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Perceived safety during human-robot interaction with an autonomous mobile robot

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ABSTRACT

Autonomous mobile robots (AMRs) are being rapidly implemented in the manufacturing and warehousing industries. Research could help enhance our understanding of human workers' safety perceptions and behaviors when interacting with AMRs, enabling the improvement of collision-avoidance strategies and criteria for safer interactions. In this study, we examined the effects of AMR shelf height, movement speed, and trajectory path on perceived safety, mental workload, robot trust, proxemic behaviors, and task performance during a simulated loading/unloading task. Overall, AMR speed and trajectory path had the largest impact on the task outcomes, while there was minimal variation across height conditions. Findings from this research can be considered for the design of AMRs and facilities that utilize them.

1. Introduction

1.1. Background

An autonomous mobile robot (AMR) can navigate an environment and perform tasks without human intervention by planning an obstacle-free path using sensors and collision avoidance technology (Alatise and Hancke, 2020; Haney and Liang, 2024; Tzafestas, 2018). They have been increasingly implemented in manufacturing and warehousing workplaces, where transporting various types of loads within a facility is one of the core tasks. Human workers frequently cross paths with AMRs in shared walkways and physically interact with them when retrieving materials from or placing materials onto the robots. Robot-related workplace hazards and risks may emerge from unintentional contact between human workers and robots, as well as work-related stress caused by interactions with robotic systems (Gualtieri et al., 2021; Murashov et al., 2016).

Robots operating near human workers affect workers' safety perceptions, consequently influencing their safety-related behaviors (Haney and Liang, 2024; Johnson et al., 2019). Lower perceived safety in general has led to maintaining larger separation distances, more hesitation, and slower movements (Haney and Liang, 2024) while higher perceived risk of potential collision has shown lower walking speed around an AMR (Chen et al., 2018). Moreover, a sudden change in movement relative to the AMR may directly increase collision risks or raise contact forces to levels that may cause severe injury resulting from a collision (Cheng et al., 2018). Therefore, changes in workers' safety perceptions and associated behavioral responses may result in ineffective human-robot collaboration and poor worker performance. However, existing industrial standards and technical innovations primarily focus on improving robot navigation and obstacle avoidance, often neglecting the influence of human behaviors (Cheng et al., 2024). Comprehensive and systematic investigations may help establish knowledge concerning human workers' safety perceptions and behaviors while interacting with AMRs to refine collision-avoidance methods and criteria for safer interactions.

1.2. Prior research

A growing body of literature has investigated AMR users' perceptions, attitudes, and behaviors during human-robot interaction (HRI) experiments with physical AMRs (Haney and Liang, 2024; Rubagotti et al., 2022). An AMR's physical, movement, and communication characteristics can affect user perceptions and acceptance (Haney and Liang, 2024; Rubagotti et al., 2022). Studies have shown that an AMR's appearance, size, approach direction or passing side, separation distance, noise, and social courtesy or intent cues are significant factors influencing a user's perceived safety and associated behavioral outcomes

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(Akalin et al., 2022; Fiore et al., 2013; Gervasi et al., 2024; Thomas and Vaughan, 2019; Weistroffer et al., 2013). An AMRs height may have a particularly significant impact on perceived safety, as it can change periodically during operation depending on the load it carries. For example, people tend to perceive taller AMRs as less safe than shorter ones when being approached by an AMR (Joosse et al., 2021; Jost et al., 2021).

An AMR's speed may change as it adapts to situational task demands. Prior studies have investigated the impact of certain movement characteristics (e.g., stopping distance, speed, and approach directions) on human trust, perceived safety and resulting behaviors, including acceptable separation distance, physical avoidance, walking speed, and acceleration (Bortot et al., 2012; Leichtmann and Nitsch, 2020; Lichtenthäler and Kirsch, 2013; Lo et al., 2019; MacArthur et al., 2017; Takayama and Pantofaru, 2009). Studies found that a larger separation distance generally improves comfort and perceived safety (Neggers et al., 2018, 2022; Pacchierotti et al., 2006). Furthermore, faster movements have been shown to result in lower perceived safety, increased anxiety and workload, and shorter acceptable separation distances (Akalin et al., 2022; Bergman and van Zandbeek, 2019; Chen et al., 2018; Koppenborg et al., 2017; Šlajpah et al., 2021; Weistroffer et al., 2013).

However, prior research suggests that the impact of robot speed on trust and perceived safety may significantly vary in scenarios where an AMR approaches a person (Haney and Liang, 2024). For instance, MacArthur et al. (2017) reported that slower approach speeds resulted in increased trust in the robot, and Brandl et al. (2016) demonstrated significantly closer acceptable distances with slower robot approach speeds; however, other studies reported that approach or movement speed did not affect perceived safety and comfort (Joosse et al., 2021; Shomin et al., 2015) or separation distance (Jost et al., 2021; Lauckner et al., 2014). Additionally, perceived predictability of an AMR's movement, rather than its speed, may determine safety perceptions and behaviors (Alves et al., 2022; Lo et al., 2019; Shrestha et al., 2018). For instance, highly variable movements (e.g., sudden speed changes) could lead to feelings of unsafety and distrust. Previous studies indicate that participants perceive greater levels of safety and trust when an AMR navigates in a manner similar to humans or communicates its intent, enhancing the predictability of its movement (Alves et al., 2022; Chadalavada et al., 2015; Mavrogiannis et al., 2019).

While prior research has investigated human perceptions and behaviors during HRI with an AMR, the findings are somewhat inconsistent and inconclusive (Haney and Liang, 2024; Rubagotti et al., 2022). Consequently, the current knowledge gaps regarding changes in human workers' safety perceptions and behaviors in relation to robot characteristics can be further explored, as human actions during collision or near-collision situations can either amplify or mitigate collision risks and impact forces.

1.3. Objective

The objective of this study was to investigate the impact of physical and movement attributes of an AMR on perceived safety, mental workload, robot trust, proxemic behaviors, and task performance during a simulated loading/unloading task. We utilized an immersive virtual reality (VR) Cave Automatic Virtual Environment (CAVE) to conduct the HRI experiment. Using VR to evaluate HRI scenarios enables researchers to conduct highly controlled and repeatable experiments at low-cost and minimal risk to human participants (Atkinson and Clark, 2014; Weistroffer et al., 2013). Prior research has demonstrated that using VR for HRI experiments yields similar perceived safety and behavioral responses approximate to those observed during interaction with physical robots (Mitchell et al., 2020). For this research, we formulated the following questions:

RQ1: Does taller height and faster movement speed lead to lower perceived safety and robot trust, higher mental workload, slower walking speeds, increased separation distance, and increased task completion time?

RQ2: Does a curved path, as opposed to a straight path, affect perceived safety?

RQ3: What is the interaction between the distinct physical and movement characteristics and their impact on perceived safety and behaviors?

RQ4: In what ways do individual characteristics, including age, sex, years of relevant work experience, and experience working with robots, affect perceived safety and behaviors toward the AMR?

2. Methods

2.1. Experiment setup

The experiment was conducted in a projection-based VR CAVE (MechDyne Corporation, Marshalltown, Iowa, USA). The VR CAVE consisted of three walls (3.96 m wide; 3.05 m high) and a floor screen. The participants wore a pair of active-stereo shutter glasses (Volfoni 3D, Los Angeles, CA) making the environment look 3-Dimensional. A position tracking system (Advanced Realtime Tracking, Weilheim, Bayern, Germany) was used to track participant head, hands, and body position throughout the VR CAVE. Fig. 1 displays an example of the VR CAVE environment.

The virtual AMR was a digital model of the Freight100 from Zebra Technologies. The Freight100 has a height of 359 mm and a base footprint of 528 mm wide and 573 mm long. The Unity game engine (Unity Technologies, San Francisco, CA) was the basis of the interactive environment. The AMR's movement was animated in the Unity platform. The environment consisted of a warehouse with shelving units containing cardboard boxes and the virtual AMR. The AMR height was adjusted by attaching a cart with one, two, or three shelves to the AMR base. The hand trackers enabled participants to pick up and place the virtual boxes during the experiment. The experiment task consisted of a straight path and curved path layout, as seen in Fig. 2. The virtual boxes were 508 mm^3 in size. The boxes that the participants interacted with were positioned on the second shelf at a height of 1168 mm.

Fig. 1. Example of the VR CAVE environment and an illustrative photo of an individual loading a box onto the robot with a height of 1.0 m for the straight path layout.

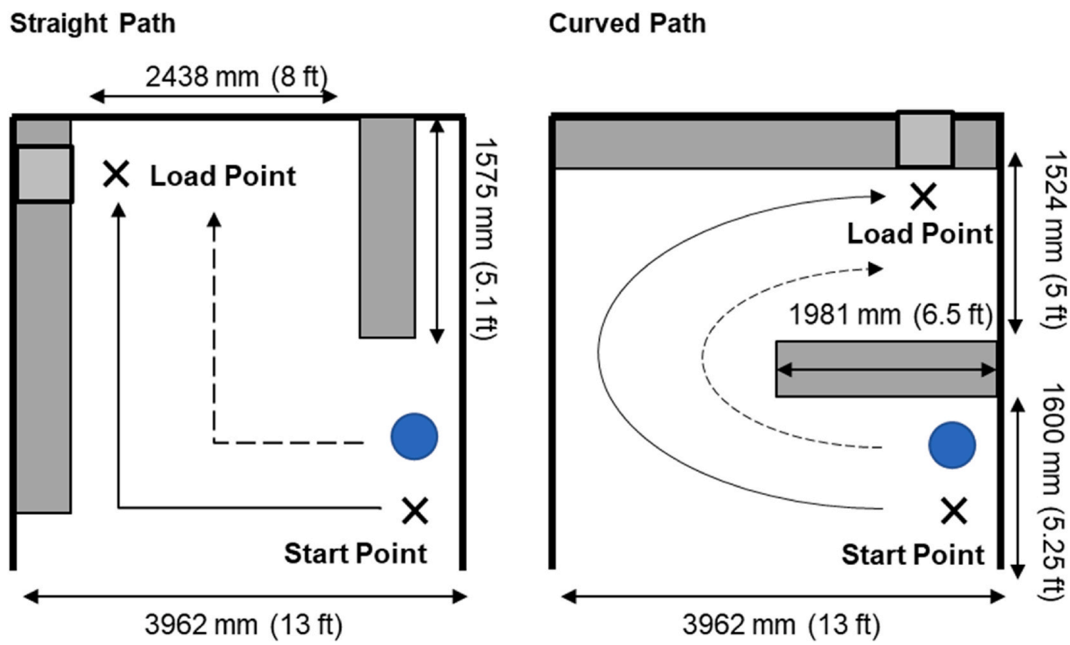

Fig. 2. Experiment setup showing a top-down view of the shelving layouts for the straight (left) and curved (right) trajectory path conditions. Participants walked from the start point to the load point (represented by the X mark) and loaded a box from the shelf onto the AMR (represented by the circle).

2.2. Experiment design and procedure

After providing informed consent, participants responded to questionnaires on demographics, relevant work experience, experience working with robots, and the Negative Attitude towards Robot Scale (NARS) (Nomura et al., 2006). The NARS score (ranging from 14 to 70) is the summation of ratings of 14 questionnaire items (1-5 Likert scale), where a higher score indicates a more negative attitude toward robots. We then applied motion capture markers to the participant's feet, waist, and hands. Prior to the experiment trials, participants completed a 10-min practice session to become familiar with the VR environment which included practice trials picking up and releasing the virtual objects.

This study was a within-subjects experiment. We manipulated the robot size (0.5 m, 1.0 m, and 1.5 m in height), robot movement speed (0.5 m/s, 1.0 m/s, and 1.5 m/s), and shelving layout (Straight Path vs. Curved Path). Every participant completed all 18 conditions (3 sizes x 3 movement speeds x 2 layouts) for a total of 18 trials. The presentation of the conditions was randomized across participants. The trial number for each condition was counterbalanced across participants to minimize learning effects.

Each trial consisted of an AMR loading task. Participants were instructed to walk to a load point, pick a box from the shelf, place it on the empty AMR, and return to the start point. Fig. 2 shows a top-down view of the two layouts. The AMR was positioned to the right of the participant at the start point and moved toward the load point when the participant started walking. The AMR stopped at the load point and continued down the aisle once receiving the box from the participant. After each trial, participants answered survey questions about their perceived safety, mental workload, and trust in the AMR.

The total duration of the experiment for each participant was approximately 90 min. This included informed consent and questionnaires (10 min), a 10-min familiarization and practice session, and completion of the 18 experimental trials. Short breaks were provided as needed to minimize fatigue.

2.3. Independent variables

The independent variables consisted of the AMR shelf height (0.5, 1.0, and 1.5 m), speed (0.5, 1.0, and 1.5 m/s), and trajectory path (straight vs. curved). The shelving layout required the participant to either walk straight down the aisle to the load point (straight) or walk around the end of a shelf in a curved trajectory to the load point (curved) as indicated in Fig. 2.

2.4. Dependent variables

There were three categories of dependent variables including self-reported measures (subjective), task performance (objective), and human motion behaviors (objective). Self-reported measures included perceived safety, mental workload, and robot trust. Perceived safety was evaluated by ratings for “surprise” and “fear”, on a 6-level scale with 1-“never” to 6-“very much” (Nonaka et al., 2004). Mental workload was measured using the NASA Task Load Index (NASA TLX), which consists of 6 subscales each rated on a 1 to 20 scale with 1 being “low” and 20 being “high.” The six subscales are combined using a weighting system to achieve an overall TLX score ranging from 0 to 100. A higher score indicates a higher perceived workload (Hart and Staveland, 1988). Robot trust was measured using ratings for 10 items (i.e.., function successfully, act consistently, reliable, predictable, dependable, meet the needs of the mission, have errors, provide appropriate information, unresponsive, and malfunction) on a scale from 0 to 100%, which was adapted from the 14-item list in Schaefer (2013). Total trust score was calculated by averaging the ratings for all 10 items (Note: ratings for have errors, unresponsive, and malfunction were reversed).

Task performance measures included the approach time (i.e., start of the trial to the time point when the participant first grasped the box on the shelf) and the load time (i.e., the time point when the participant first grasped the box on the shelf to when the box was placed on the AMR).

Human motion behaviors included the average and maximum walking speed (m/s) and the maximum distance (m) to the robot during the approach phase. Walking speed was estimated using the motion capture marker cluster located on the participant's lower back. Distance between the participant and the robot corresponded to the distance between the motion capture marker cluster on the lower back to the center of the robot.

2.5. Participants

Fifty-six (56) adults (29 males and 27 females) from the general population of Morgantown, WV participated in the experiment. Participants were recruited using flyers that were distributed around the local public area and shared with the local University population. The mean (SD) age of the participant sample was 24.8 (7.3) years. All participants reported being healthy, having normal or corrected to normal vision and hearing, not prone to nausea from virtual reality experiences, and had relevant work experience (e.g., working in manufacturing, warehousing, or in a stockroom). The mean (SD) years of relevant work experience was 3.0 (4.8). Nine (16%) of the 56 participants reported having some experience working with robots. This study was reviewed and approved (Protocol ID: 19-NIOSH-83) by the CDC NIOSH Institutional Review Board (IRB).[1]

2.6. Statistical analysis

All statistical analyses were conducted using SPSS v29 (IBM Corporation, Armonk, NY, USA) with statistical significance achieved when $p < 0.05$. We compared the effect of participant characteristics (i.e., age, sex, years of relevant work experience, experience working with robots) on the NARS score using a mixed effects model. Linear mixed effects models were used to test for the effect of the independent variables on the dependent variables. Mixed effects models generally provide more flexibility in accounting for variability at different levels, such as individual differences between participants or variations between groups. All two-way interactions and the three-way interaction were included in the models. Covariates in the model included participant age, sex (male vs. female), trial number (1-18), years of relevant work experience, experience working with robots (yes vs. no), and the total NARS score. Bonferroni tests were used for post-hoc pairwise comparisons. The p-values for these tests were adjusted to account for multiple comparisons so that statistical significance was achieved when $p < 0.05$. All statistical results were presented as the estimated marginal means (SE) in the original units.

3. Results

Table A1 in the appendix presents a summary of the p-values from the mixed effects models investigating the effect of the AMR shelf height, AMR speed, and trajectory path, and all two-way and three-way interactions on the dependent variables.

3.1. Participant characteristics

Age, sex, years of relevant work experience, and experience working with robots did not affect any of the dependent variables. The total NARS score had a significant impact on approach time, where a lower total NARS score was associated with shorter approach times ($p < 0.001$). No other significant effects of the total NARS score were found. The mean (SE) NARS score of the participant sample was 35.8 (1.15). Age, sex, years of relevant work experience, and experience working with robots had no effect the NARS score.

3.2. Perceived safety

Ratings for surprise and fear were nearly identical across the conditions. Surprise significantly decreased with higher trial numbers ($p < 0.001$), while fear had no significant change. Shelf height did not impact surprise nor fear. The main effects of speed and trajectory path were significant for both surprise (speed: $p < 0.001$; trajectory path: $p < 0.001$) and fear (speed: $p < 0.001$; trajectory path: $p < 0.001$) ratings.

Surprise ratings for the 1.5 m/s speed (1.50 ± 0.07) were significantly higher than the 1.0 m/s speed (1.27 ± 0.07; $p < 0.001$) and the 0.5 m/s speed (1.27 ± 0.07; $p < 0.001$). The curved path had significantly higher surprise ratings (1.45 ± 0.07) compared to the straight path (1.24 ± 0.07; $p < 0.001$). Likewise, fear ratings for the 1.5 m/s speed (1.17 ± 0.04) were significantly higher than the 1.0 m/s speed (1.08 ± 0.04; $p < 0.001$) and the 0.5 m/s speed (1.05 ± 0.04; $p < 0.001$). The curved path had significantly higher fear ratings (1.15 ± 0.04) compared to the straight path (1.05 ± 0.04; $p < 0.001$). The two-way interaction between speed and trajectory path was significant for surprise ($p < 0.001$) and fear ($p < 0.001$) ratings. Table 1 shows the surprise and fear ratings by trajectory path and speed conditions. The difference in ratings were observed for the 1.5 m/s speed condition. Additionally, across speed conditions, the trends were the same for the curved path, but there was no difference within the straight path. The other interaction effects were not significant.

3.3. Robot trust

Total trust score increased with increasing trial number ($p < 0.001$). Shelf height did not impact total trust score. The main effects of speed ($p < 0.001$) and trajectory path ($p < 0.001$) were significant. Total trust scores for the 0.5 m/s speed condition (91.62 ± 1.07) were significantly lower than the 1.0 m/s condition (92.93 ± 1.07; $p < 0.001$). The curved path had significantly lower total trust scores (91.28 ± 1.06) compared to the straight path (93.21 ± 1.06; $p < 0.001$). The two-way interaction between speed and trajectory path was significant ($p = 0.047$). Fig. 3 displays the trend in total trust scores by speed and trajectory path. Within the curved path, the 1.0 m/s speed condition had significantly higher total trust scores than the 0.5 m/s speed ($p < 0.001$) and the 1.5 m/s speed ($p = 0.002$). There were no differences in total trust scores between the speed conditions for the straight path. The other interaction effects were not significant.

3.4. Mental workload

The NASA TLX score decreased with increasing trial number ($p < 0.001$). The main effects of shelf height ($p < 0.001$), speed ($p < 0.001$), and trajectory path ($p < 0.001$) were significant. The NASA TLX score for the 1.5 m shelf height (45.22 ± 5.96) was significantly higher than the scores for the 1.0 m shelf height (37.09 ± 5.96; $p < 0.001$) and 0.5 m shelf height (39.45 ± 5.96; $p = 0.002$). The 1.5 m/s speed had significantly higher NASA TLX scores (44.19 ± 5.96) compared to the 1.0 m/s speed (38.65 ± 5.96; $p = 0.004$) and 0.5 m/s speed (38.92 ± 5.96; $p = 0.007$). The curved path had significantly higher NASA TLX scores (43.18 ± 5.91) compared to the straight path (38.00 ± 5.91; $p < 0.001$). The two-way interaction between speed and trajectory path was significant ($p = 0.011$). Fig. 4 displays the trend in NASA TLX score by speed and trajectory path. The speed did not impact the NASA TLX score within the straight path. For the curved path, the 1.5 m/s speed had

Table 1
Comparison of the mean Surprise and Fear ratings ± standard error between the trajectory path conditions, within each AMR speed condition.

	Speed (m/s)	Ratings (1-6 scale)		p-value
		Straight Path	Curved Path	
Surprise	0.5	1.228 ± 0.075	1.317 ± 0.075	0.148
	1	1.222 ± 0.075	1.314 ± 0.075	0.136
	1.5	**1.282 ± 0.075**	**1.721 ± 0.075**	**< 0.001***
Fear	0.5	1.041 ± 0.042	1.054 ± 0.042	0.722
	1	1.060 ± 0.042	1.095 ± 0.042	0.309
	1.5	**1.054 ± 0.042**	**1.286 ± 0.042**	**< 0.001***

Note: The bolded values and asterisks indicate a significant comparison between paths.

[1] See 45 C.F.R. part 46; 21 C.F.R. part 56.

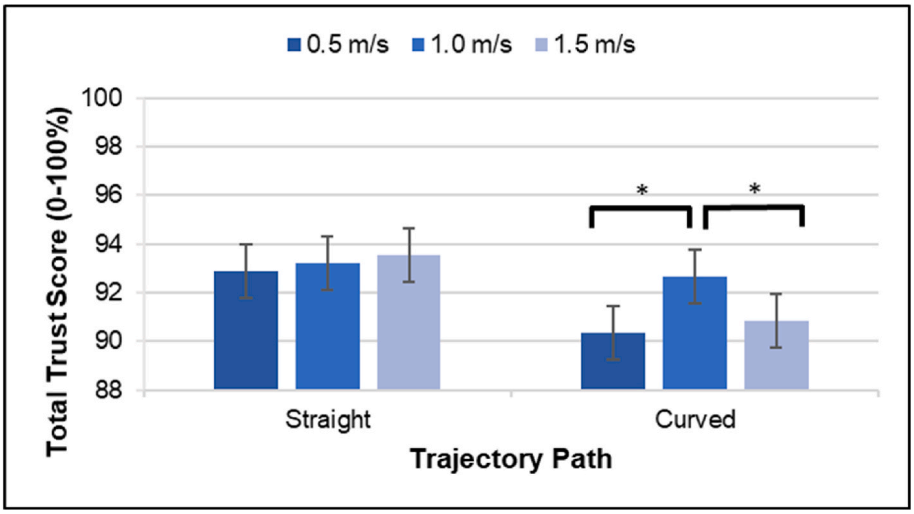

Fig. 3. Total trust ratings by AMR speed and trajectory path. An asterisk (*) indicates a statistically significant difference between comparisons.

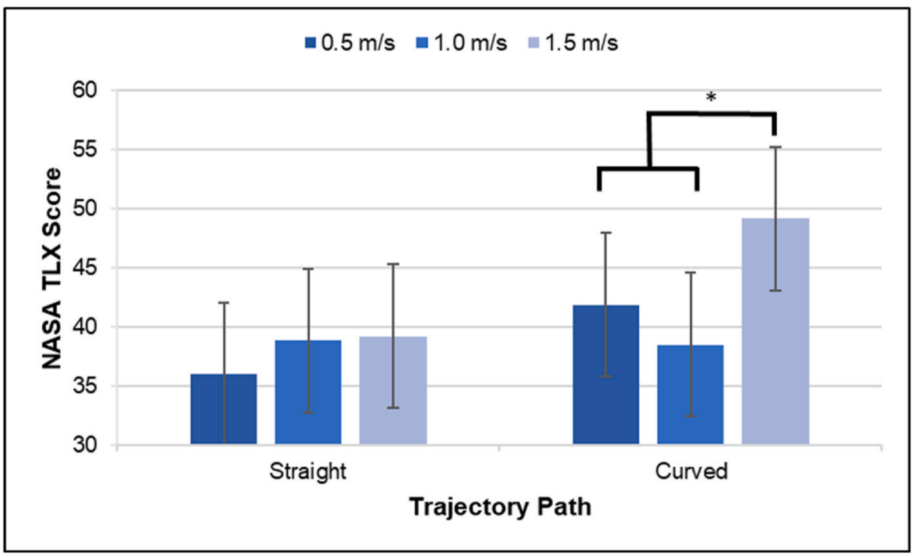

Fig. 4. The total NASA TLX score by AMR speed and trajectory path. An asterisk (*) indicates a statistically significant difference between comparisons.

significantly higher scores compared to the 1.0 m/s speed ($p < 0.001$) and 0.5 m/s speed ($p = 0.008$). The other two-way interactions and the three-way interaction were not significant.

3.5. Task performance

The main effects of speed ($p < 0.001$) and trajectory path ($p < 0.001$) on approach time were significant. Approach time was significantly longer for the 0.5 m/s speed (6.64 ± 0.16) compared to the 1.0 m/s speed (6.31 ± 0.16; $p < 0.001$) and 1.5 m/s speed (6.22 ± 0.16; $p < 0.001$). The curved path had significantly longer approach times (7.44 ± 0.16) compared to the straight path (5.34 ± 0.16; $p < 0.001$). The two-way interactions between shelf height and speed ($p = 0.047$) and speed and trajectory path ($p < 0.001$) were significant (Table 2). The trend in approach time across speed conditions was only prevalent for the 1.0 m shelf height condition, where approach time was significantly longer for the 0.5 m/s speed (6.89 ± 0.18) compared to the 1.0 m/s speed (6.26 ± 0.18; $p < 0.001$) and 1.5 m/s speed (6.21 ± 0.18; $p < 0.001$). Likewise,

Table 2
Two-way interaction effect of speed and trajectory path on approach time and load time. Superscripts next to the mean values indicate pairwise comparisons, where different letters signify significant differences between groups.

Task Time	Trajectory Path	Mean ± SE: Speed Condition			Speed x Trajectory Effect
		0.5 m/s	1 m/s	1.5 m/s	p-value
Approach Time (s)	Straight	5.45 ± 0.17^{a}	5.33 ± 0.17^{a}	5.22 ± 0.17^{a}	0.022*
	Curved	7.81 ± 0.17^{a}	7.29 ± 0.17^{b}	7.22 ± 0.17^{b}	
Load Time (s)	Straight	3.91 ± 0.13^{a}	3.37 ± 0.13^{b}	3.18 ± 0.13^{b}	<0.001*
	Curved	5.30 ± 0.13^{a}	3.04 ± 0.13^{b}	2.75 ± 0.13^{c}	

the trend in approach time across speed conditions was only prevalent for the curved path (Table 2). The other interaction effects for approach time were not significant.

Load time decreased with increasing trial number ($p < 0.001$). The main effects of shelf height ($p < 0.001$), speed ($p < 0.001$), and trajectory path ($p = 0.002$) were all significant. The 0.5 m shelf height condition (3.76 ± 0.12) had a significantly longer load time than the 1.5 m shelf height (3.42 ± 0.12; $p < 0.001$). The load time for the 0.5 m/s speed condition (4.61 ± 0.12) was significantly longer than the load time for the 1.0 m/s speed (3.20 ± 0.12; $p < 0.001$) and the 1.5 m/s speed (4.61 ± 0.12; $p < 0.001$), and the load time for the 1.0 m/s speed was significantly longer than the load time for the 1.5 m/s speed ($p = 0.011$). The curved path had a significantly longer load time (3.70 ± 0.12) compared to the straight path (3.49 ± 0.12; $p = 0.002$). The two-way interaction between speed and trajectory path ($p < 0.001$) was significant (Table 2). For the straight path, the load time for the 0.5 m/s speed was significantly longer than the load time for the 1.0 m/s speed and the 1.5 speed. Whereas, for the curved path, the load time for the 0.5 m/s speed was significantly longer than the load time for 1.0 m/s speed and the 1.5 speed, and the load time for the 1.0 m/s speed was significantly longer than the 1.5 m/s speed. Lastly, the three-way interaction between shelf height, speed, and trajectory path was significant ($p = 0.045$). For the 0.5 m/s speed and curved path, the 0.5 m shelf height condition (5.72 ± 0.18) had a significantly longer load time than the 1.0 m shelf height (5.09 ± 0.18; $p = 0.007$) and the 1.5 m shelf height (5.10 ± 0.18; $p = 0.007$).

3.6. Human motion behaviors

Trial number did not impact the human motion behavior variables. The average and maximum walking speed had little variation across conditions. The maximum walking speed was higher for the 0.5 m/s speed (1.69 ± 0.12) compared to the 1.0 m/s speed (1.34 ± 0.12; $p = 0.063$) and the 1.5 m/s speed (1.35 ± 0.12; $p = 0.082$), though these comparisons lost significance at the pairwise level.

Speed ($p < 0.001$) and trajectory path ($p < 0.001$) had a significant effect on the maximum distance to the robot. The maximum distance was significantly farther for the 0.5 m/s speed (2.429 ± 0.063), compared to the 1.0 m/s speed (2.069 ± 0.063; $p < 0.001$) and the 1.5 m/s speed (2.070 ± 0.064; $p < 0.001$). Maximum distance increased for the curved path (2.650 ± 0.063) compared to the straight path (2.029 ± 0.053; $p < 0.001$). Lastly, the interaction between speed and trajectory path was significant ($p = 0.023$). There were no differences in maximum distance within the straight path. For the curved path, the maximum distance for the 0.5 m/s speed (2.612 ± 0.088) was significantly farther than the 1.0 m/s (2.266 ± 0.088; $p = 0.015$) and the 1.5 m/s (2.170 ± 0.089; $p = 0.001$) speeds. The other interaction effects were not significant.

4. Discussion

The purpose of this research was to investigate how AMR size, movement speed, and trajectory path affect perceived safety, mental workload, robot trust, proxemic behaviors, and task performance during HRI with an AMR. Speed and trajectory path had the most frequent impact on the task outcomes. Shelf height impacted task performance and mental workload, but had no effect on human behavior, perceived safety, and robot trust. Personal characteristics had no effect on the task outcomes. Additionally, participants reported high levels of perceived safety (i.e., low ratings for surprise and fear), high levels of trust in the robot, and low mental workload scores, across all task conditions.

4.1. Self-reported measures and task performance

In our experiment, the straight path resulted in faster task times, higher levels of trust, increased perceived safety, and decreased mental workload compared to the curved path. This result can likely be explained because of the increased visibility of the AMR in the straight path condition. Robot speed only impacted the task outcomes within the curved condition. The fastest speed of 1.5 m/s resulted in lower perceived safety and higher mental workload scores, as expected. Interestingly, the 1.0 m/s speed had higher robot trust scores compared to the 0.5 m/s and 1.5 speed conditions. Participants reported that the robot was less reliable and less consistent when the robot traveled too slow or too fast. This finding suggests the presence of an optimal speed range for collaborative AMR interactions, rather than a linear relationship between speed and trust. Past research on HRI involving physical AMRs reported that slower approach speeds result in significantly higher trust in the robot (MacArthur et al. (2017), while others have reported that approach speed has no significant effect on perceived safety (Joosse et al., 2021; Shomin et al., 2015). However, differences in robot design characteristics and exact movement speeds of these specific studies could explain the contradictory findings. Further work would benefit by examining adaptive speed control strategies in which AMRs dynamically adjust speed based on human proximity, task phase, or environmental visibility to support both efficiency and user trust. Additionally, studies using physical AMRs are needed to determine whether these effects persist in real-world settings where perceived risk and physical consequences of collision are higher.

Shelf height impacted mental workload and task time. Given that the box initially rested on a shelf with a height of 1.2 m, the transfer distance to the 0.5 m shelf was longer than the distance to the 1.5 shelf, which could explain the increase in load time. Additionally, our results showed that the tallest robot shelf height required more physical demand and effort which led to higher mental workload ratings compared to the shorter heights. We found no significant effect of shelf height on perceived safety and robot trust. Previous research has shown that people perceive taller AMRs to be less safe than shorter ones when being approached by a physical AMR (Joosse et al., 2021; Jost et al., 2021). It is possible that in our study, participants felt less threatened by the taller AMR because they were working collaboratively with it to complete a task or because there was no inherent sense of danger since it was virtual.

4.2. Human behavior

Robot speed had a minimal effect on human-robot proxemics and participant walking speed, while shelf height had no effect. We found slightly higher maximum walking speeds with the slowest speed at 0.5 m/s, but there was no change in average walking speed. Chen et al. (2018) studied human behavior when interacting with a physical AMR near an exit corridor and found that the faster the robot moves, the lower the mean walking velocity becomes. In our study, it's likely that participant walking speed human-robot proxemics had minimal variation across task conditions due to the space limitations of the VR CAVE.

The maximum distance to the robot was greater for the slowest robot speed. Participants were able to create a larger separation distance from the robot when it was navigating at the slower speed. Prior research shows that increasing separation distance leads to higher ratings of comfort and safety (Neggers et al., 2018, 2022; Pacchierotti et al., 2006). The effect of speed on acceptable separation distances is less clear. Brandl et al. (2016) reported significantly closer acceptable distances with slower robot approach speeds, while Jost et al. (2021) and Lauckner et al. (2014) found no effect of speed on separation distance. Differences in the specific speeds, robot design characteristics, and AMR physicality (e.g., virtual vs. physical) of these studies could explain the contradictions.

4.3. Implications for design

The findings from this study provide practical guidance for the design and deployment of AMRs in manufacturing and warehousing environments. Straight approach paths were associated with higher perceived safety, greater trust, lower mental workload, and improved task performance compared to curved paths, likely due to increased visibility and predictability of the robot's motion. From an applied perspective, facility layouts and AMR navigation strategies should prioritize straight-line approaches to human–robot interaction points when feasible, particularly in shared aisleways. In addition, the results suggest that an intermediate approach speed (1.0 m/s) may represent an optimal range for collaborative loading tasks, balancing operational efficiency with user trust and perceived safety. While slower speeds may unnecessarily reduce efficiency and faster speeds may increase workload and reduce perceived safety, moderate speeds may support both productivity and positive HRI. These findings highlight the importance of context-aware navigation strategies in which AMR speed and path planning are adapted based on task type, environmental geometry, and visibility conditions.

Safe and efficient navigation is a primary concern for AMRs that operate in the vicinity of human workers. There are various obstacle avoidance techniques that AMRs employ to navigate between waypoints in the work environment (Pandey et al., 2017). Human-aware navigation refers to the ability of an AMR to navigate in environments shared with humans while considering human behaviors, safety, comfort, and social norms (Kruse et al., 2013). While this navigation technique is currently more common in social mobile robots that are employed in public spaces, industrial mobile robots are shifting toward this technology to operate safely in dynamic environments with human workers. Navigation techniques could be improved by considering human workers' perceived safety to maintain a stress-free environment.

4.4. Limitations

There were a few limitations to this study. Our sample population consisted of participants from Morgantown, WV, which could impact the generalizability of the results. Only a small subset of participants (9 of 56) reported prior experience working with robots. As a result, the findings are most representative of workers with general material-handling experience who are relatively unfamiliar with robotic systems. This sample may therefore reflect early-stage implementation scenarios in which workers are newly introduced to AMRs. Future research should examine whether these findings generalize to more experienced industrial populations, including workers with prolonged exposure to AMRs and task-specific operational roles.

A primary limitation of this study is that all interactions were conducted within a VR environment. While VR can approximate real-world HRI and provide controlled experimental conditions, participants are aware that the robot cannot cause physical harm, which may influence measures of perceived safety, fear, trust, and natural movement. Consequently, the behavioral and affective responses observed in this study may not fully generalize to real-world industrial settings where actual physical risk is present. This limitation is reflected in the uniformly high perceived safety and trust ratings and the low fear ratings observed across conditions, which likely represent ceiling effects associated with the reduced perceived risk in the VR environment. Whether these perceptual differences would translate into safety-relevant behavior in real-world industrial settings remains an open question and warrants further investigation using physical AMR platforms.

Additionally, the physical constraints of the VR CAVE may limit participants' natural movement, including avoidance behavior and proxemic adaptation, and could contribute to the minimal variation observed in walking speed and proxemic measures. Therefore, the results are best interpreted as reflecting relative differences between experimental conditions rather than absolute safety levels that would directly apply to real-world AMR operations.

Participants might have behaved or perceived the robot differently if the task was more difficult and were able to spend more time interacting or walking alongside the robot. The robot's movement might have become more predictable and less threatening as the experiment progressed, which is evidenced by the improvement in task parameters as the trial number increased. This study could have benefited from the collection of physiological parameters, such as heart rate and skin temperature to complement the behavioral parameters and subjective responses. Additionally, eye-tracking data would have provided insight into where participants directed their gaze and attention while completing the task.

4.5. Conclusions

Results from this study suggest robot design characteristics and trajectory path affect how humans behave around and perceive AMRs in a collaborative work environment. Overall, robot speed and trajectory path had the largest impact on the task outcomes, while there was minimal variation across AMR shelf height conditions. Despite these significant findings, participants generally felt safe working alongside the robot and reported high levels of robot trust and low mental workload across all task conditions.

Regarding future research directions, there are several areas that warrant further investigation. For example, testing on how robot design and movement characteristics affect human-robot proxemics and perceived safety in different task conditions is necessary. Autonomous mobile robots are versatile and interact with human workers in various fashions in the workplace and people's behavior and perceptions may change depending on the type of task they are performing. Facilities that utilize AMRs will typically employ a fleet of them, as opposed to just one. Therefore, workers are likely to encounter multiple robots while traversing aisleways, and it is unknown how the presence of two or more AMRs systematically affects human behavior and perceived safety.

CRediT authorship contribution statement

Justin M. Haney: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Douglas Ammons:** Writing – review & editing, Methodology. **HeeSun Choi:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Disclaimer

The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the National Institute for Occupational Safety and Health (NIOSH), Centers for Disease Control and Prevention (CDC). Mention of any company or product does not constitute endorsement by NIOSH, CDC.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1
Results of the mixed effects models for every dependent variable. The values represent the *p*-values with $p < 0.05^*$ indicating a significant effect.

Dependent Variable	Shelf Height	Speed	Trajectory Path	Shelf Height * Speed	Shelf Height * Trajectory Path	Speed * Trajectory Path	Shelf Height * Speed * Trajectory Path
Perceived Safety							
Surprise	0.549	<0.001*	<0.001*	0.074	0.442	<0.001*	0.162
Fear	0.234	<0.001*	<0.001*	0.672	0.121	<0.001*	0.407
Trust							
Function Successfully	0.206	<0.001*	<0.001*	0.556	0.671	0.152	0.483
Act Consistently	0.111	0.016*	<0.001*	0.63	0.342	0.027*	0.129
Reliable	0.135	0.005*	<0.001*	0.96	0.439	0.003*	0.538
Predictable	0.504	<0.001*	<0.001*	0.719	0.359	0.005*	0.08
Dependable	0.865	0.007*	<0.001*	0.827	0.791	0.017*	0.907
Meet Needs of Mission	0.177	0.022*	0.003*	0.560	0.204	0.130	0.736
Have Errors Reversed	0.356	0.135	<0.001*	0.75	0.176	0.159	0.947
Provide Appropriate Info	0.829	0.778	0.327	0.839	0.251	0.067	0.329
Unresponsive Reversed	0.419	0.003*	0.018*	0.898	0.027*	0.539	0.777
Malfunction Reversed	0.86	0.253	<0.001*	0.854	0.287	0.51	0.893
Trust Total	0.562	0.002*	<0.001*	0.918	0.586	0.009*	0.611
Mental Workload							
Mental Demand	0.004*	0.268	0.038*	0.453	0.901	0.047*	0.898
Physical Demand	<0.001*	0.334	0.953	0.947	0.659	0.356	0.728
Temporal Demand	0.909	<0.001*	<0.001*	0.083	0.669	<0.001*	0.151
Performance	0.125	0.683	0.828	0.596	0.746	0.017*	0.222
Effort	<0.001*	0.001*	0.286	0.398	0.907	0.502	0.628
Frustration	0.002*	<0.001*	<0.001*	0.598	0.288	0.01*	0.84
NASA TLX Total	<0.001*	0.001*	<0.001*	0.337	0.801	0.011*	0.911
Task Performance							
Approach Time	0.371	<0.001*	<0.001*	0.047*	0.164	0.022*	0.905
Load Time	<0.001*	<0.001*	0.002*	0.987	0.338	<0.001*	0.045*
Human Behavior							
Max Distance to Robot	0.362	<0.001*	<0.001*	0.141	0.819	0.49	0.833
Average Walking Speed	0.452	0.841	0.984	0.399	0.877	0.789	0.574
Max Walking Speed	0.217	0.033*	0.554	0.276	0.836	0.293	0.851

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