fig. 11. Distribution of F values for each scenario (AV turning right or straight ahead along the road senario).

TABLE II

RESULTS OF TESTS OF THE MEAN FOR EACH SCENARIO.

p-value of F-test	0.327(>0.05)
test result	Inequality of dispersion was not observed.
t-value	5.653
p-value of T-test	2.882×10^{-7}(<0.05)
test result	Significant difference in means is observed

TABLE III

RESULTS OF SHAPIRO-WILK-TESTS FOR EACH SCENARIO.

p-value of right-turn intrusion scenario	0.1804(>0.05)
test result	Follow the normal distribution.
p-value of straight ahead along the road senario	0.1484(>0.05)
test result	Follow the normal distribution.

$$\begin{cases} F' &= 1 + \frac{F-\mu_R}{3\sigma_R} \quad Right\ Turn \\ F' &= 1 + \frac{F-\mu_S}{3\sigma_S} \quad Straight \end{cases} \tag{2}$$

B. Transitions of F-$value$ before and after the learning process

The study examined the change in F'-$values$ before and after the learning process. The results, comparing the average of the F'-$values$ from the first three trials of the "learning process" with the average of the F'-$values$ from the five trials conducted in the "test process," are presented in Fig. 13. The data in Fig. 13 reveal that the two subjects

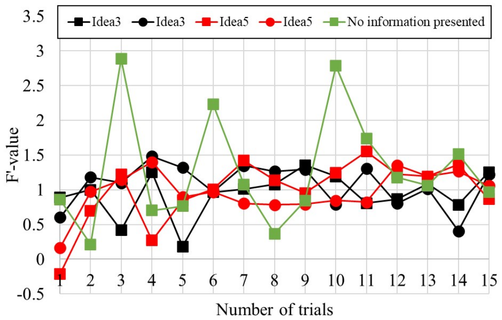

Fig. 12. F'-$values$ were calculated for the experimental results to reduce the bias of F-$values$ due to differences in scenarios.

TABLE IV
RESULTS OF TESTS OF THE MEANS FOR EACH SCENARIO.

p-value of F-test	0.004(<0.05)
test result	Inequality of dispersion was observed.
t-value	-0.792
p-value of T-test	0.4306(>0.05)
test result	Significant difference in means is not observed

who experienced behavior change Idea 5 showed a higher improvement rate of F'-$values$ before and after learning compared to the subjects who were not presented with information.

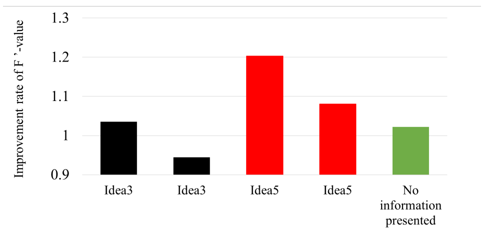

Fig. 13. Improvement rate of F'-$value$: Graph showing the average F'-$value$ after learning (11 to 15 trials) divided by the average F'-$value$ at the beginning of learning (1 to 3 trials).

C. Relationship between Pedestrian term and AV term

The study investigated the relationship between the two terms (Pedestrian term and AV term) that constitute the F-$value$. The Pearson's correlation coefficients of the Pedestrian and AV terms for each subject are presented in Fig. 14. From Fig. 14, it is evident that for behavior change Idea 5, the AV term and Pedestrian term exhibit a larger positive correlation compared to the other subjects. This suggests that pedestrians might have learned behaviors that strike a balance between the benefits of AV and their own benefits.

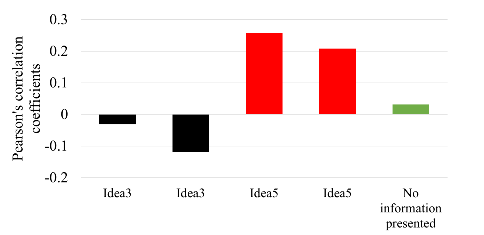

Fig. 14. Graph showing correlation between Pedestrian term and AV term during learning.

IX. CONCLUSIONS

In this study, we introduced and created an HMI prototype that aids pedestrians in learning to interact with AV through the application of AR technology and behavioral economics. The preliminary experiments and main experiments demonstrated the potential of supporting effective communication between pedestrians and AV. By providing relevant information, such as real-time displays of road safety during the learning process, the HMI prototype encouraged natural behavioral changes in pedestrians.

ACKNOWLEDGMENT

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