

Research Article

Translation, Adaptation, and Validation in Portuguese of an Acceptance Scale for Human–Robot Interaction in an Industrial Context

Ana Pinto ¹, Leticia Lemos ², Carla Carvalho ³, Joana Santos ⁴, Paulo Menezes ⁵,
 and Tatsuya Nomura ⁶

¹Faculty of Sciences and Technology, Centre for Business and Economics Research (CEBER), University of Coimbra, Coimbra, Portugal

²Faculty of Psychology and Educational Sciences, University of Coimbra, Coimbra, Portugal

³Faculty of Psychology and Educational Sciences, Center for Research in Neuropsychology and Cognitive Behavioral Intervention (CINEICC), University of Coimbra, Coimbra, Portugal

⁴Faculty of Engineering, Institute of Porto (ESS|P.Porto), LETA/INEGI, University of Porto, Porto, Portugal

⁵Institute of Systems and Robotics, Faculty of Sciences and Technology, University of Coimbra, Coimbra, Portugal

⁶Department of Media Information, Faculty of Science and Technology, Ryukoku University, Otsu, Japan

Correspondence should be addressed to Ana Pinto; ana.pinto@dem.uc.pt

Received 23 July 2024; Accepted 27 December 2024

Academic Editor: Mirko Duradoni

Copyright © 2025 Ana Pinto et al. Human Behavior and Emerging Technologies published by John Wiley & Sons Ltd. This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

Industry 4.0, characterized by the integration of advanced technologies across various industrial domains, is now evolving into Industry 5.0, which emphasizes the human perspective, resilience, and sustainability. In this context, the study of human behavior and attitudes towards human–robot interaction (HRI) is crucial for understanding the acceptance of this emerging technology, which, in turn, can drive the development of more well-designed industrial robotic systems. This paper is aimed at translating, adapting, and validating a scale designed to measure acceptance in the context of HRI within industrial settings, with a focus on collaborative robots (cobots). To conduct an exploratory factor analysis (EFA), 140 participants (male = 45%, female = 52%, and nonbinary = 3%) were recruited. The results revealed a four-factor structure for the Frankenstein Syndrome Questionnaire–Industrial Context (FSQ-IC): “general anxiety towards cobots” ($\alpha = 0.87$), “trustworthiness towards developers of cobots” ($\alpha = 0.83$), “apprehension towards cobots in the industrial context” ($\alpha = 0.73$), and “expectation of cobots in social change” ($\alpha = 0.69$). For further validation and to help ensure the validity and reliability of the adapted scale, a confirmatory factor analysis (CFA) was conducted with a sample of 210 participants (male = 45%, female = 53%, and nonbinary = 2%). The model fit indices, including a χ^2/df of 3.14 and root mean square error of approximation (RMSEA) of 0.10, indicated an acceptable fit. The goodness-of-fit index (GFI), comparative fit index (CFI), and normed fit index (NFI) were 0.88, 0.90, and 0.86, respectively, all within acceptable ranges. Convergent and discriminant validities were also analyzed. An analysis of the differences in perceptions of acceptance based on sociodemographic variables (gender, experience with robots, educational level, and age) was conducted. Only gender revealed significant differences. Considering the psychometric qualities of the instrument, the FSQ-IC is valid and reliable for assessing acceptance in HRI.

Keywords: collaborative robots; factor analysis; Frankenstein Syndrome Questionnaire (FSQ); psychometric evaluation

1. Introduction

The emergence of Industry 5.0 has advanced the research frontier of the technology-centric Industry 4.0 towards a more intelligent and harmonious socioeconomic transition, driven by both human and technological factors [1]. In this context, the focus is predominantly on the role of humans in technological transformation [2]. Therefore, adopting Industry 5.0 technologies will not undermine human value but rather increase it through human-machine collaboration [3]. In fact, humans have the necessary skills to perform tasks with greater cognitive demands and involve uncertainties [4]; however, they do not have equivalent speed, endurance, and physical power of robots for physical tasks [4, 5]. Giallanza et al. [6] emphasize that collaborative robots (cobots) present a viable solution for manufacturing industries shifting from mass production to mass customization, aiming at enhancing their competitive position in the market. According to some authors [7–10], cobots are an emerging technology that have ergonomic and safety benefits, as flexibility and productivity advantages to manufacturing systems. However, despite the benefits of using cobots, workers may be reluctant to adopt them. Considering that cobots need to collaborate harmonically with human workers, it is essential to understand employees' attitudes towards cobots in human-cobot collaborative work, namely, acceptance [11]. Worker acceptance depends on their involvement in the cobot implementation process [12]. Cobots have faced low acceptance in practical applications, particularly in industry [13].

Therefore, examining the acceptance of these machines can provide insights that can aid in the development of cobots that align with social expectations and maximize profitability for producers. In this scenario, a gap in the literature emerges, proved by a study made by Cherubini et al. [14], where the authors advocate for an assessment of robots engaged in physical collaboration with workers. This requires adapting the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) to measure acceptance, highlighting the significance and relevance of a scale like the one developed in the current study. This further emphasizes the necessity for a systematic evaluation of human-robot interaction (HRI), especially concerning cobots in the industrial context. The validation of a scale to assess human acceptance of robots in HRI in Portuguese language, particularly within the industrial sector, represents a valuable contribution to optimizing HRI design.

Our research is aimed at filling this gap by proposing the translation, adaptation, and validation of the acceptance scale known as the Frankenstein Syndrome Questionnaire (FSQ). This tool, proposed by Nomura et al. [15], emerges as a fundamental instrument to assess workers' attitudes and perceptions towards social robots. After the translation and adaptation of the scale, both in linguistic, cultural, and contextual terms, it was decided to call it Frankenstein Syndrome Questionnaire-Industrial Context (FSQ-IC) as it focuses on the acceptance of cobots in an Industrial context.

Apart from this first introductory section, the paper starts in Section 2, with the theoretical framework, which is aimed at providing a comprehensive overview of the theoretical foundations related to the concepts under investigation. Section 3 focuses on the methods, and Section 4 provides information regarding the results found from the data analysis performed. Finally, the discussion of this work, the implications, and lastly the limitations of the study are presented in Section 5.

2. Theoretical Framework

2.1. HRI. According to Sharkawy and Koustoumpardis [16], HRI is defined as “understanding, designing, developing, and evaluating the robotic system to be used with or by humans” (p. 1). The multidisciplinary field of HRI draws upon various disciplines such as psychology, engineering, and business, to explore the fusion of the physical capabilities of robots and the emotional responses generated from HRIs [17].

The uprising brought by Industry 5.0 advancements created new ways in which a robot can perform a task, as well as the environment it performs and the type of interaction it displays, hence the different types of HRI, and they are *coexistence*, where the human and robot perform side by side but do not share the same space; *synchronization*, when human and robot share the same space, but in alternate times; *cooperation*, where human and robot share the same space and perform at the same time but do not work on the same component; and *collaboration*, where human and robot share the same space, perform at the same time, and work at the same component [4].

The International Federation of Robotics (IFR) categorizes robots into two main types: industrial and service robots. Service robots are further divided into professional service robots, used for commercial tasks with clearly defined functions, and personal service robots, often known as social robots [18]. Industrial robot is defined by ISO 8373:2012 as “an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications.” On the other hand, social robots represent a distinct technology specifically designed to accompany and assist individuals in their daily lives. As such, they are integrated into various domains, operating in close proximity to people, even during their most private moments [19].

To develop effective HRI, a comprehensive understanding of human behaviors, emotions, cognition, and robot functionality is essential [20]. Mead and Mataric [21] highlight the importance of human-perceived safety and comfort in HRI tasks, indicating that technical safety measures may not always align with human perceptions. The integration of cobots into industrial settings presents new safety challenges, as robotics and worker safety are intricately linked. Traditional robot applications rely on physical or sensor-based measures to maintain separation from workers. In contrast, collaborative systems in HRI allow for close working proximity without separation

[22]. This shift introduces risks such as potential mental stress from robot proximity, alongside benefits like mitigating physical strain.

Cobots require specific capabilities and safety-focused designs to operate alongside humans, while workers must also function in environments conducive to safety and intuitive physical interaction [4]. Cobots, as defined by Franklin et al. [22], are designed to assist humans in specific tasks or work alongside them, prioritizing safety in collaborative work. Cobots offer advantages including improved efficiency, productivity, compactness, and affordability compared to traditional industrial robots [23].

Studies suggest that cobots can enhance workers' health, quality of life, and overall well-being while reducing negative outcomes associated with traditional industrial work [24]. By relieving workers of heavy-duty tasks, cobots contribute to reducing musculoskeletal diseases, which account for 45% of work-related diseases [8]. Moreover, cobots enable older workers to work in safer conditions, addressing concerns surrounding the aging population in industrialized nations [25, 26]. Market data indicates significant growth in cobot applications, with an estimated market size of \$649 million in 2019, projected to grow at a rate of 45% between 2019 and 2025 [27], showing a greater necessity to improve its applicability.

In this context, the benefits observed by the integration of cobots into the industrial sector can be considered a step towards a more sustainable and equitable future for workers and the industry as a whole.

2.2. Acceptance and Instruments. Understanding psychological factors is crucial in developing cobots for the industrial context, aiming for more effective and natural HRI. This approach considers essential elements such as trust, empathy, and acceptance, which are fundamental for the successful implementation of robots in work environments. In the industrial scenario, personalizing robotic interactions is particularly important. Adapting robots to workers' specific needs not only increases operational efficiency but also promotes greater acceptance of the technology. This may include adapting user interfaces, communication modes, and even robot movement patterns to align with individual operators' preferences and skills. Weiss et al. [28] propose a framework to evaluate HRI considering human and psychological factors (e.g., user experience, usability, and social acceptance). The study by Rossi et al. [29] tells us that trust is essential for effective human–robot collaboration (HRC). Robots must adapt to human needs (e.g., emotions and preferences) and leverage metacognition to anticipate, respond to, and mitigate errors. This ensures safe, socially acceptable behavior and fosters high-quality interactions between humans and robots. Research by Ottoni and Cerqueira [30] highlights the importance of recognizing and conveying emotions in HRI for natural, empathetic interactions. It emphasizes user-centered design to enhance system effectiveness and acceptance. Through a systematic review of 72 studies, two main themes emerged: developing methods for recognizing human emotions and representing emotions in robots for friendly interactions. Most studies evaluated per-

formance using participant-based inquiries, showcasing the growing focus on emotional dynamics in HRI.

Acceptance is a central concept in the present study; according to Zoellick et al. [31], acceptance is a precondition for the adaptation and use of technology. Acceptance can be defined as the degree to which an individual intends to use a system and, when available, incorporates the system [32]. However, Görke et al. [33] referred that the intention to adopt technology does not necessarily translate into actual adoption. In the realm of HRI, understanding and addressing acceptance challenges are crucial for the safe, ethical, and effective development and implementation of robots.

According to Akalin et al. [34], perceived safety is important for robot acceptance; however, physical safety has been more studied. Similar findings were found in a field study developed by Xu et al. [35] that showed that perceived usefulness, trust, and perceived safety were direct predictors of acceptance of a specific technology as automated vehicles (AVs). A study developed by Meissner et al. [36] concluded that a safe and well-designed robotic system is a necessary condition for the acceptance of HRC, but engagement in the implementation of HRC seems to correspond well to people's attitudes. Human workers only consider an HRI acceptable if the robot does not carry out actions that could induce fear, surprise, and discomfort or create an unpleasant social situation, even if its actions do not cause any physical harm [37]. Turja and Oksanen [38] referred that national-level factors, as social norms, regulate robot acceptance. Task complexity is another determinant of robot acceptance.

The study of acceptance instruments in HRI began with the TAM, where Davis [39] argues that an individual's intention to use a technology is influenced by two main beliefs: perceived usefulness and perceived ease of use. A few years later, Venkatesh and Davis [40] introduced TAM 2, which added new variables to the original model, such as user experience, social influence, image, and ease of learning. These pioneering studies contributed to the development of other instruments in the field of technology acceptance.

A notable example in the acceptance of social robots is the study by Heerink et al. [41], which led to the creation of the Almere Technology Acceptance Questionnaire (ATAQ). The ATAQ was designed to assess the acceptance of assistive social robots by elderly users. Another important scale in this field is the Negative Attitudes Towards Robots Scale (NARS), developed by Nomura et al. [42], which measures people's negative attitudes towards robots. Additionally, the Robotic Social Attributes Scale (RoSAS) stands out as a psychometrically validated tool that evaluates how people perceive the social attributes of robots [43]. The Multidimensional Robot Attitude Scale, on the other hand, was developed to provide a comprehensive assessment of people's attitudes towards domestic robots [44].

Although these instruments are useful for evaluating the acceptance of systems and social robots, to the best of our knowledge, there is currently no specific tool for measuring the acceptance of robots in industrial contexts.

The decision to select, adapt, and validate the FSQ (scale for social robots) as the study's instrument was driven by its

ability to effectively capture the psychological and ethical barriers to robot acceptance, particularly in contexts where a deeper understanding of these issues is crucial. This approach aligns with the principles of Industry 5.0, which prioritizes sustainability and positions humans at the core of the next phase of industrial automation.

3. Method

3.1. Study Design and Sample. This study followed a cross-sectional design, involving a sample of 346 participants. The questionnaire was distributed through our network contacts, and data were collected using the online LimeSurvey platform. Participants provided informed consent before completing the sociodemographic questionnaire and FSQ-IC. The data collection period lasted from November 21, 2023, to April 23, 2024.

The sample was obtained using a nonprobabilistic convenience sampling method, following a snowball sampling approach. Eligibility criteria for the participants were age over 18 years and ability to speak and read Portuguese.

One hundred and forty participants [45–47] (40% of the total sample) were randomly selected and utilized for the exploratory factor analysis (EFA). The randomization process ensures the representativeness of the sample and minimizes selection bias in the analysis. The demographic composition of the selected dataset includes 73 females, 63 males, and 4 nonbinary individuals. Notably, 102 participants reported having no prior experience with robots. Regarding education levels, 4 participants had completed the 1st cycle, 2 had completed the 2nd cycle, 5 had completed the 3rd cycle, 41 had completed high school, 42 had obtained a university degree, 33 held a master's degree, and 13 held a doctorate. The mean age of the participants was 33.5 years (Table 1).

For the confirmatory factor analysis (CFA), we used a sample of 210 participants [45, 48–50] (60% selected randomly from the total sample). The demographic distribution of this dataset comprised 111 females, 95 males, and 4 nonbinary individuals. Notably, 147 participants reported no prior experience with robots. The level of education of the EFA sample consists of 8 persons who completed the 1st cycle; 1 who completed the 2nd cycle; 14 who completed the 3rd cycle; 54 who completed high school; 60 who have a university education; 57 who have a master's degree; and finally, 16 who have a doctorate. The participants have a mean age of 33.5 years old (Table 2).

It is crucial to emphasize that this study complies with the fundamental ethical principles governing research involving human subjects. Before starting data collection, we obtained the necessary permissions from the authors of the original scale to conduct the cultural adaptation and validation of the FSQ-IC. The study received formal approval from the Research Ethics and Deontology Committee of the Faculty of Psychology and Educational Sciences at the University of Coimbra on July 21, 2023, under Process Number CEDI/FPCEUC:77/R_8.

TABLE 1: Descriptive statistics of the EFA sample.

Category	Total	Percentage (%)	Mean (SD)	No prior experience with robots
Gender				
Female	73	52%		62
Male	63	45%		36
Nonbinary	4	3%		4
Total	140			102
Level of education				
1st cycle	4	3%		
2nd cycle	2	1%		
3rd cycle	5	4%		
High school	41	29%		
University education	42	30%		
Master's degree	33	24%		
Doctorate	13	9%		
Mean age of participants			33.5 years (13.7)	

Note: N of participants = 140.

TABLE 2: Descriptive statistics of the CFA sample.

Category	Total	Percentage (%)	Mean (SD)	No prior experience with robots
Gender				
Female	111	53%		98
Male	95	45%		47
Nonbinary	4	2%		2
Total	210			147
Level of education				
1st cycle	8	4%		
2nd cycle	1	1%		
3rd cycle	14	7%		
High school	54	26%		
University education	60	28%		
Master's degree	57	27%		
Doctorate	16	7%		
Mean age of participants			33.5 years (13.9)	

Note: N of participants = 210.

3.2. Instrument (FSQ). The original FSQ was created to assess the acceptance of humanoid robots. The original version of the instrument was developed based on the Likert scale format with seven response options (1 = *strongly disagree* to 7 = *strongly agree*). The scale was developed through

a preliminary study involving samples from Japan and the United Kingdom [15].

The original instrument was constructed by merging items from other questionnaires, both in English and Japanese languages. The English version was established, and the Japanese version was generated through a process of back-translation. The result was a 30-item questionnaire grouped into four factors: general anxiety towards humanoid robots (13 items), apprehension towards social risks of humanoid robots (five items), trustworthiness for developers of humanoid robots (four items), expectation for humanoid robots in daily life (eight items). In the study, the first subscale (general anxiety towards humanoid robots) shows a Cronbach alpha value of 0.90; the second subscale (apprehension towards social risks of humanoid robots) has a Cronbach alpha value of 0.69; the third subscale (trustworthiness for developers of humanoid robots) has a Cronbach alpha value of 0.72; and the fourth subscale (expectation for humanoid robots in daily life) has a Cronbach alpha value of 0.72. In the study, they found a positive correlation between the first and second ($r = 0.40$), and between the third and fourth subscales ($r = 0.51$). Moreover, there were weak levels of negative correlations between the first subscale and the third ($r = -0.16$) and fourth ($r = -0.29$). There was almost no correlation between the second, third, and fourth subscales [15].

In the Portuguese-language adaptation of the FSQ, tailored for the industrial context, two items from the original version were removed for the current study, specifically, “humanoid robots can be very useful for teaching young kids” and “I am concerned that humanoid robots would be a bad influence on children.” The rationale behind this decision was that these items were related to children which were deemed irrelevant to the study’s objective of evaluating the acceptance of cobots in an industrial setting.

3.3. Translation and Validation Procedure. The cultural adaptation of the original instrument is a critical component of this study’s design, as it lays the foundation for a valid and reliable measure of acceptance of HRI. The steps involved in the cultural adaptation process serve to ensure the quality and reliability of the adapted scale and provide valuable insights into its effectiveness and suitability for its intended use. Therefore, this process was conducted in the following steps.

The translation of the FSQ from English into Portuguese was performed by two native Portuguese translators, and it was authorized by the original authors. The translated version underwent a review and evaluation process by a committee of experts (CEs), which included one of the original authors of the FSQ scale and three additional experts in the field. This group was responsible for evaluating the semantic equivalence of the translated version and making suggestions for improvement or correction.

A synthesis of the translations was created and subjected to a back-translation process by two bilingual native English translators. The back-translation was then compared with the original scale to ensure accuracy.

The final step in the translation and adaptation process involved a pilot test of the FSQ-IC. A group of eight students participated in the pilot test, which involved completing the FSQ-IC scale. It is important to note that the participants of the pilot test were deleted from the sample of the current study. The pilot test is aimed at establish the level of understanding of the questionnaire among the participants and at estimating the completion time required. Based on the results of the pilot test, any items reported as difficult to understand were modified in the final version of the instrument. A table comparing both instruments was made to clarify the distinctions between both scales (Table 3).

3.4. Data Analysis. In this present study, an EFA was performed for the investigation, as well as calculating the alpha values for the instrument. The statistical analyses of the EFA were done using the SPSS program version 27. For further validation of the scale, a confirmatory a CFA was conducted to test the validity of the structure proposed by the EFA. The statistical analysis of the CFA was done using the AMOS program. The data analysis focuses on the structure and validity of the items and their factors. The final step involves interpreting the analyses to obtain the robustness of the FSQ-IC in measuring acceptance. In this study, the correlations between the subscales were analyzed to explore the relationships and degree of association among various subscales within a broader scale. By examining how these subscales relate to each other, we gain insights into underlying patterns or dimensions of the data. This information can help in understanding the constructs being measured, validating the scale, and refining theoretical frameworks.

Additionally, the study assessed convergent and discriminant validity using the average variance extracted (AVE) ≥ 0.40) and the square root of the AVE, known as the Fornell–Larcker criterion (this value should be higher than the correlation between the constructs), respectively [51]. The reliability of the instrument was estimated from its composite reliability (CR), with values equal to or higher than 0.60 indicating adequate reliability [51].

To explore differences in acceptance perceptions related to HRI, analysis of variance (ANOVA) was used for gender, Student’s *t*-test for experience with robots, and the Kruskal–Wallis test for educational qualifications and age. These analyses were performed using SPSS software (v. 27, SPSS Inc., Chicago, Illinois). This comprehensive approach ensured a thorough validation of the scale and a deeper understanding of the factors influencing HRI.

4. Results

4.1. EFA of the FSQ-IC and Reliability. Regarding the structure of the FSQ-IC, this work takes into consideration the past structure presented by studies evolving the FSQ. Given its history of unstable structure, the analysis was carefully carried out.

The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy analysis showed a value of 0.833, which indicates that the dataset has a high degree of adequacy for factor analysis. A KMO value above 0.6 is generally acceptable

TABLE 3: FSQ original and FSQ-IC.

No.	Items of FSQ original	No.	Items of FSQ-IC
1	I am afraid that humanoid robots will make us forget what it is like to be human	1	I'm afraid that collaborative robots will make us forget what it means to be human. (Tenho medo que os robôs colaborativos nos façam esquecer como é ser humano)
2	Humanoid robots can create new forms of interactions both between humans and between humans and machines	2	Collaborative robots can create new forms of interaction between humans and machines. (Os robôs colaborativos podem criar novas formas de interação entre humanos e máquinas)
3	Persons and organizations related to development of humanoid robots are well-meaning	3	The people and organizations that develop collaborative robots are well-intentioned. (As pessoas e as organizações que desenvolvem os robôs colaborativos são bem-intencionadas)
4	Humanoid robots may make us even lazier	4	Collaborative robots can make us lazier. (Os robôs colaborativos podem tornar-nos mais preguiçosos).
5	Humanoid robots can be very useful for caring the elderly and disabled	5	Collaborative robots can be very useful for older workers and/or those with some degree of disability. (Os robôs colaborativos podem ser muito úteis para trabalhadores mais velhos e/ou com algum grau de deficiência)
6	Humanoid robots should perform repetitive and boring routine tasks instead of leaving them to people	6	Collaborative robots should perform monotonous and repetitive tasks instead of workers. (Os robôs colaborativos devem realizar tarefas monótonas e repetitivas em vez destas serem realizadas pelos trabalhadores)
7	People interacting with humanoid robots could sometimes lead to problems in relationships between people	7	The interaction of workers with collaborative robots may sometimes lead to issues in relationships between workers. (A interação dos trabalhadores com os robôs colaborativos poderá, por vezes, originar problemas no relacionamento entre trabalhadores)
8	I am afraid that humanoid robots will encourage less interaction between humans	8	I fear that collaborative robots may encourage us to interact less in our workplace. (Tenho receio que os robôs colaborativos nos incentivem a interagir menos no nosso local de trabalho)
9	The development of humanoid robots is a blasphemy against nature	9	The development of collaborative robots is an affront to nature. (O desenvolvimento de robôs colaborativos é uma afronta contra a natureza)
10	I do not know why, but I like the idea of humanoid robots	10	I do not know why, but I like the idea of collaborative robots. (Não sei porquê, mas gosto da ideia de robôs colaborativos)
11	I would feel uneasy if humanoid robots really had emotions or independent thoughts	11	I would feel uncomfortable if collaborative robots truly had emotions and autonomous thoughts. (Sentir-me-ia desconfortável se os robôs colaborativos realmente tivessem emoções e pensamentos autónomos)
12	If humanoid robots cause accidents or trouble, persons and organizations related to development of them should give sufficient compensation to the victims	12	If collaborative robots cause accidents or problems in the workplace, the people and organizations involved in their development should compensate the victims. (Se os robôs colaborativos causarem acidentes ou problemas no local de trabalho, as pessoas e as organizações relacionadas com o desenvolvimento deles, devem pagar uma indemnização às vítimas)
13	I can trust persons and organizations related to development of humanoid robots	13	I can trust the people and organizations that develop collaborative robots. (Posso confiar nas pessoas e nas organizações que desenvolvem os robôs colaborativos)
14	Widespread use of humanoid robots would mean that it would be costly for us to maintain them	14	The widespread use of collaborative robots assumes that it will be more expensive for organizations to keep people in jobs. (O uso generalizado de robôs colaborativos pressupõe que será mais caro para as organizações manter as pessoas nos postos de trabalho)
15	I would hate the idea of robots or artificial intelligences making judgments about things	15	I would hate the idea of collaborative robots or artificial intelligence making judgments about things. (Odiaria a ideia dos robôs colaborativos ou da inteligência artificial fazerem julgamentos acerca das coisas que ocorrem no meu local de trabalho).

TABLE 3: Continued.

No.	Items of FSQ original	No.	Items of FSQ-IC
16	Humanoid robots are a natural product of our civilization	16	Collaborative robots are a natural outcome of our civilization's technological progress. (Os robôs colaborativos são um resultado natural do progresso tecnológico da nossa civilização)
17	Humanoid robots can make our lives easier	17	Collaborative robots can make workers' lives easier. (Os robôs colaborativos podem facilitar a vida dos trabalhadores)
18	I feel that if we become over-dependent on humanoid robots, something bad might happen	18	I feel that if we become overly dependent on collaborative robots in the workplace, there may be some negative consequences for workers. (Sinto que se nos tornarmos excessivamente dependentes dos robôs colaborativos, ao nível do trabalho, poderão ocorrer algumas consequências negativas para os trabalhadores)
19	I do not know why, but humanoid robots scare me	19	For some reason, collaborative robots scare me. (Por alguma razão os robôs colaborativos assustam-me)
20	I feel that in the future, society will be dominated by humanoid robots	20	I feel that in the future, the industry will be dominated by collaborative robots. (Sinto que no futuro, a indústria será dominada por robôs colaborativos)
21	Humanoid robots should perform dangerous tasks, for example in disaster areas, deep sea, and space	21	Collaborative robots should perform dangerous tasks in companies, for example in emergency situations. (Os robôs colaborativos devem realizar tarefas perigosas nas empresas, por exemplo em situações de emergência)
22	Many humanoid robots in society will make it less warm	22	Many collaborative robots in a company could make it feel colder. (Muitos robôs colaborativos numa empresa poderão torná-la mais fria).
23	I trust persons and organizations related to the development of humanoid robots to disclose sufficient information to the public, including negative information	23	I trust the people and organizations that develop collaborative robots to share information with workers, including the negative aspects. (Confio nas pessoas e nas organizações que desenvolvem robôs colaborativos para divulgar informações aos trabalhadores, incluindo as negativas)
24	Technologies needed for the development of humanoid robots belong to scientific fields that humans should not study	24	The technologies used for the development of collaborative robots belong to scientific fields that humans should not study. (As tecnologias usadas para o desenvolvimento de robôs colaborativos pertencem a áreas científicas que os humanos não deveriam estudar)
25	Something bad might happen if humanoid robots developed into human beings	25	Something bad could happen if collaborative robots become workers in the industry. (Algo de mau pode acontecer se os robôs colaborativos se transformarem em trabalhadores da indústria)
26	Persons and organizations related to development of humanoid robots will consider the needs, thoughts, and feelings of their users	26	People and organizations that develop collaborative robots must take into account the needs, thoughts, and feelings of their workers. (As pessoas e as organizações que desenvolvem os robôs colaborativos devem ter em consideração as necessidades, pensamentos e sentimentos dos seus trabalhadores)
27	The development of humanoid robots is blasphemous	27	The development of collaborative robots is absurd for our companies. (O desenvolvimento de robôs colaborativos é um absurdo para as nossas empresas)
28	Widespread use of humanoid robots would take away jobs from people	28	The widespread use of collaborative robots in companies could displace workers from them. (O uso generalizado de robôs colaborativos nas empresas poderia retirar os trabalhadores das mesmas)

TABLE 4: Factor loadings.

Item No.	Factor loading				Item sentence
	I	II	III	IV	
1	0.850				I'm afraid that collaborative robots will make us forget what it means to be human
4	0.600				Collaborative robots can make us lazier
8	0.747				I fear that collaborative robots may encourage us to interact less in our workplace
9	0.854				The development of collaborative robots is an affront to nature
19	0.748				For some reason, collaborative robots scare me
20	0.551				I feel that in the future, the industry will be dominated by collaborative robots
24	0.684				The technologies used for the development of collaborative robots belong to scientific fields that humans should not study
27	0.513				The development of collaborative robots is absurd for our companies
3		0.717			The people and organizations that develop collaborative robots are well-intentioned
13		0.937			I can trust the people and organizations that develop collaborative robots
23		0.921			I trust the people and organizations that develop collaborative robots to share information with workers, including the negative aspects
11			0.569		I would feel uncomfortable if collaborative robots truly had emotions and autonomous thoughts
12			0.717		If collaborative robots cause accidents or problems in the workplace, the people and organizations involved in their development should compensate the victims
15			0.567		I would hate the idea of collaborative robots or artificial intelligence making judgments about things
26			0.606		People and organizations that develop collaborative robots must take into account the needs, thoughts, and feelings of their workers
2				0.709	In the industry, collaborative robots can create new forms of interaction between humans and machines
5				0.906	Collaborative robots can be very useful for older workers and/or those with some degree of disability
17				0.573	Collaborative robots can make workers' lives easier

[52]. In addition, Bartlett's test of sphericity was conducted as well. The results show an approximate chi-square value of 2135.628 with 378 df. The associated significance value (Sig.) is 0.001, which is less than the conventional threshold of 0.05. This indicates that the correlation matrix is significantly different from an identity matrix, providing evidence to proceed with factor analysis.

To evaluate the subscales of the FSQ-IC, an EFA was conducted using the maximum likelihood extraction method and Promax rotation and a 0.50 suppression value [49] for the 28 items, forcing four factors. This decision was made based on the analysis steps of past versions of the FSQ previously presented, like the original scale development by Nomura et al. [15], where a tentative four-factor structure was proposed, and subsequent studies, such as Krägeloh et al.'s work [53], utilized this structure. To enhance the clarity and usability of the factor solution, a suppression threshold of 0.50 was applied, meaning that factor loadings below this value were excluded from interpretation to focus on more salient item contributions. Subsequently, the four-factor structure was developed, mirroring the same tentative shown in the original authors' work, which followed a comprehensive analysis, which included input from one of the original authors (see Table 4).

Regarding the scale structure in the EFA, Factor 1 exhibited a structure with more factors than the other three. In the interest of parsimony and without compromising any analysis, in the CFA, we reduced the items of Factor 1 by selecting the four items with the highest loadings from the EFA. This reduction not only simplifies the model but also ensures that

the most significant items are retained, thereby maintaining the integrity and robustness of the analysis (see Figure 1). When examining the subscales individually, the analysis revealed the following values:

- 0.86 for Factor 1: "general anxiety towards cobots" with eight items (1, 4, 8, 9, 19, 20, 24, and 27). After the mentioned modifications, Factor 1 is now composed of four items (1, 8, 9, and 19) with a Cronbach alpha of 0.87;
- 0.83 for Factor 2: "trustworthiness to developers of cobots" with three items (3, 13, and 23);
- 0.66 for Factor 3: "apprehension to cobots in the industrial context" with three items (11, 12, and 15);
- 0.69 for Factor 4: "expectation of cobots in social change" with three items (2, 5, and 17).

Moreover, the study identified a significant positive correlation between the second and the fourth subscales ($r = 0.4$). Conversely, negative correlations were observed between the first and second subscales ($r = -0.5$), between the first and fourth subscales ($r = -0.39$), and between the third and fourth subscales ($r = -0.27$). However, no significant correlation was found between the first and third subscales and between the second and third subscales (see Table 5).

4.2. CFA of the FSQ-IC and Validity. In assessing the validity of the FSQ-IC, a CFA was employed. The model fit indices

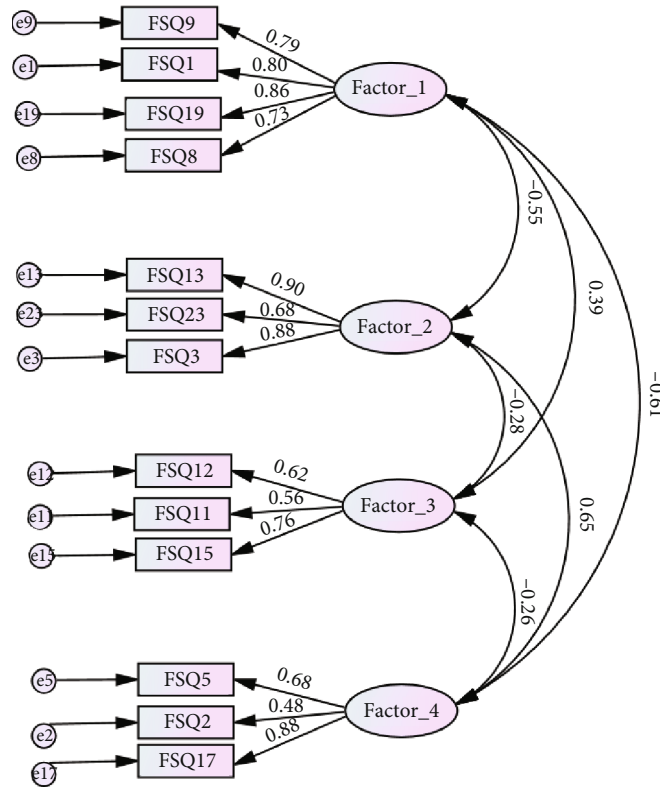


FIGURE 1: CFA structure of the FSQ-IC. *Note.* Factor 1: “general anxiety towards collaborative robots”; Factor 2: “trustworthiness to developers of collaborative robots”; Factor 3: “apprehension to collaborative robots in the industrial context”; Factor 4: “expectation of collaborative robots in social change.”

TABLE 5: Pearson correlation coefficient EFA.

	I	II	III	IV
I	1	-0.539**	0.074	-0.385**
II	-0.539**	1	-0.036	0.475**
III	0.074	-0.036	1	-0.270**
IV	-0.385**	0.475**	-0.270**	1

Note: I: general anxiety towards collaborative robots; II: trustworthiness to developers of collaborative robots; III: apprehension towards collaborative robots in the industrial context; IV: expectations of collaborative robots in social change.

**Correlation is significant at the 0.01 level (two-tailed).

revealed varying degrees of fit adequacy. The chi-square to degrees of freedom ratio (χ^2/df) reached a value of 3.14, indicating an acceptable fit according to Maroco [54], who posits that values between 2 and 5 are sufficient. The root mean square error of approximation (RMSEA) was recorded at 0.10, positioning it at the upper limit for acceptable fit, characterized by values ranging from 0.05 to 0.10. Absolute and comparative fit indices included the goodness-of-fit index (GFI), the comparative fit index (CFI), and the normed fit index (NFI). The GFI stood at 0.88, while the CFI was 0.90 and the NFI was 0.86, all reflecting a satisfactory model fit as these values fall between 0.80 and 0.90, which are considered satisfactory according to Maroco

[54]. During the analysis, it was necessary to exclude item 26, which exhibited a factor loading of 0.39, below the minimum acceptable threshold of 0.40 for significant factor loading. This exclusion was essential to enhance the overall model fit indices and the interpretative clarity of the factors (see Table 6). For this model, the analysis shows that the $CR \geq 0.60$ (range of 0.69 and 0.89) and $AVE \geq 0.40$ (range of 0.43 and 0.68) [51].

The convergent validity, as evaluated by the AVE, indicates the amount of variance a latent variable captures from its observable indicators. Ideally, the AVE value should exceed 0.40 [55]. In our study, it falls within the range of 0.43–0.68, therefore presenting theoretical support. Discriminant validity, on the other hand, examines the extent to which a latent variable is distinct from others. The Fornell–Larcker criterion, calculated as the square root of the AVE, serves this purpose. Our findings reveal that this criterion surpasses the correlation values among the constructs, as illustrated in Table 7.

Moreover, the study identified a significant positive correlation between the second and the fourth subscales ($r = 0.54$) and between the first and the third subscales ($r = 0.30$). Conversely, negative correlations were observed between the first and second subscales ($r = -0.46$), between the first and fourth subscales ($r = -0.43$), between the second and the third subscales ($r = -0.21$), and between the third and fourth subscales ($r = -0.26$) (see Table 7).

TABLE 6: CFA results.

Scales	χ^2 /df	RMSEA	GFI	CFI	NFI
Frankenstein Syndrome Questionnaire–Industrial Context (FSQ-IC)	3.14	0.10	0.88	0.90	0.86

TABLE 7: Pearson correlation coefficient CFA.

	I	II	III	IV	$\sqrt{\text{AVE}}$
I	1	-0.459**	0.295**	-0.429**	0.796
II	-0.459**	1	-0.209**	0.540**	0.826
III	0.295**	-0.209**	1	-0.261**	0.652
IV	-0.429**	0.540**	-0.261**	1	0.701

Note: I: general anxiety towards collaborative robots; II: trustworthiness to developers of collaborative robots; III: apprehension towards collaborative robots in the industrial context; IV: expectations of collaborative robots in social change.

**Correlation is significant at the 0.01 level (two-tailed).

4.3. ANOVA, Student's *t*-Test, and Kruskal–Wallis Test. An ANOVA was conducted to examine differences in acceptance perception of HRI among three gender groups: male, female, and nonbinary. The results indicated a statistically significant difference in acceptance among the groups ($F(2, 207) = 6.27$, $p \leq 0.001$). To identify which groups differed significantly, a Tukey post hoc test was conducted. The post hoc comparison revealed no significant difference between the male and female groups ($M = 1.57$, standard deviation (SD) = 0.86, $p = 0.16$). However, there was a significant difference between the nonbinary group and the female group ($M = 8.64$, $SD = 3.12$, $p = 0.02$) as well as between the nonbinary group and the male group ($M = 10.21$, $SD = 3.13$, $p \leq 0.001$).

To investigate whether experience with robots influences acceptance in HRI, Student's *t*-test was conducted. The analysis revealed no significant difference between participants with and without experience with robots ($t(208) = -0.46$, $p = 0.65$).

Finally, the Kruskal–Wallis test revealed no significant differences based on educational qualifications ($H = 4.35$, $p = 0.63$) or age ($H = 3.54$, $p = 0.17$ —comparisons between the groups 26–40 years and above 41 years ($p = 0.57$), the groups 26–40 years and until 25 years ($p = 0.40$), and the groups above 41 years and until 25 years ($p = 1.00$) did not show significant differences).

5. Discussion

This research was designed to develop and validate a scale—the FSQ-IC—for assessing the acceptance of the users of cobots within industrial settings. The EFA confirmed the suitability of a four-factor structure previously proposed by researchers such as Krägeloh et al. [53] and Nomura et al. [15], which is advantageous for its clarity in factor interpretability and comprehensive content coverage. The involvement of the original author of the FSQ scale was crucial in analyzing and discussing the optimal structure and designation of each factor for the FSQ-IC, ensuring the scale's developmental integrity and continuity. Although the designation of each factor varies slightly

from the original FSQ, these adjustments contribute to the precision and relevance of the FSQ-IC in its current application. This structure was tested for internal consistency, with Cronbach alpha values ranging from 0.69 to 0.87, indicating good reliability across the subscales, and an item-total correlation analysis that reinforced the structure proposed.

Concerning the correlation analysis conducted, each identified subscale captures distinct aspects of attitudes and perceptions related to the deployment of cobots. For instance, the noted apprehension towards cobots in industrial contexts (Factor 3) showed a weaker correlation with other factors, suggesting unique dynamics specific to workplace-related fears, which may diverge from influences on general anxiety towards cobots (Factor 1) or expectation of cobots in social change (Factor 4). Bröhl et al. [56] tested a human–robot collaboration acceptance model (HRCAM) and identified that factors such as demonstrability, self-efficacy, robot anxiety, social implications, and data protection exhibited medium to large correlation coefficients ($0.30 < 0.50$).

The CFA conducted was aimed at substantiating its factorial structure and validity found by the EFA. The resulting fit indices have an acceptable level of fit which aligns with Maroco's [54] criteria. The RMSEA stood at the upper threshold of acceptability, and both the GFI and the CFI achieved satisfactory values. These findings fully validate the FSQ-IC scale and the robustness of its measurements on acceptance. The validation is supported by robust statistical analyses, including both convergent and discriminant validity measures, which are relevant for assessing the accuracy and reliability of the scale's constructs. For this model, the analysis demonstrated that the CR was well above the minimum threshold, with values ranging from 0.69 to 0.89, suggesting that the scale is reliable in its measurement of various aspects of acceptance. Additionally, the AVE values ranged from 0.43 to 0.68, achieving the recommended threshold of 0.40 set by Lam [51]. Furthermore, the discriminant validity, assessed through the Fornell–Larcker criterion, indicates that the latent variables are distinct and measure different constructs. This was demonstrated as the square roots of the AVE values for each factor were greater than the correlations between the factors, thereby underscoring the unique contributions of each dimension to the overall construct of cobot acceptance.

The ANOVA, Student's *t*-test, and the Kruskal–Wallis test were conducted to enhance the understanding of insights provided by the sample. The objective was to further comprehend the influence of gender, prior experience with robots, academic qualifications, and age on the acceptance levels among individuals. The results indicate that gender plays a significant role in the acceptance of HRI especially highlighting the differences between nonbinary individuals and other gender groups. It is noteworthy that the small

sample size of the nonbinary group limits the generalization of these findings. Abel et al. [57] reinforce the importance of gender in the HRI, particularly regarding the human ability to distinguish between anthropomorphic and robotic movements, which can subsequently affect robot acceptance. In their study, the results showed that males were more sensitive to distinctions between robotic and anthropomorphic movements.

On the other hand, experience with robots does not seem to influence acceptance, suggesting that familiarity with the technology is not crucial in shaping attitudes towards HRI. A possible cause for this could be that people's attitudes towards robots are more influenced by individual and sometimes irrational feelings [36]. Furthermore, the absence of significant differences based on education and age indicates that the acceptance of HRI may be a relatively uniform characteristic across different age groups and educational levels. Similar results were found by Kuo et al. [58] between age and acceptance of healthcare robots. In a study developed by Bishop et al. [59] with social robots, gender and education were found not to correlate with acceptance, but age and mood were associated with acceptance. However, other authors found that male with longer education were more prone to accept robots at work [38]. Wagner-Hartl et al. [60] identified a significant effect of age on robot acceptance, with younger participants finding scenarios involving robots more acceptable than older workers, which may be explained by their greater access to information.

6. Limitations and Future Research

Despite the valuable contributions and insights provided by this study, several limitations should be acknowledged, each pointing to important directions for future research. Primarily, the study utilized a convenience sample gathered through an online survey, which might introduce selection bias and limit the generalizability of the findings. The composition of this sample may not fully represent the broader Portuguese population, potentially affecting the external validity of the study's conclusions. The use of larger and more balanced samples across their constituent groups (e.g., gender) is necessary to confirm these results and deepen understanding of the underlying dynamics. An equally important limitation concerns the extension of the cross-cultural applicability of the findings. The theoretical and empirical foundations of the study may reflect cultural nuances inherent to the Portuguese context, potentially restricting the relevance of these results to other cultural settings. Moreover, the implementation of a cross-sectional design in this study constrains the ability to infer causality from the observed relationships. Longitudinal studies would be highly beneficial to examine how attitudes towards cobots evolve over time, especially as individuals gain more exposure to these technologies. Another limitation arises from the reliance on self-reported data, which can be susceptible to biases such as social desirability or response bias. Such biases could skew participants' responses, thereby affecting the validity of the data collected. Additionally, while the analyses adhered to theoretical guidelines, the interpretation

of factor loadings and saturation remains somewhat subjective and could be open to different interpretations. In this context, the CFA played a critical role in validating the structure suggested by the EFA, offering a more robust framework for understanding the scales' constructs.

Overall, these limitations underscore the need for future research. The FSQ-IC scale, still under development, offers a preliminary framework but may not yet capture the full spectrum of factors influencing acceptance, such as safety concerns, which are crucial in environments where humans closely interact with machines. The scale could also benefit from further optimization through empirical testing and refinement. From a statistical perspective, while an RMSEA ≤ 0.10 may be considered acceptable, an RMSEA < 0.08 is generally preferred to ensure greater confidence in the model's fit. To improve reliability and applicability of this scale, future research should focus on expanding the application of the scale across different industrial contexts, increasing the number of participants. Additionally, new dimensions could be developed, such as perceptions of safety related to cobots. Its enhancements could significantly impact regulatory standards and industrial practices, informing policymakers and industry leaders about key factors that affect cobot adoption. This ongoing development has the potential to contribute to industry standards and facilitate better integration of cobots into the workforce, ensuring that these systems are not only efficient but also well accepted by human operators.

Addressing these issues would not only enhance the validity and applicability of the FSQ-IC scale within industrial contexts but also deepen our understanding of attitudes towards robots among specific groups, such as workers who interact daily with cobots or those directly involved in their design and production. Applying this scale to a sample with greater variability in terms of age, gender, and level of education would be an interesting contribution, considering the impact of these individual variables on acceptance. Gaining a clearer insight into acceptance patterns within the Portuguese population could significantly improve the working conditions of employees and the broader impact on industrial operations. This understanding is crucial for developing tailored interventions that effectively address the concerns and expectations of various stakeholders involved with cobots.

7. Conclusions

The purpose of this study is to enable researchers and practitioners in Portugal to evaluate individuals' attitudes and perceptions towards cobots, with a specific focus on acceptance. Through factor analysis, particularly EFA, important insights were revealed about the structure of the FSQ-IC. The EFA results highlighted that while the distribution of items across factors could be more balanced, the alignment with the original FSQ [61] distribution remains consistent. This is true even though the assigned factors' designation varies slightly from the original model. This alignment supports the internal consistency of the scale, confirming that the scale reliably measures the intended constructs and is suitable for use in future research.

Further, the correlation analysis elucidated the relationships between the four subscales. These findings indicate that the subscales effectively capture a range of dimensions related to attitudes and perceptions. This comprehensive analysis not only underscores the validity of the scale but also enhances our understanding of the nuanced interactions that define cobot acceptance.

Following the CFA, a more comprehensive understanding of the FSQ-IC structure was achieved. Further analyses underscored the scale’s convergent validity, which reflects the extent to which a latent variable captures variance from its observable indicators. Additionally, discriminant validity, which assesses the distinctiveness of each latent variable from others, was evaluated and these findings collectively validate the robustness and integrity of the FSQ-IC, establishing a solid foundation for its application.

Finally, the ANOVA, Student’s *t*-test, and the Kruskal–Wallis test—regarding the variables of gender, experience with robots, educational qualifications, and age—allowed us to verify results that are very important to consider in the development and implementation of robotic technologies, as they highlight the need to consider the perspectives of different groups, which may (or may not) impact the acceptance of HRI.

In sum, the FSQ-IC scale exhibits strong psychometric properties, with confirmed reliability and validity, making it a robust tool for assessing the acceptance of cobots in industrial contexts. These attributes highlight the scale’s potential utility in both research and practical applications.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Disclosure

This work incorporates results presented in the master’s thesis of Leticia Lemos, available at <https://estudogeral.uc.pt/handle/10316/116590>.

Conflicts of Interest

The authors declare no conflicts of interest.

Funding

This research is supported by FCT—Fundação para a Ciência e a Tecnologia (UIDB/05037/2020).

References

[1] M. Breque, L. De Nul, and A. Petridis, “Industry 5.0: towards a sustainable, human-centric, and resilient European industry,” *Directorate-General for Research and Innovation, European Commission*, 2021.

[2] N. Jafari, M. Azarian, and H. Yu, “Moving from Industry 4.0 to Industry 5.0: what are the implications for smart logistics?,” *Logistics*, vol. 6, no. 2, p. 26, 2022.

[3] M. Di Nardo and H. Yu, “Special Issue “Industry 5.0: the prelude to the sixth industrial revolution.”,” *Applied System Innovation*, vol. 4, no. 3, p. 45, 2021.

[4] A. Castro, F. Silva, and V. Santos, “Trends of human-robot collaboration in industry contexts: handover, learning, and metrics,” *Sensors*, vol. 21, no. 12, p. 4113, 2021.

[5] W. Wang, Y. Chen, and R. Li, “Learning and comfort in human–robot interaction: a review,” *Applied Sciences*, vol. 9, p. 5152, 2019.

[6] A. Giallanza, G. La Scalia, R. Micale, and C. M. La Fata, “Occupational health and safety issues in human-robot collaboration: state of the art and open challenges,” *Safety Science*, vol. 169, Article ID 106313, 2024.

[7] J. de Gea Fernández, D. Mronga, M. Günther et al., “Multi-modal sensor-based whole-body control for human–robot collaboration in industrial settings,” *Robotics and Autonomous Systems*, vol. 94, pp. 102–119, 2017.

[8] European Agency for Safety and Health at Work, *Work-related musculoskeletal disorders: prevalence, costs and demographics in the EU*, Publications Office of the European Union, 2019, <https://osha.europa.eu/en/publications/summary-msds-facts-and-figures-overview-prevalence-costs-and-demographics-msds-europe>.

[9] A. Colim, R. Morgado, P. Carneiro et al., “Lean manufacturing and ergonomics integration: Defining productivity and well-being indicators in a human–robot workstation,” *Sustainability*, vol. 13, no. 4, p. 1931, 2021.

[10] A. Keshvarparast, D. Battini, O. Battaia, and A. Pirayesh, “Collaborative robots in manufacturing and assembly systems: literature review and future research agenda,” *Journal of Intelligent Manufacturing*, vol. 35, no. 5, pp. 2065–2118, 2024.

[11] S. Liao, L. Lin, and Q. Chen, “Research on the acceptance of collaborative robots for the Industry 5.0 era: The mediating effect of perceived competence and the moderating effect of robot use self-efficacy,” *International Journal of Industrial Ergonomics*, vol. 95, Article ID 103455, 2023.

[12] G. F. Prassida and U. Asfari, “A conceptual model for the acceptance of collaborative robots in Industry 5.0,” *Procedia Computer Science*, vol. 197, pp. 61–67, 2022.

[13] O. S. M. Zapata, Y. G. Correa, L. R. Yoshioka, and J. R. Silva, “Modeling requirements for collaborative robotic services,” *Eng*, vol. 4, no. 4, pp. 2941–2959, 2023.

[14] A. Cherubini, B. Navarro, R. Passama et al., “Interdisciplinary evaluation of a robot physically collaborating with workers,” *PLoS One*, vol. 18, no. 10, Article ID 0291410, 2023.

[15] T. Nomura, K. Sugimoto, D. S. Syrdal, and K. Dautenhahn, “Social acceptance of humanoid robots in Japan: a survey for development of the Frankenstein Syndrome Questionnaire,” in *2012 12th IEEE-RAS International Conference on Humanoid Robots (Humanoids 2012)*, pp. 242–247, Osaka, Japan, 2012.

[16] A.-N. Sharkawy and P. N. Koustoumpardis, “Human–robot interaction: a review and analysis on variable admittance control, safety, and perspectives,” *Machines*, vol. 10, no. 7, p. 591, 2022.

[17] A. Sharkawy, “A survey on applications of human-robot interaction,” *Sensors & Transducers*, vol. 251, pp. 19–27, 2021, https://www.sensorsportal.com/HTML/DIGEST/P_SI_781.htm.

- [18] M. Jung, M. J. S. Lazaro, and M. H. Yun, "Evaluation of methodologies and measures on the usability of social robots: a systematic review," *Applied Sciences*, vol. 11, no. 4, p. 1388, 2021.
- [19] M. Sarrica, S. Brondi, and L. Fortunati, "How many facets does a "social robot" have? A review of scientific and popular definitions online," *Information Technology & People*, vol. 33, no. 1, pp. 1–21, 2020.
- [20] I. Bermudez, S. Badia, P. A. Silva et al., "Virtual reality for safe testing and development in collaborative robotics: challenges and perspectives," *Electronics*, vol. 11, no. 11, p. 1726, 2022.
- [21] R. Mead and M. J. Mataric, "Proxemics and performance: subjective human evaluations of autonomous sociable robot distance and social signal understanding," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Hamburg, Germany, 2015.
- [22] C. S. Franklin, E. G. Dominguez, J. D. Fryman, and M. L. Lewandowski, "Collaborative robotics: new era of human-robot cooperation in the workplace," *Journal of Safety Research*, vol. 74, pp. 153–160, 2020.
- [23] F. Ranz, T. Komenda, G. Reisinger, P. Hold, V. Hummel, and W. Sihm, "A morphology of human robot collaboration systems for industrial assembly," *Procedia CIRP*, vol. 72, pp. 99–104, 2018.
- [24] G. M. Costa, M. R. Petry, and A. P. Moreira, "Augmented reality for human-robot collaboration and cooperation in industrial applications: a systematic literature review," *Sensors*, vol. 22, no. 7, p. 2725, 2022.
- [25] European Union Statistics Office [EUROSTAT], *European Union Statistics Office [EUROSTAT]. (2021)*, EUROSTAT: Your key to European statistics, 2021, Retrieved from <https://ec.europa.eu/eurostat>.
- [26] Instituto Nacional de Estatística, *Estatísticas Demográficas: 2021*, INE, Lisboa, 2023, <https://www.ine.pt/xurl/pub/13932532>.
- [27] Z. M. Bi, M. Luo, Z. Miao, B. Zhang, W. J. Zhang, and L. Wang, "Safety assurance mechanisms of collaborative robotic systems in manufacturing," *Robotics and Computer-Integrated Manufacturing*, vol. 67, Article ID 102022, 2021.
- [28] A. Weiss, R. Bernhaupt, M. Lankes, and M. Tscheligi, "The USUS evaluation framework for human-robot interaction," *AISB2009: Proceedings Of The Symposium On New Frontiers In Human-Robot Interaction*, vol. 4, no. 1, pp. 158–159, 2009.
- [29] A. Rossi, P. Holthaus, G. Perugia, S. Moros, and M. Scheunemann, "Trust, acceptance, and social cues in human-robot interaction (SCRITA)," *International Journal of Social Robotics*, vol. 13, no. 8, pp. 1833–1834, 2021.
- [30] L. T. C. Ottoni and J. J. F. Cerqueira, "A systematic review of human-robot interaction: the use of emotions and the evaluation of their performance," *International Journal of Social Robotics*, vol. 16, no. 11–12, pp. 2169–2188, 2024.
- [31] J. C. Zoellick, A. Kuhlmeier, L. Schenk, and S. Blüher, "Method-oriented systematic review on the simple scale for acceptance measurement in advanced transport telematics," *PLoS One*, vol. 16, no. 3, Article ID e0248107, 2021.
- [32] E. Adell, "Acceptance of driver support systems," in *Proceedings of the European conference on human-centred design for intelligent transport systems*, vol. 2, Humanist VCE, Ifsttar—Lyon-Bron, Berlin, Germany, 2009, https://www.researchgate.net/publication/229049067_Acceptance_of_driver_support_systems.
- [33] M. Görke, S. Blankemeyer, D. Pischke, A. Oubari, A. Raatz, and P. Nyhuis, "Sichere und akzeptierte Kollaboration von Mensch und Maschine," *Zeitschrift für Wirtschaftlichen Fabrikbetrieb*, vol. 112, no. 1–2, pp. 41–45, 2017.
- [34] N. Akalin, A. Kristoffersson, and A. Loutfi, "Do you feel safe with your robot? Factors influencing perceived safety in human-robot interaction based on subjective and objective measures," *International Journal of Human-Computer Studies*, vol. 158, Article ID 102744, 2022.
- [35] Z. Xu, K. Zhang, H. Min, Z. Wang, X. Zhao, and P. Liu, "What drives people to accept automated vehicles? Findings from a field experiment," *Transportation Research Part C: Emerging Technologies*, vol. 95, pp. 320–334, 2018.
- [36] A. Meissner, A. Trübswetter, A. Conti-Kufner, and J. Schmidler, "Friend or Foe? Understanding Assembly Workers' Acceptance of Human-robot Collaboration," *ACM Transactions on Human-Robot Interaction*, vol. 10, pp. 1–30, 2020.
- [37] E. A. Sisbot, L. F. Marin-Urias, X. Broquere, D. Sidobre, and R. Alami, "Synthesizing robot motions adapted to human presence," *International Journal of Social Robotics*, vol. 2, no. 3, pp. 329–343, 2010.
- [38] T. Turja and A. Oksanen, "Robot Acceptance at Work: A Multilevel Analysis Based on 27 EU Countries," *International Journal of Social Robotics*, vol. 11, pp. 679–689, 2019.
- [39] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 1989.
- [40] V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: four longitudinal field studies," *Management Science*, vol. 46, no. 2, pp. 186–204, 2000.
- [41] M. Heerink, B. Kröse, V. Evers, and B. Wielinga, "Assessing acceptance of assistive social agent technology by older adults: the Almere model," *International Journal of Social Robotics*, vol. 2, no. 4, pp. 361–375, 2010.
- [42] T. Nomura, T. Suzuki, T. Kanda, and K. Kato, "Measurement of negative attitudes toward robots," *Interaction Studies*, vol. 7, no. 3, pp. 437–454, 2006.
- [43] C. Carpinella, A. Wyman, M. Perez, and S. Stroessner, "The robotic social attributes scale (RoSAS) development and validation," in *Proceedings of the 2017 ACM/IEEE International Conference on human-robot interaction*, Vienna, Austria, 2017.
- [44] T. Ninomiya, A. Fujita, D. Suzuki, and H. Umemuro, "Development of the Multi-dimensional Robot Attitude Scale: Constructs of People's Attitudes Towards Domestic Robots," in *Social Robotics. ICSR 2015*, A. Tapus, E. André, J. C. Martin, F. Ferland, and M. Ammi, Eds., vol. 9388 of Lecture Notes in Computer Science(), Springer, Cham, 2015.
- [45] P. M. Bentler and C. P. Chou, "Practical issues in structural modeling," *Sociological Methods & Research*, vol. 16, no. 1, pp. 78–117, 1987.
- [46] P. Kline, *An easy guide to factor analysis*, Routledge, 1994.
- [47] R. Maccallum, K. F. Widaman, S. Zhang, and S. Hong, "Sample size in factor analysis," *Psychological Methods*, vol. 4, no. 1, pp. 84–99, 1999.
- [48] T. R. Hinkin, "A brief tutorial on the development of measures for use in survey questionnaires," *Organizational Research Methods*, vol. 2, no. 1, pp. 104–121, 1998.
- [49] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate data analysis*, Pearson, 8th edition, 2019.

- [50] R. B. Kline, *Principles and practice of structural equation modeling*, Guilford Press, 4th edition, 2015.
- [51] L. W. Lam, "Impact of competitiveness on salespeople's commitment and performance," *Journal of Business Research*, vol. 65, no. 9, pp. 1328–1334, 2012.
- [52] N. Shrestha, "Factor analysis as a tool for survey analysis," *American Journal of Applied Mathematics and Statistics*, vol. 9, no. 1, pp. 4–11, 2021.
- [53] C. U. Krägeloh, J. Bharatharaj, S. K. S. Kutty, P. R. Nirmala, and L. Huang, "Questionnaires to measure acceptability of social robots: a critical review," *Robotics*, vol. 8, no. 4, p. 88, 2019.
- [54] J. Maroco, *Análise Estatística. Com utilização do SPSS*, Edições Sílabo, Lisboa, 2010.
- [55] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research*, vol. 18, no. 1, pp. 39–50, 1981.
- [56] C. Bröhl, J. Nelles, C. Brandl, A. Mertens, and V. Nitsch, "Human–robot collaboration acceptance model: development and comparison for Germany, Japan, China and the USA," *International Journal of Social Robotics*, vol. 11, pp. 709–726, 2019.
- [57] M. Abel, S. Kuz, H. J. Patel et al., "Gender effects in observation of robotic and humanoid actions," *Frontiers in Psychology*, vol. 11, pp. 1078–1664, 2020.
- [58] I. H. Kuo, E. Broadbent, Y. I. Lee et al., "Age and gender factors in user acceptance of healthcare robots," in *RO-MAN 2009 - The 18th IEEE International Symposium on Robot and Human Interactive Communication*, pp. 214–219, Toyama, Japan, 2009.
- [59] L. Bishop, A. Van Maris, S. Dogramadzi, and N. Zook, "Social robots: The influence of human and robot characteristics on acceptance," *Paladyn*, vol. 10, no. 1, pp. 346–358, 2019.
- [60] V. Wagner-Hartl, R. Schmid, and K. Gleichauf, "The influence of task complexity on acceptance and trust in human-robot interaction: Gender and age differences," in *Cognitive Computing and Internet of Things. AHFE (2022) International Conference*, L. Paletta and H. Ayaz, Eds., vol. 43, AHFE Open Access, AHFE International, USA, 2022.
- [61] T. Nomura, "Cultural differences in social acceptance of robots," in *2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, pp. 534–538, Lisbon, Portugal, 2017.