Hindawi
Human Behavior and Emerging Technologies
Volume 2022, Article ID 6437441, 12 pages
https://doi.org/10.1155/2022/6437441

Research Article

A Trust Scale for Human-Robot Interaction: Translation, Adaptation, and Validation of a Human Computer Trust Scale

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Received 3 October 2022; Revised 2 December 2022; Accepted 3 December 2022; Published 16 December 2022

Academic Editor: Zheng Yan

Recently there has been an increasing demand for technologies (automated and intelligent machines) that brings benefits to organizations and society. Similar to the widespread use of personal computers in the past, today's needs are towards facilitating human-machine technology appropriation, especially in highly risky and regulated industries like robotics, manufacturing, automation, military, finance, or healthcare. In this context, trust can be used as a critical element to instruct how human-machine interaction should occur. Considering the context-dependency and multidimensional trust, this study seeks to find a way to measure the effects of perceived trust in a collaborative robot (cobot), regardless of its literal credibility as a real person. This article aims at translating, adapting, and validating a Human-Computer Trust Scale (HCTM) in human-robot interaction (HRI) context and its application to cobots. The Human-Robot Interaction Trust Scale (HRITS) involved 239 participants and included eleven items. The 2nd order CFA with a general factor called "trust" have proven to be empirically robust ($CFI = .94$; $TLI = .93$; $SRMR = .04$; and $RMSEA = .05$) [$CR = .84$; $AVE = .58$, and $MaxR(H) = .92$]; results indicated a good measurement of the general factor trust, and the model satisfied the criteria for measure trust. An analysis of the differences in perceptions of trust by gender was conducted using a t-test. This analysis showed that statistical differences by gender exist ($p = .04$). This study's results allowed for a better understanding of trust in HRI, specifically regarding cobots. The validation of a Portuguese scale for trust assessment in HRI can give a valuable contribution to designing collaborative environments between humans and robots.

1. Introduction

The adoption of the Industry 4.0 paradigm is viewed, by industrial companies, as a way to improve efficiency, flexibility, agility, and resilience in the value chain. In the vertical and horizontal integration processes, the companies relied on the integration of the physical and virtual worlds through cyber-physical systems and the interconnection of humans, machines, and devices through the Internet of Things. However, manufacturing companies in Europe are more conscious and oriented towards the transition to the age of sustainable well-being. Therefore, companies are now focused on the well-being of workers, the need for social inclusion, and the adoption of technologies to complement human capabilities whenever possible [1]. Therefore, the technology-driven main focus is giving place to a human-centric approach, which is one of the most important characteristics of Industry 5.0. Under this paradigm, the technologies should be selected and adopted based on an ethical rationale of how those support human needs and not only based on a purely technical or economic perspective. Thus, to design a safe and beneficial working environment, it is critical to consider societal constraints and respect the human rights and the skill requirements for workers [2].

Technologies that involve human-machine interaction, such as collaboration with robots and machines, are being used to generate products and services. A collaborative robot is one of the enabling technologies of Industry 4.0 [3] that has been receiving special attention due to its growing integration into the industry [4]. The combination of the "strength and the efficiency of robots with the high degree of dexterity and the cognitive capabilities of humans" provides the desired flexibility [5] (p. 666). This technology can interact with the operators in a shared workspace [6], resulting in several benefits when compared to traditional robots [7] such as improved ergonomics, quality, and flexibility [8].

This level of interaction between humans and the cobot raises a critical issue, trust. Trusting is the key to fostering interaction between human and machine. The perceived trust can dictate the trust's depth and length in human-robot interaction. Thus, there is a need to find trust reassurance to regulatory practices in suing technological artefacts such as cobots.

Trust in these contexts is understood not as a social interaction mediated by robots but instead as a human-machine interaction. It is a highly risky and regulated setting where humans depend on robot actions to fulfil their goals. Trust is seen as a key to improving operations and a feeling of safety between robots and the operator [9]. Also, it is seen as an attitude that an agent (robot) will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability.

Recently, we have seen efforts to understand the effects of trust in various digital artefacts, including robotics and artificial intelligence (AI). Some latest examples are "Trustworthy AI (TAI)" [10, 11], "Human-Centered AI" [12], or "Ethical guidelines for Trustworthy AI" [13].

In 1996, Muir and Moray [14] proposed a scale to measure trust in automation. Since then, many studies have emerged with a similar purpose of developing scales those include empirically Derived (ED) [15], Human-Computer Trust (HTC) [16], SHAPE Automation Trust Index (SATI) [9, 17], Trust Perceived Scale-HRI [18, 19], and HRI Trust Scale [20]. Those are examples of scales empirically developed to understand how trust is perceived in technologically enhanced scenarios. Yet, these scales have their limitations. The ED instrument, for instance, assesses trust in automation in general, not considering the system's intricate interactions with human-robot. The focus is on measuring the propensity to trust than trust in a specific system. The HTC showed agreement between items and target dimensions but stopped confirming factor analysis. In the same regard, the SATI scale neglected psychometric tests of construct validity. In the Trust Perception Scale-HRI, the items are based on data collected identifying robot features from pictures and their perceived functional characteristics. While the development of the scale was guided by the triadic (human, robot, and environment) model of trust inspired by Yagoda and Gillan [20], a factor analysis of the resulting scale found four components corresponding roughly to capability, behavior, task, and appearance. Capability and behavior are two dimensions commonly considered in interpersonal trust [21]. The HRI Trust Scale is incomplete as a measure of trust and is intended to be paired with Rotter's interpersonal trust inventory when applied [22].

While considering context-dependency and multidimensional trust, this study seeks to develop a scale to measure the effects of the perceived trust of humans in a cobot, regardless of its literal credibility as a real person. This study aims at translating, adapting, and validating a Human-Computer Trust Scale (HCTM) in human-robot interaction (HRI) contexts and applies it to cobots.

The remainder of this paper is organized as follows: Section 2 introduces the basic concepts of trust, human-robot trust, and the adopted theoretical model. Section 3 describes the method. In Section 4, the results are presented. Section 5 presents the discussion. Lastly, Section 6 concludes this paper.

2. Theoretical Background

2.1. Trust. According to Lee et al. [23] (p. 683), "the quality, depth, and length of the use of a technology or service are also significantly affected by users' trust in it." Recent developments in artificial intelligence (AI) and machine learning applications have led to an increasing interest from academics, government, and practitioners, in studying the effects of trust in technology. The results of these studies culminate in a range of critical views on how trust can be a crucial function in society or its effects in leveraging digital interactions [24]. Nevertheless, trust complexity brought additional challenges, like the failure to recognize its subjective and multidimensional nature or lead to various interpretations and understandings of what it represents and its potential implications [14, 25, 26]. Consequently, trust literature has an oversupply of frameworks and models, making it challenging to recognize how to use it to facilitate human-computer interactions (HCIs) [27]. Recent studies in human-robot interaction (HRI), such as Ullman and Malle [28], also present some limitations [29] (e.g., they do not present in the study results factors that measure trust applied to all robots; they are insensitive to the context where the HRI occurs).

Additionally, today's complex interaction context makes it difficult to distinguish between characteristics of trusted human, human-to-machine exchanges [27, 30–32].

These different perspectives and interpretations of trust in technology and its possible implications make it difficult for practitioners to undertake it when designing digital artefacts. Eventually, they avoid the subject and do not convey trust values in their system design, both real and perceived. Making it more accessible to deceptive and unethical business practices takes upon the design, leading as well to trust warranties that diminish trust in technology.

2.2. Human-Robot Trust. Trust has since long been addressed in various disciplines (e.g., social psychology, economy, philosophy, and industrial organization). Each domain that explores trust, affects either an attitude, an intention, or a behavior [14, 16].

We see trust as the "willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action necessary to the trustor, irrespective of the ability to monitor or control that other party" [25] (p. 712), as well as trust is a calculative orientation towards risk [30]; by trusting, we assume a potential gain, while by distrusting, we are avoiding a possible loss [33, 34].

Thus, a violation of trust usually does not lie in a single isolated interpersonal event, for instance, a lack of cooperation. Trusting is, therefore, a significant event that is likely to have an impact on the parties and their relationship. Trust is also transitive and changes over time. As automation and artificial intelligence, robots are increasingly involved in the community; ensuring trust in them is essential. Trust also reflects a state of mind and confidence in one's predisposition to trust another (robot intelligent machine). According to Kuipers [24], trust is also related to ethics and society's welfare as it is a critical element to foster cooperation between humans and robots. Trusting a robot can be a reinsurance element supporting people's decisions to engage and cooperate towards an expected outcome.

The lack of clear trust reinsurance elements in the interaction process can lead to miscommunications or trigger adverse reactions between two entities: humans and automation/artificial intelligence machines. It can also injure the relationship's efficacy and effectiveness, for instance, diminishing cooperation between humans and machines. Hence, the importance of understanding what are the trust reinsurance elements humans value when interacting with these machines, and ensuring that these values fit the technical framework that people label, is a critical aspect. In other words, the robot needs to learn, behave, and communicate in the same way those other entities have done in the past. Even though some researchers and practitioners can share a different understanding of trust and its representation, there is a need to have a measurement mechanism that can assess the human perception of trust in technology in a specific context.

2.3. Adopted Theoretical Model. The human-computer trust model (HCTM) by Gulati et al. [35] is a result of an empirical validation process with statistical modelling techniques. They developed a model consisting of initial factors that affect trust in technology based on a detailed scientific literature review. They also identified the main factors to predict trust in technology with a certain degree of statistical certainty. Those factors were identified [26]: reciprocity, competence, benevolence, predictability, honesty, trust predisposition, and willingness. To claim a high degree of statistical certainty, the authors carried out four studies with four different technologies: e-voting, Siri, homes for life, and e-school [35–37]. They applied a novel technique, called design fiction, allowing them to study trust perception with technologies, or devices, that do not exist yet in the market but would soon appear. The authors identified three factors that can assess, with a high degree of statistical certainty, trust in human-technology interactions: risk perception, competency, and benevolence. The authors proposed a scale with these three attributes, and they proved its statistical validity in all four studies mentioned above [37].

Considering the results of Gulati et al. [35] studies, and aware that trust assessment is context- and culture-dependent, this study aims at assessing the factors that can predict trust in human-robot interaction in the industrial context. Thus, four assumptions that affect, or predict, user's trust when interacting with a robot were considered (Figure 1):

H1. Trust can be explained by risk perception in human-robot interaction (HRI).

The perceived risk is measured by honesty and willingness [35] when humans interact with the robot. The impact of perceived risk on the degree of trust is relevant for understanding whether the user's subjective view of the risk corresponds to the safety level (i.e., objective risk) of HRI. Undertrust and overtrust situations can be problematic in the quality of HRI [18, 19] which can increase errors and accidents in the workplace due to users' misuse. The risk perceived by the user must be compatible with the abilities allowed by the interaction itself and not increase the probability risk of a cognitive bias leading to (1) the user's decision not to use cobot or (2) to the use of it in the wrong way. This discrepancy between the perceived risk and security may occur due to using the central concepts of interaction design [38], the nonidentification of specific affordances, and the nondetection of certain constraints for the user's intended actions regarding contingencies of the interaction. The tendency is trust, at a given time, to be influenced by past experiences and negative experiences, having more weight than positive ones. Even though, over time and with repeated interactions, the degree of trust stabilizes [39].

H2. Trust can be explained by benevolence in HRI.

In benevolence, the entrusted acts in the best interest of those who trust [35], which proves to be relevant to trust, facilitating the correct assessment of risk. Mcknight et al. [32] refer that individuals who perceive a particular technology as providing the necessary help will perceive fewer risks and uncertainties in its use. Without this assessment, the user will not have a perceived risk adequately informed, and it is unlikely that the degree of confidence is at the optimum. Schaefer [19] mentioned in his study that the amount of feedback, availability of information, type of indication, accuracy and truth of the input, and effective communication to minimize conflicting information for the operator are factors related to the robot that influence the degree of trust. Thus, benevolence starts from a base that the notion of causality is closely linked to the concept of the gulf of evaluation [38]—the effort that the user needs to make to understand the state of the system.

H3. Trust can be explained by competence in HRI.

Competence is the notion of functionality closely linked to the concept of the gulf of execution [38] in an attempt to understand how the object operates. This aspect affects the notion of control, which can decrease the user's confidence by not understanding the interaction and, consequently, not trusting what they do not fully understand. In this sense, lack of control can even increase human stress [40]. Messeri et al. [41] demonstrate that in HRI the robot's leadership increases the user's physiological and psychological stress

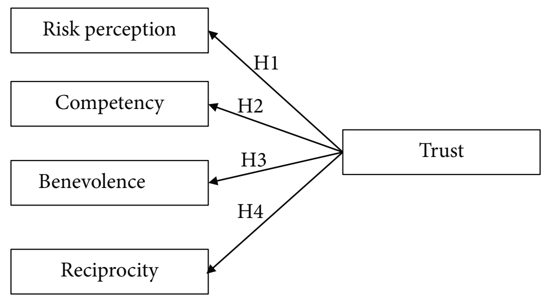

Figure 1: Theoretical model for trust in HRI.

when the robot is being led. Phillips et al. [42] demonstrate in their study the importance of a robot being reliable/capable in the user's confidence. This fact is reinforced by the reliability when reliability is defined by the reduction of errors of the automaton itself [21]. This fact can also be linked to emotional factors, such as comfort with automation [21], since it considers the degree of control the user has over the object, the degree of familiarity and proximity to it, and the similarity of intention.

H4. Trust can be explained by reciprocity in HRI.

The notion of reciprocity is related to the emotional satisfaction factor. For instance, as Gulati et al. [36] explained, if human users feel that technology is helpful, they will respond positively by adopting and using it in the system and developing a symbiotic relationship with the system. So, the concept of reciprocity can be fundamentally related to a degree of cooperation between two parties or even in fostering greater proximity and familiarity with the technology in an interaction process and eventually affecting the desire of using the robot itself. Using Guo and Yang's [43] analysis, this fact can stabilize the degree of trust of human employees, not allowing negative experiences that can impact HRI. Although the reciprocity attribute has no statistical significance in all four of Gulati et al.'s studies [35, 36], it was considered valid in the two studied contexts. Thus, this construct in this study model was considered an essential aspect of the application context (HRI).

3. Materials and Methods

3.1. Study Design and Sample. The study design is descriptive, observational, and cross-sectional. A nonprobabilistic and convenience sample collected by the snowball method was used. A total of 239 participants, 123 (51.5%) females and 116 (48.5%) males, aged between 18 and 27 years old completed the survey. This sample included university students from management, engineering, and industrial management areas. Data were collected between February 2020 and April 2020. Most of the participants did not report significant knowledge about cobots, and for that reason, the cobot concept was explained before the survey application. At the beginning of each survey, participants were advised to see a video and read the user story provided before answering the questions. The video aimed at illustrating the use of cobots in real scenarios, where human collaborates with cobots in an industrial context. These collaborative scenarios are related to assembly and package tasks, as well as safety issues (e.g., collisions). In this context, a collaborative workspace is where the cobot and human share the same space and execute the tasks at the same time [44]. For participants to quickly establish a parallel between the technical artefact and their perceptions of trust, it was used as a stimulus, the concept of Technology probe and design fiction [45], also known, in psychology, as vignette-based study (quantitative) [46]. The use of technological probes helped participants visualize better what current cobot technology forms might look like. Contrary to science fiction, which presents something that does not exist, the selected video illustrated a collaboration between an industrial robot and an industrial worker. It allowed the participants to imagine what type of human-robot interactions might look like. This method also enabled participants to probe, explore, and critique possible future interactions with collaborative robots in an industrial context [47]. The video was carefully selected to ensure that the message provided was neutral. The vignette technique is used in social science to explore perceptions, opinions, beliefs, and attitudes to depict scenarios and situations [48].

3.2. Instrument. The HCTM is a scale of trust that focuses on the human-artefact relationship. This scale was thoroughly empirically ascertained in diverse, human-artefact complex settings [35–37]. In this study, the users' trust in HRI context includes AI and robotic elements. The HCTM scale is a self-administered scale composed by 11 items that are divided in four subscales: risk perception (3 items—inverted items in this subscale), competency (3 items), benevolence (3 items), and reciprocity (2 items). Individuals respond to the constituent items of the four subscales mentioned above using a five-point Likert scale (1–"strongly disagree" to 5–"strongly agree"). In Table 1, the original HCTM can be seen. With the intention to make this scale easy to use, Gulati et al. [35] present the scale using placeholders (they refer to the ellipsis (…) as a placeholder). This placeholder needs to be filled in by the user of the scale. For instance, in items 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, and 11, the placeholder needs to be replaced with the artefact with which the user of the scale intends to measure trust, in this case cobots. Considering that this scale was adapted for a new context, it was given the name of Human-Robot Interaction Trust Scale (HRITS).

Table 1: HCTM original and Portuguese version (HRITS).

	Original HCTM					Portuguese version of HRITS				
	Strongly disagree 1	Disagree 2	Neutral 3	Agree 4	Strongly agree 5	Discordo totalmente 1	Discordo 2	Neutro 3	Concordo 4	Concordo totalmente 5
Risk perception										
Item 1 - rp01	I believe that there could be negative consequences when using (...)					Acredito que pode haver consequências negativas quando interajo com um robô colaborativo				
Item 2 - rp02	I feel I must be cautious when using (...)					Sinto que devo ter cuidado ao interagir com um robô colaborativo				
Item 3 - rp03	It is risky to interact with (...)					É arriscado interagir com um robô colaborativo				
Benevolence										
Item 4 – ben01	I believe that (...) will act in my best interest					Acredito que um robô colaborativo atuará no sentido de me ajudar a cumprir os meus objetivos				
Item 5 – ben02	I believe that (...) will do its best to help me if I need help					Acredito que um robô colaborativo fará o que lhe for pedido Para me ajudar				
Item 6 – ben03	I believe that (...) is interested in under- standing my needs and preferences					Acredito que um robô colaborativo agirá de acordo com as minhas necessidades e preferências				
Competency										
Item 7 – com01	I think that (...) is competent and effective in (...)					Penso que um robô colaborativo é competente e eficaz em Manter uma distância de segurança previamente definida do humano				
Item 8 – com02	I think that (...) performs its role as (...) very well					Acho que um robô colaborativo desempenha muito bem o seu papel Como assistente do homem				
Item 9 – com03	I believe that (...) has all the functionalities I would expect from					Acredito que um robô colaborativo tem todas as funcionalidades de segurança necessárias Para interagir com o humano				
Reciprocity										
Item 10 – rec01	When sharing something with (...), I believe that I will get a response					Ao partilhar algo com um robô colaborativo, espero ter um retorno significativo; resposta eficaz				
Item 11 – rec02	When sharing something with (...), I expect to get back a meaningful & knowledgeable response					Ao partilhar algo com um robô colaborativo pré-programado Para efetuar uma determinada ação, acredito que receberei uma resposta de acordo com a ação esperada				

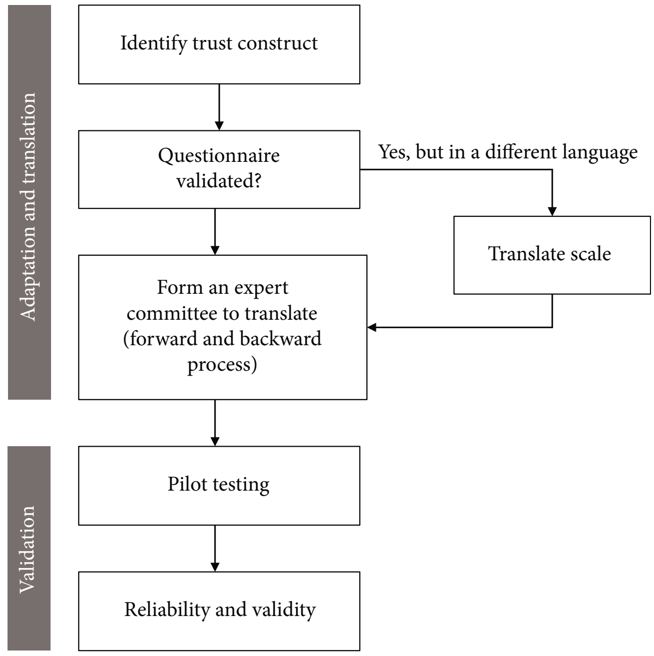

Figure 2: The adaptation, translation, and validation process.

3.3. Translation and Validation Procedure. The current study builds on prior works [35, 37, 49] and focuses on translating, adapting, and empirically ascertaining which attributes of the model hold in human-robot interactions. The study was carried out following the process outlined by M. Hill and A. Hill's [50] and Tsang et al.'s [51] guidelines. This process is divided into stage 1, adaptation and translating of the scale, and stage 2, procedures to validate the scale (see Figure 2).

Regarding cultural adaptation, with the authors' permission of the original scale, the HCTM was translated from English into Portuguese by two independent native Portuguese translators. Subsequently, a synthesis of the translations was made and submitted in two rounds to a committee of experts (CE) of four professionals with at least five years of research experience to review and evaluate the semantic equivalence. One of the original authors of the HCTM was part of the CE. The experts were also asked to make comments and suggestions for adapting the items so that they would be understandable and applicable in the Portuguese context. Once the recommendations made by the CE had been consolidated and agreement had been reached among the experts, the preliminary version obtained was backtranslated by two bilingual native English translators and compared with the original text. With this initial version, the pilot test was carried out in person with sixteen university students. These individuals were subsequently excluded from participating in the main study. Instead, they were provided with the HRITS scale, a sociodemographic information form, and another way to report their comments on the scale. This pilot test was used to establish whether the scale could be satisfactorily understood and completed by all students and estimate the completion time required, and for this, we used the think-aloud protocol [52]. The items reported as difficult to understand were modified in the final version of the instrument. The final version HRITS is in Table 1.

3.4. Data Analysis. The psychometric characteristics of the HRITS (construct validity factorial, convergent, discriminant, and reliability) were evaluated and published [53]. In addition, another assessment was performed using a factorial validity analysis estimated using confirmatory analysis (CFA) with the AMOS software (v.26, SPSS Inc., Chicago, IL) using the maximum likelihood (ML) method.

To contribute to the objective of this study and in accordance to Yasir [54], Confirmatory Factor Analysis (CFA) was used. CFA was selected considering that the aim was to test a proposed theory [55, 56]. Additionally, CFA is a technique intended for large samples where the n of 100 is usually the reference for the minimum number of cases required. All CFA application requirements were fulfilled, including the position of outliers.

To assess the adjustment of the model, the criteria of Brown [57] and Kline [58] were considered. The quality of the model's fit to the data was assessed using the Chi-squared (χ^2), standardized root mean square residual (SRMR), comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA) with confidence interval 90%. The adjustment was considered adequate when χ^2 reveals a statistically non-significant value, SRMR $< .08$, CFI and TLI $\geq .90$, and RMSEA $< .10$ [57, 58]. The factor weights (α) of the items in the HRITS were evaluated and considered adequate if $\alpha \geq .45$ [59]. After adjusting the model to the data, a second-order hierarchical model (SOHM) was also tested, proposing a general factor called "trust."

Table 2: Intercorrelations between the four factors from 1st-order CFA.

Trust	1	2	3	4
Risk perception (RP) (1)	1	.103	**.293****	**.183****
Benevolence (BEN) (2)		1	**.487****	**.451****
Competency (COM) (3)			1	**.436****
Reciprocity (REC) (4)				1

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Finally, convergent validity was assessed through average variance extracted (AVE ≥ .50). The reliability of the instrument was estimated from the composite reliability (CR). Values equal to or higher than .70 were indicative of adequate reliability.

To investigate differences in trust perceptions in the relationship between humans and robots (HRI) by gender, independent t-test was used the with the SPSS software (v.26, SPSS Inc., Chicago, IL).

4. Results

In the first step, the CFA was performed to confirm the 4-factor structure. As can be seen in Table 2, model fit indexes showed that the 4-factor model resulting from CFA: χ^2(38.06) = 75.94, SRMR = .06, TLI = .91, CFI = .94, RMSEA = .07, and CI90% (.04–.09). In Figure 3, the results obtained for factor loadings were also adequate for all items. The intercorrelations between the four factors are reported in Table 2. From the correlated four-factor CFA, the model-implied interscale correlations between the 4 factors ranged from .18 to .49 ($p < .01$).

As can be seen in Table 2, most of the correlations were moderate. The risk perception, competency, benevolence, and reciprocity subscales showed problems concerning the reliability: .73, .66, .65, and .58, respectively (CR < 0.70), and convergent validity: .48, .39, .39, and .41, respectively (AVE < 0.50). For these reasons it was performed a 2nd order CFA.

In the 2nd order CFA (Table 3, Figure 4), a model with the same 11 observed variables and a general factor called "trust" was tested. For this second model, the CR was 0.84, AVE was .58, and MaxR(H) was .92. The hypotheses (H1, H2, H3, and H4) proposed in the Section 2.3. were confirmed. The results showed a good model fit for the present sample (χ^2 (40.06) = 80.96; p ≤ .001; SRMR = .06; TLI = .90; CFI = .93; RMSEA = .07; and CI90% (.05–.09)).

Table 4 presented the means, standard deviations, skewness, and kurtosis of each item of the HRITS in general and by gender. Considering global score, benevolence subscale had the items with the highest scores. This trend was also verified for male and female.

To identify possible differences between gender in the trust perception, an independent t-test was used. Statistically significant differences were identified between gender in global score ($p = .04$). Male had more trust in the relationship between humans and collaborative robots ($M = 3.79$) than the female ($M = 3.66$) (see Table 5). Only for competence subscale, there were verified statically significant differences between male and female. Competence score was 3.82 for male and 3.56 for female (see Table 5).

The HRITS has good psychometric properties. All items of general factor trust model had high factor loadings that suggested a stronger factor contribution to those variable (risk perception = .40; benevolence = .77; competence = .93; and reciprocity = .83). The results regarding the CR (CR = .84) suggested that the items of the HRITS are homogeneous for the sample under study. The analysis of the responses regarding risk perceived, benevolence, competence, and reciprocity was also performed. Through analysing the obtained values, it is possible to verify that the benevolence subscale was where the individuals responded with higher values, and the risk perceived the worst.

5. Discussion

The inappropriate application of trust in technology results in misuse, abuse, or disuse of that robot [60]. As remarked before, trust is a key for sustainable relations, even those with a robot [24]. Trust can be a risk reassurance between a trustor and a trustee (e.g., HRI) [36, 61]. However, what is not clear is how to measure the trust of humans and robots (cobots) when working together. Understanding the factors that influence the levels of perception of trust in HRI is very important to ensure that our design propositions can communicate signs of being trustworthy [21]. It is important to ensure an adequate balance between peoples' commitments and their predisposition to interact/collaborate with automated AI machines (robots). Although there are tools capable of measuring trust in HRI, most of them have problems related to the trust assessment, since they are used in the context of automation in general and not applied to cobots in particular. Some of the existing scales that measure trust in the HRI need more robust statistical analysis [15–17].

Overall, the results of this study provide preliminary evidence that the HRITS scale is a useful and psychometrically sound instrument to assess users' trust in HRI context. The 2nd-order CFA is a technique for interpreting multidimensional scales by bringing various dimensions under the rubric of a common higher-level factor. Generally, 2nd-order CFA provides a better theoretical explanation of the data than 1st-order CFA, because while 1st-order CFA leaves the meaning of the correlations between the factors unexplained, 2nd-order CFA considers theoretically these correlations [62]. So, the results of the 2nd confirmatory factorial analysis supported the H1, H2, H3, and H4 described in Section 2.3.

Benevolence was the subscale with the highest scores. In case of innovative interfirm networks, the benevolence-based trust works as a performance facilitator, promoting honest communication and knowledge sharing and successful collaboration, in general [63]. Toreini et al. [64] consider that benevolence or integrity assessments can only be carried out indirectly by the entity that develops or applies the AI-

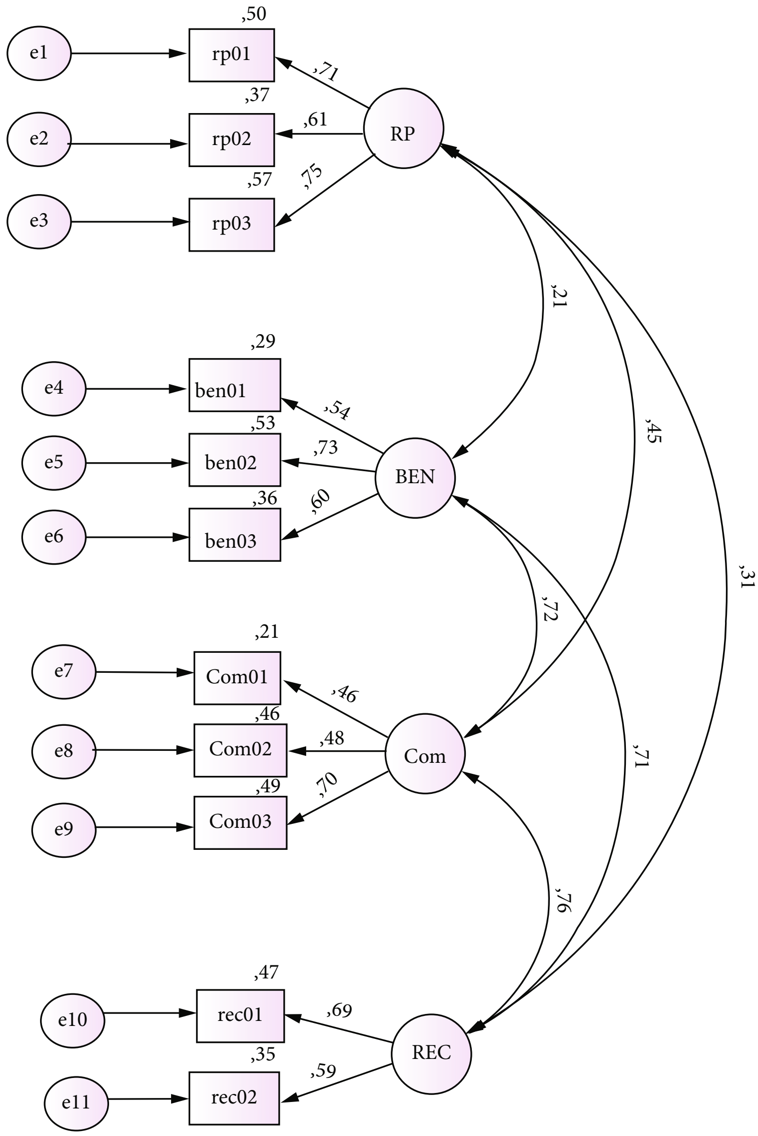

Figure 3: Final four-factor structure 1st-order CFA (standardized solution, where the values close to the measurement errors correspond to the explained variance proportions (R^2)). RP=risk perceived; BEN=benevolence; Com=competence; REC=reciprocity.

Table 3: Summary of results of model fit indexes from 1st- and 2nd-order CFA.

Model	χ^2	SRMR	TLI	CFI	RMSEA	Confidence interval (90%)
Four-factor structure (11 items) 1st-order CFA	75.94*** df = 38.06	.06	.91	.94	.07	.04-.09
General trust-factor structure (11 items) 2nd-order CFA	80.96*** df = 40.06	.06	.90	.93	.07	.05-.09

*$p < .05$; **$p < .01$; ***$p < .001$. df: degree of freedom.

based solution, given that personal data protection issues may arise.

Additionally, the results demonstrated that male had more trust in cobots than women, which was also found by Sheehan [65] in a study that verified that female consumers had greater trust concerns than men and were less likely to engage in purchasing over the web. Buchan et al. [66] compared choices in the Investment Game between men and women and found that men trust more than women. A possible reason for this could be the fact that women are more anxious than men about IT use, reducing their self-effectiveness and increasing perceptions of IT requiring greater effort [67], and the "impostor syndrome." This syndrome—or a fear of failure—-has a real impact on women, and men's reactions to women's discomfort with technology is often mocking or dismissive, making many women more reluctant to engage [68].

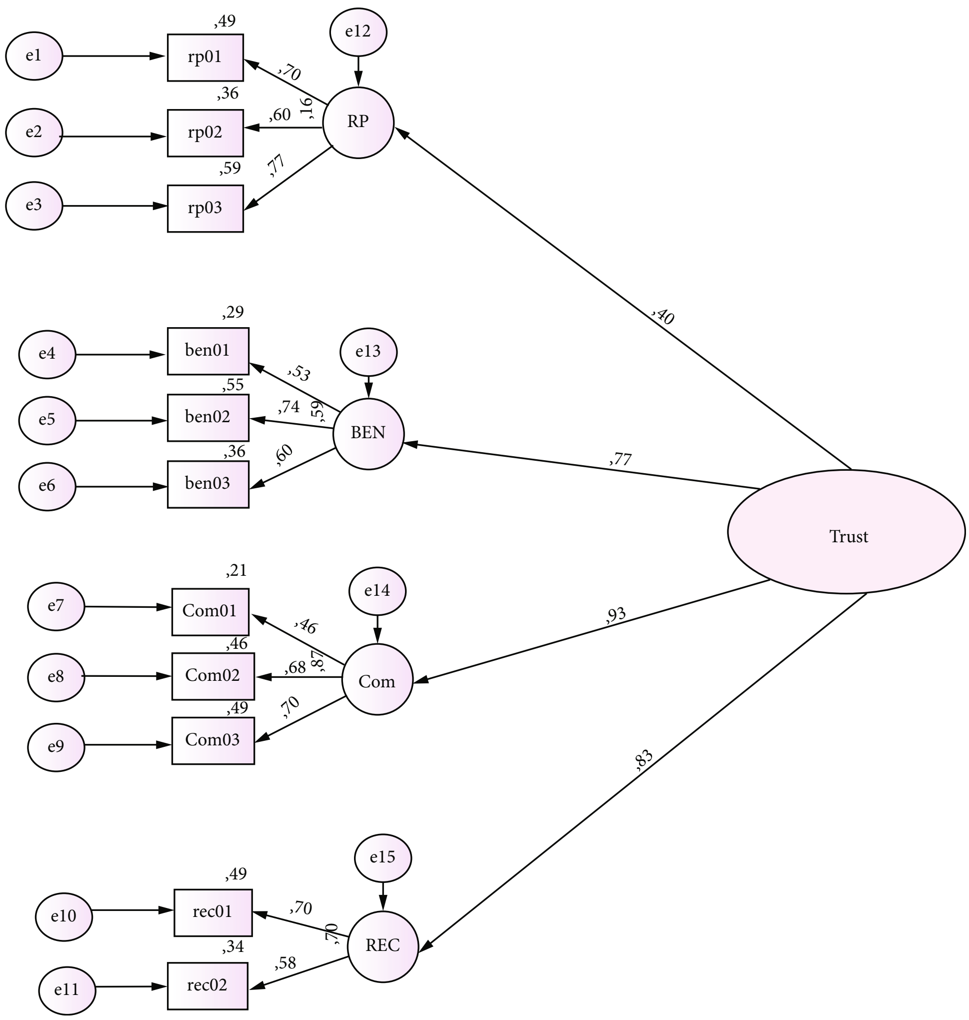

Figure 4: 2nd-order CFA–general trust-factor structure: (standardized solution, where the values close to the measurement errors correspond to the explained variance proportions (R^2)). RP=risk perceived; BEN=benevolence; Com=competence; REC=reciprocity.

Table 4: Summary of the results of the descriptive analysis from 1st- and 2nd-order CFA.

Item	Global score ($n = 239$)				Male score ($n = 123$)				Female score ($n = 116$)			
	M	SD	Sk	Ku	M	SD	Sk	Ku	M	SD	Sk	Ku
Risk perception												
Item 1–rp01	3.21	1.05	-.29	-.53	3.22	1.10	-.46	-.67	3.19	1.00	-.09	-.31
Item 2–rp02	2.77	1.05	.17	-.66	2.71	1.03	.28	-.54	2.82	1.06	.08	-.72
Item 3–rp03	3.85	.80	-.63	.74	3.86	.74	-.67	1.37	3.85	0.85	-.59	.35
Benevolence												
Item 4–ben01	4.26	.86	-1.63	3.70	4.26	.88	-.1.64	3.59	4.27	.84	-.1.64	4.01
Item 5–ben02	4.13	.87	-1.11	1.46	4.19	.86	-1.45	2.77	4.07	.87	-.83	.55
Item 6–ben03	3.65	.91	-.51	.06	3.82	.84	-.63	.49	3.49	.95	-.37	-.17
Competence												
Item 7–com01	3.74	.90	-.52	.20	3.90	.84	-.61	.49	3.59	.94	-.40	.05
Item 8–com02	3.85	.82	-.49	.34	4.05	.72	-.36	-.15	3.66	.87	-.43	.32
Item 9–com03	3.52	.85	-.18	.02	3.59	.87	-.23	-.17	3.46	.83	-.16	.29
Reciprocity									3.84	.82	-.76	1.26
Item 10–rec01	3.94	.82	-.78	1.17	4.04	.80	-.82	1.22	4.00	.91	-.85	.69
Item 11–rec02	4.00	.88	-.94	1.14	4.00	.84	-1.06	1.86	3.19	1.00	-.09	-.31

M: mean; SD: standard deviation; Sk: skewness; Ku: kurtosis.

Table 5: Descriptive analysis and gender differences of HRIST (global and by factors).

	n	M	DP	t	p
Trust (global score)					
Gender				-2.04	.04
Male	116	3.79*	.47		
Female	123	3.66*	.50		
Trust (risk perception score)					
Gender				.20	.84
Male	116	3.26	.07		
Female	123	3.28	.07		
Trust (benevolence score)					
Gender				-1.69	.09
Male	116	4.09	.06		
Female	123	3.94	.06		
Trust (competency score)					
Gender				-2.85	.01
Male	116	3.82*	.07		
Female	123	3.56*	.06		
Trust (reciprocity score)					
Gender				-1.12	.26
Male	116	4.02	.07		
Female	123	3.92	.06		

M: mean; SD: standard deviation; t: Student's test. $^*p < .05$.

6. Conclusions

This study was carried out to perform the translation and cultural adaptation of the Portuguese version of the HRITS scale and examine its psychometric properties among a sample of university students, to obtain a scale with good properties.

Considering previous works [35–37], this study showed that the model HCTM is consistent with the nature of the construct (or factor) in human-robot interactions.

The results of the confirmatory factorial analysis of the general factor trust model provided satisfactory fit indexes in terms of convergent reliability and internal consistency.

Although HRITS scale seems to be a valuable tool to assess trust in HRI in industrial settings, the participants of this study were selected by convenience and their characteristics can limit the generalization of the findings. Moreover, the HRITS can be enriched by including other dimensions (factors), for example, moral aspects and cognitive and emotional trust [28, 69]. Additionally, to test divergent validity it would be interesting to use other trust scales.

In future research, we suggest to explore, in more detail, cultural and gender effects on trust in technology. As suggested by Ajenaghughrure et al. [70], the development of longitudinal studies (using HRITS) to capture user trust dynamics through time, exploring novel approaches to measure unobtrusively variations, could be done in future research.

Data Availability

Data is available on request from the authors.

Conflicts of Interest

The authors declare no conflict of interests.

Acknowledgments

This work has been funded by national funds through the FCT — Fundação para a Ciência e a Tecnologia, I.P., Project UIDB/05037/2020.

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