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Interactions Between Workers and Automated Guided Vehicles: Impact of eHMI Design

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Abstract
As manufacturing facilities integrate Autonomated Guided Vehicles (AGVs) to improve workflow efficiency, enhancing human-AGV interaction remains critical for workplace safety. While prior research has focused on vehicle and pedestrian motion prediction, effective interaction requires two-way communication, where the AGVs clearly convey intentions to the workers to enhance safety. This study investigates the impact of external Human-Machine Interface (eHMI) integrated with a predictive model on AGV-worker interaction. We designed LED light strip patterns to convey intentions and selected optimal designs through an online survey. We deployed three types of AGVs in a virtual reality (VR) environment: Control, Prediction, and eHMI + Prediction. Participants completed tasks while interacting with AGVs, followed by subjective assessments of trust, perceived safety, perceived performance, and understandability. A one-way repeated measures ANOVA revealed a significant improvement in perceived safety from eHMI + Prediction condition compared to the Control condition, suggesting that explicit communication via eHMI enhances perceived safety in AGV interactions.

Keywords
Autonomated Guided Vehicles (AGV), external Human-Machine Interface (eHMI), safety

Introduction

As automation continues to transform industrial workflows, manufacturing facilities are increasingly integrating Autonomated Guided Vehicles (AGVs) to enhance efficiency, reduce physical strain, and optimize production processes (Li & Huang, 2024). While AGVs improve logistics and minimize repetitive human tasks, their effectiveness depends not only on technological advancements but also on continuous interactions between AGVs and workers in complicated environments. Research on AGV-human interaction has mainly focused on motion prediction models, based on physics, pattern, and planning-based approaches (Rudenko et al., 2020). While these models enable AGVs to predict pedestrian movements, effective interaction requires a two-way communication, where the AGVs convey their intentions to the workers to enhance AGV predictability and workplace safety by improving trust in automation and transparency (Bhat et al., 2024). An approach to addressing the challenge of effectively communicating action with humans is the use of an external Human-Machine Interface (eHMI) design on the AGV.

eHMI Designs in Conventional Vehicle

Research on eHMI design has explored various interface modalities that convey vehicle intentions, primarily in the context of vehicle–pedestrian interaction. Carmona et al. (2021) offers a comprehensive review of recent developments in this area, categorizing eHMI designs into six types: (1) displays (Clamann et al., 2017; Urmson et al., 2015), (2) LED light strips (Böckle et al., 2017; Habibovic et al., 2019; Mahadevan et al., 2018), (3) front brake lights (Antonescu, 2013; Petzoldt et al., 2018), (4) projections, (5) visual contact simulation (Chang et al., 2017), and (6) auditory interfaces. Habibovic et al. (2019) reported that their eHMI system has the potential to enhance perceived safety and energy efficiency, although they

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also suggested that vehicle motion alone might be sufficient to convey intention. In a study with a limited participant pool, Böckle et al. (2017) found that their interface improved pedestrians' perceived safety and comfort when interacting with shared autonomous vehicles. Additionally, Chang et al. (2017) developed a robotic eye mechanism to simulate eye contact in a virtual reality setting, which was found to support faster, more accurate crossing decisions and enhance perceived safety.

Previous research has primarily focused on interactions between conventional vehicles and pedestrians. However, a significant gap remains in understanding how interactions between AGVs and workers align or diverge from those in earlier studies. Unlike pedestrian settings, manufacturing environments are highly dynamic, with workers navigating freely between workstations. These different environments pose unique challenges for AGV deployment and interactions. As such, effective AGV integration requires not only accurate prediction of worker trajectories but also the ability for workers to anticipate AGV behavior.

Yang et al. (2024) introduced Finite Automaton Models (FAMs) as a method for predicting worker behavior. However, the approach does not incorporate methods for conveying the predictive outcomes through AGV behavior. Therefore, the present study extends on FAMs by incorporating eHMI designs, allowing the AGV to communicate its intentions based on predictive modeling. This integration aims to enhance mutual understanding between AGVs and workers in complex industrial settings. We anticipate that the AGV with both functionalities would show better performance compared to the current status of the AGV.

Methods

Design Selection

The ideation process considered types of messages that the AGV needs to convey based on the classification of walking behavior in the previous study (Yang et al., 2024) and the corresponding behavior of the AGV during the interaction with the worker. The two models are presented in Figure 1.

We selected five states of the AGV behavior: Constant Speed, Accelerate, Decelerate, Stopped, and Turn Signal. We used the 15 design principles (Lee et al., 2017) in selecting the four design parameters: number/pattern, intensity, frequency, and the direction of the LED, and generated 24 designs in total. We have deployed an online survey to select eHMI designs with LED light strips, asking which state represents each design the most. Based on the results and through internal evaluation, we have selected one design to represent each message type (Figure 2).

Participants

We collected data from 15 participants (12 Male, 3 Female, Age = 26.33 ± 5.51 years) with normal or corrected-to-normal vision. Each participant received a base payment of $30 for their participation and an additional $15 depending on their task performance. The study was approved by the University of Michigan Institutional Review Board (HUM00248627).

Apparatus and Stimuli

VR Environment of Manufacturing Facility. We designed a Virtual Reality testbed to represent a manufacturing plant environment using Unreal Engine 5.3.2. The manufacturing environment represented an actual Composite Wing Center, where equipment is carried by AGVs.

VR Headset and Omnidirectional Treadmill. Participants were requested to interact in the VR environment by wearing a VR headset (Meta Quest Pro headset with two handheld controllers) and walking on the omnidirectional treadmill (KAT Walk C2 Omnidirectional treadmill). The illustration of the VR environment and equipment can be seen in Figure 3.

Experimental Design

The experiment used a within-subjects design with different types of AGV as the independent variable. Three different types of AGV conditions were presented to the participants: Control, Prediction loaded AGV, and eHMI + Prediction loaded AGV. The control condition represents the current AGV used in the manufacturing facility, where the AGV recognizes its surroundings and responds based on a fixed distance. The AGV would slow down if the worker is inside the slowdown zone and stop if the worker is inside the stopping zone (Figure 4). The prediction algorithm used in both prediction and eHMI + Prediction is based on the Finite Automaton Model (Yang et al., 2024), which predicts the workers' state and trajectory. The AGV predicts the worker's state and trajectory 4 s ahead of time and determines whether the worker's position is within the slowdown or stopping zone. The prediction is deactivated if the predicted worker's state is "At Station" or "Approach Station" from Figure 1. If the prediction results indicate that the worker's future position is within the future AGV's yellow zone, it performs a slowdown behavior. Different types of AGVs were presented randomly to the participants in order to mitigate any learning and training effects. Four subjective measurements were rated through a 7-point Likert scale as dependent variables: trust, perceived safety, perceived performance, and understandability.

- Trust: "I trust the AGV to interact with me well"
- Perceived Safety: "I feel safe sharing the same space with the AGV"
- Perceived Performance: "The AGV behaved as I expected during the interaction with me"

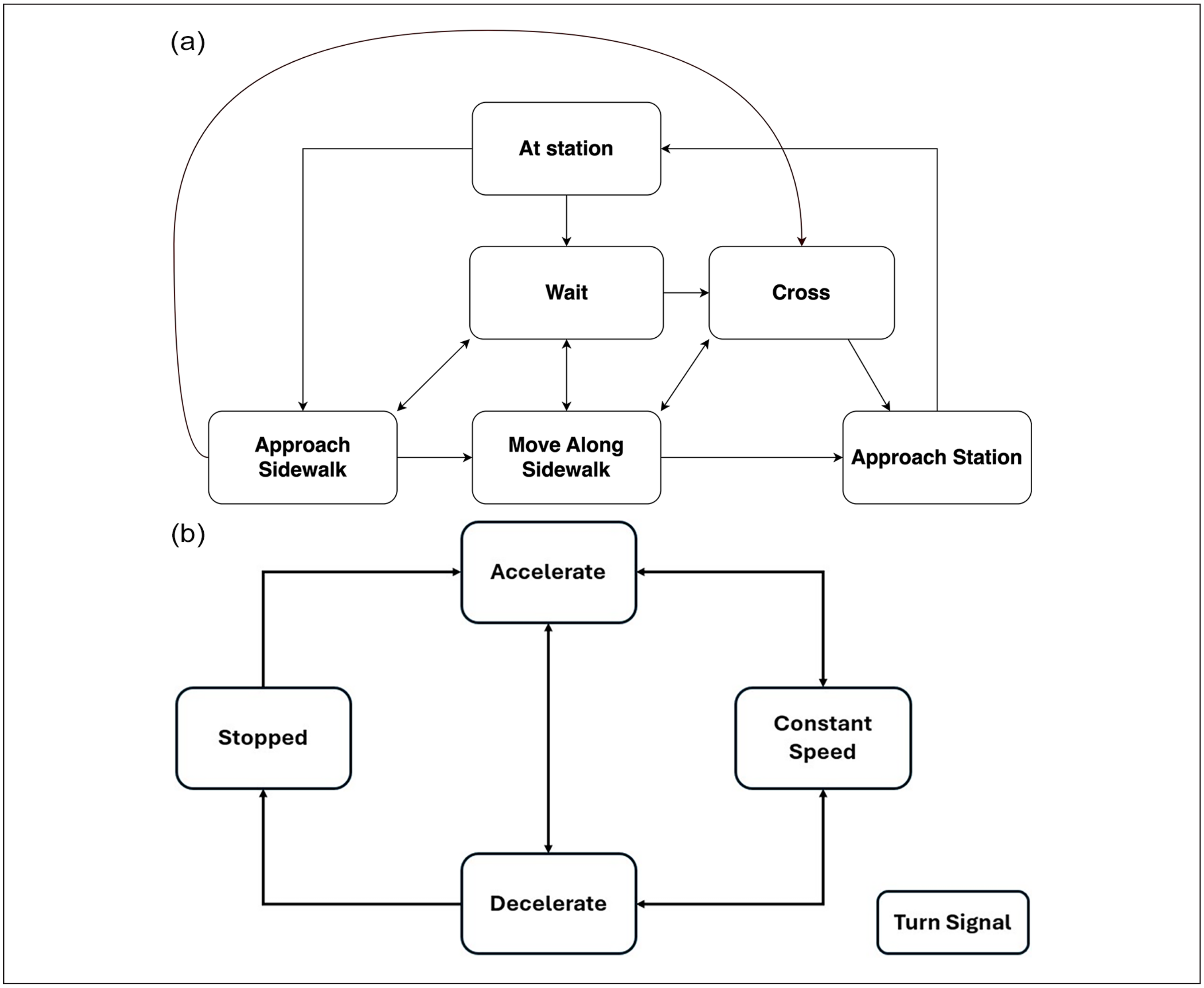

Figure 1. (a) Finite automaton model. (b) AGV behavior states. (a) normal operation loop of finite automaton model from Yang et al. (2024). (b) Five states of AGV behavior model.

Figure 2. Example illustration of the selected eHMI design for the constant speed message type.

- Understandability: "I understood what the AGV was trying to do during the interaction with me"

Procedure

Participants provided informed consent upon arrival and were given an introduction session before the experiment. The introduction included general information related to the field of AGV and how to use the equipment. After completing the introduction session, the participants filled out a demographic survey, followed by wearing the equipment with the help of the experimenter (wearing the footwear for the omnidirectional treadmill, getting on the treadmill, and wearing the headset and controllers). Participants completed

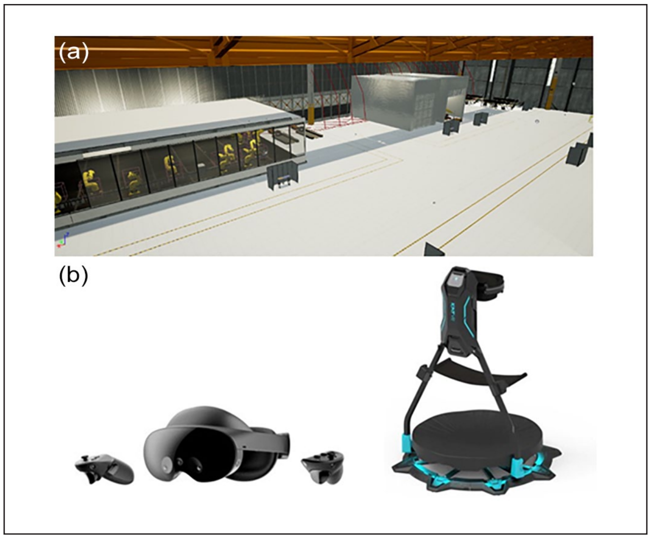

Figure 3. (a) VR environment overview. (b) Equipment used in the VR setup.

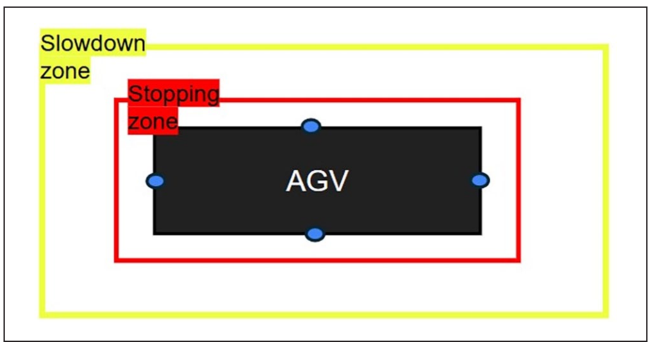

Figure 4. Slowdown and stopping zones depicted as yellow and red boundaries around the AGV.

a training session that helped familiarize them with walking on the treadmill, viewing the VR environment through the headset, and using the controllers to interact with objects inside the VR environment. Then they performed 10 trials per condition, resulting in a total of 30 trials throughout the entire experiment. Each trial required the participant to carry a toolbox from one station to another while memorizing a three-digit number displayed on the toolbox. When picking up the toolbox, a three-digit number was visible and disappeared after 3 s. The participant had to place the toolbox at the target station at the location corresponding to the three-digit number (Figure 5). The location of the stations and the AGV paths were designed to include the six types of human-robot spatial interaction (Molina et al., 2024) between workers and the AGV. After each trial, the participants were asked to indicate whether they noticed the AGV around them during the trial, and respond to four subjective ratings of their trust, perceived safety, perceived performance, and understandability on the AGV on a 7-point Likert scale.

Data Preprocessing and Analysis

The data from the subjective measurements were preprocessed by averaging out the values of the trials within the same condition for each participant. We then conducted a one-way repeated measures Analysis of Variance (ANOVA) to compare the differences in trust, perceived safety, perceived performance, and understandability across different conditions.

Results and Discussion

The results from ANOVA indicated that there was a significant difference across conditions in perceived safety ($F(2, 14) = 4.408$, $p = .022$). Further pairwise comparison indicated that there was a significant difference between the control condition and the eHMI+prediction condition in perceived safety ($p = .048$), indicating a higher rating of perceived safety in eHMI+prediction condition over the control condition. No other significant difference was found across all measurements: trust ($F(2, 14) = 2.785$, $p = .079$), perceived performance ($F(2, 14) = 2.425$, $p = .107$), understandability ($F(2, 14) = 2.225$, $p = .127$) (Figure 6).

In this study, we aimed to evaluate the effectiveness of the trajectory prediction algorithm and the light strip pattern eHMI design on trust, perceived safety, perceived performance, and understandability in AGV-worker interaction. We hypothesized that the eHMI + Prediction condition would perform better in terms of the subjective ratings. In order to validate our hypothesis, we conducted a human-subject experiment in a VR environment for the participants to interact with three different types of AGVs. The preliminary results indicated a significant difference in perceived safety, where the eHMI + Prediction condition showed higher ratings compared to the Control condition. This aligns with previous studies in conventional vehicle interaction, where the results indicated enhanced perceived safety by incorporating eHMI designs on the vehicle (Böckle et al., 2017; Chang et al., 2017; Habibovic et al., 2019). The insignificance between the Control condition and the Prediction condition and between the Prediction condition and the eHMI + Prediction condition indicates that using both the prediction algorithm and the eHMI design can significantly enhance perceived safety better than utilizing the prediction algorithm alone, emphasizing the importance of automation conveying its intention to make an effective two-way communication. The current study has several limitations. First, this is a preliminary result with a small sample size of 15 participants. We anticipate potential possibility that the non-significance with p values around .1 might change when we gather more participants in the future. Second, this study focused on the LED light strip pattern type of eHMI design, and the results might differ when different types of eHMI are incorporated. Third, the participants did not go through a training process to learn about the eHMI design, which

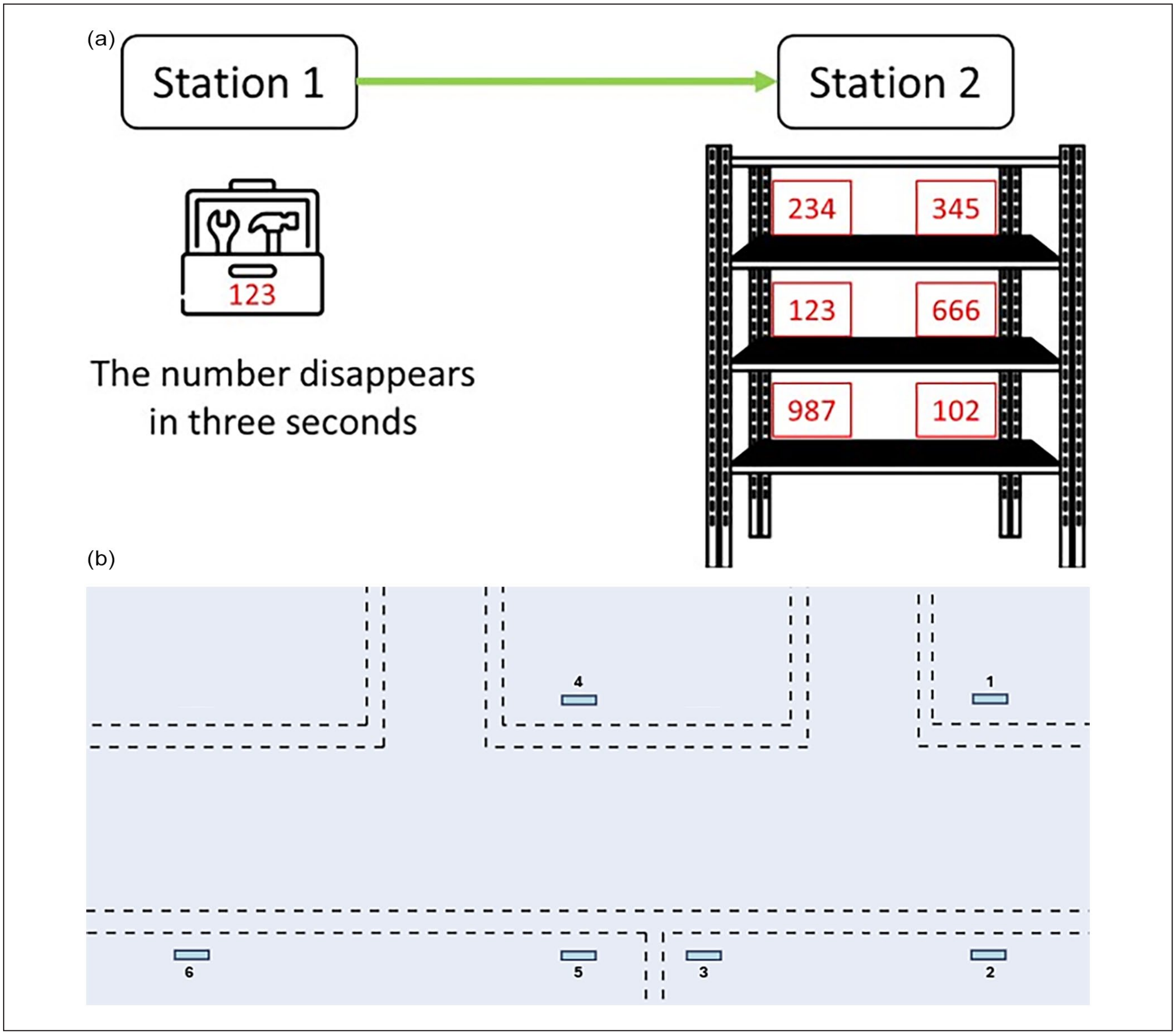

Figure 5. (a) Toolbox delivery task. (b) Top view of the VR environment with station locations.

means the current results rely on the intuitiveness and instincts of the design.

Conclusion

Our study aimed to evaluate the effectiveness of the previously developed trajectory prediction algorithm, along with the eHMI design on AGV-worker interaction. Our study also aimed to contribute in confirming whether the results from the interaction between conventional vehicles and pedestrian is observed the same in AGV-worker interaction. Our results indicate that the AGV with both functionalities enhances perceived safety in the workplace. Future research should focus on further investigating the effectiveness of different types of eHMI designs considering the environmental factors of the workplace.

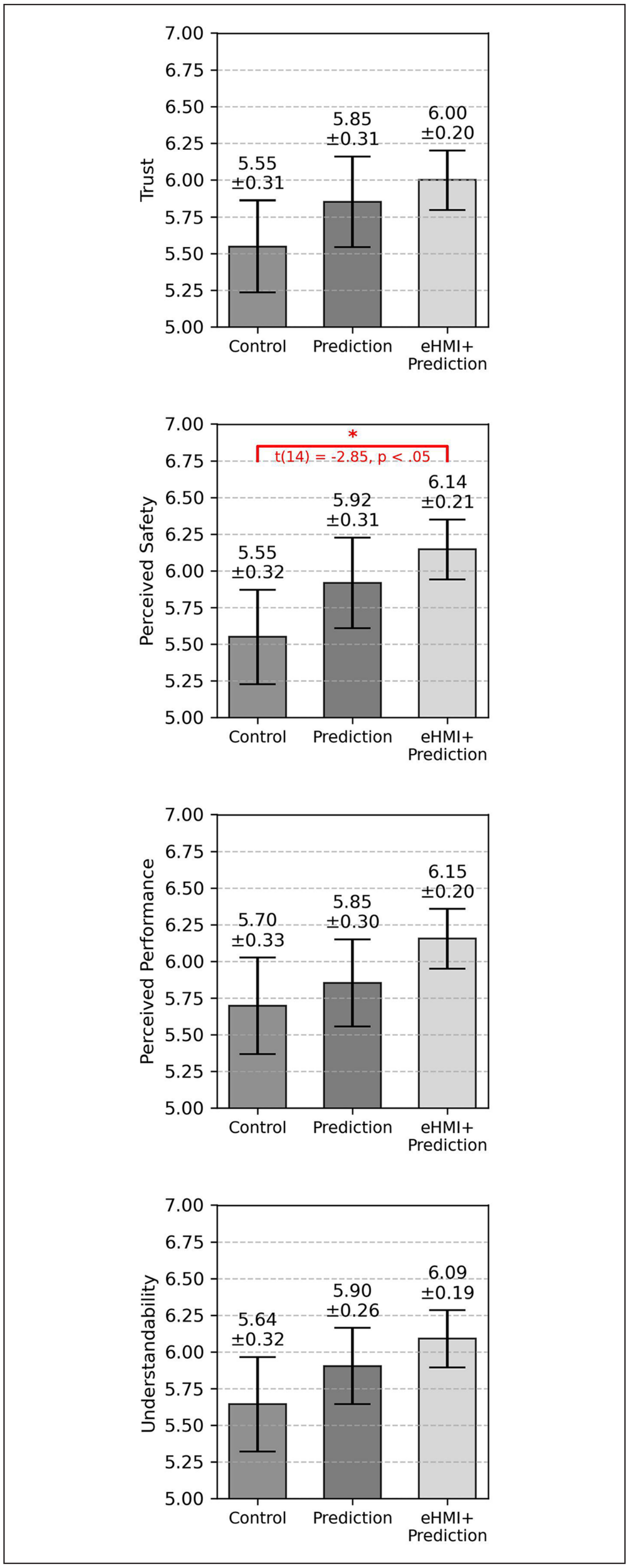

Figure 6. Bar graphs showing post hoc multiple comparisons. (*: $p < .05$). Numbers above bars represent the mean and standard error for each condition.

Declaration of Conflicting Interests

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