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CLASSIFICATION OF CONSTRUCTION PROFESSIONALS' ATTITUDES TOWARD USING ROBOTS IN APPLICATIONS OF HUMAN ROBOT COLLABORATION

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SUMMARY*: Robotics are an emerging technology in the construction industry that have the potential to improve productivity and safety in both offsite and onsite applications. However, due to the highly customized nature of architectural and engineering designs and the dynamic environment of construction job sites, most robotic systems still require human intervention to function properly. This collaboration between human workers and robots, known as Human-Robot Collaboration (HRC), faces economic, technical, and social barriers to widespread adoption. While much research has been focused on reducing the technical barriers of HRC implementation in the construction industry, there has been less attention given to social barriers, such as technology acceptance. Therefore, this study aimed to explore the attitudes of construction professionals towards HRC in their workplace. A survey was conducted among recent graduates of a Construction Management program in the U.S., and a latent class analysis was conducted to identify distinct sub-groups, or classes, of attitudes towards HRC. The results of the study revealed three distinct classes of attitudes held by respondents—Controller, Assistant, and Partner—each representing a comfort level with a different set of interactions with robots. Tests of association between membership in these classes and the demographics of respondents revealed no significant relationships, suggesting that attitudes towards HRC are not attributable to differences in gender, age, experience, or education. These findings provide insights for manufacturers of construction robotics about potential users' attitudes towards HRC, which can be considered in the design and implementation of new robotic systems that are more likely to be accepted by practitioners.*

KEYWORDS*: HRC, Technology acceptance, Construction robotics.*

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1. INTRODUCTION

The use of robotic technology to automate production work is slowly growing within the construction industry. While robotic systems are mostly seen in offsite prefabrication and modularization applications, there have been recent attempts to apply robotics on jobsites (Delgado et al. 2019; Lundeen et al. 2017). Due to the high degree of design customization and dynamic nature of construction jobsites, robots in onsite applications cannot currently function fully autonomously, and require some level of human intervention, known as Human-Robot Collaboration (HRC) to perform their work (Liu et al. 2021). The construction industry is notoriously slow in accepting new technology and while certain technologies, such as Building Information Modeling (BIM), have demonstrated the ability of the industry to embrace innovation (Davies and Harty 2013; Lee et al. 2015), HRC still faces multiple barriers to acceptance.

Like most innovations, the barriers to HRC are economic, technical, and social in nature (Delgado et al. 2019; Taherdoost 2018). Economically, robotic systems are still expensive and in case of maintenance, investigating the problem requires employees or consultants with expertise. In addition, the repair process may be lengthy and result in costly downtime (Anderson and Anderson 2016; Pradhananga et al. 2021). Technical barriers are related to ensuring proper functionality and operation of the robot in the field. In controlled, offsite factory environments, robots are isolated from uncertainty, allowing them to follow their programming with speed and efficiency. On the jobsite, conditions change rapidly, and robots need the ability to respond accordingly. Researchers are currently applying artificial intelligence (AI) and machine learning (ML) to robotics in the field and are making strides in overcoming this technical barrier (Mukhamediev et al. 2022). Lastly, the social barriers refer to workers' acceptance of the new technology, including how they interact with and generally accept robotic systems when working alongside them (Park et al. 2023). For example, widely recognized social barriers include a lack of trust in robots' decision-making abilities, discomfort in collaborating with autonomous systems, or resistance to changing traditional workflows due to fear of job displacement. Additional barriers include perceived unpredictability, which creates anxiety and hesitation (Nomura et al., 2006), and job security concerns, leading to resistance against automation (Arntz et al., 2016). Attachment to traditional work methods may cause reluctance to adopt robots (Wilcox et al., 2013), and while perceived intelligence and autonomy can improve trust, workers may see robots as either unreliable or too advanced to depend on (Waytz et al., 2014). Workplace hierarchy also play a role, as some employees resist taking instructions from robotic systems (Elprama et al., 2017).

If human workers do not accept robots in the workplace, it can lead to decreased job satisfaction, increased stress and anxiety, reduced productivity, and even job loss (Arntz et al. 2016; Bauer et al. 2008; Nomura et al. 2004; Zanchettin et al. 2015). Acceptance is a critical precursor to innovation adoption because without a positive perception and willingness to integrate robotic systems, organizations may struggle with implementation, leading to inefficiencies and resistance that limit the technology's potential benefits. While acceptance models have been studied recently in the construction domain for both BIM and smart construction processes (Lee et al. 2015; Liu et al. 2018), acceptance of HRC is not fully understood. There is little research on how construction professionals perceive the potential barriers or lack thereof when it comes to integrating robots in their workflow, and how these attitudes might influence the adoption of HRC technology in the industry. To improve the likelihood that robotic technologies are accepted, adopted, and used in the field, there is a need to understand the attitudes of construction professionals towards using HRC.

To begin addressing these challenges, the goal of this research is to explore the attitudes of construction professionals with respect to different degrees of interaction possible in HRC. To achieve this goal, this research surveyed recent graduates of the undergraduate and graduate Construction Management program at the University of Florida (UF) in the U.S. to evaluate their attitudes on different levels of implementation of HRC in their workplace. A latent class analysis (LCA) was used to identify distinct clusters of attitudes in these responses, which provide a clearer typology of beliefs held by current construction professionals. The demographics of participants, such as their age, gender, education level, and cultural background, were also examined with ANOVA techniques to determine if attitudes toward HRC vary by demography. The findings provide valuable information for manufacturers of construction robotics, which can help them better understand the potential users of their technology, and better align their designed systems with these existing attitudes.

2. LITERATURE REVIEW

The integration of human-robot collaboration (HRC) in construction presents a transformative approach to addressing longstanding industry challenges, including labor shortages, safety concerns, and productivity limitations. However, the inherently dynamic and unstructured nature of construction sites has constrained the widespread adoption of robotic systems, necessitating varying degrees of human interaction. To understand the factors influencing the implementation of these technologies, it is critical to examine the broader theoretical frameworks that govern technology adoption and acceptance. This literature review first explores the role of HRC in construction applications, highlighting key advancements and implementation challenges. Subsequently, it examines the principles of technology adoption, drawing on Rogers' diffusion of innovation theory to contextualize the adoption process within the construction industry. Building on this foundation, the Technology Acceptance Model (TAM) is discussed as a pivotal framework for analyzing user perceptions and attitudes toward novel construction technologies. The review further examines empirical approaches for measuring attitudes toward technology use, emphasizing the factors shaping user acceptance of HRC. By bridging these topics, this review provides a comprehensive understanding of the relationships between technological advancement, adoption dynamics, and user attitudes, thereby offering insights into the mechanisms that facilitate or hinder the successful deployment of HRC in construction.

2.1 HRC in construction applications

Automated and semi-automated construction robots can address problems facing the construction industry such as reducing accident and injury rates, supplementing labor shortages, and improving the quality and productivity of construction processes. However, the application of construction robots has been limited due to the dynamic and unpredictable nature of jobsites. Construction jobsites are highly unstructured, dynamic, and fast-changing, and robots in construction applications often require human worker assistance to perform different tasks (Liu et al. 2021). HRC represents a new operating model for the construction industry that can affect the design of work tasks and the role of human workers (Pan and Zhang 2021; Paulson Jr 1985). In recent years, novel on-site construction robots have been developed and piloted or implemented in a limited capacity. Some of these robots completely replace a part of human work and perform tasks such as painting (e.g., CANVAS), layout (e.g., DUSTY), bricklaying (e.g., SAM) (Brosque and Fischer 2022), earthwork (Kim et al. 2020), visual inspection (Kim et al. 2022), data capture (e.g., Spot), while others are used as tools or piece of equipment to assist in completing tasks such as handling and preparation materials (Kim et al. 2022). These robotic systems come in different sizes and shapes and require different levels of human interaction. Given this breadth of implementations, user acceptance of the technologies are likely to be varied and complex.

2.2 Technology adoption

Innovation diffusion theory was initially advanced by Rogers (1983) and provided a model for how the use of innovations, including new technologies, spreads among individuals and organizations. In this model, diffusion is viewed as a process, starting with awareness or exposure to the innovation, and ending with its implementation and continued use if the innovation is deemed beneficial. When individuals see the advantages and implications of a new concept, they are more likely to embrace it, leading to its seamless adoption into their lives or practices (Taherdoost 2018). Individuals navigating this process were categorized into five groups based on when they adopted the innovation. The Innovator group were the first to embrace new ideas, having a high-risk tolerance and the resources to mitigate their exposure should the innovation fail. The Innovators were followed by the Early Adopter group and Early Majority group, who are each increasingly more pragmatic and deliberate in their adoption. The Late Majority group was skeptical and would only adopt an innovation after it was already widespread, often due to social pressure. Lastly, the Laggard group is the last to adopt, and considered highly resistant to change and focused on traditions, rather than novelty. The proportion of individuals in each of these groups was believed to follow an S-curve when plotted over time, such that the extremes (e.g., Innovator and Laggard) were much rarer in practice. While Rogers' (Rogers and Williams 1983) work has been fundamental in understanding innovation adoption at a conceptual level, complementary behavioral models are needed to understand individual adoption decisions, which are driven by acceptance.

2.3 Technology Acceptance Model (TAM)

Following the introduction of diverse computer and information systems in organizations, the acceptance of innovations by users has gained significant attention from both researchers and practitioners. A considerable amount of research has been conducted to identify the behavioral factors that influence users' beliefs and attitudes towards accepting technology, as well as those that contribute to their resistance. The Technology Acceptance Model (TAM) is a widely used theoretical framework that helps researchers to understand how users perceive and adopt new technologies. Originally proposed by Davis (1985), TAM has undergone several developments to incorporate new factors and variables that influence user acceptance of technology. The TAM has been extensively used to investigate the adoption of various technologies and is one of the most influential theories in this area (Wixom and Todd 2005).

The conceptual model for technology acceptance proposed by Davis (1985) was based on prior work by Fishbein and Ajzen (1977), who formulated the Theory of Reasoned Action, and other related studies. Davis suggested that the actual usage of technology is a response that can be explained or predicted by user motivation, which, in turn, is directly influenced by an external stimulus consisting of the actual system's features and capabilities. To refine the conceptual model, Davis (1989) proposed the TAM in which he hypothesized that the attitude of a user toward the system was a major determinant of whether the user will use or reject the system. The attitude of the user, in turn, was influenced by two major beliefs, perceived usefulness and perceived ease of use, with the perceived ease of use having a direct influence on the perceived usefulness. Finally, both beliefs were hypothesized to be directly influenced by the system design characteristics.

The primary TAM consists of four key components (see Figure 1): perceived usefulness, perceived ease of use, attitude toward using, and behavioral intention. Perceived usefulness refers to the user's belief that the system will improve their performance, while perceived ease of use refers to the user's belief that the system is easy to use (Marangunić and Granić 2015). Attitude toward using is defined as a person's particular beliefs and the extent of their emotional inclination towards a particular system (Liu et al. 2018). Behavioral intention refers to the user's intention to use the system. These three components are interrelated and determine the user's actual usage behavior (Sharp 2006). In 1989, Davis and his associates found that attitude did not fully mediate the perceived usefulness and the perceived ease of use. The model shows there is a direct relation between perceived usefulness and behavioral intention to use, but also there is some indirect path between these two elements through attitude toward using that technology (Davis 1989).

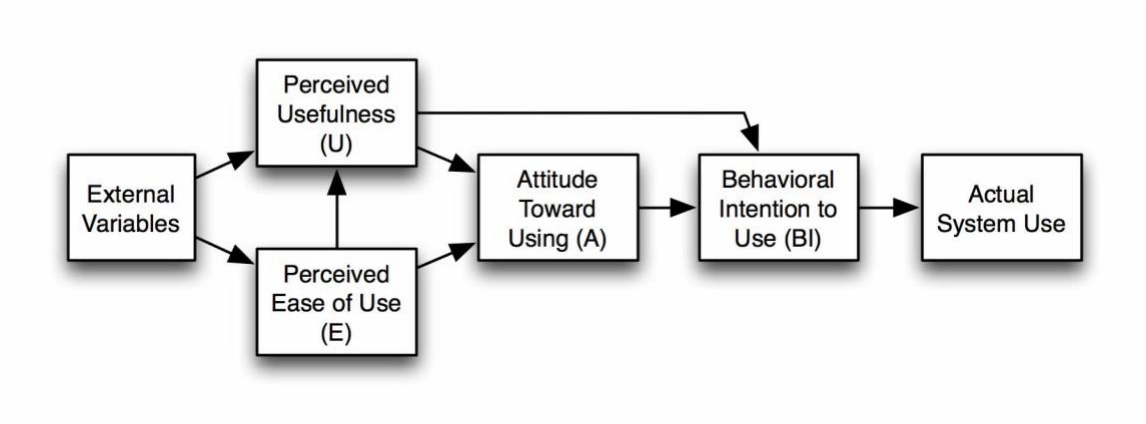

Figure 1: Technology Acceptance Model (TAM) (Davis 1989).

2.4 Attitude toward using technology

According to the TAM, what a person believes about a system, such as how useful and easy it is to use, affects how they feel about using it. This feeling is called their "attitude toward using," and it can be either positive or negative (Fishbein and Ajzen 1977). Attitude is a fundamental predictor of an individual's behavioral patterns regarding technology usage (Liu et al. 2018) and a favorable attitude towards technology is expected to generate a higher level of intention to adopt it, ultimately resulting in increased usage (Taylor and Todd 1995).

2.4.1 Measuring attitude toward using technology

Table 1: Measuring attitude toward using different technologies according to variable studies.

Study	Participants	Technology	Example Survey Items	Measurement Scale	Domain
(Spilski and others 2022)	Crafts in 5 small construction companies in Germany (N=87)	Digital assistance systems	- I find it very useful to use technical innovations in the construction craft in my work - In the end, it brings more advantages when I use technical innovations in my work	A 7-point Likert scale from totally disagree to totally agree, 2 total items	Construction
(Abdullah et al. 2015)	Undergraduate students at Koya university (N=800)	Information Technology (IT)	- IT allows me to have all the information I need for my studies. - I believe that IT makes the study activities more interesting.	A 5-point Likert scale from strongly disagree to strongly agree, 7 total items	Education
(Yusuf and Balogun 2011)	Undergraduate student-teachers enrolled in concurrent teacher education programs (N=407)	Information and Communication Technology (ICT)	- ICT provides better learning experiences. - ICT gives opportunity to learn more. - I won't have anything to do with ICT.	A 4-point Likert scale from strongly disagree to strongly agree, 14 total items	Education
(Pan 2020)	Chinese undergraduate students (N=332)	Technology-based self-directed learning	- Using this technology was a good idea. - Using this technology was pleasant.	A 6-point Likert scale from strongly disagree to strongly agree, 3 total items	Education
(Fogarty et al. 2001)	Students at the University of Southern Queensland enrolled in the course Algebra and Calculus (N=289)	Computers and graphic calculators in the learning mathematics	- I know computers are important but I don't feel I need to use them to learn mathematics. - I think using technology is too new and strange to make it worthwhile for learning mathematics.	A 5-point Likert scale from strongly agree to strongly disagree, 11 total items	Education
(Schepman and Rodway 2020)	Non-students, residing in the UK and aged over 18 (N=100)	Artificial Intelligence	- I am interested in using artificially intelligent systems in my daily life. - There are many beneficial applications of Artificial Intelligence.	A 3-point Likert scale from disagree to agree, 20 total items	General

Scholars have used different methods to measure attitudes towards using technology. One of the most common methods is through self-report survey questionnaires and interviews. Researchers develop questionnaires based on a literature review of the technology and create items to assess attitudes towards a specific technology, such as information and communication technology (ICT), the internet, artificial intelligence (AI), and learning technologies. These questionnaires typically use a Likert scale for each item, where respondents indicate their level of agreement or disagreement with each item. This method allows researchers to gather data on individual attitudes towards technology in a standardized and measurable way. Table 1 provides some examples of how attitudes towards technology have been measured in different studies. In these studies, researchers often use multi-item scales to measure attitudes toward using each technology. These scales can range from a minimum of two (Spilski et al. 2022) items to a maximum of 20 (Schepman and Rodway 2020) items and use Likert-scales that range from three (Schepman and Rodway 2020) to seven (Spilski et al. 2022) categories. Each item is then aggregated into a single, unidimensional measure to represent attitude towards use. One common aggregation method is to compute a mean of the individual item scores after converting the Likert categories into a quantitative numerical scale. However, this method assumes that all items are equally important, independent, and indicative of the same underlying attitude. Another method of aggregation is indexing, where a rule or formula is used to convert item scores into a single index. This method allows for items to be weighted and combined differently depending on the attitude being measured. However, while intended to better represent the underlying attitude, the creation of the indexing formula can also introduce subjectivity into the aggregation method. As an alternative to means and indexes, typologies can be used to group item scores into categories. Typologies allow for multidimensionality, recognizing that more than one related attitude may be represented by the item scores (Woehr et al. 2015).

2.4.2 Categories of attitudes toward using technology

It is essential to recognize and understand the different patterns of attitudes towards using technology to develop strategies that can help individuals overcome barriers to technology adoption and increase their willingness to use new technologies. Positive attitudes towards technology use are common among individuals who see technology as a useful and efficient tool to help them accomplish tasks (Huedo-Martínez et al. 2018). They may also view technology as a source of enjoyment. These individuals are likely to adopt and use new technologies readily (Svenningsson et al. 2021). On the other hand, negative attitudes towards technology use are prevalent among individuals who see technology as an obstacle or a source of stress. These individuals may resist the adoption of new technologies and prefer traditional methods of doing things. Negative attitudes towards technology can also arise due to privacy and security concerns (Huedo-Martínez et al. 2018). An undecided attitude towards technology is common among individuals who see both the benefits and drawbacks of its use. These individuals may be open to trying new technologies but may hesitate to fully adopt them until they are confident in their usefulness (Venkatesh et al. 2012). Lastly, the perception of technology as a helpful tool in accomplishing tasks is a common attitude towards technology use among individuals who value efficiency and productivity (Teo 2011).

2.4.3 Attitudes toward HRC

The demand for service robotic systems has surged in recent times, especially in homes and industrial workplaces. This has led to the development of efficient robots with complex sensing and motor control capabilities. These robotic systems range from robotic manipulators (Albu-Schäffer et al. 2007) to full humanoids (Kaneko et al. 2008; Ott et al. 2006; Radford et al. 2015; Tsagarakis et al. 2017) and are expected to assist users in various tasks that require collaborative efforts for safe, energy-efficient and time-efficient performance (Alami et al. 2006; Haddadin et al. 2009; De Santis et al. 2008). Human-robot collaboration (HRC) involves the interaction between human workers and robots in a shared workspace, where both the robot and human workers work together to achieve a common goal. The primary aim of HRC is to enhance human abilities and productivity, instead of replacing human workers with robots (Ajoudani et al. 2018; Bauer et al. 2008; Krüger et al. 2009). This concept is applicable in various industries, including healthcare, manufacturing, agriculture, and construction (Asan et al. 2020; Hentout et al. 2019; Liang et al. 2021; Vasconez et al. 2019).

Individuals may have different attitudes towards HRC, and their attitude can influence their acceptance of robotic systems. Ultimately, their level of acceptance affects the way they use the technology, which can significantly impact the success of HRC implementation (Meissner et al. 2020). HRC is a broad concept and represents multiple ways in which humans and robots could interact. While scholars may articulate these ways differently, there are generally four levels of interaction that are consistently identified: coexistence, cooperation, coordination, and collaboration. Coexistence refers to a scenario where humans and robots share the same environment but do not directly interact or communicate with each other. They work independently, pursuing their respective tasks without any interdependence or coordination (Aaltonen et al. 2018; Behrens et al. 2015). Cooperation involves humans and robots working together towards a common goal, while maintaining separate roles and responsibilities (Chen et al. 2013; Krüger et al. 2009). Coordination within the framework of HRC entails a more advanced level of interaction and adaptation between humans and robots, where they actively collaborate and adjust their actions in order to achieve common goals and tasks efficiently (Pini et al. 2015; Shi et al. 2012). Collaboration refers to the highest level of interaction, where humans and robots work as equals, possessing a deep mutual understanding and engaging in coordinated action to achieve a shared objective (Helms et al. 2002; Matheson et al. 2019).

2.5 Components of Attitudes Toward Using Robots

Attitudes toward robotics in the workplace are influenced by various psychological, social, and contextual factors. These attitudes determine how individuals perceive, interact with, and accept robotic systems in professional settings. Factors such as perceived safety, trust, personal experience, and the nature of the tasks assigned to robots play a crucial role in shaping these attitudes (Ajzen, 1991; Osterman et al., 2020). Understanding these components helps in evaluating workers' readiness and willingness to integrate robotic systems into their workflows. The following sections discuss key aspects that impact attitudes toward working with robots.

2.5.1 Comfort Working Alongside Robots

The level of comfort individuals feel when working alongside robots varies significantly. Some employees prefer collaborating with robotic systems, appreciating their efficiency and precision. Others, however, experience unease or discomfort, often stemming from concerns about safety, job displacement, or the impact on workplace dynamics (Osterman et al., 2020). Research suggests that the presence of robots can alter human workers' perceptions of their roles and relationships with supervisors, potentially leading to job insecurity or reduced job satisfaction. Factors such as prior experience with automation, training, and the perceived reliability of robotic systems can influence an individual's comfort level in shared workspaces (Rodriguez-Lizundia et al., 2015; Welfare et al., 2019).

2.5.2 Taking Direction from Robots

Employees' willingness to take direction from robots varies based on their perception of robotic authority and competence. Some workers view robots as valuable assistants capable of enhancing task efficiency, while others resist taking instructions from non-human agents, fearing a loss of autonomy (Riek et al., 2009). Studies indicate that workers with positive attitudes toward robotics are more likely to accept robots as supervisors or guides, particularly when the technology is presented as an aid rather than a replacement. The level of trust in robotic systems, as well as the clarity and effectiveness of robotic communication, plays a significant role in shaping these attitudes (Hinds et al., 2004; Zacharias et al., 2007).

2.5.3 Comfort Controlling a Robot

The ability to control a robot in the workplace can be a source of both empowerment and anxiety. Some employees feel uneasy managing robotic systems due to a lack of familiarity, concerns about making errors, or uncertainty about the robot's responses (Hourlier et al., 2016). Factors such as ease of use, intuitive interface design, and adequate training can improve confidence and comfort in controlling robots. Additionally, a lack of social presence in human-robot interactions can contribute to a sense of detachment, making some individuals hesitant to take on control roles in automated environments (Venås et al., 2024).

2.5.4 Dependence on Robots

The extent to which individuals are willing to depend on robots in the workplace is largely influenced by the type of tasks being automated. Many workers are comfortable relying on robots for repetitive, labor-intensive, or hazardous tasks, recognizing their potential to enhance safety and efficiency (Frey & Osborne, 2017). However, dependence on automation can also raise concerns about over-reliance, particularly in situations where human oversight remains necessary. Workers' trust in robotic reliability and accuracy, along with organizational policies on human-robot collaboration, significantly impact their willingness to depend on these technologies (Alhaji et al., 2020; Schoeller et al., 2021).

2.5.5 Acceptance of Robots Making Decisions Independently

While automation can improve decision-making processes, most workers remain hesitant about allowing robots to make independent decisions without human oversight. Research indicates that employees feel more comfortable with robotic decision-making when there is a human "backup" to intervene in case of errors (Scott, 2018). This skepticism is often linked to concerns about accountability, ethical implications, and the potential for unintended consequences in decision-making processes. Ensuring transparency, explainability, and human-in-the-loop frameworks can help alleviate concerns and foster greater acceptance of autonomous decision-making by robots (Turja, 2019).

2.5.6 Working with robots that resemble a person

Working with robots that resemble a person can significantly influence user perceptions and interactions. According to Walters et al. (2009), human-like appearance and embodiment in robots impact users' comfort levels, trust, and engagement in human-robot interaction trials. While anthropomorphic designs can enhance social acceptance and intuitive interaction, they may also raise unrealistic expectations or concerns about autonomy.

Understanding these perceptions is crucial for designing robotic systems that effectively balance familiarity and functionality in workplace settings.

2.6 Point of departure

While much research has focused on identifying and solving the technical challenges of implementing Human-Robot Collaboration (HRC) in construction, relatively little attention has been given to the social challenges, particularly technology acceptance. Existing studies have examined technology adoption frameworks, such as Lee et al. (2015), which evaluated an acceptance model for Building Information Modeling (BIM), and Lui et al. (2018), which explored the evolving acceptance of smart construction systems. However, none have specifically investigated construction professionals' attitudes toward HRC. Moreover, research on technology acceptance in construction tends to reduce attitudes to unidimensional measures, often categorizing them as simply favorable or unfavorable, when in reality, attitudes toward HRC are more complex and multidimensional. For instance, professionals may be open to collaborating with robots in certain tasks while resisting direct control over them. Additionally, previous studies have not accounted for the variety of ways HRC can be implemented, from direct on-site collaboration to automated off-site processes, further influencing the complexity of attitudes. This study aims to address these gaps by classifying the range of attitudes toward HRC and examining how different implementation strategies shape these perspectives. We used the broader categories of attitudes toward using HRC as indicators of a latent categorical variable representing attitudes towards using HRC, and classify them accordingly (Figure 2). By moving beyond binary classifications, our findings will provide deeper insights into the nuanced acceptance of HRC, informing strategies for its successful integration in the construction industry.

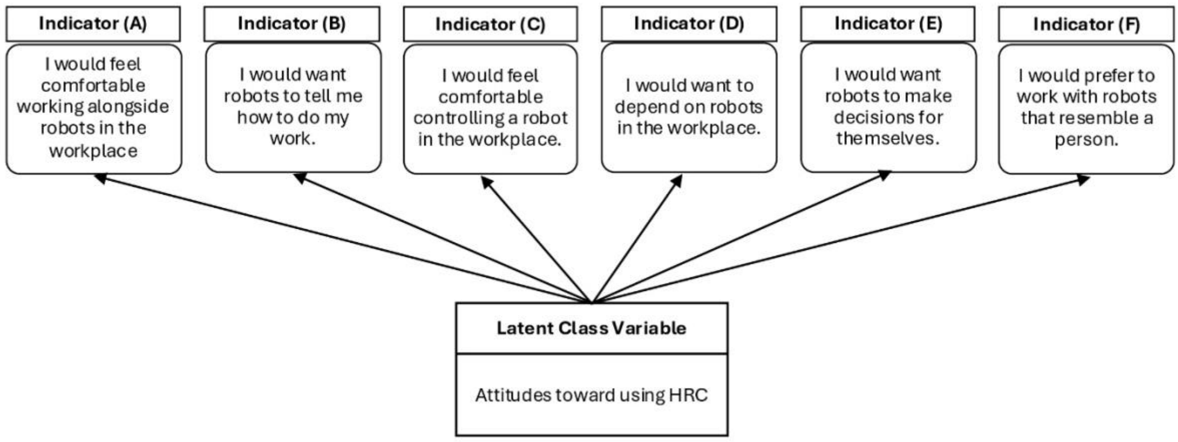

Figure 2: Indicators for classifying latent attitude classes toward using HRC.

3. RESEARCH METHODS

To address the research problem, this study used the information found in the literature review related to the level and modality of interaction and collaboration between human workers and robots in the workplace, to develop a survey questionnaire. This data collection was created in Qualtrics, and the survey was distributed to recent graduates of a construction management program. A binary Latent Class Analysis (LCA) was then performed on the survey data to determine discrete groupings in participants' attitudes toward interacting with robots in the workplace. Moreover, demographic variables such as age, gender, and educational level were examined with ANOVA and Chi-Square test to evaluate the association between those demographic variable and attitudes towards the adoption of HRC within each class.

3.1 Participants

The data were collected from construction professionals who graduated from of the undergraduate and graduate Construction Management program at the University of Florida (UF) between the years of 2001 and 2021. As of Fall 2022, UF had a total enrollment of 41,180 undergraduate students and 10,017 graduate students, and was ranked among the top five public universities and top thirty national universities in the United States, according to the 2023 Best Colleges ranking released by US News and World Report. This Construction Management program was started in 1935 and is accredited by the American Council for Construction Education (ACCE). The program graduates approximately 100 undergraduate students each year, and after graduation, most students accept entry-level positions with general contracting and construction management firms with regional offices in the Southeastern United States.

3.2 Survey questionnaire design and distribution

To reach these participants, a survey questionnaire was developed and administered. The survey was divided into two sections. In the first section, participants were asked to indicate the level of agreement with six statements, using a 4-point Likert scale that ranged from strongly agree to strongly disagree, with no neutral option. The purpose of these statements was to understand how construction professionals feel about different levels of robotic integration in their workplace. The statements were informed by the characteristics of robots and forms of interaction identified from literature on HRC (see Table 2). Several statements were negatively worded, and the list of statements was randomized on the survey to minimize the risk of acquiescence and question order bias, respectively. In the second section, respondents were asked to provide demographic information about themselves, including their gender, age, education, role in their organization, and years of their experience in the construction industry.

The use of a neutral response option in 5-point and 7-point Likert scales is a topic of debate among survey researchers. Providing a neutral option can be useful when participants genuinely have no opinion. However, studies show that, in practice, a neutral option often represents a variety of opinions, including a lack of understanding of the statement or topic, a reluctance to answer, or even mild agreement (Sturgis et al. 2014). When this type of ambiguity exists, responses tend to be biased towards the neutral option. Conversely, excluding a neutral option can encourage more thoughtful and decisive responses, leading to clearer results (Edwards and Smith 2014). In our study, a 4-point Likert scale was used without a neutral option for two reasons. Firstly, we aimed to prompt respondents to express definitive opinions and excluding the neutral option allowed the survey to capture stronger and more accurate feelings, avoiding default selections. Second, the analysis method, Latent Class Analysis (LCA), is best used with used with two categories of data, and including a middle option prevents the separation of agreement and disagreement into binary categories. Therefore, using a 4-point Likert scale represents a trade-off between a loss of granularity in the data in exchange for increased clarity in the results, allowing the latent classes to become more distinct and interpretable.

The survey was piloted to a selected small group of respondents in two stages, and the wording of the statements was improved for clarity through the piloting process. In the first stage of the piloting process, two project managers and one superintendent engaged in a video conference call with the research team. They performed a think-aloud review of the survey, opening and sharing it on their screen. Encouraged to vocalize any encountered difficulties or confusion without intervention, this process aimed to refine question clarity and sequencing. In the second stage in the piloting process, the survey was sent to a sample of 15 project managers within a construction management firm, serving as a representative subset of our actual survey participants. Feedback from the second stage led to the removal of several questions deemed too similar, contributing unnecessarily to the survey's length without commensurate added value.

The final survey was distributed via email in December 2022 to a total of 1,772 students who graduated in the past 20 years, with a message explaining the purpose of the study and a statement on the confidentiality of their individual responses. An external link to the survey, hosted on Qualtrics, was provided at the end of the email, and participants were encouraged to respond within two weeks. At the end of the first week, a follow-up email was sent to all participants reminding them to complete the questionnaire if they had not done so already. A total of 241 emails were returned undeliverable, meaning that the survey is assumed to have reached 1,531 professionals or 86.4% of the population.

Table 2: Item response statements related to attitudes toward HRC in the workplace.

Item Response Statements	Supporting Literature Citation
(A) I would feel comfortable working alongside robots in the workplace.	(Osterman et al. 2020; Rodriguez-Lizundia et al., 2015; Welfare et al., 2019)
(B) I would want robots to tell me how to do my work.	(Hinds et al., 2004; Riek et al. 2008; Zacharias et al., 2007)
(C) I would feel comfortable controlling a robot in the workplace.	(Hourlier et al. 2016; Venås et al., 2024)
(D) I would want to depend on robots in the workplace.	(Alhaji et al., 2020; Frey and Osborne 2017; Schoeller et al., 2021)
(E) I would want robots to make decisions for themselves.	(Scott 2018; Turja, 2019)
(F) I would prefer to work with robots that resemble a person.	(Walters et al. 2009).

3.3 Data analysis

An individual's attitude towards a technology is often more complex than simply being "for" or "against" its use. Technologies can have both general and specialized uses, for which attitudes may differ. For example, an individual may feel positively about AI in general, but negatively toward AI use in content moderation on social media platforms. This research acknowledges that similar nuance in attitudes may also exist for HRC applications in the construction industry. Therefore, this study uses a latent class model to investigate the existence of distinct patterns in preferences among construction professionals with respect to interacting with robotic systems in the workplace. A latent class analysis (LCA) was performed using the poLCA package in RStudio, based on the six survey statements provided in Table 2. LCA was selected as the primary analytical method over comparable categorization techniques, such as factor analysis, latent profile analysis, and latent trait analysis. This choice was made for the unique capability of LCA to uncover complex and unobservable patterns in item responses, where linear relationships might not apply, and because the study collects qualitative data, for which LCA is particularly well-suited (Law and Harrington 2016). In addition, LCA allows for multidimensional solutions, which allow a more nuanced exploration of attitudes towards HRC in the construction industry.

For the analysis, the indicated level of agreement for each respondent on each statement was condensed into a dichotomous response, where "Agree" and "Strongly Agree" were recoded as "1" and "Disagree" and "Strongly Disagree" were recoded as "0". The LCA identifies patterns in these dichotomous responses, which represent underlying (i.e., "latent") subgroups within the sample that share similar attitudes. Determining the number of subgroups found in the sample is a critical consideration for LCA. LCA identifies hidden subgroups within a dataset by analyzing how individuals respond to individual survey response items. The analysis assumes that item responses are governed by unobserved class memberships and through model specification and parameter estimation, calculates the likelihood of individuals belonging to these various latent classes. Statistical algorithms fit the model to the data, which is then evaluated for its fit using different criteria. The resulting classes reveal distinct response patterns, aiding interpretation and understanding of group differences, often used in fields like psychology, sociology, and marketing for segmenting populations and tailoring interventions or strategies to specific subgroups (Law and Harrington 2016).

A variety of fit criteria, including the maximum likelihood (ML), Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), and entropy were considered when selecting the best latent class model from among alternatives. While a higher ML may indicate that a model fits the data well, it is not always a guarantee of the best model (Linzer and Lewis 2011). The model with the lowest AIC and BIC can also suggest a good fit (Weller et al. 2020). Entropy ranges between 0 and 1, with values above 0.8 indicating a good distinction between classes (Celeux and Soromenho 1996). Lastly, studies recommend that classes should not contain less than 10% of the sample, thus the distribution of classes is also an important consideration (Shanahan et al. 2013).

Once the best latent class model was determined, each respondent was assigned to the closest matching class, based on their posterior class membership probabilities, to represent each individual's attitudes held toward HRC in the construction workplace. Class membership was then used as a categorical variable in tests of association between the demographics of participants and attitudes toward HRC. The statistical tests used depended on the demographic variables being considered. An ANOVA test was used when the demographic variable was continuous (e.g., age, years of construction industry experience, and percentage of working onsite), while a chi-square test was used when the demographic variable was categorical (e.g., gender, education, and role in their organization). In all tests, a p-value of 0.05 was selected to determine the significance of the relationship.

4. RESULTS

The results of this study are presented in three sections. The first section provides a summary of the respondent demographics, which provides context for the attitudinal data. The second section presents the results of the LCA, which identified three distinct class memberships, with different patterns of attitudes regarding working alongside robots in the construction workplace. The final section presents the results of the association tests, which illustrate how attitudes toward using HRC may differ by participant demography.

4.1 Respondent demographics

Table 3: Demographics of survey respondents divided by class membership.

Description	*Controller* (*n*=13)		*Assistant* (*n*=44)		*Partner* (*n*=51)		**Total** (*n*=108)	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Gender								
Male	9	69.2%	39	88.6%	44	86.3%	92	85.2%
Female	4	30.8%	5	11.4%	7	13.7%	16	14.8%
Age								
18-24	1	7.7%	3	6.8%	2	3.9%	6	5.6%
25-34	4	30.8%	20	45.5%	17	33.3%	41	38.0%
35-44	8	61.5%	17	38.6%	26	51.0%	51	47.2%
45-54	0	0.0%	3	6.8%	5	9.8%	8	7.4%
Above 55	0	0.0%	1	2.3%	0	0.0%	1	0.9%
Education								
Graduate or professional degree	3	23.0%	17	38.6%	26	51.0%	46	42.6%
Bachelor's degree	10	76.9%	27	61.4%	25	49.0%	62	57.4%
Construction experience								
1-3 years	1	7.7%	8	18.2%	7	13.7%	16	14.8%
4-5 years	0	0.0%	7	15.9%	3	5.9%	10	9.3%
6-10 years	3	23.0%	9	20.5%	8	15.7%	20	18.5%
10+ years	9	69.2%	20	45.5%	33	64.7%	62	57.4%
Role								
Designer	0	0.0%	0	0.0%	1	2.0%	1	0.9%
Project manager	4	30.8%	26	59.0%	30	58.8%	60	55.6%
Superintendent	2	15.4%	6	13.6%	5	9.8%	13	12.0%
Owner or developer	3	23.0%	8	18.2%	10	19.6%	21	19.4%
Project executive	3	23.0%	4	9.1%	2	3.9%	9	8.3%
Percentage of time onsite								
0-25 %	10	76.9%	22	50.0%	33	64.7%	65	60.2%
26-50 %	1	7.7%	10	22.7%	7	13.7%	18	16.7%
51-75 %	0	0.0%	3	6.8%	3	5.9%	6	5.6%
76-100 %	2	15.4%	9	20.5%	8	15.7%	19	17.6%

By the end of the data collection period, a total of 130 survey responses were received. Of those, 116 were complete, representing a 7.5% response rate. Most respondents were male (85.2% of sample), which is consistent with the percentage of male students enrolled in the program. Since the survey distribution reached former student that graduated between 2001 and 2021, 47.2% of participants were between the age of 35 to 44, and 42.6% went on to obtain a graduate or professional degree. The years of experience reported by respondents closely aligned with their age, with 57.4% having more than 10 years of experience. The most common positions held by respondents were project manager (55.6%), owner or developer (19.4%) and superintendent (12.0%). Most participants spend less than 25% of their time on site (60.2%), which is consistent with the percentage of project managers and their level of education. A complete summary of respondent demographics is provided in Table 3. Among the 116 complete responses, eight did not provide demographic information.

4.2 Latent classification

Prior to performing the LCA, item response frequencies were examined for each statement to confirm the quality of the indicator for a latent class model. High-quality indicators are those item responses that enable clearer differentiation between classes. Therefore, indicators that have low variability in responses (e.g., similar levels of agreement across all respondents) are unlikely to meaningfully contribute to class differences. Removing these types of indicators can improve the parsimony of latent class models, without altering their meaning. When examining item response frequencies in Table 4, only the last statement, Statement F ("I would prefer to work with robots that resemble a person"), shows low variability in responses with a nearly unanimous selection of "Disagree" or "Strongly Disagree" by participants. That suggested that this statement will not be class differentiator and was removed from further analysis. The remaining statements show greater variability and were all included in the LCA.

Table 4: Item response frequencies (n=116).

	Response Frequencies			
Item Response Statements	Strongly Disagree	Disagree	Agree	Strongly Agree
(A) I would feel comfortable working alongside robots in the workplace.	1.7 (%)	13.8 (%)	64.7 (%)	19.8 (%)
(B) I would want robots to tell me how to do my work.	19.8 (%)	44.8 (%)	31 (%)	4.3 (%)
(C) I would feel comfortable controlling a robot in the workplace.	6.9 (%)	10.3 (%)	59.5 (%)	23.3(%)
(D) I would want to depend on robots in the workplace.	12.1 (%)	37.1 (%)	41.4 (%)	9.5 (%)
(E) I would want robots to make decisions for themselves.	24.1 (%)	37.9 (%)	34.5 (%)	3.4 (%)
(F) I would prefer to work with robots that resemble a person.	25 (%)	62.1 (%)	10.3 (%)	2.6 (%)

Table 5 shows the fit results of different LCA models using the five indicator statements with a different number of assumed classes. For each model, their associated AIC, BIC, and log-likelihood values are summarized. From this summary, a 3-class model was found to have the lowest AIC and BIC, and the largest log-likelihood value, when compared against 1-class, 2-class, 4-class, 5-class, and 6-class alternatives, while also having an acceptable entropy above 0.80. All class models had average posterior probability greater than 0.80. The 4-class, 5-class, and 6-class models are resulted in one or more small class sizes, with the smallest being less than the recommended 10% of the sample. Taken together, these criteria support the use of a 3-class model of attitudes towards HRC in the construction workplace.

A graphical representation of the 3-class latent model is shown in Figure 3. The horizontal axis lists the five items from the survey. The vertical axis contains the average probability of class membership for each of the items, with values closer to 1 indicating a higher likelihood that the attitude is present within the class. Each item was coded such that higher probabilities corresponded to agreement with the item. To assist in interpretation, each class was given a name to represent the collection of attitudes within the class that had high (i.e., greater than 0.70) average probabilities.

Table 5: Model comparisons with different number of classes.

Class	AIC	BIC	Log-likelihood	Entropy	Average Latent Class Posterior Probability	Smallest Class Size (%)
1	682	695	-336	--	0.83	100 (%)
2	649	679	-313	0.746	0.82	44 (%)
3	647	694	-306	0.803	0.87	15 (%)
4	646	709	-300	0.890	0.90	7 (%)
5	656	736	-299	0.905	0.94	5 (%)
6	667	763	-298	0.882	0.92	2 (%)

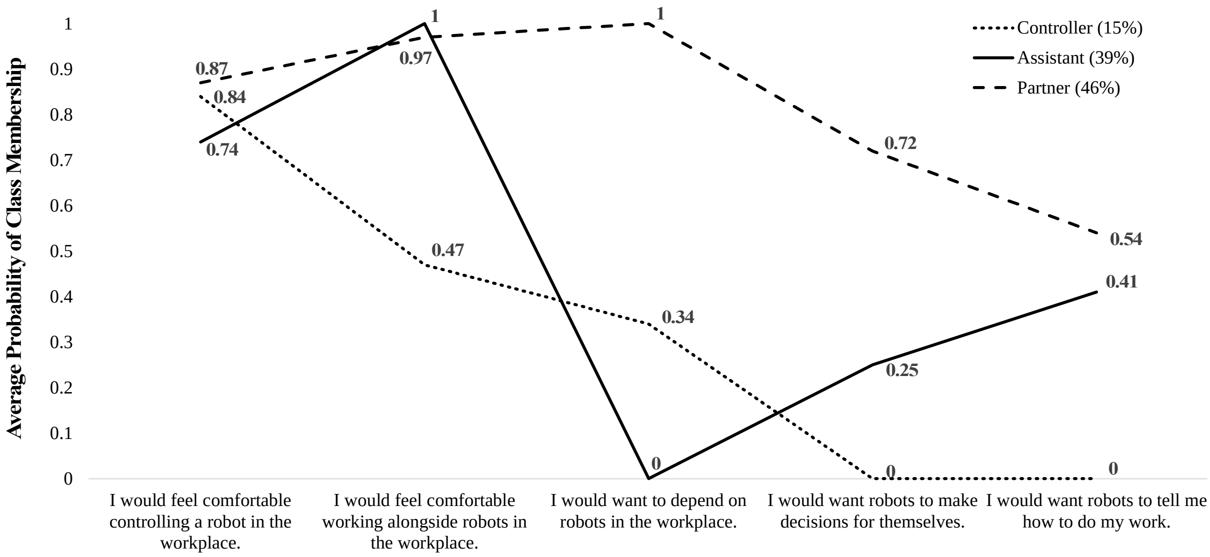

Figure 3: Latent class profiles of attitudes towards robotics in the construction workplace (n=116).

The Controller class was characterized by its favorable view of controlling a robot in the workplace (ave. probability=0.84), but with only low to moderate comfort working alongside robots (0.47) and depending on robots (0.34), and highly unfavorable views of robots making decisions for themselves (0.00) and being told how to work by the robot (0.00). The Controller class was the least represented class in the study, accounting for approximately 15% of the sample, or 17 participants. Within this class, the sample membership was mostly male (69.2% of class) between the ages of 35-44 (61.5%), with a bachelor's degree (76.9%) and over 10 years of experience (69.2%). Members spent only 0-25% of their time onsite (76.9%) and were managers and senior managers. When compared to the overall population demographics, the Controller class has respondents that were proportionally more women (30.8% in class versus 14.8% overall), in the older 35-44 age group (61.5% in class versus 47.2% overall), without a graduate or professional degree (76.9% in class versus 57.4% overall), at the executive level within their organization (23% in class versus 8.3% overall), and spending less than 25% of their time onsite (76.9% in class versus 60.2% overall).

The Assistant class was characterized by its favorable view of controlling a robot (ave. probability=0.74) and comfort working alongside a robot in the workplace (1.00). The Assistant class had no desire to depend on robots (0.00) and had low to moderate support for robots making decisions for themselves (0.25) and being told how to do their work by a robot (0.41). The Assistant class accounted for 39% of the sample, or 46 participants. Within this class, the sample membership was mostly male (88.6% of class) between the ages of 25-34 (45.5%) with a bachelor's degree (61.4%) and serving in project management roles (59.0%). The experience of the members varied, with approximately half being under 10 years (54.5%) and half being over 10 years (45.5%). More members in this class reported being onsite between 26-50% of the time (22.7%) and 76-100% of the time (20.5%), but half were onsite only 0-25% of the time (50.0%). When compared to the overall population demographics, the Assistant class has proportionally more respondents that are younger, less than 34 years of age (52.3% in class versus 43.6% overall), and spend over 25% of their time onsite (50% in class versus 39.9% overall).

Lastly, the Partner class was characterized by moderate to high support of all attitudinal items. Participants in this class claimed to be comfortable controlling a robot (ave. probability=0.87), working alongside robots (0.97), depending on robots (1.00), and allowing robots to make decisions for themselves (0.72). The Partner class was the only class with participants that were more likely than not to accept taking direction from robots when performing their work (0.54). The Partner class was the most represented class in the study, containing 46% of the sample, or 53 participants. Within this class, the sample membership was mostly male (86.3% of class) between the ages of 35-44 (51%) and having over 10 years of experience (64.7%). Members in this class commonly had graduate or professional degrees (51.0%), served in project management roles (58.8%), and spent only 0-25% of their time onsite (64.7%). When compared to the overall population demographics, the Partner class has a larger proportion of respondents with graduate or professional degrees (51% in class versus 42.6% overall).

4.3 Association between classes and demographics

Demographic data was composed of a mix of continuous variables including age, years of construction experience, and percentage of time spent working onsite, and categorial variables, such as gender, educational level, and role in the organization. For the continuous variables, an ANOVA was used to determine if their mean value varied across the three classes of attitudes. The results indicated no significant association between class membership and age ($F(2, 104)=0.99$, $p=0.374$), class membership and years of construction experience ($F(2, 105)=0.86$, $p=0.422$), or class membership and percentage of time working onsite ($F(2, 105)=1.40$, $p=0.251$). For the categorical variables, chi-square testing was used to determine if there was dependence between those variables and the three classes of attitudes. The results showed no dependence between class membership and gender ($\chi2(2, 108)=3.09$, $p=0.214$), class membership and education ($\chi2(2, 108=3.77$, $p=0.152$), or class membership and role ($\chi2(8, 104)=8.05$, $p=0.428$).

5. DISCUSSION

The results of this study provide important insights into the attitudes of individuals toward HRC applications in the construction workplace. The identification of three distinct classes of attitudes (Controller, Assistant, and Partner) confirms that these attitudes complex and that construction professionals are currently more comfortable with some aspects of HRC than others. This method of identifying attitudes provides several benefits over past technology acceptance research that adopts a psychometric approach to reduces attitude towards use to the mean of several Likert-scale questions. Because attitudes are not directly observable, their measurement will always be inadequate and incomplete to some degree.

The classes identified have alignment with the levels of cooperation between a human worker and a robot identified by Müller (2017). The Controller class is representative of the traditional, non-collaborative working where the human worker is separated from the robot, perhaps controlling the robot via teleoperation. The Assistant class is comfortable working in the same space as the robot, but not taking direction or depending on the robot. This class closely aligns with the Müller et al.'s "co-existence" classification of working. Lastly, the Partner class was the most receptive group in the sample to working alongside robots, but was hesitant to take directions from a robot, aligning this class with the "cooperation" classification of working rather than full "collaboration." Because LCA as a methodology can only identify sub-groups within the sample, larger samples may be able identify more classes that represent the remaining two classifications, "synchronized" and "collaboration."

The three classes of attitudes also have alignment with Rogers (1983) well-known categories of adopters on the innovation diffusion curve. The Controller class was largely resistant to HRC, seeing robotics are piece of equipment or tool to be used, which likely aligns members of this class with the "late majority" or "laggard" categories of adopters. These individuals may view HRC with a high degree of skepticism and be unwilling to accept the technology until most of the industry has already adopted HRC-enabled processes. The Assistant class was more open to sharing a workspace with robots but was not comfortable depending on the robot and its ability to make decisions for itself. This class may align with the "early majority" category of adopters. Members of the Assistant class spent more of their time onsite and may have seen robotic systems in use in construction applications, leading them to accept the technology sooner than the Controller class. The Partner class is supportive of a high degree of autonomous HRC and mostly aligned with the "early adopter" category. Members of this class were the most highly educated, with approximately 50% having graduate or professional degrees, which is commonly correlated with earlier adoptions (Szczepanowski et al. 2020).

The psychological differences among these classes arise from trust (Hancock et al., 2011), control, safety concerns (Ljungblad et al., 2012b), and perception of autonomy (Thrun, 2004). The Controller class prefers controlling robots but feels less comfortable working alongside them, likely due to a strong need for control, lower trust in robotic decision-making, and concerns about safety risks. The Assistant class is comfortable working with robots but prefers not to depend on them, possibly because they see value in collaboration but still feel humans should have the autonomy to make the final decision, especially in situations where safety is a concern. The Partner class has the highest acceptance of HRC, likely due to greater trust in robotic capabilities, confidence in their safety, and a higher level of comfort with automation in decision-making.

The finding that there were no significant associations between class membership and the demographics of participants, suggests that attitudes toward using HRC are not necessarily based on factors such as age, gender, education level, years of experience, percentage of time working onsite, or organizational role. One possible explanation for this finding is that attitudes may be influenced more meaningfully by other external factors, such as the level of exposure that individuals have to robotics in their jobs or by media influences (Naneva et al. 2020). Increase levels of exposure may make workers more comfortable with the idea of robotic and awareness of their capabilities (Savela et al., 2022). Another explanation is that the U.S. construction industry is resistant to adopting new technologies due to concerns over cost, project delays, and the reliability of existing methods. Professionals prefer familiar technologies to mitigate risks and avoid potential financial losses (Daniel et al., 2024; Omari et al., 2023). Additionally, according to the TAM (Figure 1), demographics may only affect attitudes indirectly, through the perceived usefulness and ease of use of the HRC applications. Users without an engineering background or prior knowledge of robotic systems may perceive these technologies as less useful due to a lack of familiarity and understanding (Szczepanowski et al., 2020). Similarly, cultural differences influence how people accept and adapt to robotic systems. For example, Bartneck et al. (2009) highlight that attitudes toward robots vary across cultures, with Japan exhibiting a higher level of acceptance compared to American and European countries. This is largely due to Japan's advanced robotic market and research, which have contributed to greater public exposure and familiarity with robots. As a result, people in Japan tend to perceive robots as easier to use and integrate into daily life, whereas individuals in regions with less exposure may find them more complex or intimidating. This study did not measure these elements, but the results suggest that future research could explore these factors further

We acknowledge several limitations in this study. First, the sample was somewhat narrow and consisted only of college graduates from a construction management program. This group represents early-to-mid career individuals who are often in project management positions and making decisions for others, rather than those who would work directly with robotic systems in the field. As a result, the attitudes of this group may not necessarily represent the attitudes of trade workers which limits the generalizability of this work beyond the sampled group. However, onsite workers who interact with robotic systems directly, are an important group to understand with respect to technology acceptance and adoption in future studies. This group's attitude toward using robots differs as they may have a greater fear of job displacement compared to others. Onsite workers tend to have less formal education and exposure to the broader construction industry beyond their trade or specialization, so their perspectives may be narrower and more distrustful. Based on our scale, they are more likely to be classified within the controller category. Second, latent class analysis can only identify sub-groups within the sample. While this study identified three distinct classes of attitudes, we cannot claim that these classes capture the full breadth of attitudes held by construction professionals. A larger data set may enable the identification of more classes, enhancing the generalizability of the findings to the broader industry. Lastly, this study reflects the current state of attitudes among construction professionals. However, as these professionals gain more experience with robotic systems, these attitudes are likely to evolve over time depending on how they are implemented in onsite and offsite applications. For example, social, economic, and technical challenges for robotic systems are thoughtfully addressed by manufacturers, we anticipate that construction professionals will become more at ease with robotics and confident in their abilities. They may shift the attitude of professionals towards the Partner class and away from the Assistant or Controller classes. However, if robotic systems are implemented poorly and manufacturers overlook the preferences, attitudes, and perceptions of construction professionals, they risk creating robotics that are not widely accepted. This trajectory may result in further distrust of robotic systems and increase the number of professionals in the Controller class, who prefer not to engage with HRC.

Despite these limitations, the findings of this study provide valuable insights into the acceptance of HRC technology in construction. By classifying professionals' attitudes, this research advances knowledge in the field of HRC technology acceptance, particularly in understanding the psychological and practical factors influencing adoption. The results contribute to the Technology Acceptance Model (TAM) literature by highlighting how perceived usefulness and ease of use shape professionals' willingness to engage with robotic systems through their attitudes. For practitioners, these findings can guide manufacturers of construction robotics in designing systems that align with user expectations, reducing resistance to adoption. For example, integrating user-centered design principles—such as enhancing intuitive interfaces and providing hands-on training—can improve acceptance.

Future research should further explore the role of perceived usefulness and ease of use in shaping attitudes toward HRC applications, particularly by examining variations across demographic groups. Understanding how factors like age, experience, and job role influence technology acceptance could refine targeted training programs and adoption strategies. Academically, this study provides a foundation for expanding TAM-based research in construction robotics, offering a framework for future studies on human-robot collaboration in construction management.

6. CONCLUSION

In conclusion, this study examined the attitudes of construction professionals towards using Human-Robot Collaboration (HRC) in the workplace. While much research has focused on technical and economic barriers to HRC implementation, this study specifically addressed social barriers related to technology acceptance. The findings revealed three distinct classes of attitudes: Controller, Assistant, and Partner, representing different levels of comfort and interaction with robots.

The Controller class demonstrated a favorable view of controlling robots but had lower comfort levels working alongside robots or depending on their capabilities. The Assistant class was comfortable working with robots but preferred not to depend on them or have robots make independent decisions. The Partner class displayed the highest acceptance of HRC, being comfortable with all aspects of interaction and even accepting direction from robots. The study found no significant relationships between class membership and demographics such as gender, age, experience, or education. This suggests that attitudes towards HRC are not necessarily influenced by these factors among construction professionals.

Future research can build upon these findings in several ways. First, larger sample sizes can be utilized to identify additional classes representing different levels of collaboration. This would provide a more comprehensive understanding of attitudes towards HRC. Additionally, exploring the reasons behind the attitudes of each class can provide valuable insights into the factors that influence technology acceptance in the construction industry. Secondly, future research could be focused on trade workers' attitudes towards using HRC in their work. Since trade workers are the end users of many HRC systems, understanding their perspectives, concerns, and acceptance of this technology is crucial for its successful implementation in the construction industry. Furthermore, longitudinal studies can be conducted to track the changes in attitudes over time as the industry becomes more familiar with HRC and as technological advancements continue to shape the field. This would allow for a better understanding of the dynamics of technology acceptance and the potential shifts in attitudes towards HRC.

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