

ACCEPTANCE OF HUMAN-ROBOT COLLABORATION: A COGNITIVE-AFFECTIVE-NORMATIVE APPROACH

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Abstract

Industry 5.0 represents a new paradigm in industrial organisation, evolving from Industry 4.0 toward human-centric and collaborative production environments. This study examines the acceptance of human-robot collaboration (HRC) technologies, such as collaborative robots (cobots), by analysing both acceptance and resistance pathways within the cognitive-affective-normative (CAN) technology acceptance framework. The model incorporates cognitive factors (performance expectancy and effort expectancy), affective factors (positive emotions, negative emotions, and anxiety), and normative influences (social influence). Data were collected from 126 industrial workers and analysed using correlational techniques and fuzzy set qualitative comparative analysis (fsQCA). The results reveal positive correlations between performance expectancy, effort expectancy, social influence, and positive emotions with favourable attitudes toward HRC. In contrast, negative emotions and anxiety are negatively associated with favourable judgements. The configurational analysis highlights multiple, asymmetric pathways leading to both acceptance and rejection. Performance expectancy emerges as the most recurrent condition in configurations explaining acceptance, whereas the absence of performance expectancy and the presence of negative emotions frequently characterise rejection pathways. These findings contribute to a more nuanced understanding of how cognitive, affective, and normative factors interact in shaping workers' attitudes toward collaborative robotic environments in the context of Industry 5.0.

Keywords: Industry 5.0; human-robot collaboration; collaborative robots; cognitive-affective-normative model; fuzzy set qualitative comparative analysis

1. INTRODUCTION

Robotic technology has transformed the manufacturing industry since the third industrial revolution. During the 1960s, robots were introduced (Kragic et al., 2018), leading to the widespread adoption of automated production and electronic technologies, as well as emerging information technologies (Demir et al., 2019). The fourth industrial revolution, commonly referred to as Industry 4.0, emerged in the early 2010s. It is characterised by the integration of robotic and digital technologies, blurring the boundaries between them and enhancing productivity and efficiency (Leesakul et al., 2022). It is also associated with mass production and mass customisation (Demir et al., 2019).

Industry 5.0 is a logical continuation of its predecessor, Industry 4.0, aiming to interconnect human intelligence with the precision and efficiency of machines through the use of artificial intelligence in industrial production (Breque et al., 2021). It has evolved as a response to challenges faced by Industry 4.0 by prioritising human centricity and addressing broader societal needs (Khan et al., 2023). These challenges include improving technology integration, addressing data security issues (Khan et al., 2023), shifting from a product-centred

manufacturing approach to a human-centred one (Pozo et al., 2022), and promoting a circular, sustainable, and responsible economy that favours renewable energy over fossil fuels (Demir et al., 2019).

A central issue in Industry 5.0 is the concept of human–robot coworking or human–robot collaboration (HRC). In this context, robots and humans collaborate whenever possible, with humans focusing on creative tasks and robots handling the remaining activities (Demir et al., 2019). In cooperation and collaboration scenarios, humans and robots perform tasks together in a shared workspace. Whereas collaboration involves humans and robots working jointly on the same tasks, cooperation refers to tasks primarily linked through related phases (Jahanmahin et al., 2022).

The move toward Industry 5.0 seeks to unite humans and machines, fostering resource-efficient and user-centred manufacturing. This vision extends beyond efficiency and productivity, placing the well-being of workers at the core of industrial processes (Lagomarsino et al., 2022). Future manufacturing systems are expected to incorporate customised products within highly adaptable mass production environments. Therefore, innovative approaches such as flexible robotic tools and intelligent decision-making software platforms must be explored. It is imperative that robots can be operated swiftly and intuitively by humans while ensuring safe, close interaction (Villani et al., 2018).

One relevant example of Industry 5.0 is collaborative robots (cobots), whose applications range from industrial assembly to supplementary processes (Taesi et al., 2023). Research indicates that global cobot sales are projected to increase from \$116 million in 2015 to \$11.5 billion in 2025, with the number of units sold rising to approximately 700,000 (Liao et al., 2023). Human–robot collaboration must prioritise a human-centred approach, aiming to minimise occupational risks, particularly mechanical ones, and enhance health and safety. Governments should also strive to maximise operator well-being during interactions with robots and other workstation elements in terms of physical and cognitive ergonomics (Gualtieri et al., 2020; Storm et al., 2022).

The literature suggests that employee acceptance and collaboration with implemented technologies play crucial roles in determining organisational success. Factors influencing employee acceptance can disrupt operations and hinder the seamless integration of technology (Huang & Rust, 2018; Çiğdem et al., 2023). Although robotisation was initially conceived in the industrial sector, significant research has recently focused on the service sector, particularly on the ongoing substitution of human labour by technology (Acemoglu & Restrepo, 2020).

A positive perception of a company is crucial for its success. In this regard, the proper implementation of robotisation processes, particularly within the workforce, is vital. This implementation has direct and indirect effects on various stakeholders, including employees, customers, suppliers, shareholders, and society at large (Kim et al., 2022). It helps attract and retain talent and builds trust (Harvey & Morris, 2012). Conversely, perceptions of conflict arising from digitalisation processes within the organisation may result in customer loss (Modliński et al., 2023).

The preceding discussion highlights the issues motivating this paper, which aims to expand the literature on the factors influencing workers' attitudes toward HRC. Our approach is based on the cognitive–affective–normative (CAN) framework for explaining technology acceptance proposed by Reinares-Lara et al. (2016) and Pelegrín-Borondo et al. (2017). The explanatory variables considered include two cognitive factors—performance expectancy and effort expectancy—and one normative factor, social influence. These factors are commonly included in theoretical frameworks such as the Technology Acceptance Model (TAM) developed by Davis (1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) exposed in Venkatesh et al. (2003). Emotional variables are measured using the Positive and Negative Affect Schedule (PANAS) scale (Watson et al., 1988).

Specifically, our research objectives (ROs) are as follows:

RO1: To measure the correlation between each explanatory variable and surveyed workers' attitudes toward HRC.

RO2: To examine how cognitive–affective–normative (CAN) factors combine to produce positive and negative attitudes toward working in an HRC environment.

Given the complexity of evaluating new production models, fuzzy set qualitative comparative analysis (fsQCA) is an appropriate method and is widely used in organisational and management research (Pappas & Woodside, 2021).

2. LITERATURE REVIEW

2.1. General considerations

The acceptance of robot technologies based on HRC, such as cobots, is analysed through the cognitive–affective–normative (CAN) (Pelegrín-Borondo et al., 2016; Reinares-Lara et al., 2016; Reinares-Lara et al., 2018). In its basic formulation, as shown in Figure 1, CAN builds upon widely used models of attitudes toward new technologies, such as TAM (Davis, 1989) and its extensions TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008), as well as UTAUT (Venkatesh et al., 2003). Additional factors related to the emotions elicited by the use of the evaluated technology were incorporated into the model, and these emotions were measured using the PANAS scale (Watson et al., 1988).

CAN model aligns with the goals of Industry 5.0, where not only efficiency and productivity are relevant but also the well-being of workers during the production process and positive externalities for society (Aheleroff et al., 2022). CAN captures concepts of efficiency and productivity traditionally measured in TAM and UTAUT, such as perceived usefulness (performance expectancy in UTAUT) and perceived ease of use (effort expectancy in UTAUT). Additionally, TAM2 and UTAUT introduce the relevance of users' judgements of technologies in relation to social norms or social influence. This refers to how users perceive that a particular technology is compatible with the beliefs and norms of the social group(s) to which they belong (Venkatesh & Davis, 2000; Venkatesh et al., 2003). In the CAN model, this dimension is referred to as normative and encompasses the broader societal impact that technological innovations in an Industry 5.0 environment should generate. Unlike previous industrial paradigms that focused primarily on profitability and productivity improvements, Industry 5.0 also emphasises socioeconomic goals such as sustainability, resilience, and inclusivity (Aheleroff et al., 2022).

The main contribution of the CAN model lies in recognising the importance of the emotional–affective dimension in the perception and adoption of technologies. It is widely acknowledged that emotions play a crucial role in human decision-making and judgement formation (Angie et al., 2011; Lerner et al., 2015). Moreover, emotions and feelings significantly affect workers' well-being in the workplace (Troth et al., 2021). The CAN model distinguishes between positive emotions, negative emotions, and anxiety.

Therefore, emotions are considered relevant when evaluating the usage intention of a technology—an aspect typically addressed in technology acceptance studies (Davis, 1989)—or, more broadly, when assessing attitudes toward the evaluated technology, especially when its use is mandatory. In our context, we examine workers' perceptions of technologies such as cobots, which must coexist with them in the workplace regardless of personal preference. Accordingly, we focus on the attitudes or judgements they hold toward their presence in the workplace, defined as the “learned predisposition to respond in a consistently favourable or unfavourable manner with respect to a given object” (Fishbein & Ajzen, 1975).

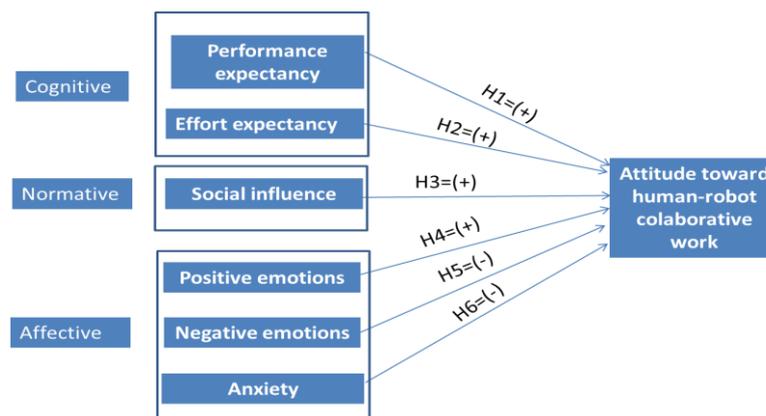


FIGURE 1-COGNITIVE-AFFECTIVE-NORMATIVE ATTITUDES TOWARD HUMAN-ROBOT COLLABORATIVE WORK

Source: Based on Reinares-Lara et al. (2018).

2.2. Development of statistical hypotheses about human–robot collaboration judgement with cognitive-affective-normative groundwork

The CAN model distinguishes among cognitive variables (performance expectancy and effort expectancy), affective variables (positive emotions, negative emotions, and anxiety), and normative variables (social norms) (Pelegrín-Borondo et al. 2016; Reinares-Lara et al., 2018).

Performance expectancy is defined as the perception that a given technology or system will help users accomplish one or more desired tasks (Venkatesh et al., 2003). It is often the most influential determinant of evaluations of newly introduced (and frequently mandatory) information systems (Venkatesh & Davis, 2000). This logic applies to the context examined in this study and is consistent with evidence showing that perceived robot performance is a key factor shaping workers' interactions with robots (Gruber & Hancock, 2021).

Because Industry 5.0 is human-centric, this new generation of robots is safer than traditional industrial robots (Galin et al., 2020; Taesi et al., 2023), enabling workers to avoid issues such as workplace accidents, which can result in decreased productivity, among other undesirable consequences. The prevention of occupational diseases may also be enhanced, as robots can potentially reduce work-related musculoskeletal disorders caused by repetitive and heavy tasks, from which the human operator is relieved (Cardoso et al., 2021). The literature on collaborative robot environments also highlights that technological robustness is an essential requirement. It is commonly accepted that robots should be designed to handle heavy payloads efficiently while performing tasks autonomously in a stable and reliable manner. Likewise, their battery systems should support quick recharging and provide extended operating times to ensure uninterrupted performance (Heo et al., 2024).

Collaborative robots are more flexible than traditional industrial robots and can be easily redirected to perform different tasks (Taesi et al., 2023), generating potential gains in less standardised production processes. On the other hand, this new generation of robots is often safer because they frequently perform certain tasks more slowly than industrial robots, thereby increasing operator safety (Villani et al., 2018).

Performance expectancy has been shown to be a key determinant of attitudes toward, and adoption of, robots across several settings, including service robots and chatbots (Wirtz et al., 2018; Kasilingam et al., 2020; Brachten et al., 2021; Kim, 2023; Andrés Sánchez & Gené-Albesa, 2023; Silva et al., 2023), medical assistance (Kremer et al., 2020; Andrés-Sánchez et al., 2022), and social robots (Saari et al., 2022). It has also been reported as relevant for cobots and human–robot collaboration (HRC) (Bröhl et al., 2016; Porubčinová & Fidlerová, 2020; Nguyen et al., 2022; Prassida & Asfari, 2022; Picco et al., 2024). Thus, the following statistical hypothesis is proposed:

H1: Performance expectancy is positively correlated with judgement regarding human–robot collaboration.

Effort expectancy (Venkatesh et al., 2003), or perceived ease of use (Davis, 1989), is the second cognitive construct considered in the CAN model. It is defined as the expectation that a particular object or system can be used effortlessly by the user (Davis, 1989).

Compared with traditional industrial robots, technologies such as cobots have characteristics that make their use simpler and more convenient. These robots are smaller than industrial robots (Kopp et al., 2021). They are also portable and do not necessarily need to be installed in a fixed location, which increases convenience for human operators (Berx et al., 2022). Conversely, unlike traditional industrial robots, humans share workspace with cobots; therefore, operators must be properly positioned to work comfortably, and ergonomic considerations have been extensively studied in the literature. This is because human movements must be compatible with those of the collaborating robot (Brun & Violand, 2021). Ensuring such compatibility is more complex than designing industrial facilities where robots and humans occupy completely separate spaces (Colim et al., 2021).

The programming of cobots is generally simpler and more intuitive than that of industrial robots (Kopp et al., 2021; Cardoso et al., 2021). In fact, even advanced models are capable of learning from human instructions delivered through gestures or natural language (Sowa et al., 2021).

Although HRC can improve ergonomics, productivity, and quality, their adoption in factories remains limited, partly because many companies lack fast, practical methodologies and tools to quickly assess workstations,

identify where HRC adds value, and plan the integration of robots into existing processes (Oberc et al., 2019). Implementing this technology demands decisions that go beyond technical viability: organisations must jointly consider productivity outcomes and workforce consequences, particularly in highly integrated assembly settings where heterogeneous materials and a growing variety of components are combined into increasingly complex products (Calvo & Gil, 2022).

The fact that the operator forms part of an integrated system with the robot means that greater attention is required from the human (Libert et al., 2020). Consequently, issues such as linguistic framing can influence the usability of chatbot technology (Kopp et al., 2023). Additionally, the fluency of the interaction between humans and robots is a critical factor (Paliga & Pollack, 2021), as a lack of synchronisation between tasks performed by the robot and the operator may create bottlenecks within the human–robot team (Van Dijk et al., 2023), generating cognitive workload that could lead to stress (Panchetti et al., 2023). Van Looy (2022) shows that a common employee demand is for organizations to accompany robotization processes with training, reskilling, and coaching to ensure effortless interactions.

Equipping cobots with the ability to balance task and human requirements, by adjusting motion rhythm, adapting physical interaction, and improving communication patterns, could help reduce employee workload (Carissoli et al., 2023). Currently, the development of HRC primarily follows either a human-centric or robot-centric approach, in which human and robotic agents reactively execute tasks based on predefined instructions. This approach falls short of achieving effective integration between robotic automation and human cognition (Li et al., 2023). Moreover, managing safety in HRC environments requires a shift in focus from techno-centric approaches to socio-technical ones (Adriaensen et al., 2022). This transition necessitates adjustments and learning in occupational safety practices among all stakeholders involved.

The relevance of the link of judgements about robotic technologies and effort expectancy has been highlighted in prior research, including robotic surgery (BenMessaoud et al., 2011), service robots (Wirtz et al., 2018), social robots (De Graaf & Allouch, 2013), and production models based on HRC (Porubčinová & Fidlerová, 2020; Prassida & Asfari, 2022). Moreover, across these domains, this relationship has also been empirically supported (Bröhl et al., 2016; Kremer et al., 2020; Andrés-Sánchez et al., 2022; Kasilingam et al., 2020; Babamiri et al., 2022; Nguyen et al., 2022). Thus, we propose the following:

H2: Low required effort is positively correlated with judgement regarding human–robot collaboration.

In the CAN model, the normative aspect arising from social pressure to perform or not perform certain actions is considered relevant and is measured through social influence. Social influence is defined as the potential user's perception that people who are important to them believe they should use a particular object or system (Venkatesh et al., 2003). The use of technology in the workplace is often imposed (Turja & Oksanen, 2019); therefore, judgement formation is influenced by managers who drive the robotisation process. If managers convincingly communicate that its use adds value, this message is likely to be internalised by end-users (Venkatesh & Davis, 2000).

Undoubtedly, robotisation processes have a significant impact on employment (Autor & Salomons, 2018; Acemoglu & Restrepo, 2020), and this perception can strongly shape social norms through social networks, media coverage, and the views and concerns of close social contacts. In this context, individuals may receive messages encouraging them to remain in low-tech environments to avoid perceived risks. However, it should also be considered that the philosophy of collaborative robots is not to replace humans but to collaborate with them in physically demanding tasks, maximising the strengths of both robots and humans in production processes (Wahlström et al., 2020; Picco et al., 2024). In fact, collaborative human–robot work models imply not only potential job displacement but also the creation of new, higher-quality roles (Baltrusch et al., 2022), as well as the promotion of sustainable employability (Villani et al., 2018; Picco et al., 2024).

The growth in the use of collaborative robots is a relevant component of Industry 5.0, whose goals align with the values of twenty-first-century societies, such as sustainability and the development of a green and circular economy (Wahlström et al., 2020; European Parliamentary Research Service, 2023), as well as fostering the involvement of persons with disabilities in industrial production activities (European Parliamentary Research Service, 2023).

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The relevance of social influence in the adoption of robotic technology has been suggested across different fields of application (BenMessaoud et al., 2011; Wirtz et al., 2018; Porubčinová & Fidlerová, 2020; Prassida & Asfari, 2022) and has been empirically tested in the medical field (Kremer et al., 2020; Andrés-Sánchez et al., 2022), consumer care (Silva et al., 2023; Andrés-Sánchez & Gené-Albesa, 2023), the context of companion robots (De Graaf & Allouch, 2013), and the manufacturing industry (Nguyen et al., 2022). Thus, we propose the following:

H3: Social influence is positively correlated with judgement regarding human–robot collaboration.

In a collaborative environment, humans and robots become members of the same working team, blurring the boundaries between the operator and the machine (Baumgartner et al., 2022). Therefore, emotional connection represents a significant element in effective human–robot collaboration and can be strengthened by fostering team identification and self-extension support (Porubčinová & Fidlerová, 2020). Employees' appraisals of robots generate a wide range of emotions, including feelings of connection that encourage positive attitudes toward robots in the workplace (Gkinko & Elbanna, 2022). In this context, technologies such as cobots often elicit mixed feelings among employees, who may perceive themselves as being in either a cooperative or competitive relationship with the robot (Ellwart et al., 2022).

The definition adopted in the CAN framework focuses on emotion and relies on componential emotion theory (Scherer, 2005). This theory outlines the essential characteristics required to define emotion, including the presence of a stimulus, attribution of its cause, cognitive evaluation, physiological response, the experience of pleasure or displeasure, a qualitative sense of uniqueness, a tendency toward characteristic action, and short duration. It is widely accepted that emotions influence human attitudes (Angie et al., 2011; Lerner et al., 2015) and significantly affect workers' well-being in the workplace (Troth et al., 2021).

Ensuring the actual safety of a robot is only one aspect; it is equally crucial that users experience a sense of security to foster acceptance (Kildal et al., 2018). While cognitive trust is important, emotional trust—grounded in perceived genuine care from the other party—is also vital. Emotions may persist despite conflicting cognitive evaluations (Gkinko & Elbanna, 2023). Additional emotions identified in the literature as significant to understand cobots adoption include enjoyment (Elprama et al., 2016; Heo et al., 2024), anxiety (Gruber & Hancock, 2021; Liao et al., 2024), feelings of psychological comfort and discomfort (Zanchettin et al., 2013), and self-esteem (He et al., 2023). Storm et al. (2022) highlight the increasing attention in the HRC literature to not only designing robots for physical safety, such as implementing advanced collision-avoidance systems, but also addressing psychological safety and mental well-being. Indeed, the physical form of a robot can influence emotions such as perceived risk and trust in the robotic collaborator (Liu et al., 2023).

The concept of human–robot collaboration in Industry 5.0 offers the possibility of enhancing work quality through the creation of a more engaging workplace environment and greater opportunities for self-development. In this context, employees are expected to act as strategic decision-makers and adaptable problem-solvers, thereby enjoying greater autonomy in their professional development (Leesakul et al., 2022).

Numerous studies suggest that high operating speeds, short distances between the user and the robot, and linear motion paths increase cognitive workload, amplifying feelings of fear, surprise, and discomfort. Similarly, higher movement velocity substantially elevates cognitive effort (Baltrusch et al., 2022).

Furthermore, Liao et al. (2024) underscore the significance of perceived intelligence in shaping employees' emotional, psychological, and attitudinal responses. Their research suggests that when cobots are perceived as possessing superior intellectual capabilities compared to humans, they may elicit concerns about technological unemployment and generate anxiety regarding future job stability.

Within the affective dimension, we distinguish between favourable and unfavourable feelings. While positive emotions capture favourable affective reactions, within unfavourable feelings, CAN model differentiates between general negative emotions and anxiety-related emotions (Pelegrín-Borondo et al., 2016; Reinares-Lara et al., 2018). Although both belong to the broader domain of negative affective states, prior psychological research supports their conceptual differentiation. Negative emotions capture a broad dimension of subjective distress and unpleasurable engagement, encompassing feelings such as irritability, hostility, shame, or upset (Watson et al., 1988). This construct reflects general emotional discomfort that may arise as a reaction to situational demands. In contrast, anxiety constitutes a more specific emotional state characterised by

physiological hyperarousal, tension, and anticipatory apprehension (Clark & Watson, 1991). It is defined as a subjective feeling of tension, apprehension, nervousness, and worry associated with activation of the autonomic nervous system (Spielberger, 1983). The tripartite model of anxiety and depression explicitly distinguishes general distress from anxiety-specific hyperactivation, thereby providing theoretical grounds for modelling anxiety separately from general negative emotions (Clark & Watson, 1991).

This distinction is particularly relevant in HRC environments. General negative emotions may stem from frustration, perceived difficulty, or momentary discomfort during task execution, whereas anxiety-related emotions are more closely associated with uncertainty, perceived technological unpredictability, or concerns about safety and job stability (Nomura et al., 2006). In technology adoption contexts, anxiety has been identified as a distinct affective mechanism influencing users' evaluations and behavioural responses (Venkatesh et al., 2003). Thus, it is proposed:

H4. Positive emotions are positively correlated with judgement regarding human–robot collaboration.

H5. Negative emotions are negatively correlated with judgement regarding human–robot collaboration.

H6. Anxiety is negatively correlated with judgement regarding human–robot collaboration.

2.3. Development of configurational laws about the judgement of human–robot collaboration in the workplace with the CAN groundwork

The use of fsQCA allows us to capture that a given outcome may result from several combinations of factors (Woodside, 2014). This technique may shed light on the antecedents of human–robot collaboration in the workplace, as there is no single typology of individuals with favourable or unfavourable judgements of HRC. For example, in the context of cobots, Paluch et al. (2022) classify users with favourable judgements as supporters and embracers, whereas those with unfavourable judgements are described as resisters and saboteurs.

Attitudes toward robots are significantly influenced by users' personal traits, such as openness, neuroticism, and technology self-efficacy (Latikka et al., 2021). Two individuals with different personality profiles may arrive at the same judgement through entirely different pathways. Paluch et al. (2022) suggest that among those who accept a particular technology, there are supporters and embracers, whereas those who reject it can be divided into resisters and saboteurs. Even if a supporter reaches a judgement about technologies such as cobots similar to that of an embracer, the underlying process leading to that judgement is likely to differ.

It is therefore reasonable to assume that there is more than one pathway leading to the same judgement regarding collaborative human–robot work. In this context, fsQCA provides a powerful tool for analysing the acceptance of new technologies, as it captures nuances that correlational analysis may overlook (Pappas & Woodside, 2021; Andrés-Sánchez et al., 2022).

Positive and negative attitudes toward technology are often asymmetric. While acceptability does not necessarily drive acceptance, unacceptability may drive resistance and non-acceptance (Gauttier, 2019). In this regard, fsQCA is particularly suitable for addressing asymmetric relationships between variables, although it can also accommodate symmetrical relationships (Pappas & Woodside, 2021). In the field of surgical robotics, using a UTAUT-based framework, Andrés-Sánchez et al. (2022) reported that the configurations associated with acceptance and rejection are markedly different.

With fsQCA, strong hypotheses—typically formulated in correlational approaches and justified in Section 2.1—are not established. Instead, “soft” laws are proposed (Rutten & Rubinson, 2022), often referred to as propositions or tenets. Accordingly, we propose the following, which are graphically represented in Figure 2:

Proposition 1 (P1): Configurations preceding a favourable attitude toward collaborative human–robot work typically involve combinations of some of the following conditions: the presence of performance expectancy, effort expectancy, social influence, and positive emotions, together with the absence of negative emotions and/or anxiety. These conditions do not need to occur simultaneously; rather, different combinations of them may be sufficient to produce a favourable judgement.

Proposition 2 (P2): Configurations preceding an unfavourable attitude toward collaborative human–robot work typically involve combinations of some of the following conditions: the absence of performance expectancy, effort expectancy, social influence, and positive emotions, together with the presence of negative emotions and/or anxiety. These conditions do not need to occur simultaneously; rather, different combinations of them may be sufficient to produce an unfavourable judgement.

Proposition 3 (P3): The configurations for favourable and unfavourable judgements of collaborative human–robot work are asymmetric.

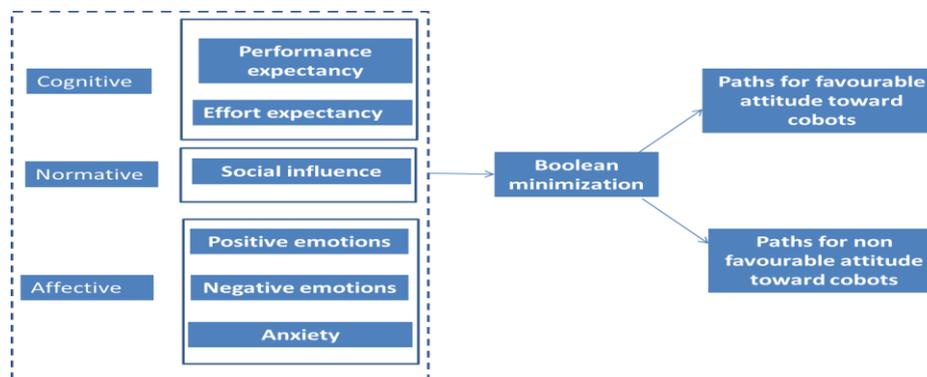


FIGURE 2-CONCEPTUAL FRAMEWORK FOR CONFIGURATIONAL ANALYSIS OF ATTITUDES TOWARD HUMAN–ROBOT COLLABORATIVE WORK

3. RESEARCH METHODOLOGY

3.1. Materials

This study is based on a survey of 126 individuals who regularly interact with robots in their jobs; their profile is provided in Table 1. Only a specific part of the questionnaire was used; specifically, questions related to the CAN acceptance model were developed theoretically and are displayed in Table 2.

The questionnaire was initially distributed in Spanish to eight members of academia and human resource professionals, allowing for improvements. Despite the small sample size, this initial distribution allowed a preliminary assessment of the validity and discriminant capacity of the scales. The questionnaire was subsequently distributed in Spanish, English, and Japanese. The English and Japanese versions were reviewed by academics fluent in those languages and familiar with the present study.

The questionnaire was published on the Zoho Survey platform for 115 days, from November 24, 2022, until March 18, 2023, and was answered online by participants. To maximize participation, social networks, such as LinkedIn, Facebook, Instagram, and Twitter, were promoted. It was also distributed through several organizations, including the Spanish Association of Managers of Social Responsibility (DIRSE), the Spanish Association for People Management (AEDIPE), and the Spanish Association of Robotics and Automation (AER), along with several companies and organisations specifically involved in recent processes of robotization and automation.

The final number of responses was 138, but 12 were excluded because they were incomplete. Therefore, only 126 of the 138 responses were used. With respect to sex, 42.86% of the responses were from women, and 57.14% were from men. The average age of the respondents was 39.60 years (standard deviation 14.80 years). In terms of age distribution, 39.68% were under 35 years, 33.33% were in the 35–50 years age range, and the remaining 26.98% were older than 50 years.

The survey included a question on the years of experience that the respondent had in the current workplace where they interacted with the cobot. The proportion of respondents with up to five years of experience was 31.75%, that with between five and 20 years of experience was 26.19%, and that with over 20 years of experience was 42.06%.

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Regarding the typology of interactions with a robot in the workplace established by Scholtz (2003), 28.57% acknowledged operator interactions, 31.75% had a bystander role, 15.08% were involved in a mechanic or programmer job, and 15.08% declared having a supervisory role.

Finally, 64.29% of the responses were from questionnaires redacted in Spanish, 23.81% from the English version, and 11.90% from the Japanese questionnaire.

Commonly used questions in analyses utilizing the CAN focus on the adoption of new technologies (Reinares-Lara et al., 2016; Pelegrín-Borondo et al., 2017). All the questions were answered on an eleven-point Likert scale ranging from 0 to 10, with 5 representing a neutral evaluation.

Thus, the scale related to attitude (ATT) was based on that of Bhattacharjee and Premkumar (2004). The scales for performance expectancy (PE), effort expectancy (EE), and social influence (SI) were based on those used by Davis (1989) in the TAM framework and Venkatesh and Davis (2000) in a TAM2 setting.

The scales for positive emotions (POSEM), negative emotions (NEGEM), and anxiety emotions (ANXEM) are based on the PANAS scale (Watson et al., 1988). Following the approach of Reinares-Lara et al. (2018), for POSEM, we distinguished sensations as interested, excited, determined, enthusiastic, proud, inspired, strong and active. For NEGEM, we differentiated feelings of being distressed, upset, confused, ashamed, hostile, afraid, irritable, and alert. Finally, in ANXEM we distinguish feelings of being nervous, attentive, and jittery.

TABLE 1-SAMPLE PROFILE IN OUR STUDY (N=126)

Category	Responses by item
Sex	Women: 42.86% Men: 57.14%
Age (Mean=39.60 years, SD=14.80 years)	Age ≤ 35 years: 39.68% 35 < Age ≤ 50 years: 33.33% Age > 50 years: 26.98%
Years of experience (Mean=16.85, SD=13.40)	<=5 years: 31.75% 5 years<experience<=20 years: 26.19% experience>20 years: 42.06%
Role with the robot	Operator interaction: 28.57% Bystander role: 31.75% Mechanic or programmer role: 15.08% Peer role: 15.08% Supervisory role: 9.52%
Language	Spanish: 64.29% English: 23.81% Japanese: 11.90%

3.2. Methods

The steps followed to perform the fsQCA followed the framework developed in Pappas and Woodside (2021). In such studies, which rely on the use of scales to measure latent variables, the following steps are undertaken:

Step 1: Conduct an analysis of the scale and discriminant validity. Scale reliability was assessed with the following indicators: Cronbach's alpha, convergent reliability (CR), and average variance extracted (AVE). Similarly, we examine factor loadings.

Step 2: Fit the correlation matrix of the constructs and assess the scales' discriminant validity via the Fornell-Larcker criterion (1981). The Pearson correlations between latent variables also enable an analysis of the signs of the relationships between explanatory variables and judgement about collaborative robots from a correlational perspective, allowing us to test the statistical hypotheses H1-H6.

Step 3: Calibrate the membership functions of the variables involved in the analysis. To do this, we first aggregated the items for each latent variable. An appropriate alternative if the scale is validated is to use factor loading (DiStefano et al., 2009), as was done by Andrés-Sánchez et al. (2022). Here, we consider the values of absolute membership and nonmembership to be the 90th and 10th percentiles, respectively. As usual, the crossover point was set at the 50th percentile.

Step 4: Perform a necessity analysis to identify whether the participation of latent variables is a necessary condition for a favourable judgement (ATT) or an unfavourable judgement (\neg ATT). Thus, ' \neg ' stands for the negation or absence of a specific factor.

Step 5: Obtain sufficient conditions for ATT and \neg ATT in the so-called parsimonious and intermediate solution by using the McCluskey algorithm. These solutions embed a set of paths (also called configurations, prime implicates or recipes) that lead to the same outcome (the favourable or nonfavourable perception of HRC). We have built a hypothesis about the factors participating in the configurations from the hypothesis developed in section 2.2., which must be considered in the correlation analysis.

Step 6: Fit the parsimonious solutions for ATT and \neg ATT. They allow identification in the prime implicates of the intermediate solution in which the core and peripheral conditions are.

Step 7: Interpret the solutions obtained for ATT and \neg ATT

4. RESULTS AND DISCUSSIONS

4.1. Statistical and correlational analysis

Table 2 shows that the prevailing attitude toward collaborating with robots is positive. For all four attitude items, the average rating clearly exceeded 5, which was considered the neutral point. Specifically, the ratings ranged between 7.78 and 8.41. Similarly, the cognitive constructs PE and EE also exhibit average ratings clearly above the neutral value of 5. The PE indicators ranged between 7.21 and 8.62, and the EE indicators ranged between 6.65 and 7.17. The normative latent variable, social influence, also shows a positive evaluation, although less pronounced than ATT, PE, or EE. The average ratings for its three items range between 5.70 and 5.95.

Table 2 further indicates that affective items related to POSEM are rated above 5 (ranging from 6.02 for proud to 7.78 for interested). In contrast, items associated with NEGEM are rated below the neutral value (ranging from 4.04 for alert to 1.99 for ashamed), suggesting generally low levels of negative emotions. Items associated with anxiety range between 3.42 (jittery) and 5.23 (attentive), indicating moderate to low anxiety levels overall.

Table 2 also shows that Cronbach's α and composite reliability exceed 0.7 for all latent variables. Additionally, the AVE is greater than 0.5 for all constructs. Therefore, the scales demonstrate satisfactory internal consistency. Table 3 confirms that the latent variables exhibit discriminant validity according to the Fornell and Larcker (1981) criterion, as the square root of the AVE for each construct exceeds its correlations with other variables. Notably, although NEGEM and ANXEM both represent unfavourable affective states and are positively correlated, the discriminant validity criterion is satisfied. This result provides additional empirical support for treating negative emotions and anxiety as conceptually distinct constructs.

Table 2 shows that the factor loadings of almost all items exceed 0.7, indicating that they are well represented by their respective latent variables. The only exceptions are alert (factor loading = 0.59) and attentive (factor loading = 0.69). However, values between 0.50 and 0.70 may be considered acceptable when other measures of internal consistency and discriminant validity are satisfactory (Hair et al., 2019).

Table 3 presents the Pearson correlations between all constructs and ATT. All proposed hypotheses are supported. The correlation coefficient for PE is 0.770 ($p < 0.01$). For EE, $\text{corr} = 0.421$ ($p < 0.01$); for SI, $\text{corr} = 0.504$ ($p < 0.01$); for POSEM, $\text{corr} = 0.633$ ($p < 0.01$); for NEGEM, $\text{corr} = -0.385$ ($p < 0.01$); and for ANXEM, $\text{corr} = -0.227$ ($p < 0.05$).

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TABLE 2-DESCRIPTIVE STATISTICS OF THE ITEMS USED IN THIS PAPER AND SCALE RELIABILITY MEASURES

Item	Mean	Standard deviation	Factor loading	α	CR	AVE
<i>Attitude (ATT)</i>				0.88	0.92	0.75
ATT1 Human-robot collaboration is a good idea.	8.12	1.95	0.89			
ATT2 Human-robot collaboration is a wise move.	7.78	2.23	0.84			
ATT3 Human-robot collaboration is a step up.	8.29	1.78	0.88			
ATT4 Human-robot collaboration is an effective idea.	8.41	1.72	0.86			
<i>Performance expectancy (PE)</i>				0.85	0.90	0.70
PE1 I would consider useful to work in a human-robot collaboration environment.	7.83	2.24	0.81			
PE2 Human-robot collaboration environments increase the chances of achieving important goals.	7.21	2.67	0.76			
PE3 Human-robot collaboration environment would allow me to perform tasks more quickly.	8.62	1.76	0.88			
PE4 Human-robot collaboration increases my productivity.	8.25	2.24	0.90			
<i>Effort expectancy (EE)</i>				0.93	0.95	0.83
EE1 Human-robot collaboration setting would be effortless for me.	7.16	2.66	0.93			
EE2 Human robot collaboration is be clear and understandable.	6.65	2.42	0.88			
EE3 It would be easy to work in a human-robot collaboration environment.	6.86	2.36	0.92			
EE4 It would be easy for me to become skillful working in a human-robot collaboration environment.	7.17	2.37	0.92			
<i>Social influence (SI)</i>				0.92	0.95	0.86
SI1 People who are important to me, think I should work in a human-robot collaboration environment	5.70	2.47	0.91			
SI2 People who influence my behaviour think I should work in a human-robot collaboration	5.75	2.50	0.94			
SI3 People whose opinions I value would prefer that I would work in a human-robot collaboration environment	5.95	2.61	0.92			
<i>Positive emotions (due to developing tasks in a human-robot collaboration environment) (POSEM)</i>				0.93	0.94	0.68
POSEM 1. Interested	7.78	2.09	0.75			
POSEM 2. Excited	6.30	2.53	0.79			
POSEM 3. Determined	6.82	2.44	0.86			
POSEM 4. Enthusiastic	6.39	2.42	0.86			
POSEM 5. Proud	6.02	2.91	0.84			
POSEM 6. Inspired	6.10	2.74	0.83			
POSEM 7. Strong	6.76	2.53	0.84			
POSEM 8. Active	6.75	2.48	0.80			
<i>Negative emotions (due to developing tasks in a human-robot collaboration environment) (NEGEM)</i>				0.92	0.93	0.62
NEGEM 1. Distressed	3.55	2.74	0.59			
NEGEM 2. Upset	2.81	2.70	0.81			
NEGEM 3. Confused	3.31	2.73	0.86			
NEGEM 4. Ashamed	1.99	2.24	0.76			
NEGEM 5. Scared	2.79	2.69	0.85			
NEGEM 6. Hostile	2.19	2.39	0.81			
NEGEM 7. Afraid	2.49	2.58	0.87			
NEGEM 8. Irritable	2.68	2.50	0.85			
NEGEM 9. Alert	4.04	2.95	0.59			
<i>Anxiety emotions (due to developing tasks in a human-robot collaboration environment) (ANXEM)</i>				0.76	0.86	0.68
ANXEM 1. Jittery	3.42	2.66	0.89			
ANXEM 2. Nervous	3.45	2.82	0.89			
ANXEM 3. Attentive	5.23	2.83	0.68			

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TABLE 3-CORRELATION MATRIX AND FORNELL-LARKER DISCRIMINANT VALIDITY CRITERIA

	ATT	PE	EE	SI	POSEM	NEGEM	ANXEM
ATT	0.866						
PE	0.770**	0.840					
EE	0.421**	0.486**	0.913				
SI	0.504**	0.521**	0.478**	0.925			
POSEM	0.633**	0.682**	0.534**	0.579**	0.824		
NEGEM	-0.385**	-0.372**	-0.461**	-0.283**	-0.395**	0.785	
ANXEM	-0.227*	-0.214*	-0.295**	-0.117	-0.239**	0.704**	0.827

Note: In the principal diagonal is the square root of the AVE. As *** and **, we symbolize that the correlation is significant at the 1% and 5% significance levels, respectively.

4.2. Fuzzy set qualitative comparative analysis results

Table 4 presents the thresholds for full membership (90th percentile), full nonmembership (10th percentile), and the crossover point (50th percentile) for the constructs used in this study. These values were established based on standardised factor scores. Membership values between the 10th and 50th percentiles and between the 50th and 90th percentiles were calibrated using linear interpolation.

Table 5 assesses the potential existence of necessary conditions for positive and non-positive judgements. In no case does the presence or absence of any construct reach the threshold to be considered a necessary condition, as consistency values are well below the 0.9 benchmark. When the outcome is ATT, the consistency of the presence of PE, EE, SI, and POSEM is greater than that of their absence. The absence of NEGEM and ANXEM also exhibits higher consistency than their presence. Conversely, when the outcome is \neg ATT, the consistency of the absence of PE, EE, SI, and POSEM is greater than that of their presence, while the presence of NEGEM and ANXEM shows higher consistency than their absence.

Tables 6 and 7 present the intermediate solution configurations for positive and non-positive attitudes toward collaboration with robots. In Table 6, the solution for ATT consists of seven prime implicates with overall consistency (cons) of 0.801 and coverage (cov) of 0.859. Table 7 shows that the solution for \neg ATT comprises six configurations with cons = 0.821 and cov = 0.787.

In Table 6, positive attitude configurations include the presence of performance expectancy (four times as a core condition), effort expectancy (once as a core condition and twice as a peripheral condition), social influence (twice as a core condition and once as a peripheral condition), and positive emotions (twice as a core condition and once as a peripheral condition). These findings are consistent with the positive correlations of PE, EE, SI, and POSEM with ATT.

In contrast, the role of negative emotions in the ATT configurations does not exhibit a univocal pattern. The absence of NEGEM appears in two configurations (once as a core condition and once as a peripheral condition). However, despite its negative correlation with ATT, its presence also appears in the seventh configuration (EE•SI•NEGEM). This finding suggests that, in this configuration, the potential negative effect of negative emotions may be offset by perceived ease of use and positive social influence in collaborative environments. The participation of anxiety in the ATT solution is limited. Its presence appears only in the fourth configuration (PE•ANXEM), and solely as a peripheral condition. In this case, the potential adverse influence of anxiety-related emotions may be compensated by strong perceived usefulness.

Among the seven configurations explaining positive attitudes toward human–robot collaboration, one is purely affective (the first). Five configurations combine two typologies: the second is cognitive–normative; the third is normative–affective; and the fourth, fifth, and sixth are cognitive–affective. The seventh configuration includes variables from all three CAN dimensions.

Table 7 presents the six configurations associated with unfavourable judgements (\neg ATT). The absence of performance expectancy (five times as a core condition), effort expectancy (three times as a core condition), social influence (once as a core condition and once as a peripheral condition), and positive emotions (three times as a core condition) is observed. Similarly, the presence of NEGEM appears in four configurations (three as a core condition and one as a peripheral condition), indicating its relevance in unfavourable judgements.

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Thus, the conditions \neg PE, \neg EE, \neg SI, and \neg POSEM in the configurations of \neg ATT are consistent with the correlations observed in the correlational analysis.

Table 7 also shows that anxiety-related emotions do not operate uniformly in unfavourable judgements. The presence of ANXEM is a core condition in one configuration, whereas its absence appears in two configurations (once as a core condition and once as a peripheral condition). Therefore, the role of anxiety in explaining unfavourable attitudes depends on the specific configurational context.

In all cases, the prime implicates combine at least two of the three CAN dimensions. Most configurations primarily involve cognitive and affective variables (first, third, fourth, and fifth). One configuration is exclusively cognitive–normative (the second). Additionally, the configuration \neg EE• \neg SI• \neg POSEM•NEGEM•ANXEM incorporates variables from all three typologies.

The explanations of favourable and unfavourable judgements of HRC are clearly asymmetric. In both outcomes, performance expectancy emerges as the most recurrent condition. However, while the presence of EE appears as a core condition only once in ATT configurations, its absence is a core condition in three of the six \neg ATT configurations. Regarding negative emotions, both their presence and absence appear in configurations explaining ATT, whereas in the \neg ATT solutions, whenever NEGEM is present, it plays a central role. Importantly, no configuration explaining ATT has a simple symmetrical counterpart in \neg ATT, and vice versa. For example, the purely affective configuration POSEM• \neg NEGEM explaining ATT does not correspond to a mirror configuration such as \neg POSEM•NEGEM for \neg ATT, but rather to more complex combinations such as \neg PE• \neg POSEM•NEGEM or \neg EE• \neg SI• \neg POSEM•NEGEM•ANXEM.

TABLE 4-ABSOLUTE NONMEMBERSHIP, ABSOLUTE MEMBERSHIP FUNCTIONS AND CROSSOVER POINTS

Percentile	ATT	PE	EE	SI	POSEM	NEGEM	ANXEM
10%	-1.325	-1.479	-1.214	-1.196	-1.040	-1.172	-1.252
50%	0.065	0.168	0.135	-0.204	0.048	-0.130	-0.114
90%	1.110	1.053	1.195	1.509	1.231	1.314	1.402

TABLE 5-NECESSITY ANALYSIS OF POSITIVE AND NEGATIVE ATTITUDES

	ATT		\neg ATT	
	Cons	Cov	Cons	Cov
PE	0.835	0.833	0.514	0.427
\neg PE	0.426	0.512	0.799	0.802
EE	0.717	0.772	0.523	0.471
\neg EE	0.509	0.563	0.746	0.687
SI	0.734	0.770	0.534	0.467
\neg SI	0.491	0.559	0.737	0.698
POSEM	0.738	0.817	0.458	0.422
\neg POSEM	0.478	0.514	0.802	0.718
NEGEM	0.484	0.542	0.710	0.662
\neg NEGEM	0.689	0.743	0.509	0.451
ANXEM	0.539	0.585	0.675	0.610
\neg ANXEM	0.641	0.705	0.541	0.495

TABLE 6-INTERMEDIATE SOLUTION FOR ATT

	1	2	3	4	5	6	7
PE		•		•	•	•	
EE					•	•	•
SI		•	•				•
POSEM	•		•			•	
NEGEM	⊗				⊗		•
ANXEM				•			
Cov	0.575	0.665	0.609	0.460	0.521	0.574	0.316
Cons	0.849	0.882	0.855	0.838	0.891	0.907	0.856
Cov	0.859						
Cons	0.801						

Note: Circle • indicates the presence of a factor as a condition, circle ⊗ indicates the absence of a factor, and a blank indicates no relevance in the prime implicate. Large circles represent core conditions, and small circles represent peripheral conditions.

TABLE 7-INTERMEDIATE SOLUTION FOR \neg ATT

	1	2	3	4	5	6
PE	⊗	⊗	⊗	⊗	⊗	
EE		⊗			⊗	⊗
SI		⊗				⊗
POSEM	⊗			⊗		⊗
NEGEM			•	•	•	•
ANXEM	⊗		⊗			•
cov	0.398	0.551	0.301	0.564	0.527	0.426
cons	0.865	0.873	0.885	0.889	0.888	0.865
cov	0.787					
cons	0.821					

Note: Circle • indicates the presence of a factor as a condition, circle ⊗ indicates the absence of a factor, and a blank indicates no relevance in the prime implicate. Large circles represent core conditions, and small circles represent peripheral conditions.

4.3. Discussions

This study examines the acceptance of human–robot collaborative work through a survey of 126 workers regularly engaged in such environments. Grounded in the cognitive–affective–normative (CAN) framework (Pelegrín-Borondo et al., 2016; Reinares-Lara et al., 2016; Reinares-Lara et al., 2018), the analysis combines correlational techniques with fuzzy-set qualitative comparative analysis (fsQCA). The assessment of discriminant validity and correlational relationships prior to the fsQCA enables evaluation of the direction and strength of associations between the explanatory latent variables and workers' judgements regarding human–robot collaboration (HRC). The use of fsQCA further allows the identification of multiple configurations associated with favourable judgements (ATT) and unfavourable judgements (\neg ATT), which are not necessarily symmetrical.

Regarding the first research objective, a positive relationship was observed between the cognitive variables in the CAN model (performance expectancy and effort expectancy) and attitudes toward HRC. These findings are consistent with previous research in healthcare robotics (BenMessaoud et al., 2011; Kremer et al., 2020; Andrés-Sánchez et al., 2022), social robotics (De Graaf & Allouch, 2013; Saari et al., 2022), service robotics (Wirtz et al., 2018; Kasilingam et al., 2020; Kim, 2023; Andrés Sánchez & Gené-Albesa, 2023; Silva et al., 2023), and collaborative robotics (Bröhl et al., 2016; Porubčinová & Fidlerová, 2020; Nguyen et al., 2022; Prassida & Asfari, 2022; Picco et al., 2024).

Similarly, effort expectancy exhibits a positive association with attitudes toward HRC, in line with empirical findings reported by Bröhl et al. (2016), Kremer et al. (2020), Andrés-Sánchez et al. (2022), Kasilingam et al. (2020), Babamiri et al. (2022), and Nguyen et al. (2022).

Social influence is also positively correlated with the acceptance of collaboration with robots. This relationship has been suggested and empirically tested across various applications of robotic technology (BenMessaoud et al., 2011; Wirtz et al., 2018; Porubčinová & Fidlerová, 2020; Prassida & Asfari, 2022; De Graaf & Allouch, 2013; Kremer et al., 2020; Andrés-Sánchez et al., 2022; Nguyen et al., 2022; Andrés-Sánchez & Gené-Albesa, 2023; Silva et al., 2023).

In collaborative human–robot environments, both actors form part of the same working unit (Baumgartner et al., 2022), and the robot may be perceived as a form of workplace colleague (Paluch, 2022). This proximity positions emotions and anxiety as relevant determinants of usage attitudes (Porubčinová & Fidlerová, 2020). The positive correlation between positive emotions and attitude, and the negative correlations of negative emotions and anxiety, are consistent with extensive evidence regarding the affective dimension of technology acceptance. Relevant affective constructs include emotional trust (Gkinko & Elbanna, 2023), perceived safety (Kildal et al., 2018), enjoyment (Elprama et al., 2016; Heo et al., 2024), anxiety (Gruber & Hancock, 2021), psychological comfort and discomfort (Zanchettin et al., 2013), fear (Ivanov et al., 2020), and the “uncanny valley” effect (Sowa et al., 2021).

Workers' judgements regarding HRC are also influenced by personality traits such as optimism or extraversion (Latikka et al., 2021). Consequently, there is no single worker profile that uniformly accepts or rejects

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collaborative robotics (Paluch et al., 2022). This consideration motivates the second research objective, which examines how CAN factors combine to generate distinct profiles of favourable and unfavourable attitudes toward collaborative work with robots.

The fsQCA analysis identifies seven configurations associated with favourable attitudes (ATT) and six associated with unfavourable attitudes (\neg ATT). Performance expectancy, effort expectancy, social influence, and positive emotions appear in configurations of both ATT and \neg ATT, with signs consistent with the correlational findings. Although no necessary condition reaches the conventional 0.9 consistency threshold, performance expectancy emerges as the most recurrent core condition in sufficient configurations. It appears as a core condition in four of the seven ATT configurations and in the majority of the \neg ATT configurations, highlighting its central explanatory role.

The role of negative emotions and anxiety, however, is more configurationally contingent. Anxiety appears only once in ATT configurations and solely as a peripheral condition. In \neg ATT solutions, anxiety is present as a core condition in one configuration but absent in another, indicating that its influence depends on the broader configurational context. Similarly, negative emotions participate in two ATT configurations, once as absent (consistent with correlational expectations) and once as present, suggesting that their potential negative effect may be offset by other favourable conditions. In contrast, in \neg ATT configurations, negative emotions consistently reinforce unfavourable judgements whenever they appear, aligning with their negative correlation with attitude.

These findings make both theoretical and practical contributions. The results confirm that extending the CAN framework—rooted in TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003)—provides a valid theoretical basis for explaining acceptance of human–machine collaborative environments. The model has previously demonstrated explanatory capacity in contexts involving close human–technology interaction (Pelegrín-Borondo et al., 2017; Reinares-Lara et al., 2018), and this study extends its applicability to collaborative robotics.

From a methodological perspective, the integration of fsQCA complements correlational analysis. While correlational techniques estimate average linear relationships between variables and attitudes, fsQCA uncovers multiple pathways through which combinations of cognitive, affective, and normative factors lead to favourable or unfavourable judgements (Pappas & Woodside, 2021).

Overall, the results demonstrate that attitudes toward collaborative robotic technologies emerge from multiple asymmetric pathways. The presence or absence of specific CAN dimensions does not operate in isolation but in combination with others, giving rise to distinct worker profiles that are far from symmetrical.

The successful implementation of automation processes influences organisational performance (Kim et al., 2022), and a prerequisite is broad worker acceptance. For employers, understanding both the direction of individual variable effects and the configurational profiles associated with acceptance or resistance provides valuable guidance for designing implementation strategies in human–robot collaborative environments.

5. CONCLUSIONS

This study explores the determinants influencing workers' judgements in collaborative human–robot environments involving technologies such as cobots. The findings indicate that the CAN model provides a suitable conceptual framework for understanding whether such judgements are favourable or unfavourable. Moreover, the model allows us to capture how the presence or absence of the latent variables included in CAN act as configurational conditions explaining workers' attitudes toward HRC technologies.

The limitations of this study highlight directions for future research. The primary data are derived from a cross-sectional survey conducted at a specific point in time. However, given that Industry 5.0 and robotic technologies are continuously evolving, longitudinal research designs would provide a more comprehensive understanding of how attitudes toward HRC develop and change over time.

In addition, the sample size is relatively modest and includes respondents occupying different roles within human–robot environments (operator interaction, bystander role, mechanic or programmer role, peer role, supervisory role), as well as participants from different cultural contexts, given that the survey was administered

in Spanish, English, and Japanese. Future research could benefit from expanding both the overall sample size and the representation within each interaction role and cultural context. Such expansion would enable more robust conclusions regarding the influence of occupational role and cultural background on attitudes toward collaborative human–robot work.

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