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A literature review on safety perception and trust during human-robot interaction with autonomous mobile robots that apply to industrial environments

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Abstract

Introduction: Autonomous mobile robots are rapidly emerging in the workplace, which potentially creates new hazards for human workers that interact with them.

Purpose: We aimed to systematically review previous research on human-robot interaction with autonomous mobile robots that apply to industrial environments, and to identify research needs to improve worker safety and trust.

Methods: We completed a systematic review following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology. We focused on articles that contained experiments with human participants and that included findings associated with improving safety and/or trust of workers who interact with mobile robots in industrial environments. We identified 50 articles that fit inclusion/exclusion criteria for the review.

Results: Almost all of the reported experiments were conducted in a controlled laboratory setting. There were 27 different types of autonomous mobile robots. Only two studies involved industrial mobile robots that were commercially available and could be implemented in an industrial environment. Most studies used questionnaires, with the most common topic relating to participant perceptions of various robot traits, while few directly evaluated perceived safety and

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Occupational Applications: Autonomous mobile robots are used in manufacturing and warehousing industries, to transport material across the facility and deliver parts to work cells. Human workers might encounter or interact with these robots in aisle ways or at their workstation. It is important to consider factors that impact worker safety and trust when implementing autonomous mobile robots in the workplace. This paper reviews prior research that aims to improve the safety of human-robot interaction with autonomous mobile robots and identifies needs for future research. Researchers used a variety of questionnaires and behavioral assessment methods to measure perceived safety. Factors such as robot appearance, approach speed, and approach direction, significantly affect perceived safety. Additionally, projection of signals on the floor, turn signals, and haptic communication devices, can improve the predictability and overall safety of robot navigation.

trust using questionnaires. Behavioral and physiological assessment methods were used in 70 and 8% of the studies, respectively. Separation distance between the participant and robot was the most common behavioral assessment method. A variety of robot characteristics were found to have a significant effect on human perception of safety and other similar concepts.

Conclusions: Future research requires rigorous reporting of participant demographics and experience level with robots. We found that 34 and 44% of references failed to report the mean age of their participant sample and their experience with robots, respectively. Among several gaps that we identified in the literature were a lack of field experiments, sparse research involving multiple mobile robots, and limited use of industrial mobile robots in experiments with human participants.

Keywords

Human-robot interaction; autonomous mobile robot; safety; trust

1. Introduction

1.1. Motivation

Recent advancements in mobile robotics have led to a rise of their implementation in industrial environments, especially in manufacturing and warehousing industries. Factors driving this growth include the potential to perform tasks that are endangering or monotonous to human workers, and to possibly perform such tasks in a more efficient manner. However, the implementation of mobile robots in industrial environments introduces new hazards and risks for worker injury. Safety is a key concept in the development of mobile robots and their implementation in industrial environments. Human-robot interaction (HRI) is an extensive and rapidly expanding field in robotics research (Liang & Cheng, 2023; Sheridan, 2016), and the concept of safety has been widely investigated in HRI research (Lasota et al., 2017; Markis et al., 2019; Vasic & Billard, 2013). Lasota et al. (2017) defined two forms of safety: physical and psychological. Physical safety refers to the prevention of unintentional contact between a human and robot that can cause physical discomfort or injury. Psychological safety involves the prevention of stressful interactions that might cause indirect psychological discomfort or harm. In this review paper, we survey the literature relating to studies and experiments that have investigated factors that affect safety and trust in HRI between humans and mobile robots that apply to industrial environments.

1.2. Mobile Robots and Their Applications

An industrial mobile robot is a mobile platform capable of navigating through an industrial environment to reach a specified location (American National Standards Institute/Robotic Industries Association, 2020). The mobile platform can either be an automatic guided vehicle (AGV), which traverses the environment along a predefined path, or an autonomous mobile robot (AMR), which relies on obstacle and collision avoidance technology to compute an obstacle-free path from one location to another. Therefore, AMRs are more advantageous in warehousing and manufacturing industries that require frequent restructuring of the facility, handling and transporting heavy components, and interacting with human workers (Angerer et al., 2012).

Service robots, also known as social robots, are another category of AMR that interact and assist people in public spaces. These robots interact with humans in a socially acceptable fashion and convey intentions in a human-perceptible way, often including the use of human emotions (Breazeal, 2003). A service robot performs useful tasks for humans or equipment, excluding industrial automation applications and requires a degree of autonomy (International Organization for Standardization, 2021). Similar HRI safety concepts are applied to service robots, since they navigate through public environments autonomously and interact with people using similar methodologies as industrial mobile robots.

Industrial AMRs are versatile and perform various applications (Schneier et al., 2015; Unger et al., 2018). For this paper, we focus on applications relating to manufacturing and warehousing environments, because industrial AMRs are most commonly employed these industries. Industrial AMRs assist with material transport and delivery from receiving locations to storage or lineside operations. These AMRs transfer material between work cells and deliver products to storage shelves or shipping stations. In distribution and fulfillment applications, AMRs assist with picking tasks. To improve order efficiency, workers pick and place items directly onto AMRs, which then transport the items to another location. Each of these applications requires HRI. Human workers encounter path crossing situations as they navigate down the same aisleway as an AMR. They encounter different robot approach scenarios as AMRs approach workers that operate in a designated work cell. It is necessary for workers to physically interact with AMRs as they retrieve or place material directly onto the robot.

1.3. Mobile Robot Navigation

Safe and efficient navigation is a fundamental problem for AMRs, which researchers have tried continually to solve for the past two decades (Pandey et al., 2017), and there are several papers that present recent advancements in mobile robot navigation and obstacle avoidance (e.g., Fauadi et al., 2018; Pandey et al., 2017; Tzafestas, 2018). The aim of navigation is to search for an optimal path between two waypoints while maintaining obstacle avoidance. Autonomous mobile robots utilize sensor-based measurements for navigation and obstacle avoidance including vision-based sensors, infrared sensors, sonar sensors, position sensing device sensors, laser range finders, inertial sensors, and bar codes.

Navigation methods for AMRs need to consider constraints of human comfort and social rules. Human-aware navigation is a combination of research involving HRI and robot motion planning (Kruse et al., 2013). This navigation technique is mostly related to AMRs that are designed to interact with humans in a public environment, like tour guide robots that are deployed in museums. Kruse et al. (2013) reviewed various approaches to human-aware navigation and offered a general classification scheme for the presented methods. In addition to obstacle avoidance techniques, the major human-aware navigation capabilities that an AMR could exhibit, based on previous research, include respecting personal zones and affordance spaces, avoiding culturally inappropriate behaviors, avoiding erratic motions or noises that cause distraction, reducing velocity when approaching a person, approaching from the front for explicit interaction, and modulating gaze direction. Currently, there is no standard for AMRs to include human-aware navigation techniques. However, such techniques could be beneficial, since workers interact with AMRs and operate alongside of them in industrial environments.

It is crucial for an AMR to reveal information about its current state and movement intentions to achieve effective collaboration with human workers, trust in the robot, and more engaging human-robot social interactions. Unlike AGVs, which follow guided pathways, the route of an AMR is less restricted. Workers encounter and cross paths with AMRs in industrial environments as they travel down aisles or between shelves. Workers must comprehend an AMR's movement intention to safely avoid the robot's path and prevent a collision. Communication in HRI relies on different sense channels, including hearing (sounds and speech), sight (light and gestures), and touch (Bonarini, 2020). Industrial mobile robots utilize each of these channels for communicating with human workers. This paper reviews past research on the effectiveness of different methods in conveying navigation intention.

1.4. Perceived Safety Assessment Methods in HRI Research

Not only is it necessary for robots to operate safely in the same environment as a worker, but it is also critical that workers perceive them as safe. In the context of HRI, "perceived safety" refers to the user's perception of danger when interacting with a robot, and the user's level of comfort during this interaction (Bartneck et al., 2009). A lack of perceived safety can affect the acceptance of robots in the workplace and can have negative effects on a worker's mental health. In HRI research, perceived safety hasn't always been directly measured. Rubagotti et al. (2022) describes concepts related to perceived safety – including trust, comfort, fear, anxiety, and surprise – and identified four categories of assessment methods in physical HRI experiments: questionnaires, physiological measurements, behavioral assessment, and direct input devices.

Questionnaires are a common assessment method. Experimenters can ask participants to fill out pre- and post-interaction surveys that ask them to rate their perception on various items. Two standardized questionnaires that are commonly used in HRI research include: 1) the Godspeed Series Questionnaire (Bartneck et al., 2009), which evaluates the perception of a robotic system using scales of anthropomorphism, perceived intelligence, likability, animacy, and perceived safety; and (2) the Negative Attitude toward Robots Scale (Nomura et al., 2014), which assesses negative attitude towards interactions with robots, social influence of robots, and emotions in interaction with robots. Additionally, researchers have developed their own questionnaires to assess various factors during HRI.

Physiological or psychophysiological measures focus on the body's response to HRI. Bethel et al. (2007) identified papers that used psychophysiological measures in HRI studies. Some common measures include eye gaze patterns, heart rate, skin temperature, muscle activity, and respiration rate. When combined with subjective questionnaires, physiological measures are a valuable tool in assessing perceived safety during HRI.

Assessing human behavior is another common technique for measuring perceived safety. This method relies on video recordings or motion capture technology to track participant movement. Separation distance is a behavioral measure that relates to the concept of proxemics. Hall (1966) first introduced the concept of human-human proxemics, which refers to how people position themselves with respect to others. Human-robot proxemics and human-robot spatial interaction are common terms for personal space in HRI. The distance a person keeps between themselves and a robot during HRI is related to their perception of comfort and safety. Similar to physiological measures, behavioral measures, when combined with questionnaires, can enhance the quality of perceived safety assessment.

Lastly, direct input devices allow for direct feedback of a participant's subjective response during an experiment in real-time, compared to questionnaires that are administered pre- or post-interaction. One example is the work of Koay et al. (2006) that evaluated the use of a handheld comfort device, which had a slider control to receive users' feedback and that could be used to determine the comfort level of an approaching robot.

Prior review papers have summarized methods of measuring perceived safety in HRI research. Rubagotti et al. (2022) summarized various terms researchers have used to express the presence or absence of perceived safety. Bartneck et al. (2009) reviewed how past researchers have measured perceived safety and summarized methods of measuring anthropomorphism, animacy, likability, and the perceived intelligence of robots. Bethel et al. (2007) identified papers that used psychophysiological measures in HRI studies. Chapter 5 of Lasota et al. (2017) summarized HRI studies that used techniques for measuring psychological safety, including questionnaires, psychological metrics, and behavioral metrics. Additionally, they discuss how robot behaviors, such as robot features (e.g., operating speeds, separation distances, and size) and social considerations (e.g., personality traits, culture, and demographic factors), affect psychological safety factors in HRI experiments. Leichtmann and Nitsch (2020) conducted a literature review and meta-analysis on factors that affect interpersonal distances, or proxemics, in HRI studies. They concluded that most studies lacked a theoretical foundation and had methodological weaknesses.

These review papers provide valuable information that is relevant to improving safety in HRI. The current paper differs from these earlier reports, though, by focusing on factors that affect safety in HRI specifically with AMRs that are relevant to industrial environments. While Rubagotti et al. (2022) covered various types of autonomous systems, they only address 12 papers that investigated HRI with indoor mobile robots, and their primary objective was to assess methods for evaluating perceived safety. Some earlier papers provided a broad overview of assessment methods for either a broad category of robots (Bethel et al., 2007; Lasota et al., 2017) or focused on service robots that apply to public settings or personal care (Bartneck et al., 2009). Lastly, Leichtmann and Nitsch (2020) provided an overview of HRI research with AMRs that have either a mechanic or humanoid appearance, however their paper was limited to only assessing proxemic distances during HRI. Thus, there is a need for a contemporary literature review of research involving HRI with AMRs that apply to industrial environments.

1.5. Study Objectives

The objective of this paper is to systematically review previous research that investigates safety and/or trust during HRI with AMRs that apply to industrial environments. We specifically focus on studies that included the application of an experiment design in which there was a physical HRI with an AMR and the experiment task was similar to tasks that workers perform in industrial environments. In this context, we address the following research questions:

1. What are the most commonly used AMRs in HRI experiments?
2. What assessment methods are employed for measuring perceived safety and trust?
3. What experimental conditions or types of independent variables have researchers investigated in their HRI experiments?
4. What areas of research are needed to improve safety of HRI with AMRs that apply to industrial environments?

2. Methods

2.1. Search Strategy

This review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology, which is a highly cited set of guidelines that aim to establish a checklist of essential items to report in systematic reviews and meta-analyses (Page et al., 2021). We obtained a list of articles on the topic of HRI with AMRs using literature search engines such as Scopus and ScienceDirect. We searched all articles published prior to August 2022 with no earlier date limit. Search keywords used to identify relevant studies included (‘safe*’ or ‘trust*’ or ‘experiment*’ or ‘study’ or ‘participant’ or ‘autonomous*’) and (‘mobile robot*’ or ‘moving robot*’) and (‘human robot interaction’ or (‘human robot collaboration’ or ‘robot human communication’). We selected any peer-reviewed journal articles or conference proceedings that included the search keywords in the document title, abstract, or author’s list of keywords. The literature search had no language restrictions. In addition, we scanned article reference sections and selected other relevant articles to include in the screening process.

2.2. Inclusion and Exclusion Criteria

Figure 1 displays the literature search and article selection process. The initial literature search identified 937 articles after discarding duplicates. The article abstracts were imported into a web-based tool (www.covidence.org) for the screening process. Titles and abstracts of the articles obtained in the initial search were screened using the following criteria: 1) research study relating to safety and/or trust in humans interacting with an AMR; 2) the article focused primarily on HRI with an AMR; and 3) the results of the paper could be associated with improving safety of workers that interact with AMRs in an industrial environment, such as manufacturing and warehousing facilities. Exclusion criteria for the initial search phase included: 1) papers that focus primarily on technological developments (e.g., sensors, motors, vision, and improved navigation techniques); 2) research involving drones or biped robots; and 3) papers that do not include a physical HRI experiment with human participants. In the title and abstract screening phase, we determined 799 articles were irrelevant for our objectives.

A total of 138 articles were included in the full-text review phase. These were selected for inclusion in our literature review if they fit the following criteria: 1) real-world or laboratory experiments (either involving an actual robot or a virtual reality setup), with interaction between an AMR and one or more human participants; 2) the HRI experiment task was similar to common scenarios in industrial environments wherein workers interact with AMRs (e.g., AMR approaching a work cell and an AMR crossing paths with a worker while navigating down an aisleway); 3) the robot motion was autonomously determined by a motion planning algorithm, or "Wizard of Oz" control (e.g., someone was controlling the robot's movements, but it was moving as if it were autonomous); and 4) the findings were related to improving the safety of workers when interacting with an AMR in an industrial environment. Our initial inclusion criteria required HRI research involving an industrial AMR. However, we found only two references that fit this criterion. Therefore, we expanded the search to include other types of AMRs as long as the HRI task applied to industrial environments.

A total of 88 papers were excluded after the full-text review phase (Figure 1). The most common reason for exclusion was that the paper focused primarily on technological developments. While improvements in AMR technology and navigation models are important for improving safety of HRI, we decided to exclude them because it is already a thoroughly reviewed topic (Fauadi et al., 2018; Pandey et al., 2017; Tzafestas, 2018). We excluded 27 papers because their HRI experiment tasks were not related to common HRI scenarios that occur in industrial environments, thus they were outside the scope of our review. Several of the HRI experiments in these papers involved controlling or teleoperating an AMR using speech or gestures (Chinthaka et al., 2018; Green et al., 2008; Jevtić et al., 2015; Villani et al., 2017; Villani et al., 2018), haptic devices (Che, Culbertson, et al., 2018), or a remote controller (Chiou et al., 2016; Cosgun et al., 2013). Others involved experimental tasks that were not relevant to industrial environments and applied mainly to domestic (Chanseau et al., 2016; Huettenrauch et al., 2006; Mumm & Mutlu, 2011; Walters et al., 2005) or social environments (Brock et al., 2010; Hoggenmueller et al., 2020; Pourmehr et al., 2016; Walters et al., 2008; Zhang et al., 2022). We excluded 18 papers because they did not include an experiment that involved physical HRI between a human and AMR. Lastly, we excluded 11 papers that did not investigate an AMR (i.e., the robot was either a biped robot or industrial robot manipulator) and one paper where the robot's motion was not autonomous.

2.3. Data Extraction

A total of 50 articles met the review criteria after the full-text review and were included in our analysis. These articles were analyzed and coded according to the PRISMA methodology for a systematic literature review. Extracted data included general information, such as the author's name, year of publication, study objective, total number of participants, mean age, and the participant sample population (e.g., students, public, workers, etc.). We also extracted information about the experimental task, the type of AMR used in the experiment, and the independent and dependent variables used to evaluate safety and human behavior. The Appendix includes a complete list of the reviewed studies and their details (see Online Supplemental Material).

3. Results

The number of research studies involving AMRs has grown rapidly over the past decade. The range of publication years for the 50 journal articles is 2006–2022, with 84% (N = 42) being published between 2012–2022. The mean (SD) sample size was 47.8 (44.6) participants. Thirty-two of the 50 papers reported the mean age of the sample population. The mean (SD) age of participants across these references was 29.7 (10.9) years. Forty-two of the 50 references reported gender distribution. The mean (SD) female:male gender ratio of these references was 0.9 (0.5). Berx et al. (2021) was the only reference to conduct a field study with experienced workers. The majority of studies reported that they recruited participants from the general public or from a University population. Only 27 studies explicitly asked participants about their experience with robots. Table A1 in the Appendix displays a list of the 50 references with details about the experiment task, number of participants, sample population, and the assessment methods. Table A2 provides a description of the different types of AMRs used in the HRI experiments.

3.1. Mobile Robots Used in HRI Experiments That Apply to Industrial Environments

There were 27 different types of AMR base models. Four studies didn’t specify the model type. Eighteen AMRs were developed for research environments or in a research laboratory. The Pioneer 3-DX (Omron Adept Mobile Robots) was the most common, with seven studies using it in their experiments (Chen et al., 2018; Coovert et al., 2014; Rossi et al., 2017; Shiomi et al., 2014; Shrestha et al., 2016; Shrestha et al., 2018; Thomas & Vaughan, 2019). The Pioneer 3-DX is a lightweight, 2-wheel mobile robot, with an approximate height and diameter of 215 mm and 380 mm, which was developed for research and instructional purposes. Two AMRs were industrial AMRs, including the MiR 200 (Mobile Industrial Robots) and the Rob@Work (Fraunhofer Institute for Manufacturing Engineering and Automation), which were designed for industrial applications (Alves et al., 2022; Unhelkar et al., 2014). Seven were social robots designed for HRI in social environments, including the PeopleBot from Adept Mobile Robots. The PeopleBot has a Pioneer 3-DX mobile base and a chest-height extension to allow for HRI via optional attachments such as a touchscreen monitor.

Regarding AMR appearance, eight studies used AMRs that were humanoids, or designed to appear humanlike (Joosse et al., 2021; Koay et al., 2007; May et al., 2015; Mead & Mataric, 2015; Mead & Matarić, 2016; Neggers et al., 2018; Neggers et al., 2022). In other words, they contained human features, such as a head, arms, or torso. Eight studies used AMRs that were short mobile bases less than 1000 mm in height (Alves et al., 2022; Che et al., 2020; Che, Sun, et al., 2018; Chen et al., 2022; Jost et al., 2021; Neggers et al., 2022; Thomas & Vaughan, 2019; Unhelkar et al., 2014), while most of the AMRs were tall mobile bases that were greater than 1000 mm in height. Three studies used mobile manipulators (Brandl et al., 2016; Fischer et al., 2016; Takayama & Pantofaru, 2009) and three used autonomous forklifts (Bunz et al., 2016; Chadalavada et al., 2015; Chadalavada et al., 2020).

3.2. Subjective Assessment Methods Using Questionnaires

Questionnaires were used in 76% (N = 38) of the studies, and researchers used a variety of specific questionnaires assessment methods (Figure 2). The most common questionnaire topic related to participant perception of various robot traits, which includes ratings about the robot's physical appearance and personality attributes. Some researchers used standardized questionnaires about robot traits, including the Godspeed Questionnaires Series (Joosse et al., 2021; Jost et al., 2021; Mead & Matarić, 2016), the Big Five Domain Scale for personality traits (Koay et al., 2007; Syrdal et al., 2006; Takayama & Pantofaru, 2009), the Networked Minds Social Presence Inventory scale (Fiore et al., 2013; Warta et al., 2018), the Robot Attributes Scale (Suvei et al., 2018), and the Circular Mood Scale (Fiore et al., 2013). The most common traits that researchers assessed were intelligence and likability. These traits are included in the Godspeed Questionnaire Series, yet some researchers assessed them independently (Coovert et al., 2014; Fischer et al., 2016; Lo et al., 2019; Mavrogiannis et al., 2019; Siino et al., 2008). Other common traits include reliability (Batista et al., 2020; Chadalavada et al., 2015; Lo et al., 2019), cooperativeness (Fischer et al., 2016; Lo et al., 2019; Wiltshire et al., 2015), and naturalness (Shrestha et al., 2016; Shrestha et al., 2018; Wiltshire et al., 2015).

Sixteen references assessed participant comfort after an interaction with an AMR. Comfort level was often evaluated in HRI experiments where an AMR approached a participant. After the interaction, participants rated their comfort level on either a 5-point (Dautenhahn et al., 2006; Pacchierotti et al., 2006; Shomin et al., 2015; Syrdal et al., 2006; Walters et al., 2007), 7-point (Batista et al., 2020; Fernandez et al., 2018; Mead & Matarić, 2016; Neggers et al., 2018; Neggers et al., 2022; Unhelkar et al., 2014; Wiltshire et al., 2015), 8-point (Lo et al., 2019), or 9-point (Shrestha et al., 2016; Shrestha et al., 2018; Suvei et al., 2018) Likert scale.

Twelve references utilized questionnaires relating to perception of the AMR's movement intention. Several researchers assessed the predictability (Chadalavada et al., 2015; Lo et al., 2019; Mavrogiannis et al., 2019; Shrestha et al., 2016; Wiltshire et al., 2015), legibility (Alves et al., 2022; Chadalavada et al., 2020; May et al., 2015; Shrestha et al., 2018), and transparency (Chadalavada et al., 2015) of an AMR's movement during various path crossing scenarios, where a participant and AMR were moving around in the same vicinity as one another. A few researchers assessed the ability of an AMR to communicate its movement intention (Fernandez et al., 2018; Matsumaru, 2006) and participant's confidence level in regard to the AMR's movement intention (Dautenhahn et al., 2006).

Ten references assessed perception of safety using questionnaires. Researchers either asked participants to rate their perception of safety or the safety of the robot's behavior after an interaction with an AMR, using either 5-point (Chen et al., 2022; Mavrogiannis et al., 2019; Shomin et al., 2015), 7-point (Unhelkar et al., 2014; Wiltshire et al., 2015), or 8-point (Lo et al., 2019) Likert scales. Takayama and Pantofaru (2009) assessed perceived safety, yet they did not describe in detail how they measured it.

Researchers used various pre-experiment questionnaires to assess participant attributes or predispositions toward robots. These questionnaires include the Negative Attitude Toward

Robot scale (Joosse et al., 2021; Jost et al., 2021; MacArthur et al., 2017; Takayama & Pantofaru, 2009), the Cognitive Differences Scale (Fernandez et al., 2018; Hart et al., 2020), pet ownership (Takayama & Pantofaru, 2009), and technology adoption (Mead & Matarić, 2016).

Seven references evaluated participant trust in the AMR after the experimental interaction. A few researchers used validated methods, such as the Human Trust in Automation Questionnaire (Alves et al., 2022; MacArthur et al., 2017) and the Social Credibility Scale (Joosse et al., 2021). Others asked participants to rate their level of trust using 5-point (Chen et al., 2022; Mavrogiannis et al., 2019), 7-point (Che et al., 2020), and 8-point (Lo et al., 2019) Likert scales.

Some researchers evaluated User Experience after participant interaction with an AMR. Jost et al. (2021) utilized the User Experience Questionnaire developed by Laugwitz et al. (2008). In May et al. (2015), questionnaires were used for participants to rate their preference between different AMR movement signaling methods after a path crossing experiment scenario with an AMR. Likewise, in Dautenhahn et al. (2006), participants rated their preference in which direction an AMR approaches them. Similarly, post-interaction questionnaires have been used to gather general perceptions of an AMR (Berx et al., 2021; Shiomi et al., 2014; Takayama & Pantofaru, 2009).

Lastly, questionnaires have been used to evaluate the efficiency or the performance of an AMR after an interaction scenario, using 5-point (Batista et al., 2020; Walters et al., 2007) and 9-point (Shrestha et al., 2016) Likert scales. Siino et al. (2008) and Wiltshire et al. (2015) evaluated participants' sense of control using questionnaires. Only two studied assessed mental workload in their HRI experiments. Berx et al. (2021) employed the Questionnaire on the Experience and Assessment of Work, and Chen et al. (2022) utilized the NASA Task Load Index developed by Hart and Staveland (1988).

3.3. Behavioral and Physiological Assessment Methods

Figure 3 shows the different behavioral and physiological assessment methods and number of references that included them in their HRI experiments. Behavioral and physiological assessment methods were used in 70% (N = 35) and 8% (N = 4) of the reviewed references, respectively. No references included direct input devices to measure participant comfort.

Separation distance between the participant and AMR was the most common behavioral assessment method. Several references investigated the effect of AMR design and movement characteristics on minimum acceptable separation distance (Brandl et al., 2016; Jost et al., 2021; Koay et al., 2007; Kosinski et al., 2016; Lauckner et al., 2014; Mead & Mataric, 2015; Mead & Matarić, 2016; Rossi et al., 2017; Suvei et al., 2018; Takayama & Pantofaru, 2009). In these studies, an AMR approached a stationary participant, and they would signal to stop the AMR when they began to feel uncomfortable. Minimum separation distance was measured in experiment scenarios where a participant is walking toward a goal and is required to cross paths with an AMR (Bunz et al., 2016; Che, Sun, et al., 2018; Lichtenthäler et al., 2013; Lo et al., 2019; Mavrogiannis et al., 2019; May et al., 2015; Shiomi et al., 2014; Vassallo et al., 2017, 2018). In these scenarios, Bunz et al. (2016), Lo et al. (2019), and

Mavrogiannis et al. (2019) also measured path deviation, or the lateral distance participants deviated from their trajectory path. A few researchers measured the participant separation distance from the AMR at the instant they start to veer off from their trajectory path as they walk toward an approaching AMR (Chadalavada et al., 2015; Chadalavada et al., 2020; Shrestha et al., 2016).

Multiple references measured and analyzed participant kinematic parameters in their experiments, including walking speed (Bunz et al., 2016; Chen et al., 2018; Lichtenthäler et al., 2013; Lo et al., 2019; Pacchierotti et al., 2006) and acceleration (Mavrogiannis et al., 2019). Various methods were used to calculate participant kinematics. Bunz et al. (2016) computed mean walking speed from the AMR laser scanner, Pacchierotti et al. (2006) estimated mean speed from video recordings, and the remaining references utilized motion capture systems.

A few researchers evaluated parameters related to participant cooperativeness, which refers to the participant compliancy to the AMR's request, or if they give the right of way to the AMR in a path-crossing scenario. For instance, Shrestha et al. (2018) evaluated cooperation rate in response to an AMR that indicated its movement intention with a projected arrow. In other studies, researchers evaluated if participants either crossed in front or behind an AMR, in scenarios where they move toward a common goal or encounter one another at an intersection point (Che et al., 2020; Thomas & Vaughan, 2019; Vassallo et al., 2017, 2018).

Five references measured the number of conflict or hesitation events that occurred between a participant and an AMR. Hart et al. (2020) defined a conflict as an event where the participant and AMR encounter a problem navigating around each other or they nearly collide. In their experiment, an observer counted the number of conflicts that occurred during the experiment trial. Fernandez et al. (2018) counted conflict events in their study, and defined it as an event where a participant or AMR need to stop or adjust their movement trajectory to avoid a collision. Similarly, Alves et al. (2022) and Kaiser et al. (2019) measured the number of hesitation events in their experiment trials. Hesitation events were defined as situations where the participant slowed down, stopped, moved to the side, retreated, granted the robot the right to pass, visually checked the robot, moved first but tentatively, seemed somewhat forced by the robot to pass first, passed the bottleneck jointly with the robot, or both got stuck in the crossroad (Alves et al., 2022). In these studies, two observers counted the number of hesitation events from video recordings. Shrestha et al. (2018) defined a hesitation event as a change greater than 0.4 m/s in the participant's velocity profile after the initial acceleration in an experiment trial. Velocity profiles were computed from participant trajectories, which were measured using a motion capture system.

Three references analyzed trial or task time. Chen et al. (2022) investigated the effect of AMR payload and the effect of working alongside an AMR vs. working alone, working near another human, or working alongside a teleoperated robot, on the time it took to complete a brick-building task. Additionally, Chen et al. (2022) was the only reference to analyze how many errors participants committed in an experiment task. Unhelkar et al. (2014) analyzed time in a product assembly task where an AMR brought participants pieces to assemble.

They analyzed the time spent interacting with the AMR, the participant idle time, and how quickly participants were able to notice the AMR approaching the workstation. Thomas and Vaughan (2019) analyzed task completion time in their experiment, which involved participants crossing paths with an AMR at a doorway, as they delivered paperwork to the other side of the laboratory.

The least common behavioral assessment methods were avoidance behavior (Joosse et al., 2021), head orientation (Shomin et al., 2015), and path length (Che et al., 2020). Joosse et al. (2021) defined avoidance behavior as negative emotional responses to an AMR (e.g., gazing at the AMR, looking surprised, or behaving anxiously) or physical avoidance actions (e.g., stepping away). Shomin et al. (2015) analyzed video data to track participant head orientation in a task where participants worked alongside an AMR by moving blocks between workstations. Che et al. (2020) measured participant path length, or the distance traveled throughout an experiment trial, which is a method for measuring efficiency.

Four references included physiological assessment methods. Bunz et al. (2016) and Chadalavada et al. (2020) utilized eye-tracking glasses to determine where participants fixated their gaze during experimental trials. Similarly, Fischer et al. (2016) counted the number of glances away from the robot during experimental trials from video data. They hypothesized that people would not monitor the robot's behavior if they felt safe during the interaction. Chen et al. (2022) was the only study to analyze changes in pupil diameter across experiment conditions. No other physiological parameters were measured in the reviewed references.

3.4. Independent Variables Investigated in HRI Experiments with AMRs that apply to industrial environments

Researchers investigated a variety of independent variables in their HRI experiments with AMRs. Table 1 outlines the various types of independent variables and what assessment methods were used to evaluate them.

Robot Appearance—Robot appearance, size, and movement action impact human behavior. Neggers et al. (2022) and Warta et al. (2018) used questionnaires to investigate the influence of robot appearance. Neggers et al. (2022) found slightly higher perceived comfort for non-humanoid robots compared to humanoid robots. Warta et al. (2018) reported a higher level of social presence for robots with humanlike displays than with iconic and symbolic displays. However, Brandl et al. (2016) found no difference in minimum separation distance between a robot that had a mechanical vs non-mechanical appearance during an approach task. Their results showed no significant effect of robot appearance on the accepted distance in two sub-experiments with different speed profiles. The respective mean accepted distance for the fast and slow approach speeds were 1.02 and 0.84 m for the non-mechanical appearance and 1.01 and 0.84 m for the mechanical appearance.

Jost et al. (2021) examined the influence of emotional expression and robot height in an approach scenario. Robot height significantly affected the stopping distance while the emotional expression did not. Similar results were reported by Joosse et al. (2021), where the participants perceived the shorter Magabot robot (78 cm height) as safer than the taller

Giraff robot (163 cm height). Koay et al. (2007) studied the robot's action when handing over objects to a human such as the handover height preference, and their results showed that the preferences were distributed with mean of 78.9 cm.

Robot Speed—Robot speed is an important factor in HRI (Matsumaru, 2006; Walters et al., 2007). People demonstrate higher trust in the robot when it approaches them at a slower speed (MacArthur et al., 2017). Similarly, the accepted distance between the robot and the human is related to the robot's approach speed. In Brandl et al. (2016), faster robot speeds led to longer mean accepted distances, and decelerated speed profiles resulted in shorter accepted distances compared to constant speed profiles.

In path crossing situations, the robot approach speed influences human behavior and the perceived comfort of passing distances. Chen et al. (2018) studied how an AMR affects a group of people's behavior in an exit corridor environment, finding that overall speed is slowed down in the presence of the robot, and the faster the robot moves, the lower the mean velocity becomes. In contrast, the comfortable passing distances in Lauckner et al. (2014) did not vary between robot speeds of 0.6 and 0.8 m/s. In Rossi et al. (2017), human subjects were asked to perform four activities (standing, walking, sitting, or lying) while the robot approached at speeds of 0.2, 0.6, and 1 m/s. Higher robot speeds were associated with smaller accepted distances. Robot approach scenarios with different speed and speed profiles were investigated by Joosse et al. (2021). Robot speed did not significantly affect human behaviors or perceived safety. However, Jost et al. (2021) found that different robot speeds resulted in different human behaviors during a robot approach scenario. Shomin et al. (2015) compared approach speeds of 0.3 and 0.7 m/s and found no significant difference in perceived safety.

Approach Direction and Passing Side—Several studies explored the impact of the robot approach direction and passing side on human perceptions and behaviors during HRI. In a seated scenario, participants preferred the robot to approach from the side rather than the front (Dautenhahn et al., 2006). In contrast, Koay et al. (2007) found that participants preferred a front approach when a robot approached them to hand over an object.

Neggers et al. (2018) and Neggers et al. (2022) explored the passing side of a robot during interactions. In Neggers et al. (2018), the effects of the passing side were not significant, which suggests that participants were comfortable with robot passing on both the right and left sides. However, in Neggers et al. (2022), the passing side significantly influenced perceived comfort, with the front side being rated as the most comfortable and the back side as the least comfortable. Walters et al. (2007) investigated robot approaching methods in a fetch and carry task. In their experiments, participants were either seated or standing and either against other objects (table or wall) or not. Syrdal et al. (2006) also studied robot approach direction in a fetch and carry task. Their results showed that frontal approaches were perceived as the least comfortable, while the front right and front left approaches were rated as the most comfortable. On the other hand, Shomin et al. (2015) compared straight and curved approach paths in human and robot collaborative delivery tasks. Although their hypothesis was that participants would have higher ratings for the curved path, their results showed that ratings did not increase much compared with the straight path.

Unhelkar et al. (2014) examined the effect of approach angle on user comfort and awareness. Participants reported being more comfortable when approached at 45 vs. 90 degrees. In Kosinski et al. (2016), researchers investigated and developed a model to predict comfort levels based on stopping distances for different approach angles. The left flank angle (45 degrees) was rated as the least comfortable, while the right flank angle (90 degrees) was perceived as the most comfortable.

Approach and Passing Separation Distance—Researchers have investigated the impact of robot approach or passing distance on comfort and trust (Walters et al., 2007). MacArthur et al. (2017) found that robot proximity and speed were two significant factors that affected trust level in an approaching robot scenario. Human-robot passing scenarios in a corridor have been studied to determine comfortable passing distances and passing strategies (Lauckner et al., 2014; Neggers et al., 2018; Pacchierotti et al., 2006). Neggers et al. (2018) and Neggers et al. (2022) examined the effects of passing distance on perceived comfort and observed that comfort increased with increasing distances. Participants reported being least comfortable at a passing distance of 50 cm, while the highest comfort was reported at 110 cm. Pacchierotti et al. (2006) studied different lateral distances (0.2, 0.3, and 0.4 m) and their impact on user comfort, with 0.4 m rated as the most comfortable distance. Overall findings indicate that the passing distance affects human comfort level, from a minimum of 45 cm up to 80 cm.

Koay et al. (2007) investigated different factors in a robot handover task to a seated human, including approach direction, robot distance (base and hand), and gesture. Their results indicated that the participant's preference for a robot handover task is from the front direction with a mean 66.8 cm distance. Suvei et al. (2018) examined the effectiveness of the robot social gaze cue in a personal space invasion situation (20 and 50 cm distances). The gaze animation on the robot changed from "looking at the participant" to "looking in front of the participant" while approaching the participant to create the social cue. Results showed that the social cue in robot personal space invasion improves perceived safety.

Navigation Intent—Workers must be capable of understanding an AMR's movement intention to prevent unintended collisions. Several references investigated the effectiveness of projecting a signal on the floor to communicate AMR movement intention. Studies have shown when an AMR projects an arrow on the floor, the AMR's movement intention is rated as more intelligible (Matsumaru 2006) and legible (Shrestha et al., 2018). Additionally, participants perceive the AMR as more likable (Coovert et al., 2014; Shrestha et al., 2018), feel more comfortable around the AMR, and make fewer hesitated movements (Shrestha et al., 2018)

A few articles focused on HRI interaction with an autonomous forklift that projected movement intent. In Chadalavada et al. (2015), ratings of communication and predictability increased by 81% and 62%, respectively, and participants veered off course significantly further away from the AMR, when it projected its movement intention (On: 2.01 m vs Off: 1.40 m). Bunz et al. (2016) compared three types of projections, including a trajectory line, an arrow, and a rectangular white space. Participants gazed longer at the white rectangular projection, although projection type did not affect walking speed or deviation distance.

Chadalavada et al. (2020) compared projections of a trajectory line, a triangular arrow, and a blinking triangular arrow. Participants veered-off a mean of 2.72 m when any projection was used, compared to 2.01 m when no projection was used, indicating they could plan a safer trajectory. Eye-tracking data determined participants had focused more on the blinking arrow projection compared to the others, yet projection type had no effect on the number of fixations toward the robot.

Multiple researchers have evaluated the intelligibility of turn signals to convey navigation intent. The use of a visual light turn signal has been shown to improve understanding of AMR movement intention, increase participant comfort, and impact the distance they keep away from the AMR (May et al., 2015; Shrestha et al., 2016). However, not all researchers have concluded that turn signals are effective. Fernandez et al. (2018) found almost no value in the use of an LED turn signal to convey the robot's turning behavior. In a related study, Hart et al. (2020) found that the participant and robot had conflicting trajectories in 50% of the trials when the robot communicated its intent with gaze behavior, compared to 100% conflicting trajectories when it used the LED signal.

Che, Sun, et al. (2018) proposed a wearable haptic interface device to convey a robot's intent to a human by modulating vibration amplitudes and patterns. The haptic communication channel was effective and intuitive for the user. Users passed in front of the robot when they were given the right of way and expected it to slow down, even when the robot was moving aggressively. Conversely, when the robot did not communicate its intent, users tended to either pass behind the robot or keep a large distance when passing in front. In a related article (Che et al., 2020), the authors found there was increased trust and human performance when the robot used both implicit and explicit communication methods.

Robot Noise—A limited number of references investigated the effect of robot noise during HRI. Joosse et al. (2021) reported higher ratings on the Godspeed scale when the robot had intentional noise, compared to incongruent noise, during an AMR approach scenario. However, other studies have shown that supplementing a turn signal (Shrestha et al., 2016) and a projection arrow (Shrestha et al., 2018) with an auditory alert to signal navigation intent did not impact the AMR's predictability, participant comfort, or proxemics. The effect of an auditory alert alone on conveying movement intention requires further investigation.

Courtesy Cures and Proxemic Behavior—An AMR's display of courtesy cues (e.g., stopping and retreating), in various navigation scenarios, impacts perceived safety. When an AMR displays courtesy cues, researchers have shown that it is perceived as more socially present (Fiore et al., 2013), its navigation intention is more legible, (Alves et al, 2022; Kaiser et al., 2019), and there are significantly fewer hesitation events (Alves et al, 2022; Kaiser et al., 2019). However, Alves et al. (2022) found no difference in self-reported trust across various courtesy cues.

Robot navigation models or algorithms can improve human-robot proxemics. Human avoidance methods can benefit HRI, especially in crowded situations (Lo et al., 2019; Shiomi et al., 2014). Lo et al. (2019) found that AMR navigation avoidance behaviors increase perceived safety, comfort, and impact human behavior. Similarly, perceived safety improves when an AMR navigates in a similar manner as a human, compared to traditional obstacle avoidance methods, in path crossing scenarios (Shiomi et al., 2014). Likewise, Mavrogiannis et al. (2019) investigated three robot navigation strategies performed in a crowded environment. Based on the human-robot proxemics, the autonomous navigation strategy was more acceptable to participants, however there were no differences in perceived safety or trust across navigation strategies.

Crossing situations at a doorway are critical in AMR navigation due to limited space and a short response period. Thomas and Vaughan (2019) examined a new AMR navigation strategy in which it would speed-up or stop, depending on the participant's proximity to the doorway, and found that this strategy increased the participant's respect for the robot's right-of-way. Other research indicates that manipulating an AMR's navigation strategy can improve human-robot proxemics, based on the perception of who has the right-of-way at an intersection (Vassallo et al., 2017; Vassallo et al., 2018). Crossing situations while walking down a hallway or aisleway are also critical to worker safety. Perceived safety (Wiltshire et al., 2015), comfort (Wiltshire et al., 2015), cooperativeness (Wiltshire et al., 2015), and AMR social presence (Warta et al., 2018) improve when the AMR utilizes an assertive navigation stategy, compared to a passive one. Ratings of cooperativeness and intelligence also increase when an AMR directs its gaze at the participant, during a hallway interaction scenario (Fischer et al., 2016).

AMR Presence—Several studies investigated how the presence of an AMR impacts the perception of safety and other various factors during an experiment task. Berx et al. (2021) found that working with or without an AMR during a "picking task" had no impact on psychosocial workload. Chen et al. (2022) investigated the influence of AMRs on human coworkers' safety perception and efficiency in two experiments where participants performed an assembly task in a simulated grocery store environment. Working alongside an AMR increased task time and mental workload scores compared to working alone or alongside a human. Unhelkar et al. (2014) compared the efficiency and perceived safety of working with a human assistant to a mobile robot assistant in a product assembly task. Interaction and idle times were significantly higher for the robotic assistant than the human assistant, and participants reported increased comfort when the robot had an oblique approach. Joosse et al. (2021) studied how humans react to an approaching robot with different factors (noise, velocity, and height). Participants were more accepting of personal space invasion by a robot than by a human. Takayama and Pantofaru (2009) found that participants had more negative attitudes and kept larger distances from an approaching robot compared to an approaching human.

Participant Characteristics—Demographic factors and personal experiences were usually collected, but only a few studies analyzed such data to identify impacts on HRI. Most of the studies did not analyze demographic data. Matsumaru (2006) found no significant differences based on gender or age in robot navigation intent. Syrdal et al. (2006) did not observe consistent correlations between demographics, personality traits, and comfort ratings in robot fetch and carry tasks. Brandl et al. (2016) investigated age and gender in robot approaching scenarios but did not find significant effects in their experiments.

In Rossi et al. (2017), personality traits such as extraversion, agreeableness, conscientiousness, neuroticism, and openness were explored, but no relationships were found between personality and personal comfort distance in four participants activities. In Jost et al. (2021), no significant effects were found for gender or robot experience. However, pet ownership showed a significant interaction with robot height, where participants who once owned or currently owned a pet kept a smaller distance from the robot. Likewise, Takayama and Pantofaru (2009) investigated the effects of robot experience and pet ownership on separation distance. Participants with past pet ownership were more comfortable with the robot being closer, and those with at least one year of robot experience were also comfortable with being closer to the robot compared to those with less experience.

Number of Approaches and Trials—In HRI research, repeated exposure to an AMR can play a crucial role in understanding how humans perceive robot behavior over time. Comfort level (Fiore et al., 2013) and AMR social presence (Warta et al., 2018) increase over multiple experiment trials in path crossing scenarios. Likewise, Lauckner et al. (2014) found significant differences in lateral and frontal separation distances between repeated trials. Brandl et al. (2016) found the accepted minimum separation distance for an approaching AMR is shorter for later trials (N: 1–5 = 1.15m vs. N: 25–30 = 0.90m). Additionally, people adapt their proxmic preferences after an interaction with an AMR (Mead and Mataric, 2015; Mead & Matarić, 2016). These findings indicate that human comfort and proxemic preferences vary over repeated trials due to factors such as familiarity with the robot and past interaction experiences.

Number of Robots—Batista et al. (2020) was the only study to investigate the impact of multiple AMRs on HRI. Comparing interactions between one vs. a team of three AMRs, there were no significant differences found in participants' responses or experiences. However, the feedback from participants suggested that their perception of robot teams was similar to a single robot, but they raised concerns about being able to notice all three robots at the same time. Additionally, no behavioral or physiological measures were analyzed to supplement the questionnaire data. More research is needed to fully understand influence of multiple AMRs on human perceived safety in HRI.

4. Discussion

Autonomous mobile robots are being rapidly implemented in various industries because of their utility. The introduction of these emerging technologies into the workplace has presented new hazards for humans that are required to interact with them. Concurrently, research investigating safety and trust during HRI with an AMR has increased over the past decade to mitigate these hazards. We reviewed 50 articles that reported research involving HRI with an AMR to review the current state of the science and to identify any gaps that could inform future research.

4.1. Analysis of AMRs

A variety of AMRs were used in the HRI experiments. Only two references used industrial AMRs that are designed for industrial applications. This is not surprising, since industrial AMRs are more expensive and harder to customize, compared to AMRs that are designed for research settings. Companies that manufacture and sell industrial AMRs can be reluctant to provide their products to researchers for the sole purpose of conducting research with them. The Pioneer 3-DX from Adept Mobile Robots was the most common AMR, likely because it is relatively affordable and easily customizable. It is designed for laboratory and classroom use, thus making it useful for multiple applications.

Several references used social AMRs that either had a humanoid appearance or an interactive monitor screen attached to the mobile base. Social AMRs are typically employed in public and retail environments to assist people with various tasks. They were commonly used in references that focused on human-robot proxemics. The most common model was the PeopleBot from Adept Mobile Robots. While social AMRs are not designed for implementation in industrial environments, they interact with humans in a manner that is similar to industrial AMRs. One example is the FlexShelf line of AMRs from Fetch Robotics, which are used for order fulfillment applications. The FlexShelf is an industrial AMR with adjustable shelves and an interactive touchscreen to manage the fulfillment task and relay information to workers. For fulfillment applications, it approaches workers who can pick and place items from shelves onto the AMR. Therefore, social AMRs and their applications are related to industrial AMR applications in many ways.

The implementation of AMRs in warehousing and manufacturing facilities is rapidly increasing. There is a need for more HRI research involving industrial AMRs, to investigate factors that impact worker safety and trust. The majority of references in our review used AMRs designed for research purposes or social environments. While the findings from these references are important and relevant to industrial environments, they may not provide a comprehensive understanding of how workers interact with industrial AMRs.

4.2. Analysis of Assessment Methods

The use of subjective and objective data collection measures is critical for accurately quantifying human perception of safety and trust during HRI experiments with AMRs. Subjective measurements, such as questionnaires, were the most employed method. They provide a deeper insight into the thoughts and perspectives of individuals on complex aspects that may not be easily quantifiable in other ways. For example, several references used questionnaires to assess perceptions of various robot social attributes, such as likability, naturalness, and intelligence. While subjective measures offer these advantages, they can be influenced by individual biases, and their interpretation may be more open to subjectivity. In contrast, objective measures, including human behavior and physiological metrics, are less susceptible to biases and can often provide clear and unambiguous results. They can also quantify changes over time, compared to subjective assessment methods, which must be administered before or after a particular event. The most common objective measure was separation distance between the participant and AMR, and it was frequently applied to participant comfort level.

Surprisingly, we found that the questionnaires in our review mainly applied to robot traits, comfort level, and the ability to understand an AMR's movement intention. Only 20% and 14% of the references directly evaluated perceived safety and trust using questionnaires, respectively. This finding contrasts with perceived trust being the most common questionnaire topic in prior research involving shared space HRI (Hopko et al., 2022). There are a few possible explanations for this difference. Trust is an important concept for human-robot teams that work together to accomplish a common goal (Hancock et al., 2011). While every reference in our review involved an HRI experiment, the vast majority of the experiments did not involve a collaborative human-robot work task. Instead, the experiment tasks required participants to either navigate around an AMR or be approached by an AMR. Additionally, a majority of the studies involved HRI experiments with social AMRS, where it was common to evaluate AMR appearance and human-robot proxemics.

Using both subjective and objective data collection measures can offer a more comprehensive understanding of the research topic. Only 46% of the references collected questionnaires and human behavior data. A number of these found disagreement between data collection methods and therefore benefited from using both types (Alves et al., 2022; Fernandez et al., 2018; Joosse et al., 2021; Jost et al., 2021; Mavrogiannis et al., 2019; Mead & Matarić, 2016; Suvei et al., 2018). For example, in Suvei et al. (2018) there was no difference in perception of robot traits or feelings of discomfort during a robot approach task. However, the robot behavior significantly affected the minimum separation distance. Similarly, in a navigation scenario (Fernandez et al., 2018), participants reported no differences in perceived comfort or communication, yet robot behavior significantly impacted the number of conflict events during the task. Thus, integrating subjective and objective data collection measures to assess safety and trust in HRI experiments with AMRs can provide a more accurate understanding of the phenomenon being studied.

4.3. Discussion of Independent Variables in HRI Experiments

Human-robot proxemics research has focused on the perception or behavior of humans in various robot-to-human or human-to-robot approaching tasks. Experiments were focused on preferences of different factors such as AMR social cue, separation distance, speed, or approach direction. Experimental results indicate that slower speeds lead to higher trust levels and shorter accepted separation distances, although some studies indicated speed had no effect on separation distance and comfort. In general, an oblique approach direction is preferred over a frontal direction, yet one study found a frontal approach to be more favorable, and a few others concluded that approach direction had no effect on participant comfort. Among the studies of AMR separation distance during an approach task, it was unanimous that larger distances improve perceived safety and comfort, as expected. Studies also showed that the proxemics preference would change after interacting with robots (Mead and Mataric 2015). One way to improve human-robot proxemics is by using navigation strategies to approach humans or avoid collisions in a crowded environment (Shomin et al. 2015; Mavrogiannis et al., 2019). The contradictory findings across references that studied similar concepts can be explained by several factors, including differences in the type of AMR used in the HRI experiments, the experiment tasks, and the assessment methods.

For decades, researchers have worked on methods to improve the safety and efficiency of AMR navigation (Pandey et al., 2017). When humans and AMRs share the same environment, one challenge is to navigate around each other and understand or interpret their mutual navigation intent. Humans must understand an AMR's current and future status to increase trust in the robot and to lower the risk of colliding with it. We identified 16 articles that investigated different methods for conveying movement intent to a human user. As noted earlier, communication in HRI relies on different sense channels, including hearing channel, sight, and touch (Bonarini, 2020). The sight channel was the most popular for conveying movement intention, by projection of an image on the floor or via a turn signal. The results show that projecting an image on the ground increases the user's understanding of the robot's intent and increases their comfort level. Turn signals had a similar effect, but there were some contradictory findings suggesting that they were difficult to interpret unless the robot demonstrated their use prior to an interaction (Fernandez et al., 2018). Only a few papers investigated the touch channel, where researchers used a haptic interface device to convey movement intent (Che et al., 2020; Che et al., 2018).

Other factors impacting perceived safety and trust during HRI have been examined in the literature. The appearance, size, and action of robots impact human comfort level, with non-humanoid robots being slightly more preferred than humanoid robots. Additionally, shorter AMRs were perceived as more safe than taller AMRs. The presence of the robot in the experiment can also impact perceived safety, such as working alongside AMRs, teleoperated robots, with other human workers, or alone. Working alongside an AMR increased task time and mental workload scores for participants (Chen et al., 2022). Finally, individual factors, such as gender, age, previous robot experience, and pet ownership, are often collected and analyzed, but their influence has been found to be inconsistent in different scenarios (Jost et al., 2021; Matsumaru, 2006; Takayama & Pantofaru, 2009).

4.4. Future Research Needs

Our review identified several future research needs that could improve safety and trust during HRI with AMRs in industrial environments. There is a need for rigorous reporting of participant demographics and experience with robots. In our review, 44% of references failed to report the experience level of their participants with robots. Prior experience with robots has been shown to affect participant outcomes in HRI experiments (Sanders et al., 2017). Therefore, not reporting such information may lead to only a partial understanding of experiment findings. In addition, 34% of references failed to report the mean age of their participants, and 16% failed to report the gender ratio. Future HRI research with AMRs requires more robust reporting of sampling methods to provide a more comprehensive understanding of the research topic.

There is a lack of research on auditory devices that convey movement intent for industrial AMRs. A few papers investigated the hearing channel, but it was not found to be effective for the given conditions, and it was only considered as a secondary objective (Shrestha et al., 2016; Shrestha et al., 2018). Sounds and speech for human-robot communication is common among mobile service robots. Sounds can be used to express emotional state, which might make interacting with a robot more natural and realistic. Alarms and warnings can alert nearby human workers of the robot's state and intent, as well as the status of its system components. Johannsen (2001) developed an auditory display for a mobile service robot that can communicate its position, movement intention, and failures, and can relate warnings by means of nonspeech audio symbolic expressions to nearby humans. Johannsen (2004) tested the auditory display in a supermarket scenario, where robot movement intentions were communicated to the human, and found that, with training, robot audible alerts are a feasible mean of robot-to-human communication. In an industrial setting, factory noise or commotion could potentially affect the usability of such a device. However, further research is necessary to determine the effectiveness of an auditory display on an industrial AMR.

There is a need for a standardized set of questionnaires and human behavior metrics to quantify performance and perceptions of safety and trust in HRI experiments with AMRs. Only 20% and 14% of the studies explicitly measured perceived safety and trust, respectively, while other similar attributes, such as comfort, confidence, legibility, and likability were common. While these metrics generally yielded similar conclusions across the studies, a standard questionnaire would make it easier to compare findings across the literature. Only one paper involved a field experiment with experienced participants (Berx et al., 2021). While controlled laboratory experiments can provide valuable information, it can be difficult to replicate industrial environments and tasks in the laboratory. Similarly, participants who have experience working with AMRs at their workplace may have different performance or behaviors when interacting with an AMR, compared to an inexperienced person. There is a lack of research involving multiple AMRs. Typically, warehouses will employ a fleet of AMRs, as opposed to just one. Therefore, workers will often encounter multiple AMRs while traversing aisles between shelves. It is unknown how the presence of two or more AMRs affects human behavior, perceived safety, and trust. Lastly, there is limited research on industrial mobile robots. Most of the experimental robots were either custom made or were not specifically industrial mobile robots that are used in industrial environments.

4.5. Study Limitations

Our review was limited to research involving HRI with AMRs that apply to industrial environments. Research involving HRI with AMRs in social environments was included in the review, but only if the findings could be applied to industrial environments. Research on drones and biped robots was outside the scope of our study. We only included papers that involved an experiment with human participants who had a physical interaction with an AMR. Human-robot interaction research with mobile robots is a rapidly expanding field, and this review is only a small part of the existing literature.

5. Conclusions

Autonomous mobile robots are rapidly emerging in the workplace, which creates new hazards for human workers that are required to interact with them. We reviewed past research on HRI with an AMR, which yielded a few key conclusions and guidance for future research:

- There is a need for more HRI research involving industrial AMRs. The majority of the references used social AMRs or AMRs designed for research purposes, while only two studies used an industrial AMR in their HRI experiment.
- Questionnaires were the most employed assessment method, and 46% of references used both subjective and objective measures. Only 20% and 14% of the references directly evaluated perceived safety and trust using questionnaires, respectively, whereas 44% and 32% evaluated participant perception of robot traits and comfort level.
- Future research requires rigorous reporting of participant demographics and experience level with robots. We found that 34% and 44% of references failed to report the mean age of their participant sample and their experience with robots, respectively.
- We identified a variety of independent variables that researchers have investigated in HRI experiments with AMRs. Overall, we found that factors such as robot appearance, approach speed, and approach direction significantly affect perceived safety in human-robot interactions. Non-humanoid robots were generally perceived as more comfortable, and robot height affected the stopping distance during interactions. Additionally, human comfort levels and distance preferences may vary over repeated trials, potentially due to factors such as familiarity with the robot and past interaction experiences.
- The ability of a user to understand an AMR's navigation intent was a common research theme. Projection of signals on the floor, using turn signals, and haptic communication devices, improve the predictability and overall safety of AMR navigation. Similarly, the display of courtesy cues or adjustments in proxemic behavior, such as stopping or decelerating, improves the legibility of AMR navigation, but there are mixed findings on how they impact perceived safety and trust.
- We identified several gaps in the literature including a lack of field experiments, limited research involving multiple AMRs, and a limited use of industrial AMRs in experiments with human participants.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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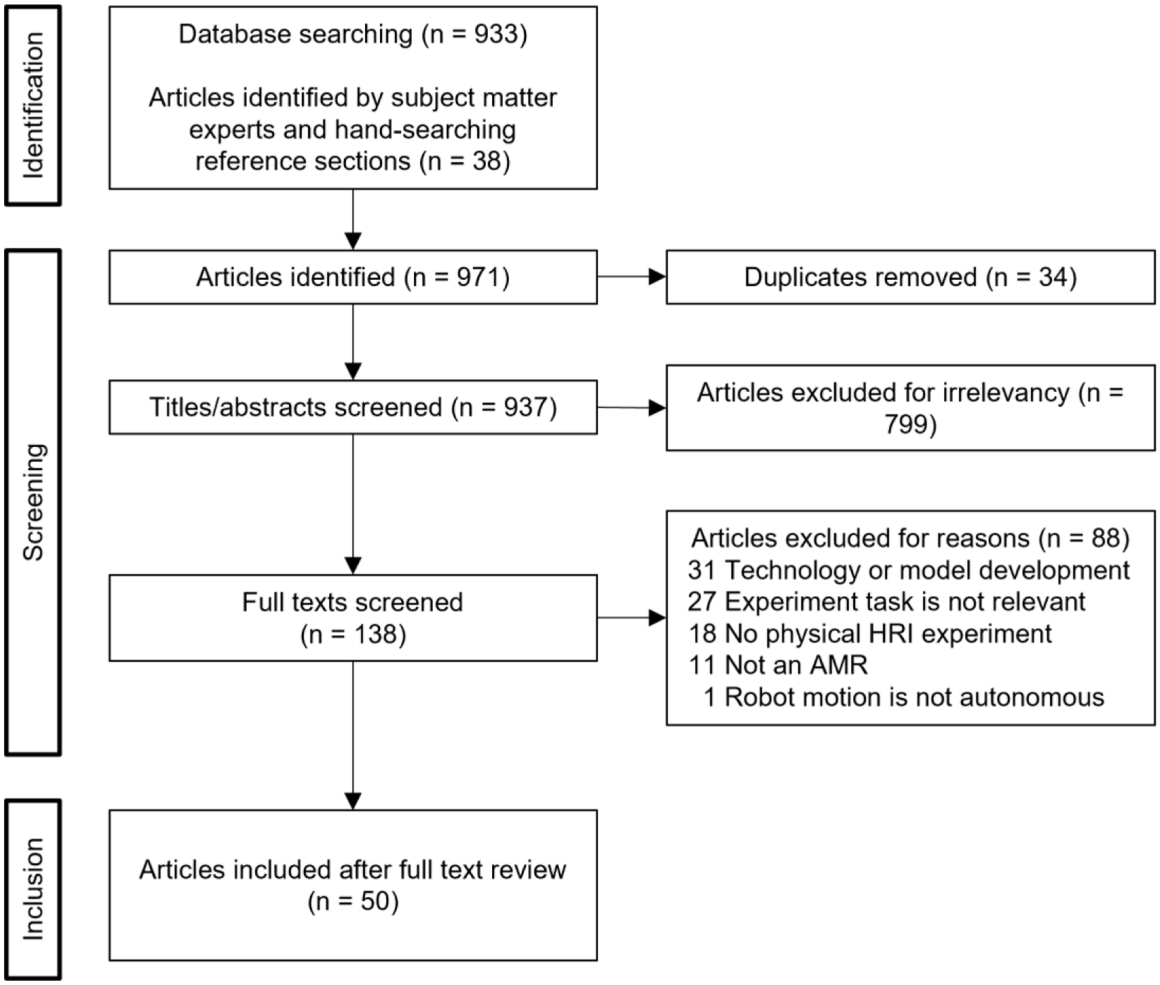

Figure 1.

Diagram of the article identification and selection process.

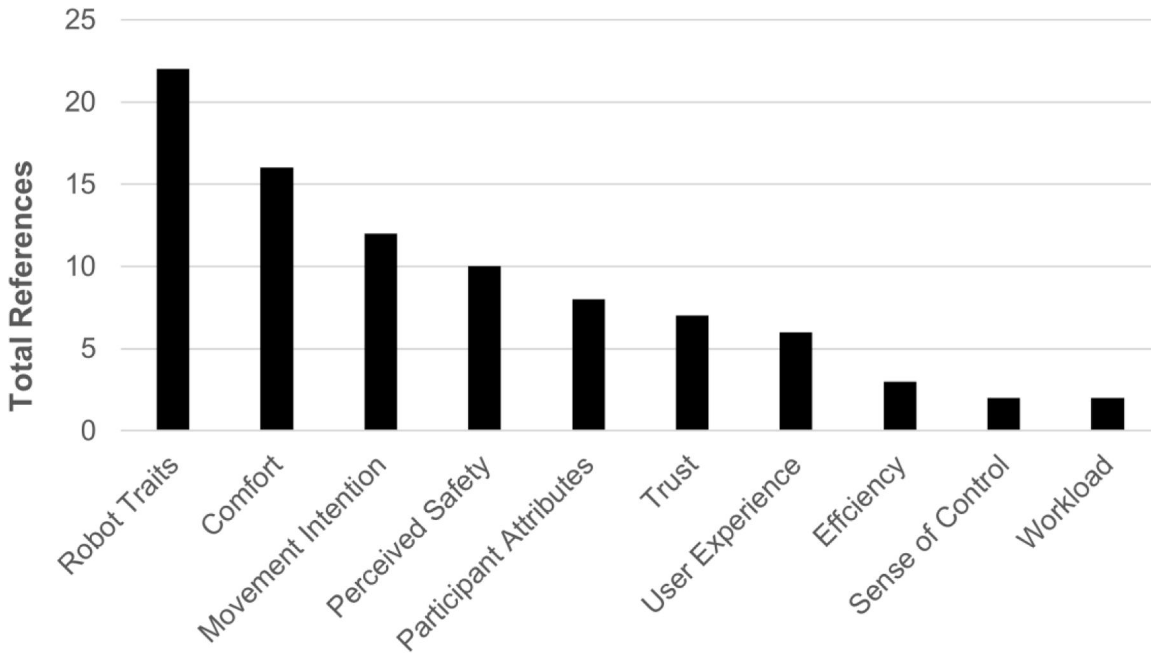

Figure 2.
Questionnaire assessment methods used in HRI experiments with AMRs.

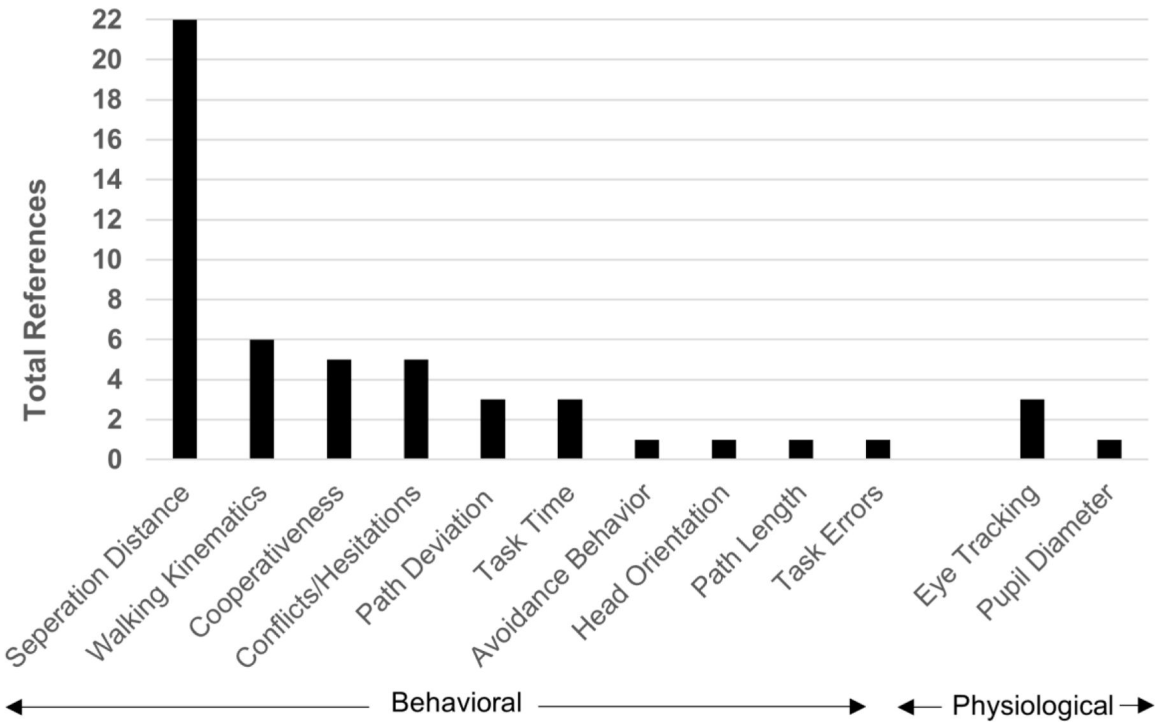

Figure 3.
Behavioral and physiological assessment methods for perceived safety in HRI experiments with AMRs.

Table 1.

Independent variables that were investigated in HRI experiments with AMRs by the references included in the review.

Independent Variable	Questionnaires	Human Behavior	Questionnaires & Human Behavior	Physiological Behavior
Robot Appearance	Neggers et al., 2022; Warta et al., 2018	Brandl et al., 2016	Joosse et al., 2021; Jost et al., 2021; Koay et al., 2007	
Robot Speed	MacArthur et al., 2017; Matsumaru, 2006; Walters et al., 2007	Brandl et al., 2016; Chen et al., 2018; Lauckner et al., 2014; Rossi et al., 2017	Joosse et al., 2021; Jost et al., 2021; Shomin et al., 2015	
Approach Direction/Passing side	Dautenhahn et al., 2006; Neggers et al., 2018; Neggers et al., 2022; Syrdal et al., 2006; Walters et al., 2007	Kosinski et al., 2016	Koay et al., 2007; Shomin et al., 2015; Unhelkar et al., 2014	
Robot Approach/ Passing Distance	MacArthur et al., 2017; Neggers et al., 2018; Neggers et al., 2022; Walters et al., 2007	Lauckner et al., 2014	Koay et al., 2007; Pacchierotti et al., 2006; Suvei et al., 2018	
Robot Navigation Intent	Coovert et al., 2014; Matsumaru, 2006	Bunz et al., 2016; Che, Sun, et al., 2018; Lichtenthäler et al., 2013	Chadalavada et al., 2015; Chadalavada et al., 2020; Che et al., 2020; Fernandez et al., 2018; Hart et al., 2020; May et al., 2015; Shrestha et al., 2016; Shrestha et al., 2018	Bunz et al., 2016; Chadalavada et al., 2020; Fischer et al., 2016
Robot Noise			Joosse et al., 2021; Shrestha et al., 2016; Shrestha et al., 2018	
Courtesy Cue/ Proxemic Behavior	Fiore et al., 2013; Siino et al., 2008; Warta et al., 2018; Wiltshire et al., 2015	Lichtenthäler et al., 2013; Vassallo et al., 2017, 2018	Alves et al., 2022; Fischer et al., 2016; Kaiser et al., 2019; Lo et al., 2019; Mavrogiannis et al., 2019; Shiomi et al., 2014; Suvei et al., 2018; Thomas & Vaughan, 2019	
AMR Presence	Berx et al., 2021		Chen et al., 2022; Joosse et al., 2021; Takayama & Pantofaru, 2009; Thomas & Vaughan, 2019; Unhelkar et al., 2014	Chen et al., 2022
Participant Characteristics	Batista et al., 2020; Matsumaru, 2006; Siino et al., 2008; Syrdal et al., 2006; Walters et al., 2007	Brandl et al., 2016; Chen et al., 2018; Lichtenthäler et al., 2013; Rossi et al., 2017	Alves et al., 2022; Jost et al., 2021; Takayama & Pantofaru, 2009	
Number of Approaches/Trials	Fiore et al., 2013; Warta et al., 2018	Brandl et al., 2016; Lauckner et al., 2014; Mead & Mataric, 2015	Mead & Matarić, 2016	
Number of robots	Batista et al., 2020			