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Understanding stakeholders' intention to use construction robots: a fuzzy-set qualitative comparative analysis

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Abstract
User acceptance is crucial for successfully adopting robotic technologies in the architecture, engineering, and construction (AEC) sector. Previous studies have focused on domestic, service, and industrial robots, leaving the construction domain unexplored. In this study, we set out to empirically understand how various dimensions of technology, environment, robot, and user lead to AEC stakeholders' intention to use construction robots. We apply the fuzzy-set qualitative comparative analysis approach to capture the complexity of human behavior and the interdependencies across dimensions. For the data collection, we sampled 216 cases in Switzerland, Germany, and Austria evaluating three scenarios of human–robot interaction. Our analysis identifies three distinct user profiles—*the lifelike robot user*, *the utilitarian robot user*, and *the lifelike-utilitarian robot user*. The results show that human–robot peering may be a fundamental solution to increase user acceptance. By testing the effect of user characteristics, we also discover a lifelike-utilitarian type of robot that is more appealing to female AEC stakeholders. The study contributes to the construction robotics literature by providing tailored design and implementation strategies. It points to future research avenues such as user experience and social factors for exploring the impact of robotics and artificial intelligence in AEC.

Keywords Automation · Construction robotics · Technology adoption · Human–robot interaction · Qualitative comparative analysis

1 Introduction

Automation and robotics have emerged in architecture, engineering, and construction (AEC), promising to address productivity, safety, and labor shortage issues (Bock 2015; Pan and Pan 2020; Jebelli et al. 2022). However, AEC firms seeking to improve their performance using such robotic technologies often report disappointing adoption rates (Forge and Blackman 2010; Ribeirinho et al. 2020). Decision-makers in these firms lack the knowledge to deploy the technologies and create value for their customers effectively (Lavikka et al. 2018). Although numerous systems have undergone feasibility testing in research and field applications (Ardiny et al. 2015; Jung et al. 2013), practitioners still struggle to fully integrate these systems into their production processes (Carra et al. 2018; Paunov et al. 2019). In overcoming these obstacles, user acceptance is a potentially critical yet overlooked component.

User acceptance is defined as the individual's attitude towards using robots as well as their intention to use them. As robots become more ubiquitous in human-inhabited environments, recent research has examined user acceptance in different contexts, including domestic, service, and industrial robots (Bröhl et al. 2019; de Graaf et al. 2017; Wirtz et al. 2018). However, only a few studies have focused on the construction domain (Sam et al. 2022; Walzer et al. 2022). The lack of research is surprising, given the comparatively high risk of automation in construction occupations (Paolillo et al. 2022) and concerns about job losses due to the introduction of robotics (Mansouri et al. 2020; Welfare et al. 2019). Studies suggest that employees are often coerced into

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accepting robotic technologies, potentially leading to psychological harm or ethical concerns (Bendel 2018; Went and Knotterus 2015). The need for user acceptance research has intensified, as according to an international survey of 1900 construction and related businesses, 81% of participants plan to incorporate robots within the next decade (ABB robotics 2021). To truly harness the potential of these technologies, it is thus necessary to explore the circumstances under which user acceptance can be increased among AEC stakeholders.

The unstructured and dynamic nature of construction environments presents unique challenges for human–robot interaction that are not present in other contexts (Stumm et al. 2016). According to Borrmann et al. (2021) and Regona et al. (2022), robotic construction sites comprise a cyber-physical system of hardware and software functions that automate both physical (e.g., repetitive, hazardous) and cognitive (e.g., analytical, creative) work tasks. With the advent of artificial intelligence (AI) technologies, the definition of robotized construction needs to be updated. Liang et al. (2021) proposed an initial taxonomy to classify human–robot teams in construction. However, to account for the continuous evolution of construction robots, they suggest incorporating other established frameworks to articulate characteristics like robot morphology and team composition (Goodrich and Schultz 2007; Onnasch and Roesler 2021).

The introduction of automation and robotics is reshaping construction work processes, resulting in diverse experiences among organizations and individuals. The varying ways AEC stakeholders embrace or resist construction robots add another layer of complexity to the inquiry about user acceptance. At the organizational level, firms face work culture challenges such as employees' aversion to change (Davila Delgado et al. 2019). At the individual level, employees tend to be acutely aware of the characteristics associated with robots, but they hold different positions on the topic (Pan and Niemeyer 2018). Scholars have highlighted knowledge gaps such as human-centered approaches and human behavior when sharing workspace with robots (Ghasempourabadi and Taraz 2021; Onososen and Musonda 2022). There is a need to focus more on AEC stakeholders' perceptions and experiences when assessing the impact of construction robots.

So far, construction robotics research has not extensively dealt with the complex associations between individual factors that shape human–robot interaction and their effects on user acceptance (Kangari and Halpin 1990). Literature on technology adoption and work systems has addressed the social and psychological implications of roboticization, including the roles of perceptions and personality traits (e.g., Harris-Watson et al. 2023; Jackson et al. 2013; Trist and Bamforth 1951). Nevertheless, these issues have been largely overlooked in construction robotics research. Recent studies have captured some of the relationships between AEC stakeholder perspectives and robot use but failed to address others. For instance, Sam et al. (2022) find that construction project managers ascribe more attributes such as productivity and durability to a robotic system when they see it as a teammate. Walzer et al. (2022) report that construction workers across various trades perceive robots differently as a potential threat to their jobs. A simplistic view examining the individual factors and their mechanisms in isolation is insufficient. Therefore, a comprehensive understanding of user acceptance is required, which would have to integrate the technological, environmental, and social aspects of human–robot interaction.

To this end, we argue that a more sophisticated approach, namely a configurational perspective, is needed to unravel the complexity of user acceptance. Configurational thinking involves examining the interdependencies among multiple factors rather than focusing on individual factors. It recognizes the existence of more than one valid pathway leading to a particular outcome. We adopt the configurational approach proposed by Chuah et al. (2021), because our study requires simultaneous consideration of concurrent dimensions in technology, environment, robot, and user. Our research question becomes: *What configuration of explanatory conditions leads to AEC stakeholders' intention to use construction robots?* We conducted both a theoretical and an empirical study to answer this question.

2 State of the art

2.1 Human–robot interaction in construction

There is no consensus in the literature regarding a precise and coherent definition of a construction robot. The history of automation and robotics in construction can be traced back to the 1970s in Japan (Bock 2006). Pioneering milestones include housing prefabrication, single-task construction robots, and integrated automated construction sites (Balaguer and Abderrahim 2008; Bock and Langenberg 2014). With the emergence of Industry 4.0 technologies, the field has evolved into a new era of robotic systems equipped with sophisticated sensors and actuators (Oesterreich and Teuteberg 2016). Recent academic efforts have demonstrated the developments in various aspects, such as rebar, plastering, and excavation robots (Doerfler et al. 2019; Ercan Jenny et al. 2023; Johns et al. 2020). Several attempts have been made to commercialize these innovations, including drywall finishing, field printing, and drilling robots (Canvas 2017; Dusty Robotics 2018; Hilti 2020).

Xu and Garcia de Soto (2020) proposed to characterize the applications of construction robots into four types: off-site prefabrication systems, on-site automated robotic systems, drones, and exoskeleton wearable devices. Pan et al. (2020a, b) suggested another categorization based on the building life cycle (off-site, on-site, operations and maintenance, demolition) and the level of task integration (task-specific, general-purpose, integrated). Nonetheless, these classifications have been complicated by advances in big data, software engineering and AI that enable new forms of robotized construction, such as autonomous construction, multi-robot systems, and collaborative robots (Afsari et al. 2018; Melenbrink et al. 2020; Wallace et al. 2020).

While humans have traditionally been separated from robots in structured assembly-line work, there is an increasing trend towards interaction between workers and robotics on construction sites (Garshasbi et al 2023). Various studies have conceptualized or tested human–robot collaboration on tasks such as installation, painting, welding, and assembly (e.g., Brosque et al. 2020; Kyjanek et al. 2019; Lee and Moon 2014). Human–robot teaming refers to leveraging the complementary skills of humans and robots with the advantage of resolving work uncertainty (Fox 2018). According to Liang et al. (2021), human employees shift their existing duties towards high-level cognitive work while receiving assistance from robots for physical activities. AI has also been integrated as potentially augmenting or replacing construction employees' decision-making for quality improvement or risk reduction (Chen and Ying 2022; Ellis 2023).

2.2 Perception, acceptance, and adoption studies

Research on perception, acceptance, and adoption advances our understanding of human engagement with robots and provides valuable insights for effective robot design and implementation. Social perceptions of a robot are based on impressions of its appearance, movement, and behavior. Studies on how humans perceive robots (e.g., Fink 2011; Stroessner and Benitez 2019) seek to understand the relationships between robot attributes and individuals' judgments. User acceptance refers to individuals' behavior regarding the adoption and use of new technologies in a work context. The most relevant studies are grounded in technology acceptance models and their extensions (TAM, Davis 1989; UTAUT, Venkatesh et al. 2003, 2012). According to the theory of the diffusion paradigm, the adoption of robotics always follows an S-curve over time, even though its social receptivity varies significantly across countries and industries (Rogers 2010).

In Table 1, we review seven papers on perception, acceptance, and adoption from within and beyond the construction domain that demonstrate a variety of research methodologies. The evidence obtained in these studies distinguishes between individual levels by sampling end-users of the robot, such as customers or employees, and organizational levels by sampling decision-makers, such as experts or innovation managers. Methodologically, most studies use a quantitative approach based on regression analysis to capture individual perspectives, an approach that may not capture the complexity of causal relationships. Some researchers rely on in-depth studies based on interviews or focus groups, but the qualitative approach limits the generalizability of their findings. Not surprisingly, mixed-method studies can overcome the drawbacks of both approaches. To achieve a good fit between method and theory, it becomes essential to maintain case sensitivity while searching for patterns in the phenomena of interest (Fiss 2007). In this regard, fuzzy-set qualitative comparative analysis provides a middle ground complementing quantitative (large-N) and qualitative (small-N) settings (De Villiers 2017; Greckhamer et al. 2013).

In the field of construction robotics, much of the current literature focuses on organizational levels. Such studies are often criticized for neglecting factors that may provide deeper insights into why adoption occurs (Kostova and Roth 2002). Very little is known about user acceptance

Table 1 Summary of the reviewed papers in perception, acceptance, and adoption

Reference	Domain	Method and level of analysis	Outcome and variables
Sam et al. (2022)	Construction robots	Survey and regression analysis Organizational: construction managers	Perception: e.g., productivity, predictability, durability
Pan and Pan (2020)	Construction robots	Survey and regression analysis Organizational: contractor companies	Adoption: e.g., relative advantage, top management support, organizational readiness
Davila Delgado et al. (2019)	Construction robots	Focus groups and mixed method Organizational: industry experts	Adoption: e.g., contractor-side economic factors, technical and work-culture factors
Bröhl et al. (2019)	Industrial robots	Survey and regression analysis Individual: manufacture workers	Acceptance: e.g., perceived usefulness, perceived ease of use, job relevance, robot anxiety
Meissner et al. (2020)	Industrial robots	Interviews and qualitative analysis Individual: assembly workers	Acceptance: e.g., perceived risks, perceived benefits, negative feelings
Chuah et al. (2021)	Service robots	Survey and fuzzy-set qualitative comparative analysis Individual: customers	Acceptance: e.g., perceived intelligence, performance Expectancy, hedonic motivation
De Graaf et al. (2017)	Domestic social robots	Survey and regression analysis Individual: users	Acceptance: e.g., personal norms, social norms, control beliefs

by individual AEC stakeholders, particularly trade workers, thus encouraging our study of user perspectives in an organizational context (Busse et al. 2017).

3 Research approach

3.1 Fuzzy-set qualitative comparative analysis

To explore possible explanations for AEC stakeholders' acceptance of construction robots, we use a methodology capable of handling the configurational perspective. Charles Ragin introduced qualitative comparative analysis (QCA), a set-theoretic method based on Boolean algebra (Ragin 1987, 2000). This method is intended to provide a deeper empirical and theoretical exploration of optimal combinations of factors associated with the presence of an outcome (Rihoux and Ragin 2009; Hughes et al. 2019). Three core principles of causal complexity are rooted in the QCA method, including (1) asymmetrical relationships (Meyer et al. 1993): the contributing function of a condition may differ across configurations, (2) equifinality (Gresov and Drazin 1997): different configurations may lead to the same outcome, and (3) conjunctural causation (Schneider and Wagemann 2012): multiple conditions in conjunction explain an outcome.

Fuzzy-set QCA (fsQCA) is a popular variant of QCA (Fiss 2007). In fsQCA, the distinction between 0 and 1 is based on continuous and interval scale variables that express the degree of presence or absence of the concept in each case. Thanks to the possibilities offered by the approach, it has increasingly accumulated conceptual, methodological, and empirical foundations in prior research (e.g., Fiss 2011; Jordan et al. 2011; Rubinson et al. 2019). Recent studies on the use and acceptance of novel technologies have brought in fsQCA to address the complex interdependencies between individual factors (e.g., Chen and Cheng 2023; Chuah et al. 2021; Mattke et al. 2022; Maier and Weitzel 2020).

Figure 1 depicts our research approach using fsQCA. The use case selection and configurational model development constitute the theoretical and conceptual building blocks. The following sections discuss our methods, including survey design, measures, data collection, and data analysis.

3.2 Use case selection

Figure 2 explains how a database of construction robots was created for the empirical study. First, we followed the case study approach to select representative examples developed since the 2010s for review (Eisenhardt 1989). Because we are interested in the differences among the examples, we used purposive sampling to select examples for maximum diversity. Then, we built a database of 12 robotic systems (see Supplementary Material) by categorizing them based on existing frameworks and taxonomies including interaction types, characteristics, and types of autonomy. Interaction types include *cell, coexistence, cooperation*, and

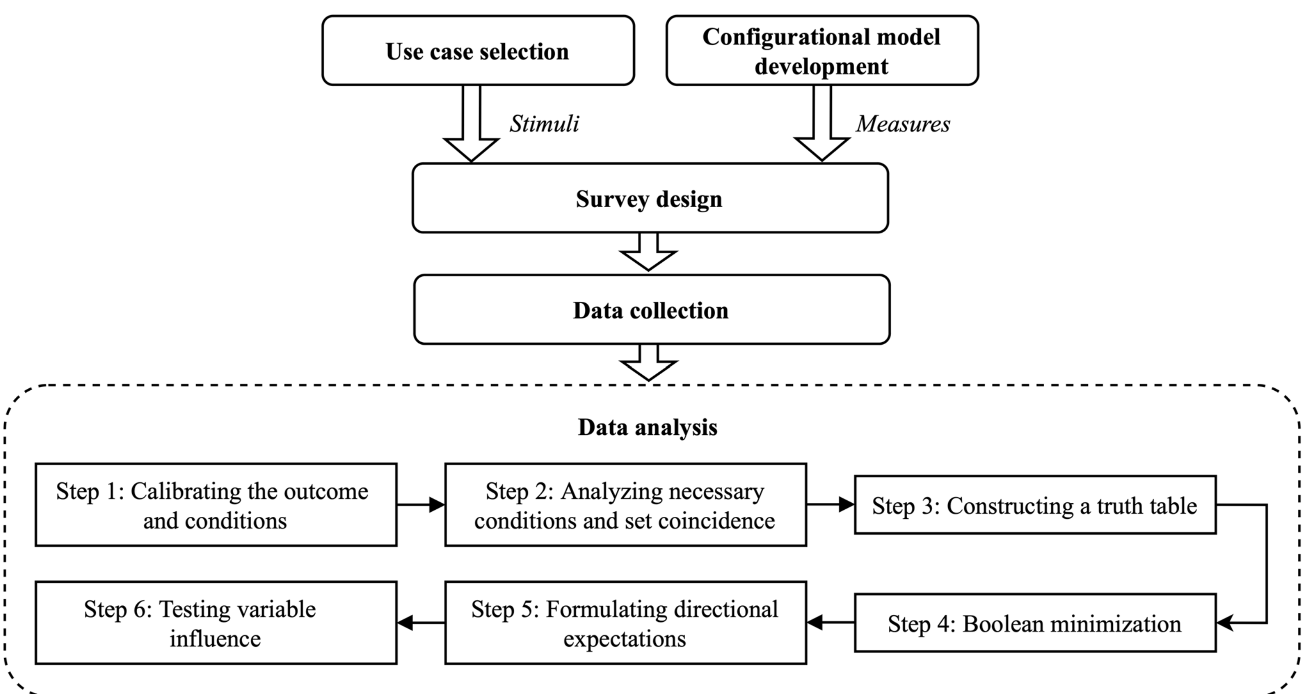

Fig. 1 Flowchart of the applied research approach

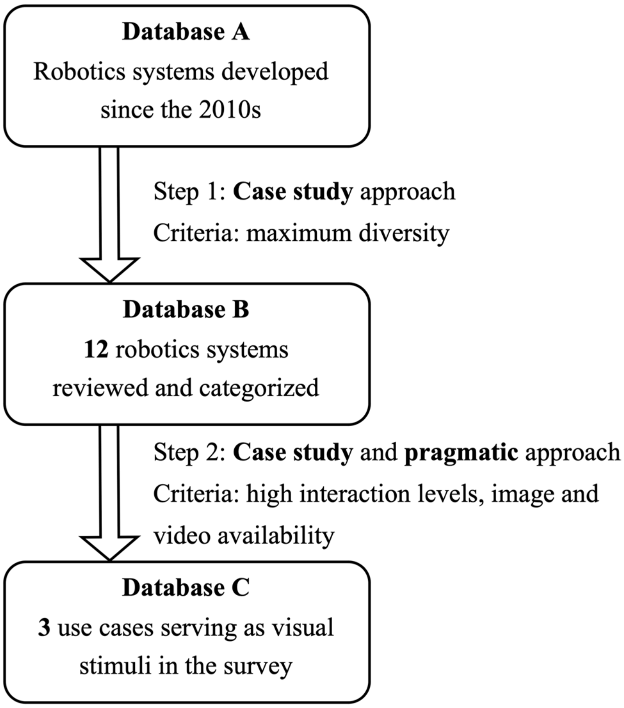

Fig. 2 Steps for the use case selection

collaboration (Kopp et al. 2021) as well as *augmentation,* which encompasses augmented reality or wearable exoskeletons (Bennett et al. 2022; Fox and Kotelba 2018). Interaction characteristics can be classified into *human roles, work steps*, and *work tasks* (Kopp et al. 2021; Scholtz 2003). Types of autonomy include *information acquisition, information analyses, decision-making,* and *action implementation* (Parasuraman et al. 2000).

The survey study concentrates on scenarios where humans and robots work side by side. As a result, only systems with relatively high levels of proximity—*cooperation, collaboration, augmentation*—were included in the database and those categorized under *cell* or *coexistence* were disqualified. Examples of the three interaction types above needed to be presented in the survey as visual stimuli that comprehensively convey the features of a robot and how it is used in the context of a construction task. For this pragmatic reason, we chose Jaibot, Baubot, and Mule, for which high quality images and videos are available and the permission to use them has been granted by the manufacturers. As shown in Table 2, Jaibot exemplifies a cooperation use case, where the human worker operates the drilling robot without being dependent on the robot (Hilti 2020). Baubot represents a collaboration use case, in which the human worker and the robot perform a welding task simultaneously (Baubot 2021a). Mule demonstrates a use case of augmentation, where the robot assists human workers by augmenting their lifting strength (Construction Robotics 2016).

3.3 Configurational model development

Figure 3 depicts the configurational model proposed for the fsQCA analysis. According to the theory of planned behavior (Ajzen 1991), the best predictor of a behavior is the intention to behave in a certain way. Here, the focal behavior

Table 2 Categorization of the three selected use cases

System name		 Jaibot drilling robot	 Baubot system	 Mule lifting robot
Interaction type		Cooperation	Collaboration	Augmentation
Interaction characteristics	Work steps	Sequential	Simultaneous	Simultaneous
	Work tasks	Linked	Shared	Shared
	Human roles	Operator	Peer	Instructor
Types of autonomy	Information acquisition		✓	
	Information analyses	✓	✓	
	Decision-making		✓	
	Action implementation	✓	✓	✓

Notes. *Work steps* distinguish the temporal relations between humans and robots when they work. *Work tasks* refer to the dependency between the tasks of the humans and the robots. *Human roles* describe the roles and responsibilities of humans when humans and robots perform a task together. *Information acquisition* refers to the sensing and documentation of input data. *Information analysis* applies to cognitive functions such as working memory and inferential processes. *Decision-making* refers to decision selection, including the selection among decision alternatives. *Action implementation* involves the actual execution of the action choice

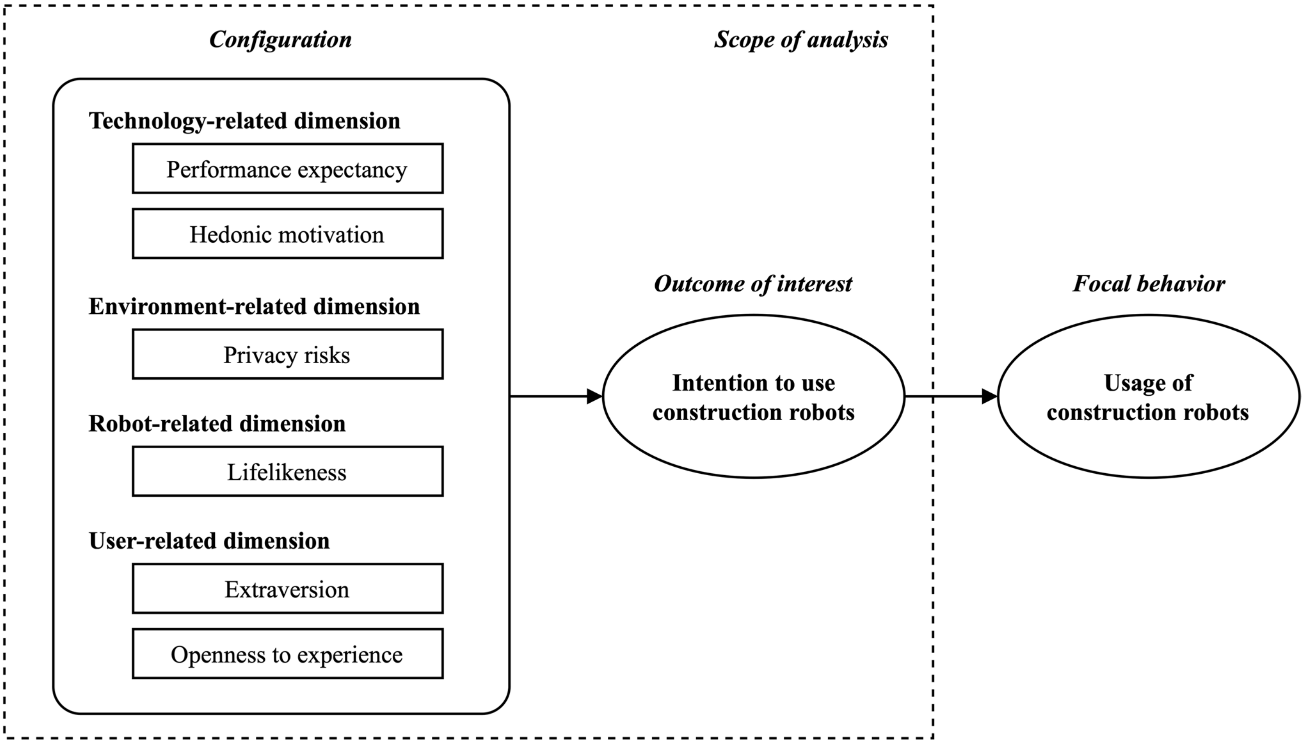

Fig. 3 Proposed configurational model

is the usage of construction robots by AEC stakeholders, which is outside the scope of analysis, as indicated by the dotted line. The cognitive antecedent of the focal behavior is the AEC stakeholders' intention to use construction robots, which is thus the outcome of interest in the fsQCA analysis. The combination of four dimensions—technology, environment, robot, and user—serves as a complex configuration leading to the outcome of interest.

The objective of the study is to empirically understand how these dimensions may combine and interact to form the intention to use construction robots, potentially explaining why an AEC stakeholder might adopt a construction robot. The *technology-related dimension* is derived from the unified theory of acceptance and use of technology models (Blut et al. 2022; Venkatesh et al. 2012). The *environment-related dimension* is based on the human–robot trust model introduced by Sanders et al. (2011). The *robot-related dimension* is based on the psychological phenomenon of pareidolia (Wodehouse et al. 2018). Finally, the *user-related dimension* stems from the Big Five personality traits (McCrae and John 1992) and personality theories that suggest traits determine human attitudes and behaviors toward a new technology (Barnett et al. 2015). In the following sections, we elaborate on the six explanatory conditions that are used to interpret the dimensions.

3.3.1 Technology-related dimension

The first condition is *performance expectancy*, which refers to the degree to which utilizing the technology is considered beneficial (Venkatesh et al. 2012). This is similar to the notion of *perceived usefulness* (Davis 1989), describing how individuals believe that using the system can improve their work performance. Based on this model, a high level of perceived usefulness leads to a high intention to use a technology. Specifically, construction robots are designed to outperform human workers in delivering precise and consistent results (Brosque and Fischer 2022). In addition, on-site construction robots are often expected to have the ability to withstand hazardous conditions and dangerous environments while performing repetitive and mundane tasks (Bock and Linner 2016).

The second condition is *hedonic motivation*. Hedonic motivation is the enjoyment or pleasure experienced when using a technology (Brown and Venkatesh 2005). A recent study found that hedonic motivation not only affects individuals' evaluation of the performance and effort expectancy of robotics but also their intention to use the technology (Lu et al. 2019). According to Lin et al. (2020), when users find a robot entertaining, they are more likely to evaluate its use positively. For example, an interface design like gamified displays (Locus Robotics 2014) or a user experience through playful conversations (Goetz et al. 2003) can trigger a fun and engaging interaction with construction robots.

3.3.2 Environment-related dimension

The third condition is environmental and known as *privacy risk*, which relates to the potential loss of control over personal information (Lutz et al. 2019). Research has shown that individuals tend to exhibit negative attitudes such as anxiety and distrust when confronted with technologies that threaten their informational privacy (Syrdal et al. 2009). As a result, these users are reluctant to adopt the technologies (Hong et al. 2020). One example of anticipated privacy risks on the construction sites could be drones that capture video footage while documenting construction progress (Knight 2015). Another case is robotic systems equipped with sensors that can appropriately interact with a person based on their position, movements, and even sensitive data such as mental states (Ryan Calo 2020).

3.3.3 Robot-related dimension

The fourth condition is *lifelikeness*, as opposed to *machine-likeness* (Bartneck et al. 2008). It represents a unifying concept encompassing anthropomorphism and animism/zoomorphism (Schmitz 2010). In a recent experiment, participants perceived an animal-like robot as a trustworthy and intelligent "pet" or "puppy" (de Visser et al. 2022). Another study confirmed that robots elicit a stronger desire to interact among individuals when perceived as human-like (Stroessner and Benitez 2019). An example of a life-like robot in construction could be Spot (Boston Dynamics 2016), the robot dog which can autonomously move between rooms and floors for real-time tasks such as inspection and surveillance.

3.3.4 User-related dimension

The fifth condition is *openness to experience,* characterized by adjectives such as *artistic, curious,* and *original* (McCrae and John 1992) when describing a person. Individuals who are high in openness to experience are motivated to seek out new experiences actively (Spielberger 2004) and are particularly reflective about the ideas they encounter (McCrae and Costa 1997). Rossi et al. (2018) conducted a study examining the effect of personality traits on acceptance. They found that individuals who showed greater openness to experience were more willing to interact with the robot.

The sixth condition is *extraversion*, which applies to individuals describing themselves with adjectives like *outgoing*, *talkative*, and *enthusiastic* (McCrae and John 1992). Individuals who score high on extraversion tend to enjoy human interactions and work well in groups, while those who score low are more reserved (Wang et al. 2012). Müller and Richert (2018) discovered that individuals with strong extraversion traits typically have favorable attitudes toward robots.

3.4 Survey design

We designed an online survey using the Qualtrics™ XM platform to capture AEC stakeholders' intention to use construction robots and their evaluative responses. The survey was structured in several sections, as shown in Table 3. Before evaluating the robot, participants viewed a brief video, graphical representations, and a text description about the use case of a construction robot. Each participant was randomly presented with one of the

Table 3 Structure of the online survey

Section	Factors/information
Introduction	Project information (purpose, confidentiality, contact person) Consent form and instruction
User questions	*Openness to experience* *Extraversion*
Use case presentation (for each use case)	Three images, one video (30 s) and text description
Robot evaluation (for each use case)	*Lifelikeness* *Performance expectancy* *Hedonic motivation* *Privacy risks* *Intention to use*
Additional questions	Robot anxiety Robot-related experience
Demographical data	Gender, category of birth years, profession, country of birth and current residence
Ending	Possibility for evaluating one more use case Possibility for leaving an email address to be informed about the study result

Notes. Items that relate to the configurational model are marked in Italics three use cases (See Appendix A). After viewing the stimuli, the participants were instructed to rate a set of scale items.

The survey was initially developed in English and then translated into 12 languages (e.g., Croatian, French, German, Italian, Portuguese, Turkish) with the aim of targeting the representative population of AEC stakeholders living in Switzerland, Germany, and Austria who may not be English speakers. To ensure the flow and clarity of all language versions of the questionnaire, we conducted proofreading with language experts before the actual data collection.

3.5 Measures

To operationalize the outcome and the conditions, a measurement model (see Appendix B) was constructed based on validated scales from the literature. The outcome of interest, i.e., *behavioral intention to use* (three items, α = 0.85), *performance expectancy* (four items, modified), and *hedonic motivation* (three items, α = 0.77) were measured using items taken from a standardized questionnaire made by Venkatesh et al. (2012). *Performance expectancy* indicators were adapted to the construction context. With minor modifications (from anthropomorphism/animacy to lifelikeness), the *lifelikeness* scales (three items, α = 0.82) were taken from related studies (van Pinxteren et al. 2019). *Privacy risks* (three items, α = 0.78) were assessed as proposed by McLean and Osei-Frimpong (2019). To measure the personality traits of *extraversion* (three items, α = 0.81) and *openness to experience* (three items, α = 0.75), the corresponding scales were adopted from the Big Five questionnaire (Caprara et al. 1993). Concerning scale types, one construct (*lifelikeness*) was measured using 5-point semantic differential scales, which present pairs of opposite adjectives at either end (*rigid—smooth, unconscious—conscious, fake—natural*). All other constructs were assessed using 5-point Likert scales, with 1 indicating "strongly disagree," 2 indicating "agree," 3 indicating "neither agree nor disagree," 4 indicating "agree," and 5 indicating "strongly agree."

3.6 Data collection

For the data collection, we targeted stakeholders from different AEC sites. These include stakeholders from the production sites, such as construction managers and trade workers, and from the planning sites, such as architects, civil engineers, and designers. They were recruited because they are in a valid position to evaluate the use of a construction robot and may be involved in the design, implementation, use, or management of construction robots. The sample also included young professionals, such as students and apprentices in their education and training. Participants were not required to have former robot-related experience to qualify for participation. To recruit the participants, we used purposive sampling aided by a snowball strategy (Parker et al. 2019), which involved contacting individuals and companies to further recruit participants from among their networks in the AEC sectors. In addition, we organized in-person participation through a tablet device on two construction sites (one in Switzerland and one in Germany).

Over 45 days from August to September 2022, the target stakeholders were invited via email and other social media channels to participate in our study voluntarily. A total of 379 individuals started the online questionnaire, of which 240 completed it. To compile the dataset for analysis, we performed several data removal steps. First, we removed 16 disqualified responses whose current residence was outside the target countries (Schneider and Wagemann 2012). Then, we excluded the 120 responses to the second evaluated use case due to a detected asymmetric transfer (Cockburn and Gutwin 2019), as reported in more detail in the Supplementary Material. Next, we reduced the dataset by random selection, to ensure an even number of responses (i.e., 72) per robot use case (Westfall et al. 2014), arriving at the final number of 216 cases included in the data analysis. The sample size is satisfactory considering the objective of our fsQCA approach and the number of explanatory conditions (Greckhamer et al. 2013; Marx and Dusa 2011). The demographic characteristics of the participants in the final sample are shown in Table 4.

Table 4 Sample characteristics (N = 216)

Characteristics	n	%
Gender		
Male	155	72%
Female	55	25%
Age group		
18–25 years	45	21%
26–35 years	78	36%
36–45 years	40	19%
46–55 years	29	13%
56–65 years	16	7%
65+ years	4	2%
Country of residence		
Switzerland	149	69%
Germany	49	23%
Austria	13	6%
Profession group		
Architect, civil engineer, designer	85	39%
Construction manager	33	15%
Trade worker	66	31%
Others (researcher, accountant, etc.)	32	15%
Robot-related experience		
None	126	58%
At home	28	13%
At workplace	50	23%
Other occasions (class, shop, etc.)	12	6%

Notes. The numbers (n) of a few subgroups do not add up to the sample size (N) of 216 due to missing values ("prefer not to answer" or not reported). We only report valid percentages (%)

3.7 Data analysis

3.7.1 Common method bias

To mitigate the potential risks of common method bias, we implemented both procedural and statistical remedies. Regarding procedural remedy, we incorporated various strategies into the survey design based on the guidelines of MacKenzie and Podsakoff (2012). Regarding statistical remedy, we conducted several tests post hoc, including Harman's single-factor test, correlation matrix procedure, and full collinearity test. The Supplementary Material provides a detailed explanation of our procedures and results. These results show that the common method bias is not a concern in our study.

3.7.2 Reliability and convergent validity

The measures were assessed for consistency and validity (see Appendix B). The results show that all constructs' composite reliability (CR) were above the threshold of 0.7, indicating acceptable reliability (Hair et al. 2017). All constructs' average variance extracted (AVE) values were greater than 0.5, confirming the establishment of convergent validity. Additionally, the heterotrait-monotrait (HTMT) ratio of correlations criterion was used to assess discriminant validity (Henseler et al. 2015). All HTMT values in the measurement model were below the conservative threshold of 0.85, suggesting that the discriminant validity was established.

3.7.3 Analyzing configurations by fsQCA

Our fsQCA approach consists of six steps following the guidelines of Mattke et al. (2022) and Arellano et al. (2020): (1) calibrating the outcome and conditions, (2) analyzing necessary conditions and set coincidence, (3) constructing a truth table, (4) conducting Boolean minimization, (5) formulating directional expectations, (6) testing variable influence. A step-by-step summary of the analysis is reported in the methodological appendix (see Supplementary Material). We used the QCA package (version 3.17) for R (Dusa 2019) for the main procedures. We also used the fs/QCA software (version 3.0) (Davey and Ragin 2016) for the necessity analysis and the IBM™ SPSS Statistics (version 28.0.1.1) for the variable tests.

4 Results

The results of the necessity analysis (see Supplementary Material) indicate that none of the six conditions alone—*performance expectancy, hedonic motivation, lifelikeness, privacy risks, extroversion,* and *openness to experience*—is necessary to yield the intention to use construction robots. Table 5 reports the configurations drawn from the sufficiency analysis. The leftmost column lists the explanatory conditions. The remaining columns summarize the six configurations associated with the presence of the outcome. The table lists the number of cases, consistency, raw coverage, and unique coverage scores for each configuration. None of the configurations has a unique coverage lower than 0.01. The overall solution consistency was 0.85, indicating a relatively high degree to which the presented combinations guarantee the outcome. Furthermore, the results showed that the overall solution yielded a coverage value of 0.70, meaning that 70% of the cases showed these six combinations of conditions. The values reported above are consistent with other model studies using fsQCA (e.g., Chuah et al. 2021; Fiss 2011).

Following Pappas and colleagues' (2019) suggestion, we distinguished the core and peripheral conditions in each configuration to aid the interpretation of our analysis. Regarding the core conditions (large circles), the resulting configurations can be categorized into three first-order solutions, which correspond to three distinct profiles of stakeholders who intend to use construction robots: configuration *A: the lifelike robot user*, configuration *B: the utilitarian robot user,* and configuration *C: the lifelike-utilitarian robot user*. More precisely, the solutions suggest that *performance expectancy* and *lifelikeness* are two explanatory conditions most strongly associated with the outcome.

Another notion in fsQCA, the so-called neutral permutation, represents the combinations of peripheral conditions (small circles) that surround and reinforce the core features of the first-order configurations (Fiss 2011). The neutral permutations from our results are discussed in more detail in the following sections.

The first solution, *the lifelike robot user*, is predominantly characterized by the presence of *lifelikeness*, implying that stakeholders intend to use robots with characteristics defined by *natural, smooth,* and *conscious* movements. This result is consistent with a large body of robot adoption studies suggesting that anthropomorphism and zoomorphism have a positive impact on individuals' responses to robots (Carpinella et al. 2017; Stroessner and Benitez 2019; Tussyadiah and Park 2018). The solution capturing *the lifelike robot user* has three neutral permutations. Users who adopt lifelike robots with low privacy risks are labeled configuration A.1 and configuration A.2, which correspond to the personality traits of openness and extraversion respectively. Configuration A.3 consists of users with both openness and extraversion, and these are motivated by the hedonic (i.e., *fun, entertaining, enjoyable*) experience, regardless of the level of privacy risk.

In the second solution, *the utilitarian robot user*'s intention to use construction robots is independently determined by *performance expectancy*. They prioritize utilitarian benefits such as *quality, precision,* and *safety*, and *time predictability* associated with the construction robot. This result is consistent with the technology acceptance literature, which

Table 5 Configuration chart

Configurations	A: The lifelike robot user			B: The utilitarian robot user		C: The lifelike-utilitarian robot user
Neutral permutations	A.1: Open* user seeking privacy	A.2: Introvert user seeking privacy	A.3: Open* and extrovert user seeking fun	B.1: Open* user seeking privacy	B.2: Open* and extrovert user seeking fun	C: Open* user seeking fun
Technology-related dimension						
Performance expectancy				⬤	⬤	⬤
Hedonic motivation			●		●	●
Environment-related dimension						
Privacy risks	⊗	⊗		⊗		
Robot-related dimension						
Lifelikeness	⬤	⬤	⬤			⬤
User-related dimension						
Openness to experience	●		●	●	●	●
Extraversion		⊗	●		●	
Number of cases (n)	52	25	21	54	25	22
Coefficients						
Consistency	0.88	0.89	0.89	0.87	0.90	0.93
Raw coverage	0.47	0.35	0.34	0.41	0.31	0.29
Unique coverage	0.06	0.05	0.01	0.06	0.01	0.02
Overall solution consistency: 0.85						
Overall solution coverage: 0.70						

Notes. The full circle (●) indicates the presence of a condition. The crossed-out circle (⊗) represents the absence (or the negation) of a condition. Large circles represent core conditions, central in explaining the intention to use. Small circles represent peripheral conditions, which contribute to the intention. Blank spaces represent "do not care" situations, indicating that a certain condition may be present or absent (i.e., irrelevant) when explaining the intention to use

*Open = open to experience

argues that the utility of using robots motivates the behavioral intention to use them (Davis 1989; Venkatesh et al. 2012). This solution has uncovered two neutral permutations. The interaction-related and user-related conditions combine with the core condition performance expectancy to motivate behavioral intention to use. Configuration B.1 indicates that open users concerned about data privacy protection intend to use robots with utilitarian features. Concurrently, configuration B.2 categorizes users who seek a fun experience with a utilitarian robot but ignore privacy risks.

The third solution is *the lifelike-utilitarian robot user* reflecting the dual combination of *lifelikeness* and *performance expectancy*. It indicates that both conditions go hand in hand with hedonic motivation to foster intention among users who are open to experience. Use intention is achieved regardless of the level of privacy risks and the degree of extraversion traits in the users. No additional neutral permutation was identified for this solution.

The results of the variable influence tests are presented in Table 6. When examining the mean differences of the influencing variables across samples, the focus was placed on statistical significance at the 1% and 5% levels (p-values highlighted with ** and ***). When comparing configuration C (n = 22) against the full sample (N = 216), two factors showed statistical significance: *gender* (compare, 0.23**) and *perception as peer* (compare, 0.36**). In addition, when comparing the sample with the intention to use (n = 107) against the full sample (N = 216), one factor, *perception as peer* (compare, 0.21***), indicated statistical significance.

4.1 Robustness tests

We conducted a full set of robustness tests to assess how sensitive our results are to changes in the model parameters. First, two lenient tests (consistency cut-off = 0.75, Test 1, and frequency cut-off = 2, Test 2 in Supplementary Material) were conducted. Second, two conservative solutions (consistency cut-off = 0.8, Test 3 and frequency cut-off = 4, Test 4 in Supplementary Material) were implemented to gain

Table 6 Differences in the means across the first-order configurations

N/n	Full sample (average)			> 0.5 sample	A sample	B sample	C sample
	216			107	51	42	22
	Descriptive statistics						
Variables	Mean	SD	Min./max				
Respondents' characteristics							
Age	3.67	2.45	1.00/10.00	− 0.26	− 0.003	− 0.36	− 0.58
Gender	1.27	0.44	1.00/2.00	0.05	− 0.03	0.09	**0.23****
Profession	1.94	1.07	0.00/3.00	0.10	0.02	0.08	0.15
Robot-related experience	0.42	0.49	0.00/1.00	0.07	− 0.05	0.08	0.22*
Contextual factors							
Country of residence	1.36	0.60	1.00/3.00	0.03	0.16	− 0.03	− 0.04
Use case	2.00	0.82	1.00/3.00	− 0.05	0.07	− 0.05	− 0.27
Other factors							
Robot anxiety	3.18	0.66	1.67/5.00	− 0.04	− 0.01	0.03	− 0.16
Perception as peer	3.34	0.80	1.00/5.00	**0.21*****	0.14	0.17	**0.36****

Notes. *p < 0.1; **p < 0.05; ***p < 0.01. The bold p-values of 0.05 or lower are considered statistically significant. > 0.5 sample stands for all cases satisfying the minimum frequency, consistency, and PRI thresholds. A sample stands for configuration A: The lifelike robot user. B sample stands for configuration B: The utilitarian robot user. C sample stands for configuration C: The lifelike-utilitarian robot user

insight into a more stringent model specification. Overall, the results indicate rather good stability of our reported results to changes in the model parameters except for the more conservative frequency cut-offs. The lenient and conservative models support our reported results with moderate to high similarity, increasing the confidence in the validity of the results.

5 Discussion

5.1 Discovering the configurational perspective

To the best of our knowledge, this is the first study to use configurational analysis on the user acceptance of construction robotics. In contrast to previous research focusing on the net effects between variables, our analysis has shed new light on this by explaining the outcome with multiple possible pathways. This configurational perspective can be translated into a set of *causal recipes*, which are narratives commonly used in the fsQCA literature (e.g., Damian and Manea 2019; Park et al. 2020). As illustrated in Fig. 4, each *recipe* suggests an appropriate combination of *sauce selection* (robot type) and *cooking technique* (interaction condition) to make a delicious *meal* (intention to use) for a particular type of user. In summary, this study underlines the importance of distinguishing sectors and domains in robotics research, as our results differ substantially from those of service robots despite using a similar theoretical model (Chuah et al. 2021).

The configurations provide important details on the relationship between user personality and attitudes toward construction robots. Most notably, our findings challenge the notion that extroverts prefer more human-like robots (Kaplan and Liberman 2018), whereas introverts prefer more machine-like robots (Walters et al. 2008). In Fig. 4, meal 1 clearly shows that introversion (i.e., the negation of extroversion) combined with lifelikeness can lead to the intention to use construction robots. Interestingly, meal 1 is the most popular recipe favored by two user groups. In addition, some users are more flexible and intend to use construction robots for a wider variety of meals. For example, users who are open to experience respond well to three possible meals (meal 1, 2, and 3 in Fig. 4). In contrast, users who possess introversion traits only take one fixed meal (meal 1 in Fig. 4), indicating a somewhat limited acceptance.

5.2 Specifying the interplay between explanatory conditions

Our findings have captured a distinct interplay between multiple conditions in promoting user acceptance of construction robots. For example, AEC stakeholders' perceptions of privacy risks vary across configurations, revealing an unexpected cohering effect with hedonic motivation. More specifically, in the presence of hedonic motivation (configurations A.3, B.2, and C in Table 5), the intention to use construction robots can be elicited regardless of perceived privacy risks. However, when hedonic motivation is not present (configurations A.1, A.2, and B.1 in Table 5), data privacy protection becomes vital. These results agree with the findings of Church et al. (2017) that people are willing to trade their privacy concerns for hedonic benefits. Nevertheless,

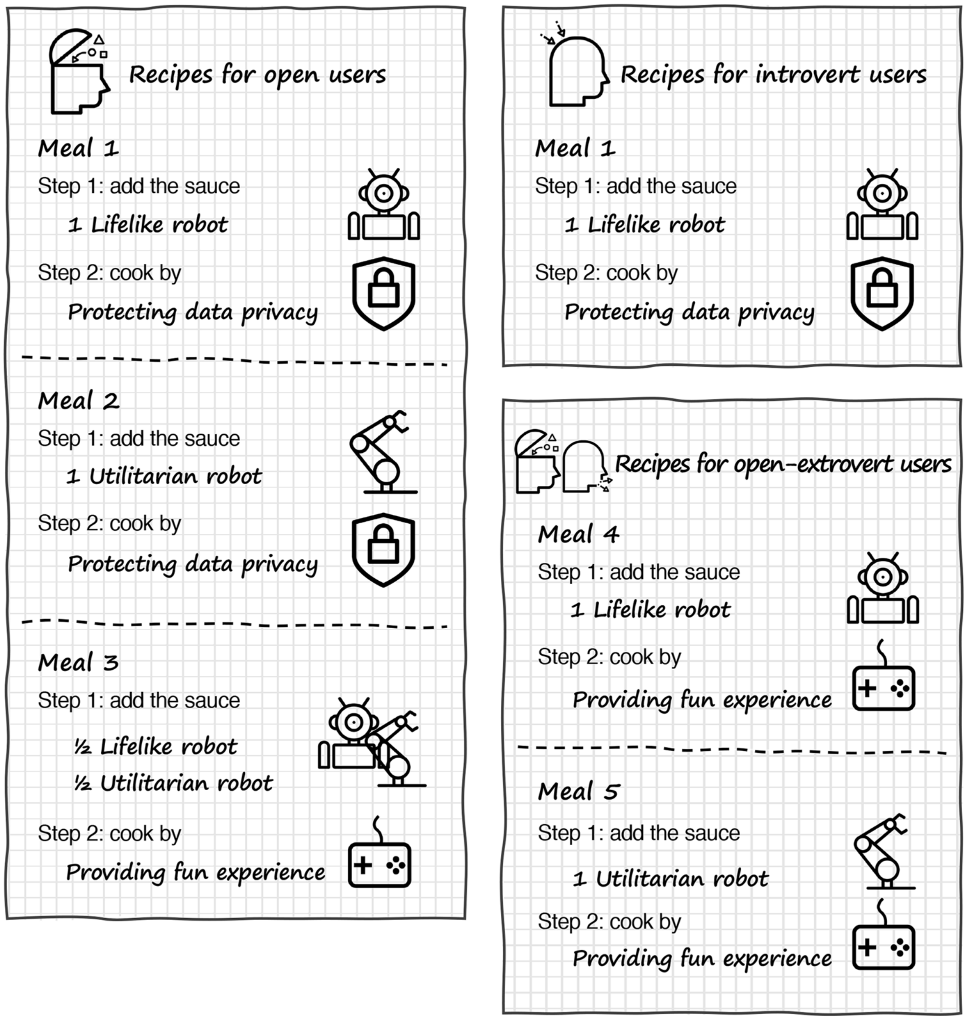

Fig. 4 Using "recipes" to demonstrate the configurational perspective

Notes. Open is short for open to experience. The icons are used for illustrative purposes only and do not denote the labeled meanings (e.g., an industrial robotic arm does not necessarily refer to "utilitarian" features, and a gamified interface does not necessarily refer to "fun" experience). Each meal requires the preparation of "one portion" of sauce, so the "half-half" represents two features combined on one robot

our coincidence analysis did not reveal a significant correlation between individuals' willingness to disclose privacy data and their enjoyment in interacting with a robot. As this example shows, our configurational method detects variable interplay rather than correlation, in contrast to a regression method.

Our findings also add interesting details to the debate in the literature surrounding the dichotomy of hedonic versus utilitarian values, showing these values' asymmetric nature (Batra and Ahtola 1991; Diefenbach et al. 2014). Recent research on technology design has put forth conflicting results on which of the two dimensions better predicts quality judgments and technology acceptance. In particular, de Graaf et al. (2017) identified a shift in users' focus from one motivation to another over a longer time. These inconsistencies arise from the cognitive phenomena of justifiability and trade-offs (e.g., Chitturi et al. 2007, 2008; Diefenbach and Hassenzahl 2011). In our study, a single driver, either hedonic or utilitarian, is sufficient to promote AEC stakeholders' use intention in some configurations (configurations A.3 and B.1 in Table 5), while the other configurations (configurations B.2 and C in Table 5) require the coexistence of both drivers. These two attributes become more or less important depending on the configurations associated with AEC stakeholders' intention to use construction robots.

5.3 Rethinking the roles of influencing factors

Surprisingly, the study determined that factors such as professions and use cases are not the primary drivers of the fsQCA results. In other words, the identified user profiles do not correspond to the participants' trades (e.g., general contractor, subcontractor, etc.). Future studies could examine emerging job profiles and what type of users would be successful on those job sites. Likewise, the interaction types portrayed in the three use cases did not yield a significant difference in the results. Only exploratory insights into the perception of the robots by individuals were discovered. For instance, the participants' responses showed that the Mule lifting robot (augmentation) was perceived as the least lifelike, while the Jaibot drilling robot (cooperation) was rated with the greatest performance expectancy. Future research could aim to correlate additional attributes (e.g., perceived intelligence) with the use cases.

In contrast, some other factors are found to significantly influence AEC stakeholders' intention to use robots. One outstanding finding is the effect of gender. In configuration C (see Table 5), female AEC stakeholders are more likely to embrace the lifelike-utilitarian type of construction robots under the circumstance of pleasant interaction. This raises new possibilities for human–robot interaction to play a role in meeting the pressing need to address diversity, equality, and inclusion in today's construction industry (Norberg and Johansson 2020; Powell and Sang 2013). However, more is still to be learned about the behavioral and attitudinal differences between genders, as well as the role of ethnicity, class, and age.

Another striking finding was the substantial difference between the sample with use intention and the full sample in the perception factor of the robot as a peer. That is to say, human–robot peering may be a fundamental solution to increase user acceptance. Nevertheless, many questions about such peering remain unanswered due to the high level of uncertainty about the potential hazards and benefits of robotics and AI (Sam and Franz 2020; Onososen et al. 2022). For example, what makes a construction robot to be perceived as a peer? According to Gray et al. (2007), a robot would be more seen as having human-like consciousness when its decision-making is driven by AI. These unknowns should be addressed in future studies as on-going "social experiments" (Schinzinger and Martin 2000; Van de Poel 2013).

5.4 Implications for practice

Because the underlying complexity of user acceptance can be attributed to the variance in user perceptions, robot designers and implementers should engage users early in technology development and deployment to better understand their demands (Wyatt 2014). A "one-size-fits-all" approach to designing and implementing construction robots for all users may not effectively lead to increased acceptance in the future. Instead, it may lead to a poor match between individuals and technology, resulting in rejection and even abandonment of the technology (Scherer 2005; Scherer and Federici 2015). Our findings recommend a "mix and match" approach (Darr et al. 1998; Snow et al. 2006). The idea here is not to find a universally optimal solution, but to create circumstances that fit each person's profile. Since the identified user profiles are independent of the trade or use case, effective human–robot interaction is more affected by the individual's perceptions. To that purpose, a personalized, intelligent interface design can enhance the user experience at a robotized workplace.

Overall, the solutions presented in this study offer practical guidance on utilizing heterogeneous strategies to promote user acceptance of robotics across the AEC industry. Yet, decision-makers often face budgetary and time constraints when trying to adopt many strategies simultaneously. Adapting the designs (e.g., reconstructing the hardware or integrating machine learning algorithms) requires intensive investments in research and infrastructure (Hayes and Jaikumar 1991; Yoshikawa 2003). Modifying the implementation plans (e.g., introducing a collaborative human–robot workflow) leads to complex changes in training procedures and safety protocols (Gołaś, 2015; Mutlu and Forlizzi 2008). Given these challenges, decision-makers should first aim to prioritize the core conditions, namely lifelikeness and performance expectancy. Subsequently, the auxiliary conditions, including fun experience and data protection, can later be incorporated to further increase user acceptance.

5.5 Methodological reflections

It is worthwhile to reflect on the implications of our fsQCA method. First, the research was not designed to explain why stakeholders resist construction robotics as a new technology. Moreover, our analysis was not based on interactions in real-world contexts or longitudinal data. As a result, our conclusions are limited by the so-called intention-behavior gap, that is, the discrepancy between individuals' intention and their actual behavior (Bhattacherjee and Sanford 2009). More research is needed to better understand the causes and effects of this gap and to align the users' intention with effective usage behavior.

While our study sought insight into participants' behavioral intentions, our survey approach could only capture self-reported attitudes and beliefs. A general problem inherent to this approach is that attitudes are often implicit and difficult to access (Greenwald and Banaji 1995). Future studies could include additional data collection methods, such as ethnographic observations that do not rely on scale measurements or narratives.

Finally, our analysis sampled a broad group of AEC stakeholders (architects, engineers, construction managers, and trade workers) to gain an overall understanding of the phenomenon. Further fsQCA analyses could segment the dataset according to the participants' roles (decision-makers and end-users, etc.) or trades (painting and masonry, etc.) to compare the results and derive more refined conclusions.

5.6 Limitations

First, the current study participants were recruited through a snowball sampling which relied on the network of the initial participants. This may have biased the sample and does not guarantee a precise representation of the AEC industry. In addition, as the sample was drawn from three European countries, so the generalizability of the results is restricted by the participants' cultural backgrounds.

Second, our study only considered six explanatory conditions and three use cases. Including other factors that may influence individuals' willingness to use robotic technology would be interesting. For example, further research could consider effort expectancy (Venkatesh et al. 2012) or autonomy (Morgeson and Humphrey 2006). Future studies should also examine use cases where the motives for use and the nature of innovation may differ from those used in the present study. These include systems with other purposes, such as 3D-printing (Anton et al. 2021; Bos et al. 2016), and those at other maturity levels, such as design science prototypes (Amtsberg et al. 2021; Mitterberger et al. 2022).

6 Conclusion and outlook

Drawing on configuration theory, our study aims to bring together the fragmented views of the human–robot interaction and user acceptance literature. Using a novel methodological approach known as fsQCA, our analysis unpacks fine-grained insights that are salient to the user acceptance of construction robots. We thus acknowledge the complexity of user acceptance and challenge the assumptions that there is "an ideal design" of a construction robot. We suggest a "mix and match" strategy for robot designers and implementers to achieve truly successful, in other words, accepted adoption of robotic technologies across AEC.

Prospectively, our study should encourage scholars and practitioners to take a more proactive stance in steering the convergence of technology, people, and organizations toward a desired future. With the rapid growth of data and the use of AI, technology augmentation and automation may become a common practice in managing organizations (Choudhary et al. 2023; Raisch and Krakowski 2020). Future projects should not underestimate the importance of considering the fit between technological and social dimensions (Clegg and Shepherd 2007; Orlikowski 1992). We therefore see the value of a socio-technical systems approach to the development and implementation of robotics and AI in AEC (Clegg 2000; Trist and Bamforth 1951; Waterson et al. 2015). We support further academic and industrial efforts that utilize work design theories (Hackman and Oldham 1980; Parker et al. 2017; Parker and Grote 2022), or value-sensitive design (VSD) principles (Davis and Nathan 2013; Friedman 1999). Future research should extend our findings by translating values such as well-being, safety, and sustainability into human-technology interactions.

Appendix A: Use case presentation

Use case	Text description	Video and image
1. Jaibot overhead drilling robot (Hilti 2020)	The robot marks and drills holes on the ceiling while the human worker operates the controller. The robot has a sensor to capture information and has the function to process digital plans	Video: https://youtu.be/DSQUzv6qhT4 (Hilti North America 2020, October 28; TP Mechanical Contractors 2022, March 02) Images: (Hilti 2023a, b, c) 
2. Baubot mobile robotic system (Baubot 2021a)	The robot handles the metal element to the desired position while the human worker performs the welding work. The robot has a sensor to capture information and has the function to process digital plans	Video: https://youtu.be/2RvDCBiQ7Vs (Baubot 2021a, b, c, April 12) Images: (Baubot 2021b, c; Baubot 2021a, b, c, April 12) 
3. Mule material lifting robot (Construction Robotics 2016)	The robot lifts the brick while the human worker guides the lifted brick to the desired position. The robot DOES NOT have a sensor to capture information	Video: https://youtu.be/Isuhuo1hW3A (Construction Robotics 2019, January 31) Images: (Construction Robotics 2023a, b; Trowel Trades Inc. 2018) 

Appendix B: Measures associated with the outcome and explanatory conditions

See Tables 7 and 8.

Table 7 Constructs, items and their reliability values

Constructs	Items	CR	AVE
1. Intention to use (Outcome)	What do you think about the use of this robot? Using the construction robot is a good idea I am willing to use this robot for this task now If I would be offered to use this robot for this task in the future, I intend to use it	0.888	0.726
2. Performance expectancy	Doing this task by using this robot would be …, compared to not using the robot … more accurate … with better quality … safer for the human worker … easier to predict the time completing the task	0.902	0.753
3. Hedonic motivation	If I would be offered to use this robot in the future, I expect that interacting with this robot: … would be fun … would be enjoyable … would be entertaining	0.799	0.577
4. Privacy risks	If I would be offered to use this robot in the future, I am concerned that: … this robot could record too much information about me … my personal information stored in the robot could be stolen … this robot could be hacked to spy on and attack me	0.911	0.774
5. Lifelikeness	How well do the following words describe your impression of the movements of the robot? Choose a point from the scale of 1 to 5: 1 = Rigid … 5 = Smooth 1 = Unconscious … 5 = Conscious 1 = Fake … 5 = Natural	0.777	0.542
6. Extraversion	I see myself as someone who: … is talkative … is outgoing and sociable … generates a lot of enthusiasm	0.838	0.636
7. Openness to experience	I see myself as someone who: … is original, comes up with new ideas … values artistic, aesthetic experiences … has an active imagination	0.794	0.562

Notes. CR = Composite reliability, AVE = Average variance extracted

Table 8 Constructs and their discriminant validity values

Constructs	1	2	3	4	5	6	7
1. Intention to use							
2. Performance expectancy	0.177						
3. Hedonic motivation	0.351	0.064					
4. Privacy risks	0.129	0.128	0.063				
5. Lifelikeness	0.486	0.191	0.153	0.024			
6. Extraversion	0.010	0.820	0.095	0.004	0.085		
7. Openness to experience	0.023	0.020	0.122	0.158	0.090	0.278	

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Author contributions SW: Conceptualization, Methodology, Investigation, Formal analysis, Data Curation, Writing—original draft, Visualization, Project administration; ANW: Conceptualization, Writing—review and editing, Project administration; AK: Conceptualization, Writing—review and editing; BD: Writing—review and editing, Supervision; DMH: Conceptualization, Methodology, Resources, Writing—review and editing, Supervision.

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Declarations

Conflict of interest No potential conflicts of interest were reported by the authors.

Ethics approval The ethics approval for this study has been granted without reservations by the ETH Zurich Ethics Commission under the ID "EK 2022-N-122: Industry Perception of Construction Robotics".

Consent to participate Participants have received a full information sheet and provided individual consent prior to participation.

Consent for publication Participants provided individual consent for the use of the collected data for publication.

Generative AI and AI-assisted technologies in the writing process During the preparation of this work the authors used ChatGPT and QuillBot in order to restructure and rephrase the texts for conciseness. The authors also used DeepL Write and Grammarly to correct grammatical and stylistic mistakes in the texts. After using these tools, the authors reviewed and edited the content as needed. The authors take full responsibility for the content of the publication.

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