A Comprehensive Evaluation of Factors Influencing Acceptance of Robotic Assistants in Field Construction Work

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Abstract: The adoption of human–robot collaboration (HRC) in various forms is widely expected to help improve productivity, reduce human physical workload, and alleviate the issues created by a skilled labor shortage in the construction industry. One potential deterrent to adoption of such collaborative work methods often cited by industry stakeholders is resistance by workers stemming from their fear of losing their jobs or having to learn new approaches and methods of performing construction work. Although significant prior studies have used path analyses to statistically evaluate hypotheses about technology adoption models by estimating the relationships in the models, no research has specifically investigated the intention to work in HRC through such an approach. This study addresses this knowledge gap and empirically investigates the factors affecting construction personnel's behavioral intention to accept HRC. HRC in this study is envisioned as robotic assistants performing the physically demanding repetitive work while construction personnel focus on cognitive tasks necessary to plan and supervise the work. An HRC adoption model based on the technology acceptance model (TAM) and innovation diffusion theory (IDT) is presented. This study expands a TAM-IDT model with new constructs such as job satisfaction and openness to training to explore an improved model that increases the understanding of construction personnel's intention to adopt HRC. Data collected from 156 construction personnel were analyzed to identify the key components based on exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The proposed model, consisting of eight external and four internal variables, was examined using structural equation modeling (SEM). Results indicated that variables such as perceived usefulness (PU) and perceived ease of use (PEU) had a positive and significant impact on behavioral intention (BI) to work in the described HRC system. Both theoretical and management implications emerging from the study are offered as insights to assist the construction industry in managing the introduction and adoption of HRC for on-site construction. **DOI: 10.1061/JMENEA.MEENG-5227.**

Author keywords: Human–robot collaboration (HRC); Construction personnel; Technology acceptance model (TAM); Innovation diffusion theory (IDT); Structural equation modeling (SEM).

Introduction

Construction is a large sector in the global economy. Construction-related spending accounts for about 13% of the world's gross domestic product (GDP) (Barbosa et al. 2017). Despite its critical significance as an industry, construction has persistently faced challenges of workforce shortage and stagnant growth in productivity (Fulford and Standing 2014; Wang et al. 2017). Construction tasks require skilled and qualified workers. However, the entry of young individuals into the construction industry has steadily decreased, resulting in the trend of an aging workforce that in turn has been leading to shortage of skilled labor across the industry (Han et al. 2008; Olsen et al. 2012; Choi 2015; Pan et al. 2020). In addition, construction productivity has grown by only 1% a year over the past two decades, compared with a growth of about 2.8% in other sectors (Barbosa et al. 2017). It is therefore imperative to consider and introduce new strategies to address worker shortages, increase interest in the construction profession among younger generations, and boost productivity across the entire construction sector.

Digitalization and automation continue to offer potential opportunities to improve the productivity of the construction industry. Robotic systems have been considered for several decades in the construction industry for both off-site and on-site work. Despite the many advantages of robotics, the construction industry has been slow to adopt robots and several of these systems remain at experimental level unlike other industries such as manufacturing where large-scale industry-wide robot deployment is common. One possible reason for this divergence is the dynamically changing nature of construction sites that have unique, unstructured, and congested field settings, resulting in challenging environments for robots to operate in (Saidi et al. 2016). In addition to the environmental factors, quasi-repetitive characteristics and arbitrary number of scenarios of construction tasks make it difficult to preprogram and use on-site robots for specific types of activities and easily transfer such systems to future sites (Liang et al. 2020). This makes it nearly impossible to conceive robots completely replacing human workers on construction sites.

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Human–robot collaboration (HRC) has been considered as a solution to overcome the limitation of noncollaborative robots (Villani et al. 2018). Human workers are responsible for tasks requiring judgment in an HRC system while collaborative robots complete physical tasks, leading to higher quality and improved safety. In this case, the role of human workers shifts from performing labor-intensive tasks to monitoring and controlling automated processes (García De Soto et al. 2019). Although there are different opinions and attitudes about the impacts of robot technologies on future employment (Fink et al. 1992; Granulo et al. 2019), such an automated work process is also more likely to attract young workers who are technology savvy (García De Soto et al. 2019) and helps to support expert old workers who enjoy their craft but need help in relieving the physical burden of performing construction tasks (Calzavara et al. 2020). However, it is difficult to determine what new skills the current or future labor force would need to acquire and what strategies can motivate adoption.

To facilitate the adoption of such technologies by construction personnel, it is essential to establish strategies to promote collaboration in human–robot teams. The success of HRC depends on the willingness of the workforce to accept it (Meissner et al. 2020). To explore acceptance of construction robots, previous studies have focused on the perspectives of enterprises or organizations but not the workers who will use and interact with the technology (Pan and Pan 2020b; Reinhardt et al. 2020). Although Kim et al. (2022) examined workers' perceptions and expectations of construction robots, the qualitative analysis was conducted using a small sample size (36 construction professionals). There are still significant limitations to understanding what affects acceptance of collaborative robots by construction personnel who are the immediate potential users in their day-to-day work on jobsites. This study focuses on the identification of various factors affecting HRC acceptance by extending previous acceptance theories and using path analysis. The target of this study is "construction personnel" which refers to any individual who is involved in the planning, supervision, and performance of the construction work on a jobsite.

The technology acceptance model (TAM) (Davis 1989) and innovation diffusion theory (IDT) (Rogers 2003) are well-known theories related to technology acceptance. In this paper, extended TAM-IDT and path analyses are adopted because the theories help in investigating critical factors and their dependent variables. In addition, previous studies in various domains showed the effects of integration of the extended TAM-IDT (Wu and Wang 2005; Oh and Yoon 2014). Path analysis shows the strength of the relationship between factors by assessing the degree to which the relationship is statistically significant (Zhang and Soomro 2016). It helps researchers in understanding users' perspective in the adoption of new technologies. Therefore, this study proposes a technology adoption model for HRC by extending previous acceptance theories to understand perceptions of construction personnel.

Research Objectives

The following two research questions are addressed in this study: What are the critical factors of a research model determining construction personnel's behavioral intention to work in the HRC system? Which hypotheses are accepted regarding the relationships between the critical factors? To address the two research questions, this study aims to validate the new research model by structural equation modeling (SEM). First, this study investigates factors that would affect HRC adoption based on the established theories and the literature review. Next, this study outlines the research model with hypotheses to explore the relationships between the factors. Finally, factor analysis and path analysis are conducted to validate the research model.

This study focuses on investigation of factors that affect construction personnel's acceptance of HRC by proposing an extended TAM-IDT model. It makes several contributions to the literature. It enhances the theoretical understanding of technology adoption in construction by proposing a technology acceptance model for HRC consisting of factors that specifically affect construction personnel's perceptions. Second, this study extends previous acceptance models by adding several new constructs such as job satisfaction, health, and openness to training. Third, it explores important constructs that affect the intention to work in HRC through examination of embedded hypothesized relationships in the proposed adoption model. Fourth, it uses a well-balanced set of 156 survey responses comprising of on-site and off-site personnel currently active in the US construction industry.

Literature Review

Acceptance-Related Theories

TAM (Davis 1989) and IDT (Rogers 2003) have been the most influential models for studying adoption of technological innovations and examining factors affecting user behavior (Zhang et al. 2008; Charness and Boot 2016). TAM aims to predict and explain behavior intention for technology use. Perceived usefulness (PU) and perceived ease of use (PEU) are two main factors of TAM, influencing users' behavior intention. TAM research can emphasize users' subjective attitudes and usage behavior toward a new technology. However, it does not focus on the characteristics of the technology and social factors (Yuen et al. 2021). It has limitations when extended to the workplace because user task environments are not fully reflected through fundamental constructs (Lee et al. 2015). TAM can thus be enhanced for more robust insights by combining it with IDT (Al-Rahmi et al. 2021).

IDT was first described by Rogers (1962) in a book titled *Diffusion of Innovations*, and updated several times including in the 5th edition version of the book (Rogers 2003). Innovation diffusion is described as a process in which a new idea or technology is communicated through specific channels over time among the members of a social system. There are five significant attributes of innovations that predict an innovation's adoption rate: relative advantage, complexity, compatibility, trialability, and observability. IDT has been used as a baseline theory to identify factors that significantly impact technology adoption and factors that do not.

TAM has been validated as a suitable mechanism by numerous research studies (Zhang et al. 2008) while IDT can be a comprehensive conceptual framework to be combined with other theoretical models (Shiau et al. 2018). Many studies leveraged the advantages of TAM and IDT by integrating the two models to provide a more robust model. Examples include technology adoption studies on autonomous vehicles (Yuen et al. 2021) and E-marketing (Kanchanatanee et al. 2014). In addition to integrating the two theories, several studies have extended advanced technology acceptance theories like TAM and IDT as a starting point to suggest new research models. In extending the established theories, additional factors have been obtained based on the results of previous studies and the characteristics of the technology and the industry in which the technology will be introduced (Wu and Wang 2005; Oh and Yoon 2014; Choi et al. 2017; Besklubova et al. 2021; Zhang et al. 2022).

Technology Adoption in the Construction Industry

Construction has been classified as a low-technology sector with low levels of expenditure for innovation (Martínez-Román et al. 2017). To address this issue, studies have been conducted to explore factors driving and hindering construction innovation. For example, Ozorhon and Oral (2017) showed that project complexity and innovation policy were the main motivations to adopt new technologies. Benefits from cost savings on labor and time were found to positively affect intention to adopt construction innovation, while initial investment costs adversely influenced the intention (Bademosi and Issa 2021). Ramilo and Embi (2014) showed that technological barriers to innovation adoption were crucial in smaller architectural organizations. In addition, market structure, ease of integration, and demonstration projects were also mentioned as factors affecting the acceptance of construction technologies (Yang et al. 2018). Pan and Pan (2020a), examining stakeholders' perceptions of future application of construction robots, showed that technological and economic areas were the most influential areas.

In order to explore adoption determinants of new technologies, researchers have proposed acceptance models for BIM (Lee et al. 2015), wearable technologies (Choi et al. 2017), construction robots (Pan and Pan 2020a), integration of a building information model (BIM) and augmented reality (AR) (Elshafey et al. 2020), 3D printing (Besklubova et al. 2021), and virtual reality (VR) in safety training (Zhang et al. 2022). The outcomes of each study provide an increased understanding of both positive and negative factors on the adoption of the respective technology.

HRC Acceptance in the Construction Industry

Researchers have investigated several approaches to introduce HRC in construction. Wang et al. (2021) developed a system for construction workers to remotely collaborate with co-robots by integrating a VR interface and the Robot Operating System (ROS). In the remote operation of construction robots, VR can also be used to train workers before they interact with robots on the job sites. It positively impacts human trust in robots and situational awareness (Adami et al. 2022). As one of the tools to support HRC, haptic devices were used to control robot arms in simulation and on real hardware for five construction tasks (Brosque et al. 2020). Liang et al. (2020) proposed a learning from demonstration (LfD) method that allows construction robots to learn how to perform quasi-repetitive tasks through human demonstration. Considering that construction workers and robots will work in a shared space, new methods using collaborative robots were developed to predict worker trajectories to avoid collisions (Hu et al. 2020) or capture workers' mental states to adjust robotic performance (Liu et al. 2021).

In previous studies for construction robot adoption, it has been expected that robots will perform physically demanding or dangerous work (Pan and Pan 2020b; Reinhardt et al. 2020; Kim et al. 2022) and human workers will act as operators or supervisors to control robots (Kim et al. 2022). In this paper, it is envisioned that construction personnel will play the critical role of planning, supervising, and teaching collaborative robots to adapt to the unstructured environment and perform useful work. Advances in technologies will enable construction personnel to collaborate with robot assistants through direct physical interaction and virtual supervision and training (Wang et al. 2021). Regarding scenarios for collaborative robots, Reinhardt et al. (2020) described that the robots can have variations in their tasks depending on human workers' behaviors and their surroundings. In this paper, robots are expected to imbibe basic work skills and perform prelearned tasks with minimal guidance but continue to require human supervision and input as deviations requiring improvisation arise in new work (Liang et al. 2020).

Research has been carried out on determinants for intention to work with robots or the adoption of HRC for the construction sector. For example, You et al. (2018) proposed the robot acceptance safety model (RASM) to examine the perceived safety of working alongside a robot and that participants were more willing to work alongside the robot when they felt it was safe to do so. To investigate determinants of construction robot adoption, Pan and Pan (2020b) evaluated a research model developed based on the technology-organization-environment (TOE) model (Tornatzky and Fleischer 1990), integrating characteristics from the IDT theory. The analysis results from the survey of building contractors showed that top management support was the most influential factor. einhardt et al. (2020) surveyed industry and trade unions about drivers and challenges to HRC adoption. Cost-effectiveness and reduced manual labor were mentioned as drivers for adoption, while safety issues and skills needed were identified as challenges. However, these two studies investigated significant factors for the robot adoption at the organizational level. Kim et al. (2022) built a theoretical model based on TAM incorporating job-related determinants for HRC in construction. They examined cross-profession and cross-specialization comparisons of construction workers' and managers' perceptions on HRC by qualitative analysis using a small sample.

In previous studies examining the introduction of construction robots, few studies have focused on the perspective of construction personnel rather than organizations or enterprises. Even though there are studies discussing HRC adoption of construction personnel, a small number of samples were analyzed qualitatively. This study proposes an extended TAM-IDT model to identify significant determinants affecting the intention of construction personnel to work in HRC. There will be many changes in the activities of construction personnel working in HRC because they are the actual end-users of the HRC technology and the first to experience and interact with collaborative robots. For this reason, our research model is extended by new constructs such as health, job satisfaction, and openness to training that may affect the acceptance of HRC. Hypothetical relationships embedded in the proposed model are evaluated through structural equation modeling (SEM) analyses using 156 survey samples obtained from active US construction personnel.

Proposed Factors for HRC Adoption Model

Overview of Proposed Model

This paper introduces an HRC acceptance model for the construction industry by extending TAM and IDT. Similar to previous studies (Wu and Wang 2005; Oh and Yoon 2014; Choi et al. 2017; Besklubova et al. 2021; Zhang et al. 2022), this study has used the two technology acceptance theories to select influencing factors and obtained other factors through the review of literature about technology adoption. The proposed model consists of (1) TAM-related factors (perceived usefulness and perceived ease of use) as mediation variables, (2) IDT-related factors (relative advantages, complexity, trialability, and observability) as external variables, and (3) six new factors (openness to training, personal competency, job satisfaction, health, life satisfaction, and perceived impact on quality of life) and behavioral intention to adopt HRC. Among the latter factors, the perceived impact on quality of life is one of the mediation variables, and the other five factors are used as

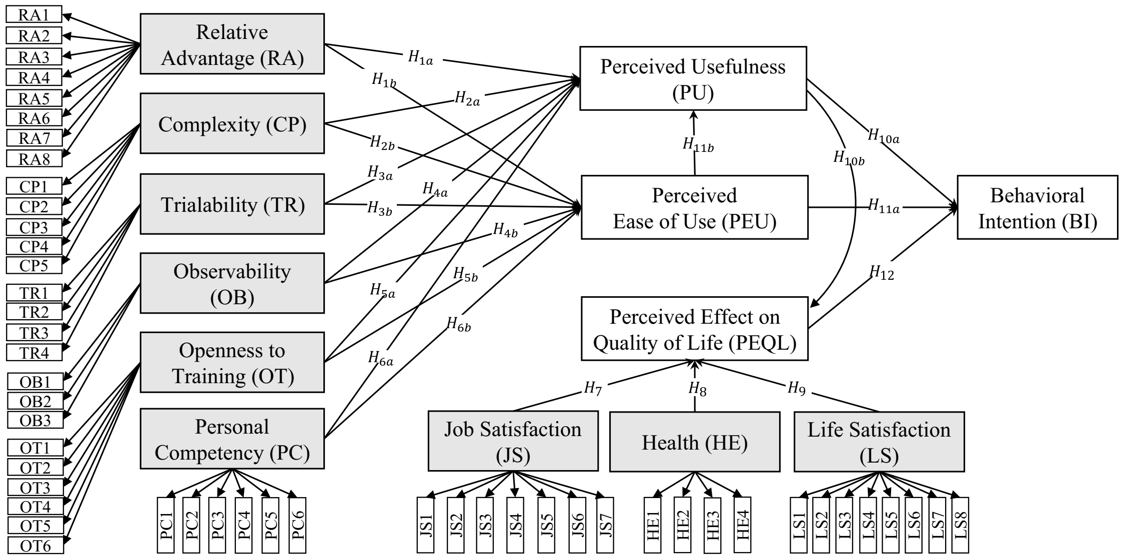

Fig. 1. Initial research model for HRC adoption in construction.

external variables. Thus, the model includes nine external variables and four internal variables including behavioral intention. The initial research model is depicted in Fig. 1. The external and internal variables and their measurement criteria are presented in Appendixes I and II.

External Variables for HRC Adoption

Relative Advantage (RA) is defined as the degree to which adopting the HRC system is perceived as more beneficial to construction personnel than the traditional approach to completing construction tasks. RA, an innovation attribute of IDT, is widely agreed on as an influential factor of innovation adoption. Labor markets have shown a growing demand for workers with strong digital skills in the United States, not limited to specific fields (Bergson-Shilcock 2020). This indicates that construction personnel who acquire skills to handle robots and other digital equipment in the HRC system can be more competitive in the job market. The construction robots can assist human workers in dull, dirty, and dangerous tasks, providing better working conditions and reducing injuries and fatalities (Lattanzi and Miller 2017; Pan et al. 2018). Construction productivity and efficiency can also be potentially improved based on reduced rework by utilizing the robots in the construction sites (Prasath Kumar et al. 2016). Therefore, the following hypotheses are proposed:

H_{1a}: The relative advantages of HRC have a positive influence on perceived usefulness.

H_{1b}: The relative advantages of HRC have a positive influence on perceived ease of use.

Complexity (CP) refers to the degree to which the HRC system is perceived to be difficult for construction personnel to understand and operate. Rogers (2003) indicated that the faster users learn how to use technology, the earlier the innovation is adopted. CP attribute has been deemed to inhibit the adoption of new technologies in several industries (Rogers 2003; Wang et al. 2010). Pradhananga et al. (2021) showed that the complex implementation of robotics is one of the significant obstacles to their adoption in the US construction industry. Construction personnel involved in HRC will provide necessary instructions to co-robots and observe the collaborative robots' work steps by wearing VR headsets with virtual tools and interacting on tablets with a BIM. However, it is expected that personnel will take time to learn and implement the technologies. Therefore, the following hypotheses are proposed:

H_{2a}: Complexity of HRC has a negative influence on perceived usefulness.

H_{2b}: Complexity of HRC has a negative influence on perceived ease of use.

Trialability (TR) is defined as the degree to which construction personnel think that they need to experience the HRC system before adopting it. IDT stipulates that trialable innovations are more likely to be adopted because personnel can learn about technologies with less effort and explain their advantages to others. For construction personnel, trialability is an essential consideration because HRC is a new concept in the construction industry. Trialability can be improved by allowing construction personnel to view a demonstration, get training, and receive instructions on HRC. It can reduce uncertainty and give the personnel more information of how to work with co-robots and use new technologies. Researchers have shown that trialability is relevant to technological innovation adoption (Lin and Chen 2012; Ramdani et al. 2013). Therefore, the following hypotheses are proposed:

H_{3a}: Trialability of HRC has a positive influence on perceived usefulness.

H_{3b}: Trialability of HRC has a positive influence on perceived ease of use.

Observability (OB) is defined as the degree to which the outcome of the innovation is noticeable by others. For instance, observability could be increased when working on construction sites that adopt HRC. It can give opportunities for construction personnel to indirectly experience the HRC system. Workers would find it easy to explain its benefits and learn its usage. Several studies have addressed the positive relationship between the intention to adopt technology and observability (Lee et al. 2011; Al-Rahmi et al. 2019). Therefore, the following hypotheses are proposed:

H_{4a}: Observability of HRC has a positive influence on perceived usefulness.

H_{4b}: Observability of HRC has a positive influence on perceived ease of use.

Openness to training (OT) is defined as the degree to which construction personnel are willing to learn job-related skills through a training system. In the construction industry, there will be more demand for workers with digital skills to be able to support robotic systems (García De Soto et al. 2019). Training and education have been considered to affect the adoption of new technologies in the construction industry with untrained workforce identified as an important barrier to adoption (Won et al. 2013; Liao and Teo 2017; Delgado et al. 2019; Pan and Pan 2020a). This means that adopting the HRC system requires a robust training system for introducing HRC work. The training will allow personnel to efficiently operate new technologies and learn the benefits of the new working system. The success of the training depends primarily on the trainees' motivation to learn (Guerrero and Sire 2001). The following are thus hypothesized:

H_{5a}: Openness to training has a positive influence on perceived usefulness.

H_{5b}: Openness to training has a positive influence on perceived ease of use.

Personal competency (PC) is defined as the degree to which construction personnel have capabilities that facilitate new technologies related to the HRC system. Regarding HRC in the construction industry, it is important that labor resources understand and use new digital equipment to adapt to the new working environment quickly. According to Cohen and Levinthal (1990), prior knowledge about basic skills and technological developments facilitates recognizing the value of new information and assimilating it. Related to new construction technologies, Lee et al. (2015) showed that personal competency has a significant impact on the perceived usefulness of BIM by measuring six items about self-efficacy and personal innovativeness. The following are thus hypothesized:

H_{6a}: Personal competency has a positive influence on perceived usefulness.

H_{6b}: Perceived competency has a positive influence on perceived ease of use.

Job satisfaction (JS) is defined as the degree to which working in the HRC system is perceived to provide construction personnel with self-motivation and satisfaction on the job. According to Salisu et al. (2015), job satisfaction can be positively affected by better work settings and employees' involvement, while poor working conditions and low rewards can cause job dissatisfaction. Construction jobs are considered dangerous, monotonous, and unreasonable (Pan et al. 2018), but automation and robotics in construction can provide better physical working conditions thereby improving safety and reducing occupational risks. In addition, the lower a worker's digital skills, the lower their income tends to be (Bergson-Shilcock 2020), so it is expected that personnel get higher earnings when they learn digital skills in an HRC environment. Concerns about job security alleviated by the positive perception that robotics can upgrade a worker's job from manual work to more value-added work (Asatiani et al. 2020). Since job satisfaction is one of the important factors influencing the quality of life (Kim et al. 2018), the following hypothesis is proposed:

H_7: Job satisfaction has a positive influence on perceived effect on quality of life.

Health (HE) is defined as the degree to which construction personnel feel their mental and physical health would be better due to the HRC system. The physical workload of construction tasks highly influenced workers' health due to awkward back posture, static postures, and repetitive movement, leading to increased chronic pain (Latza et al. 2002) and decreased ability to work (Alavinia et al. 2007). This in turn leads to substantial mental distress (Jacobsen et al. 2013). In addition, construction workers have to endure adverse physical environments, including extreme temperatures, poor air quality, and noise that induce mental stress (Leung et al. 2010). These physical pains and occupational stress affect construction workers' quality of life (Chakraborty et al. 2018). Several problems with workers' health can be potentially resolved when the workers work in the HRC system because co-robots will handle dangerous work tasks. Therefore, the following is hypothesized:

H_8: HRC systems to improve health have a positive influence on perceived effect on quality of life.

Life satisfaction (LS) is defined as the degree to which working in the HRC system is perceived to provide construction personnel opportunities to be generally satisfied with their lives. The role of human workers in HRC will be different from that of ones working in the current construction sites. Based on the level of robot autonomy, they can plan the tasks and trajectory for the robot, teleoperate the robot, or monitor the robot (Liang et al. 2021). This can lessen workers' fatigue and tiredness, which typically prevent workers from enjoying their weekends or time away from work (Brown et al. 2009). Better health conditions obtained from working in HRC can give construction personnel extended break times to participate in personal enriching activities instead of recovering from fatigue. Langdon and Sawang (2018) found that lack of personal time was one of the highest-rated stressors for construction workers. Job characteristics have become important determinants of how people assess their overall life satisfaction (Viñas-Bardolet et al. 2020). The changes from the introduction of HRC have the potential to influence construction personnel's lives positively. Previous studies have shown a positive relationship between life satisfaction and quality of life (Kaliterna et al. 2004; Kim and Ko 2018). Therefore, the following is hypothesized:

H_9: Life satisfaction obtained from the HRC has a positive influence on perceived effect on quality of life.

Internal Variables for HRC Adoption

Perceived usefulness (PU) is defined as the degree to which construction personnel believe that using the HRC system will enhance their performance while doing their job. Since Davis (1989) proposed PU as a direct predictor of behavioral intention to use new technology, previous studies have demonstrated that PU had positively correlated with acceptance of new technologies in various areas. For example, research in the construction industry have shown that PU had a significant effect on the behavioral intention to accept technologies such as BIM (Lee et al. 2015), BIM-AR (Elshafey et al. 2020), and information and communications technology (ICT) (Sorce and Issa 2021). Likewise, it is expected that PU will influence construction personnel's willingness to accept the HRC system when they recognize its usefulness.

PU can affect perceived impacts on quality of life as well since the intention to use technologies are related to activities of daily living. Kim and Lee (2014) defined PU as the extent to which users believe that the quality of life and job productivity can be improved by using a robot. In addition, improved quality of life was used to measure the PU of mobile health services (Guo et al. 2012). Thus, robot assistants can be expected to positively influence many daily activities on construction sites. Therefore, the following are hypothesized:

H_{10a}: Perceived usefulness has a positive effect on behavioral intention to work in the HRC system.

H_{10b}: Perceived usefulness has a positive effect on quality of life.

Perceived ease of use (PEU) is defined as the degree to which construction personnel believe that using the HRC system will be free of effort. It has been considered an important determinant for the acceptance of technologies (Lee et al. 2015). It has been found that PEU is positively associated with behavioral intention to use technologies (Davis 1989; Hamid et al. 2016; Sorce and Issa 2021) and has an indirect influence on the intention through PU

(Lee et al. 2015; Huang et al. 2021; Sorce and Issa 2021). Therefore, if the HRC system is considered relatively easy to use, construction personnel will be more willing to use the system. The following are thus hypothesized:

H_{11a}: Perceived ease of use has a positive effect on behavioral intention.

H_{11b}: Perceived ease of use has a positive effect on perceived usefulness.

Perceived effect on quality of life (PEQL) is the degree to which construction personnel believe that using the HRC system will enhance their quality of life, which refers to the level of general well-being, and is similar to the notion of life satisfaction that is an individual's evaluation of their life. Several studies considered both as the same concept (Senlier et al. 2009; Powdthavee et al. 2015), but the quality of life has been understood as less subjective and less fluctuating than life satisfaction (Bidzan-Bluma et al. 2020). According to the Better Life Index (BLI) developed by the Organisation for Economic Co-operation and Development (OECD), quality of life is positively related to desirable health, greater job satisfaction, safety, better housing, and higher income. Several changes from HRC in work environments and roles can be expected to improve quality of life of construction personnel. Berkowsky et al. (2017) showed that perceived impact on quality of life is a critical factor for willingness to adopt technologies. The following are thus hypothesized:

H_{12}: Perceived effect on quality of life has a positive effect on behavioral intention to work in the HRC system.

Behavior intention (BI) is the degree to which construction personnel intend to work in the HRC system. Prior studies have used it in place of actual use to measure individuals' attitudes towards new technologies when the availability of the technologies is not ensured (Chung et al. 2009; Huang et al. 2021). The behavioral intention directly or indirectly influences the actual behavior of the individual (Wu and Liu 2015). The TAM indicates that the actual use is determined by an individual's behavioral intention (Davis 1989). Therefore, this study decided to use behavioral intention as a dependent variable.

Research Methodology

Survey Structure

The authors first provided a brief overview of our vision of HRC in the construction industry in the administered survey. The introductory section of the survey described construction personnel's envisioned new roles, training plans, and benefits to workers based on previous studies (e.g., Lundeen et al. 2017, 2019; Liang et al. 2020, 2021; Wang et al. 2021). The roles of construction personnel include planning construction tasks, supervising co-robots, and teaching the co-robots how to perform tasks. The robots complete the physical construction tasks as assistants that require significant human input in planning the work. The personnel need to be equipped with new computational and interaction skills in order to plan for how the tasks will be executed by the robot assistants and to teach them work-related knowledge and at-work improvisation. Regarding their training plans, it was described in the survey that training programs or centers that teach workers how to interact with robots through virtual tools to support HRC would evolve. This information gave survey participants an understanding of what HRC means in the construction sector, and the changes construction personnel are likely to experience.

The survey consisted of two sections. The first section included questions about sociodemographics (e.g., gender, age, education, and occupation). The second section included measurement items to evaluate the importance of proposed factors. Appendixes I and II show all the measurement items used in the survey. For example, "Using the proposed HRC system will increase my productivity" is one of the measurement items for the factor perceived usefulness. Each item was measured on a 5-point Likert-type scale ranging from strongly disagree to strongly agree, depending on the extent to which each respondent agreed with statements about the measure. This scale has been widely used by previous researchers since it reduces frustration level of survey participants (Dawes 2008) and increases response rate and response quality (Sachdev and Verma 2004). A few items were reverse-coded since they were negatively worded to express the characteristics of corresponding factors.

Participants

The survey responses were collected from individuals in the US construction industry (aged 18 years or older) to identify influential factors of intention to work in the HRC system. The survey was distributed to trade unions and contractors who shared it with construction personnel. The survey was carried out between September 2021 and November 2021 using Google Forms, a free online survey platform. A total of 156 valid responses were collected for statistical and SEM analyses from wide-ranging construction personnel, which can be classified into five groups (craftsman, supervisor, manager, engineer, and director).

Craftsman and supervisor groups work on construction sites and typically identify with job titles such as bricklayers, carpenters, plumbers, technicians, and superintendents. Because the survey specified "choose all that apply" to the question about current job titles, some participants chose more than one, resulting in a total of more than 156 for the five groups (Table 1). Regarding the current work titles, three responses did not have values assigned to working experiences and were classified as "missing" in Table 1. Among the respondents, 83.33% were male, 14.74% identified as female, and 1.92% answered "prefer not to answer." The proportions of the younger-aged group (18–35 years) and the middle-aged group (older than 35 years) were 39.75% and 60.25%, respectively. More than 57% of the participants have working experience of more than 10 years in construction. Specifically, the approximate average working experience for each current title is 22.9 years for craftsman, 20.0 years for supervisors, 14.9 years for managers, 8.6 years for engineers, and 27.2 years for directors.

Analytical Approach

Factor analysis and SEM are used to identify influential factors in HRC adoption in construction. The former includes an exploratory factor analysis (EFA) and a confirmatory factor analysis (CFA).

Table 1. Overview of the survey participants ($N = 156$)

Variable	Group	Frequency	Percentage
Current work titles	Craftsman	47	30.13
	Supervisor	77	49.36
	Manager	60	38.46
	Engineer	18	11.54
	Director	6	3.85
Work experience (years)	Less than 4	16	10.26
	4–10	47	30.13
	11–20	32	20.51
	21–30	41	26.28
	Over 30	17	10.90
	Missing	3	1.92
	Total	156	100.00

Both factor analysis methods have been widely used in previous studies to validate survey items and underlying factors about acceptance of new technologies (Lee et al. 2015) as well as understanding construction projects (Liu et al. 2017; Chen et al. 2018). Fig. 2 shows the research methodology used in this study.

After designing a research model and collecting survey data, data suitability is examined by the Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity tests. The tests should be performed to confirm that the initial variables have strong correlations (Liu et al. 2018). The KMO value above 0.5 is appropriate for factor analysis, larger than 0.6 is mediocre, larger than 0.7 is middling, larger than 0.8 is meritorious, and larger than 0.9 is considered marvelous (Andersen and Herbertsson 2005). Appropriate KMO values denote that measurement items can be grouped into a smaller set of factors (Craig and Sprang 2010). The significance value of the Bartlett test of sphericity should be smaller than 0.05, indicating that the correlations among variables are high (Le et al. 2014).

EFA is conducted to identify theoretical constructs and relationships among variables for an extended TAM-IDT for HRC adoption in the construction industry. IBM SPSS Statistics 26.0 software is used for the statistical analysis in this research. The appropriateness of the proposed grouping of the variables is confirmed through EFA.

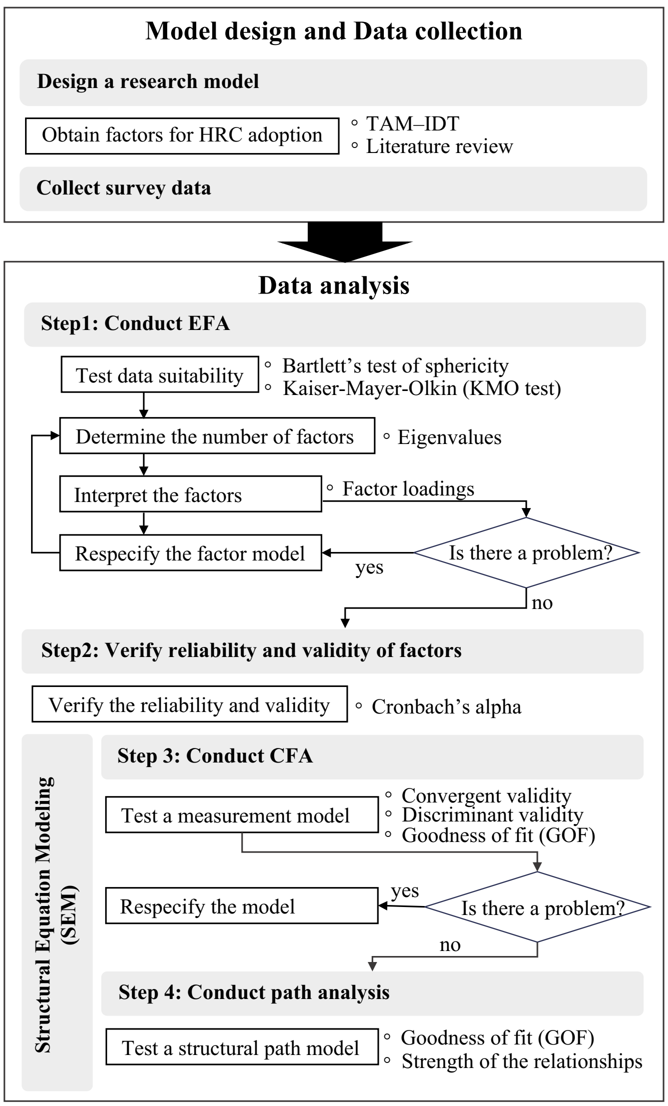

Fig. 2. Research methodology to examine factors affecting HRC adoption in construction.

At first, the number of factors was determined by the eigenvalues. The factors having eigenvalues greater than one are considered significant (Hair et al. 2010; Lee et al. 2015). Next, according to the guidelines for identifying significant factor loadings (Hair et al. 2010), a threshold of 0.45 is used since it is appropriate for the sample size of about 150. Then, the Cronbach's alpha coefficient is calculated to assess the composite reliability of each factor. The Cronbach's alpha value represents how well a group of items measures a single latent construct. The Cronbach's alpha, greater than 0.6, is regarded as acceptable (Nunnally 1978).

SEM models consist of a measurement model and a structural path model. The measurement model considers the relationships between measurement items and factors. It was tested by CFA, evaluating convergent and discriminant validity. At first, the convergent validity was verified by computing factor loadings, the average variance extracted (AVE), and composite reliability (CR). The value of the factor loading and AVEs should be higher than 0.5 (Hair et al. 2010), and the value of CR is recommended to be above 0.6 to achieve validity (Fornell and Larcker 1981). Discriminant validity is supported when the square root of every AVE is larger than any correlation value among any pair of factors (Fornell and Larcker 1981). Based on the results of CFA, a measurement model, which deals with the relationship between a factor and its variables, can be respecified to create the best fit model (Ahmed 2010). The goodness of fit (GOF) of the model is checked through multiple measures.

Finally, a path analysis is used to test multiple hypotheses simultaneously and evaluate relationships among proposed factors for HRC adoption. This study tests the relationships between variables by using the standardized path coefficient, indicating the strengths of the relationships between variables, and squared multiple correlations (R^2), representing the percentage of variance explained by independent variables (Wang and Wang 2009).

Research Findings

Exploratory Factor Analysis

The quality of the data to support EFA was examined by the KMO and Bartlett's sphericity tests. The results in Table 2 show that the data were appropriate for factor analysis.

EFA was conducted to identify the structure and relationships among items by determining the number of factors. Eight factors with eigenvalues over 1 were extracted, which accounted for 73.679% of the cumulative variance (Appendix III). The number of the factors was one less than the nine included in the initial model, indicating that the measurement items were arranged differently from the initial model. To understand the factors better, this study examined factor loadings for each item. The factor groupings based on a principal component analysis (PCA) with varimax rotation are given in Appendix IV. When using the criterion value of 0.45, a total of eight items were deleted: RA3, PC4, PC6, OT4, OT6, CP4, LS6, and JS7.

In addition, several items were moved under different factors than they were originally intended for (Appendix IV), resulting in a modified model and new hypotheses as shown in Fig. 3 and

Table 2. KMO and Bartlett's test of sphericity

Sampling adequacy measure	Value
Kasier-Meyer-Olkin (KMO)	0.893
Bartlett's test of sphericity	—
Significance	0.000

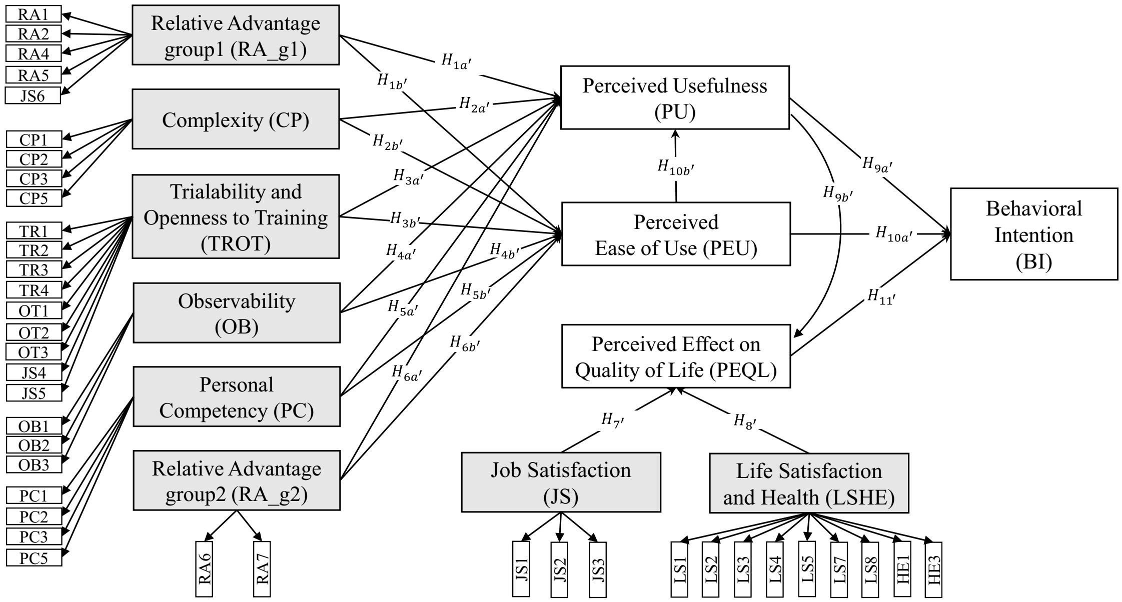

Fig. 3. Baseline (modified) model of factors influencing HRC adoption in construction.

Table 3. For example, items of RA were redistributed to two factors (RA_g1 and RA_g2), and JS items to three different factors. RA_g2 consisted of two items (RA6 and RA7) related to improving work accuracy. JS was composed of three items (JS1, JS2, and JS3) leading to personal gain or personal growth rather than improving the work environment. On the other hand, there were cases where two or more factors were regrouped into one. A factor TROT consisted of nine measurement items related to TR, OT, and JS. The items of TR and OT were similar in that they were about training and demonstration of new technologies, while both JS4 and JS5 were related to safety management. It can be explained that the TROT addressed construction personnel's expectations of management since it focused on training management and covered the ability to manage the safety of the work environment. Measurement items for LS and HE were combined into one factor, LSHE. Life satisfaction is a predictor of health (Koivumaa-Honkanen et al. 2000), and chronic pain negatively impacts life satisfaction (McNamee and Mendolia 2014). Therefore, the association between life satisfaction and health may bring about the new factor LSHE.

Reliability and Validity of Factors

Cronbach's alpha coefficients for the eight factors were calculated to verify the reliability and validity of the data. Two factors of CP and RA_g2 had values lower than the value of 0.6, which is unacceptable. The two factors' reliability was reverified by deleting one item from each. The deleted items were selected based on Cronbach's alpha test in the SPSS Statistics 26.0, which recalculated Cronbach's alpha when one item was deleted. By removing OT5 and RA8 from factors CP and RA_g2, respectively, both factors obtained satisfactory Cronbach's alpha values. Finally, Cronbach's alpha values for the eight factors ranged from 0.767 to 0.948, showing that the items were reliable and internally consistent (Appendix IV).

Table 3. Modified hypotheses based on the results of EFA

Hypotheses-a	Path-a	Hypotheses-b	Path-b
$H_{1a'}$	RA_g1 to PU	$H_{6a'}$	RA_g2 to PU
$H_{1b'}$	RA_g1 to PEU	$H_{6b'}$	RA_g2 to PEU
$H_{2a'}$	CP to PU	$H_{7'}$	JS to PEQL
$H_{2b'}$	CP to PEU	$H_{8'}$	LSHE to PEQL
$H_{3a'}$	TROT to PU	$H_{9a'}$	PU to BI
$H_{3b'}$	TROT to PEU	$H_{9b'}$	PU to PEQL
$H_{4a'}$	OB to PU	$H_{10a'}$	PEU to BI
$H_{4b'}$	OB to PEU	$H_{10b'}$	PEU to PU
$H_{5a'}$	PC to PU	$H_{11'}$	PEQL to BI
$H_{5b'}$	PC to PEU	—	—

Validation of Measurement Model

Tables 4–6 represent the results of CFA. A total of 10 measurement items were deleted because of the low factor loadings or cross-loading. Most AVEs were higher than 0.5, but AVEs for PC and PEU are 0.493 and 0.464, respectively. However, the convergent validity of the factor is adequate if AVE is less than 0.5, but CR is higher than 0.6 (Fornell and Larcker 1981). Therefore, all the AVEs and CRs for the proposed measurement model were acceptable.

The calculation results showed that there was insufficient discriminant validity. The square root of AVE for RA_g1 was 0.73, lower than 0.74, the correlation value between LSHE and RA_g1. If discriminant validity is not confirmed, it weakens the

Table 4. Results of CFA about PEQL

Factor	Code	Factor loading	AVE (CR)
LSHE	LS3	0.949	0.631
	LS1	0.946	(0.938)
	LS2	0.926	
	LS4	0.776	
	LS8	0.735	
	LS5	0.730	
	HE3	0.710	
	LS7	0.670	
	HE1	0.626	
JS	JS3	0.811	0.573
	JS1	0.789	(0.800)
	JS2	0.663	

Table 5. Results of CFA about PU and PEU

Factor	Code	Factor loading	AVE (CR)
TROT	TR3	0.906	0.627
	TR4	0.901	(0.924)
	TR2	0.894	
	TR1	0.851	
	OT1	0.780	
	OT3	0.727	
	JS5	0.700	
	OT2	0.681	
	JS4	0.627	
PC	PC1	0.733	0.493
	PC2	0.723	(0.795)
	PC3	0.698	
	PC5	0.651	
CP	CP1	0.891	0.745
	CP5	0.834	(0.854)
OB	OB2	0.930	0.734
	OB1	0.873	(0.891)
	OB3	0.758	
RA_g1	RA4	0.799	0.535
	RA1	0.772	(0.873)
	RA2	0.743	
	RA6	0.671	
	JS6	0.669	
RA_g2	RA7	0.949	0.823
	RA6	0.863	(0.903)

Table 6. Results of CFA about BI

Factor	Code	Factor loading	AVE (CR)
PU	PU3	0.805	0.563
	PU1	0.757	(0.793)
	PU2	0.683	
PEU	PEU2	0.860	0.464
	PEU1	0.711	(0.807)
	PEU5	0.684	
	PEU3	0.592	
	PEU6	0.505	
PEQL	PEQL3	0.849	0.700
	PEQL1	0.844	(0.875)
	PEQL2	0.816	
BI	BI2	0.864	0.671
	BI3	0.832	(0.911)
	BI5	0.897	
	BI1	0.806	
	BI4	0.785	

results and creates problems with interpretation of the results (Farrell 2010). One of the suggestions to deal with this issue is to identify cross-loading items in EFA and remove the offending items to improve the discriminant validity. There were cross-loadings for HE2 and HE4, which had more than one significant loading. Both items had loadings greater than 0.5 for LSHE and RA_g1, and small loading differences were identified for the two factors. Discriminant validity was established when the two measurement items were deleted from each factor as shown in Appendix V.

The GOF of the measurement model was checked through multiple measures, including the chi-square with regards to the degree of freedom (X^2/df), P close, the root-mean-square error of

Table 7. Fit indices for research model

GOF	Recommended value (Ref)	Measurement model	Baseline model	Final SEM
X^2/df	≤3.0 (Wang and Liao 2008)	2.143	2.400	2.223
P close	<0.05 (Awang 2012)	0.000	0.000	0.000
RMSEA	≤0.1 (Durdyev et al. 2018)	0.086	0.095	0.089
CFI	≥0.9 (Wang and Liao 2008)	0.788	0.730	0.765
TLI	≥0.8 (McManus et al. 2017)	0.759	0.704	0.742

approximation (RMSEA), the comparative fit index (CFI), and the Tucker-Lewis index (TLI). Table 7 lists the desirable GOF indices and model fit values. The measurement model had relatively lower CFI and TLI values, but they were close to the recommended level. Thus, the measurement model fitted relatively well.

Validation of Structural Path Model

Concerning the structural model, the GOF measures of chi-square, P close, RMSEA, CFI, and TLI were used to confirm if the model fits the data. The baseline model had a CFI value of 0.730 and a TLI value of 0.704, which was lower than the recommended levels of greater than 0.9 and 0.8 (Table 7), respectively. The base model was modified to enhance the model fit by drawing a correlation path between factors. A total of four correlations were drawn for the factors with high correlation values examined in the discriminant validity test. Correlations were drawn between TROT and OB, RA_g1 and RA_g2, LSHE and RA_g1, and LSHE and RA_g2.

Regarding TROT and OB, it was found that observability is positively related to trialability (Lin and Bautista 2017). In addition, both TROT and OB can be highly relevant because they are directly or indirectly related to personnel's experience of the HRC system. Three factors of LSHE, RA_g1, and RA_g2 are all related to the benefits of a job in HRC. After drawing the four correlations, most of the model-fit measures were found to be better than before as shown in Table 7. It can be said that the model had a good fit because three model-fit indices met the recommended value and two indices of CFI and TLI were slightly below the acceptance level (Lee et al. 2015).

Fig. 4 shows the analysis results of the structural model with significant paths as solid lines and nonsignificant paths as dashed lines and the standardized path coefficients between factors. Thirteen of the 19 path coefficients were significant at 0.1, 0.05, 0.01, and 0.001 significance levels. For the dependent factors of BI, PU, PEU, and PEQL, the R^2 coefficients were above the satisfactory level of 0.10 (Falk and Miller 1992). The model had the R^2 value of 80.1% for PU, 74.0% for BI, 70.9% for PEQL, and 60.7% for PEU.

In terms of path analysis, the results of SEM analysis provided significant support for proposed hypotheses at a significance level of 0.1, 0.05, 0.01, and 0.001, except six hypotheses ($H_{3a'}$, $H_{4a'}$, $H_{6a'}$, $H_{6b'}$, $H_{10a'}$, and $H_{11'}$). There were 10 accepted and significant hypotheses for the eight external constructs. Regarding the hypotheses affecting perceived usefulness, hypotheses $H_{1a'}$, $H_{2a'}$, and $H_{5a'}$ were accepted. RA_g1 was the determinant contributing the highest impact on the perceived usefulness ($\beta = 0.835$, $p < 0.001$), followed by CP and PC. Five hypotheses for the perceived ease of use were accepted ($H_{1b'}$, $H_{2b'}$, $H_{3b'}$, $H_{4b'}$, and $H_{5b'}$). PC had the strongest effect on the perceived ease of use ($\beta = 0.411$, <0.001), followed by CP, TROT, OB, and RA_g1. JS ($\beta = 0.651$, $p < 0.001$) and LSHE ($\beta = 0.339$, $p < 0.001$) positively influenced the perceived effect on life quality. In terms of hypotheses about internal constructs, three hypotheses of $H_{9b'}$, $H_{9a'}$, and $H_{10a'}$ were accepted. $H_{9b'}$ described that path between

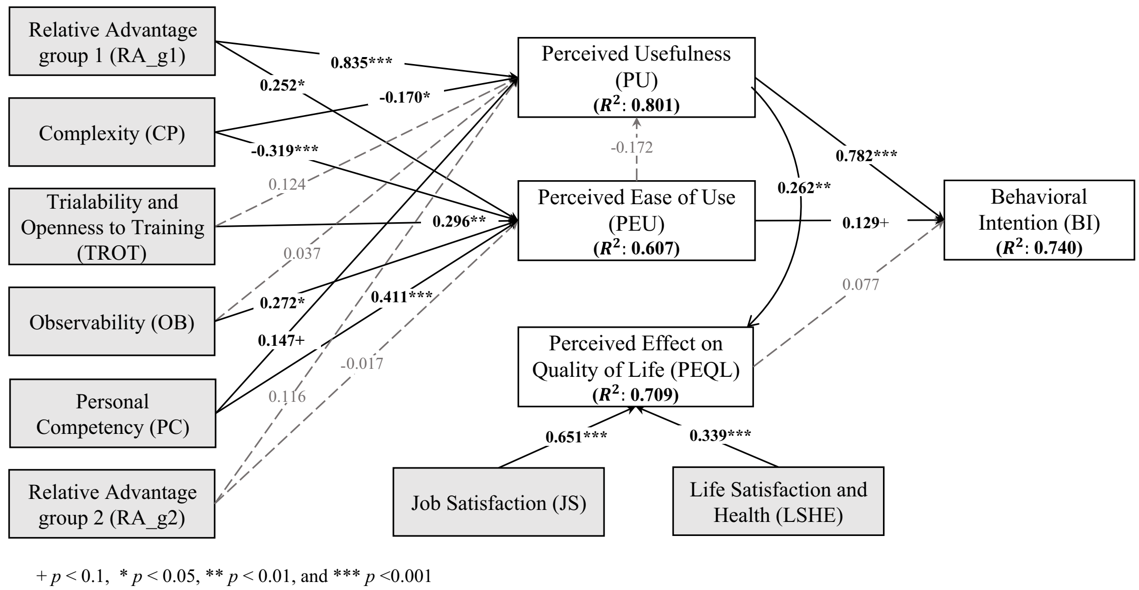

Fig. 4. Results of hypothesis testing.

PU and PEQL, indicating that the perceived usefulness enhanced the perceived effect on life quality. The findings show PU influenced BI with a path coefficient of 0.782 ($p < 0.001$) and PEU with a coefficient of 0.129 ($p < 0.1$). Appendix VI shows the results of direct, indirect, and total effects.

In summary, this study identified a total of seven factors affecting construction personnel's HRC acceptance. PU and PEU had positive impacts on behavioral intention to work in the HRC system, and PU had more significant relationship with the intention. Among external factors, five factors (RA_g1, CP, TROT, OB, and PC) positively influenced PU or PEU. It implies that it is important to emphasize the overall benefits of HRC and opportunities for experiences and proper trainings for the new paradigm of managing the work performed by construction personnel.

Discussion

Theoretical Implication

The results of this study found that two TAM-related hypotheses were supported. Both PU and PEU positively influence intention to work in the proposed HRC system. This means that construction personnel have a positive attitude toward HRC acceptance when they find the new system useful and easy to use. This finding is in conformity with previous studies (Tan et al. 2014; Abdullah et al. 2016). However, PEU had no significant relationship with PU, not consistent with the results of the previous studies (Tan et al. 2014; Lee et al. 2015; Teo et al. 2018). The path from PEU to PU can be considered insignificant under certain circumstances (Chung et al. 2010). For construction personnel who are already adept at complicated construction tasks, the ease of use of HRC may not be an essential factor for construction personnel in recognizing the usefulness of HRC.

Six hypotheses were supported for the five external factors related to IDT ($H_{1a'}$, $H_{1b'}$, $H_{2a'}$, $H_{2b'}$, $H_{3b'}$, and $H_{4b'}$), while four were not ($H_{3a'}$, $H_{4a'}$, $H_{6a'}$, and $H_{6b'}$). First, two hypotheses about RA_g1 were supported, conforming to those of the studies (Al-Rahmi et al. 2019; Yuen et al. 2021) that found that relative advantage had positive effects on PU and PEU. Surprisingly, two hypotheses on RA_g2 had no significant impact on the PU and PEU. While RA_g1 dealt with overall benefits from the advanced HRC system, RA_g2 focused on reduced rework and errors. It may be explained that construction personnel value advanced features and better working conditions over the improved accuracy brought about by the HRC.

In terms of the factor CP, the previous studies found that CP negatively and significantly influences the intention to use (Chou and Yutami 2014; Besklubova et al. 2021), which is consistent with the results of this study. This means that construction personnel are inclined to perceive the HRC system as laborious and useless when they find it complicated and complex to learn how to use. The effects of TROT and OB on PEU were statistically significant but not on PU. These results are consistent with previous studies showing that trialability (Teo et al. 2018), training (Tan et al. 2014), and observability (Al-Rahmi et al. 2019) were important factors in explaining the perceived ease of use. The two constructs of TROT and OB are associated with the availability of opportunities for experiences of the HRC system. Therefore, construction personnel tended to view the technology as easy to use when they had more opportunities to try them.

PC had a significant impact on PU and PEU. This result is consistent with Lee et al. (2015), where organizational and personal competencies correlated with PU and PEU, respectively. This finding indicated that construction personnel tended to perceive the HRC system as useful and easy to use when they have knowledge, skills, and experiences required for collaboration with robots.

The proposed adoption model includes PEQL as well as PU and PEU as middle constructs. PEQL had a positive relationship with two external constructs, JS and LSHE. It is argued that job satisfaction, life satisfaction, and health are important constructs in perceived effect on the quality of life. A significant number of construction workers exceed the generally accepted physiological thresholds for manual work (Abdelhamid and Everett 2002), leading to physical pain related to impaired quality of life (Morken et al. 2002). This problem can be solved with the help of collaborative robots at construction sites. Improved mental and physical health can contribute to them having more personal time to recover their work-life balance. Therefore, when job satisfaction, life satisfaction, and better health condition are perceived by collaboration with robots, construction personnel tend to perceive the effect on the quality of life.

This study identified that PEQL was influenced by PU in addition to JS and LSHE. The path from PU to PEQL indicated that usefulness obtained from collaborative robots had a significantly positive relationship towards perceived effect on the quality of life. Regarding this relationship, previous studies have suggested that the benefits provided by robotic systems contribute to improving the quality of life of users (Tapus 2009; Fonseca et al. 2019). Similarly, construction personnel will be able to expect to work in better working conditions, improve productivity, and reduce occupational risks, resulting in a perceived better quality of life.

This study proposed an extended TAM-IDT research model for HRC acceptance in construction. It helps enrich understanding of factors using acceptance theories in construction. In the construction industry, most studies have focused on TAM (Lee et al. 2015; Choi et al. 2017; Elshafey et al. 2020; Kim et al. 2022; Zhang et al. 2022), whereas IDT has been used in the two studies (Elshafey et al. 2020; Pan and Pan 2020a). Pan and Pan (2020a) integrated IDT with TOE to examine organizational innovation and Elshafey et al. (2020) proposed a research model in which factors of TAM, IDT, and two different theories are in the same order. This study integrated TAM and IDT and extended it using additional factors. Based on it, we identified that five factors (RA_g1, CP, TROT, OB, and PC) influenced construction personnel's HRC acceptance through PU or PEU. Next, this study explored factors related to construction personnel's HRC acceptance using path analysis and 156 survey data inputs. It directly addresses a research gap on HRC adoption in construction since previous studies dealt with perspectives of organization or conducted qualitative analysis.

Management Implication

The findings have several practical management implications for the construction industry particularly for middle and upper management in order to foster best pathways to introduce HRC and encourage acceptance on the part of construction personnel. The results suggest that construction personnel's HRC adoption can be enhanced by improving the system features. The construction firms should pay more attention to the relative advantages of HRC since the advantages are the most critical to construction personnel's recognition of the usefulness of HRC. It is also crucial that the construction companies provide effective on-the-job training and mandatory education programs that positively impact personnel's awareness about ease of use. When the construction companies design these strategies, they need to consider how to manage the complexity of the new working system. Consequently, construction personnel can develop their technical capabilities from the appropriate support they receive from the companies, and increase their likelihood of accepting the system.

The results of this study suggest that construction personnel tend to perceive that the HRC system is easy to use when they have technical capabilities of using robotic devices and no objections to the use of new technologies. In order to address the aging working population in the construction industry, construction companies can appeal to young generations who possess more digital capabilities than older and senior personnel. In addition, human workers will not perform physically strenuous and demanding tasks due to automated working conditions with collaborative robots. This study showed that these characteristics positively impacted the perceived usefulness and intention to work in the HRC system. The results are helpful for construction companies to anticipate worker acceptance and actions necessary to promote acceptance and ensure successful development. The construction companies can recruit and hire workers of diverse physical abilities extending the target population and creating job opportunities for individuals who never considered construction as a viable career path.

Conclusion

There has been growing interest in utilizing collaborative robots in the construction industry. As construction personnel face new working environments and changing roles when working with robots, it is important to identify what factors affect their HRC acceptance. This study proposed an extended TAM with concepts from the IDT and variables about quality of life, aiming to examine factors that affect behavioral intention to work in the HRC system. The proposed model verified the effect of PU and PEU on BI regarding TAM. The effects of relative advantages, complexity, trialability, and observability about IDT were also verified. It was noted that perceived usefulness and relative advantages are the most significant factors among internal and external variables. PEQL, a newly added construct in this study, had no significant impact on BI but was found to be influenced by PU.

Limitation and Future Studies

The research has a few limitations. Firstly, all the survey responses were collected in the United States, so the results could not be generalized to other countries. Future studies need to consider construction personnel in other countries to generalize the findings of the intention to adopt HRC. Second, this study did not consider different demographics and occupational factors of construction personnel when identifying critical factors for HRC adoption. To more thoroughly investigate the intention of construction personnel, future studies can consider different characteristics of construction personnel like education levels, years of working experience, and career types for further analyses.

Appendix I. Factors and Measurement Items of External Variables for HRC Acceptance

Factor	Code	Measurement criteria	Reference
Relative advantages	RA1	In an HRC system, working with robots would enable me to accomplish my tasks more quickly (be more productive) compared with the methods I use to complete the work now.	Prasath Kumar et al. (2016); Lattanzi and Miller (2017); Pan et al. (2018); Pan and Pan (2020b); and Asatiani et al. (2020)
	RA2	New working conditions of HRC system would make my work more enjoyably due to more pleasant working environment compared to current working conditions.	
	RA3	Knowing how to use the HRC system would make me more competitive in the job market.	

Appendix I. (*Continued.*)

Factor	Code	Measurement criteria	Reference
	RA4	Compared with current construction sites, a construction site where HRC is being used would run more efficiently because it will be highly equipped with automated systems.	
	RA5	Compared with current construction sites, I would receive enough help and equipment to get the job done with advanced communication system of the HRC.	
	RA6	The proposed HRC system will lead to reduced rework on the construction site.	
	RA7	The proposed HRC system will lead to reduced errors on the construction site.	
	RA8	The proposed HRC system will lead to reduced safety-related incidents on the construction site.	
Complexity	CP1	I believe that HRC systems will be complex for me to use when completing tasks on a construction site.	Pan and Pan (2020b) and Pradhananga et al. (2021)
	CP2	I believe that the implementation of HRC system on construction sites is a complex process.	
	CP3	I believe that the proposed HRC systems are bulky, heavy, and high-power.	
	CP4	I believe that HRC systems can be used for all construction activities.	
	CP5	I believe that HRC systems would be complex for me to learn.	
Trialability	TR1	Before I decide to use the proposed HRC system, I would like to try it on demonstration constructions tasks.	Lin and Chen (2012); Nikou (2019); Yuen et al. (2021); and Ramdani et al. (2013)
	TR2	Before I decide to use the proposed HRC system at work, I would like to receive instructions on how the different technologies and components of the systems function.	
	TR3	Before I decide to use the proposed HRC system at work, I would like to view a demonstration of how the technology can be implemented in my craft.	
	TR4	Before I decide to use the proposed HRC system at work, I would like to have a chance to get training by working directly with the system and learning how to interact with it while completing construction tasks.	
Observability	OB1	I will be encouraged to use the proposed HRC system if I see my colleagues and other workers using the proposed HRC system on construction jobs.	Lee et al. (2011); Al-Rahmi et al. (2019); and Nikou (2019)
	OB2	I will be encouraged to use the proposed HRC system if many construction companies decide to adopt the HRC system.	
	OB3	I will be encouraged to use the proposed HRC system if I can observe many vocational schools or unions decide to offer training opportunities with the HRC system on construction jobs.	
Openness to training	OT1	A training program for the proposed HRC system will help me to learn how to use the technology.	Won et al. (2013); Liao and Teo (2017); Delgado et al. (2019); and Pan and Pan (2020a)
	OT2	I have no objections to taking formal training courses in the use of the HRC system through vocational schools, unions, or workshops.	
	OT3	If formal training programs for the HRC system are offered by my employer, I will enroll in them.	
	OT4	I am willing to learn how to use the proposed HRC system on my own if training material is made available.	
	OT5	I worry about the cost of training associated with the HRC system.	
	OT6	I will only accept training in the HRC system if my employer pays for it.	
Personal competency	PC1	I am familiar with using tablets or headsets for virtual reality (VR) or augmented reality (AR).	Cohen and Levinthal (1990) and Lee et al. (2015)
	PC2	I have the technical capability of using robotic devices such as cleaning robots, drones, and smart gloves.	
	PC3	I am always excited about using new technological devices such as computer, smartphone, digital camera, or other electronic device.	
	PC4	I do not have any objections to using new technologies in general.	
	PC5	I feel it is easy to understand how to use a technological device alone when I first experience it.	
	PC6	I always need instructions of use when I manipulate technological devices that I am not familiar with.	
Job satisfaction	JS1	My job security would be better in the long term when working on construction sites that deploy HRC systems.	NIOSH (2010) and Bergson-Shilcock (2020)
	JS2	I would be able to develop my own abilities to use the HRC system by enrolling in new training programs.	
	JS3	My income would be better if I work in construction jobs that use the HRC system.	
	JS4	The safety of workers would be a high priority with management where HRC system is applied.	
	JS5	Where HRC system is applied, employees and management would work together to ensure the safest possible working conditions.	
	JS6	Working with co-robots in the HRC system would decrease occupational risks.	
	JS7	I will worry about my personal safety when working in close proximity to construction robots.	

Appendix I. (*Continued.*)

Factor	Code	Measurement criteria	Reference
Health	HE1	On construction jobs that adopt the proposed HRC system, my physical health would be better due to less exposure to construction site pollution (air, soil, and/or noise pollution).	Boschman et al. (2013) and Pan and Pan (2020b)
	HE2	On construction jobs that adopt the proposed HRC system, my physical health would be better because robots will do the physical work.	
	HE3	On construction jobs that adopt the proposed HRC system, less exposure to construction site pollution (air and/or noise pollution) would reduce mental health conditions from work environments.	
	HE4	On construction jobs that adopt the proposed HRC system, I would experience better mental health because the robots will do repetitive and strenuous physical work.	
Life satisfaction	LS1	When working on construction jobs that adopt the proposed HRC system, I would have enough personal time to do things that I like to do outside of work.	Loewe et al. (2014); and Langdon and Sawang (2018)
	LS2	When working on construction jobs that adopt the proposed HRC system, I would have enough time to spend with family and friends.	
	LS3	When working on construction jobs that adopt the proposed HRC system, I would have enough time to spend on entertainment and recreation.	
	LS4	By working on construction jobs that adopt the proposed HRC system, my overall health will improve.	
	LS5	Even if I get a salary that is similar to my current salary, by working on construction jobs that adopt the proposed HRC system, I would be more satisfied than now.	
	LS6	By working on construction jobs that adopt the proposed HRC system, I would feel more self-confident with my experiences to perform new kinds of work.	
	LS7	By working on construction jobs that adopt the proposed HRC system, I would be satisfied with the responsibility I have in my work.	
	LS8	By working on construction jobs that adopt the proposed HRC system, my life would be close to my ideal in most ways.	

Appendix II. Factors and Measurement Items of Internal Variables for HRC Acceptance

Factor	Code	Measurement criteria	Reference
Perceived usefulness	PU1	Using the proposed HRC system will increase my productivity.	Davis (1989)
	PU2	Using the proposed HRC system will be useful in that I could do my job regardless of any physical disability (either my arm hurts or my strength is weak) with robots.	
	PU3	Using the proposed HRC system will enhance efficiency and effectiveness on the job.	
	PU4	My training programs were very useful for my past promotions.	
	PU5	My professional certificates were very useful for my past promotions.	
	PU6	My daily work benefited significantly from past professional training.	
Perceived ease of use	PEU1	I am good with technology and using the proposed HRC system will be easy for me.	Davis (1989) and Yuen et al. (2021)
	PEU2	I will become skillful at using the proposed HRC system in a short amount of time.	
	PEU3	Interacting with the proposed HRC system would not require a lot of mental effort.	
	PEU4	If it is complicated to learn the proposed HRC system, I will be confused or frustrated when I use it.	
	PEU5	If training material is provided for how to use the new HRC system, I will review the material to be able to use the HRC system.	
	PEU6	I will need minimal training to be able to use the HRC system in my work.	
	PEU7	I do not think it will be easy for me to learn how to use the HRC system.	
Perceived effect on quality of life	PEQL1	I will work or continue working on construction jobs that adopt the proposed HRC system because it will increase my satisfaction with the work.	Loewe et al. (2014)
	PEQL2	Working on construction jobs that adopt the proposed HRC system will improve my overall quality of life by making me feel that I have the important things I wanted in life.	
	PEQL3	I feel that the proposed HRC system, if adopted by my employer, will have positive effect on me.	
Behavior intention	BI1	I intend to learn and use any new technologies such as HRC systems in the future.	Davis (1989) and Yuen et al. (2021)
	BI2	I plan to learn and use the proposed HRC system in the future.	
	BI3	I feel the proposed HRC technologies will have a positive impact on my career.	
	BI4	I feel the proposed HRC technologies will have a positive impact on the construction industry.	
	BI5	I will encourage other workers to use the proposed HRC system.	

Appendix III. Eigenvalues and Cumulative Variance

Factor	Eigenvalue >1	Cumulative variance ≥60%
1	15.097	36.822
2	5.116	49.299
3	2.532	55.474
4	2.032	60.429
5	1.655	64.467
6	1.393	67.865
7	1.349	71.155
8	1.035	73.679

Appendix IV. Exploratory Factor Analysis Results

Factor	Code	Factor loading	Cronbach's alpha
Trialability and openness to training (TROT)	TR2	0.859	0.937
	TR1	0.849	
	TR4	0.832	
	TR3	0.825	
	OT1	0.816	
	OT2	0.758	
	OT3	0.728	
	JS5	0.517	
	JS4	0.463	
Life satisfaction and health (LSHE)	LS2	0.901	0.948
	LS1	0.894	
	LS3	0.885	
	LS8	0.704	
	LS4	0.671	
	HE3	0.664	
	LS5	0.630	
	HE1	0.583	
	LS7	0.519	
	HE2	0.515	
Relative advantage group1 (RA_g1)	RA2	0.786	0.873
	RA1	0.760	
	RA4	0.632	

Appendix IV. (*Continued.*)

Factor	Code	Factor loading	Cronbach's alpha
	HE4	0.606	
	RA5	0.539	
	JS6	0.532	
Personal competency (PC)	PC2	0.790	0.790
	PC1	0.770	
	PC5	0.710	
	PC3	0.581	
Job satisfaction (JS)	JS1	0.802	0.787
	JS3	0.783	
	JS2	0.597	
Complexity (CP)	CP5	0.838	0.767
	CP1	0.834	
	CP3	0.711	
	CP2	0.633	
	OT5	—	
Observability (OB)	OB2	0.765	0.881
	OB1	0.754	
	OB3	0.586	
Relative advantage group2 (RA_g2)	RA6	0.708	0.901
	RA7	0.645	
	RA8	—	

Note: Items in bold were deleted to meet the threshold of Cronbach's alpha.

Appendix V. Correlation Matrix of Factors

Factor	TROT	LSHE	RA_g1	PC	CP	JS	RA_g2	OB
TROT	**0.79**	—	—	—	—	—	—	—
LSHE	0.25	**0.79**	—	—	—	—	—	—
RA_g1	0.47	0.65	**0.73**	—	—	—	—	—
PC	0.39	0.44	0.62	**0.70**	—	—	—	—
CP	0.00	−0.15	−0.19	−0.26	**0.86**	—	—	—
JS	0.37	0.52	0.48	0.46	−0.05	**0.76**	—	—
RA_g2	0.41	0.64	0.66	0.44	−0.05	0.41	**0.91**	—
OB	0.71	0.31	0.49	0.35	0.13	0.35	0.32	**0.86**

Note: Numbers on the diagonal (in bold) are the square roots of AVEs.

Appendix VI. Direct, Indirect, and Total Effects

Latent constructs	Total effect				Direct effect				Indirect effect			
	PU	PEU	PEQ	BI	PU	PEU	PEQ	BI	PU	PEU	PEQ	BI
TROT	0.073	0.296	0.019	0.097	0.124	0.296	0	0	−0.051	0	0.019	0.097
LSHE	0	0	0.339	0.026	0	0	0.339	0	0	0	0	0.026
RA_g1	0.792	0.252	0.207	0.668	0.835	0.252	0	0	−0.043	0	0.207	0.668
PC	0.077	0.411	0.020	0.115	0.147	0.411	0	0	−0.071	0	0.020	0.115
CP	−0.116	−0.319	−0.030	−0.134	−0.170	−0.319	—	0	0.055	0	−0.030	−0.132
JS	0	0	0.651	0.050	0	0	0.651	0	0	0	0	0.050
RA_g2	0.119	−0.017	0.031	0.093	0.116	−0.017	0	0	0.003	0	0.031	0.093
OB	−0.010	0.272	−0.003	0.027	0.037	0.272	0	0	−0.047	0	−0.003	0.027
PU	0	0	0.262	0.802	0	0	0.262	0.782	0	0	0	0.020
PEU	−0.172		−0.045	−0.008	−0.172	0	0	0.129	0	0	−0.045	−0.138
PEQ	0	0	0	0.077	0	0	0	0.077	0	0	0	0

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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