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Human-Robot Interface Usability Perception Analysis for A Virtual Assistant

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Abstract: The increasing human-robot development in both domestic and industrial environments makes it necessary to include user perception in aspects such as human-robot behavior conditioning in the design phase and evaluate the interaction model that guides user-centered development. This paper presents a statistical analysis developed to evaluate the perceived usability of a human-robot interface using factor analysis. This analysis was performed based on the interaction of a virtual assistant robot for the supervision of physical training exercises with a human user in a closed environment. Developing a theoretical model with three factors that initially group 11 variables to obtain an evaluation metric in the human-robot interaction. To collect this information, a video of the interaction between the user and the virtual bot in the supervision interface was recorded and presented to a group of participants. They then completed a survey using a Likert scale to rate each variable, which also included two open-ended questions aimed at identifying ideas for improvement to propose future research. The application of confirmatory factor analysis allows us to conclude that the model for measuring interface usability consists of a factor that groups 10 variables. In addition, future research should focus on making human-robot interactions more natural.

Keywords: Factor Analysis; Human-Robot Interface; Usability; Virtual Robot; Deep Learning.

虚拟助手的人机界面可用性感知分析

摘要：在家庭和工业环境中，人机交互的发展日益频繁，因此有必要在设计阶段将用户感知纳入人机行为调节等方面，并评估指导以用户为中心的开发的交互模型。本文介绍了一种统计分析方法，该方法使用因子分析来评估人机界面的感知可用性。该分析是基于虚拟助理机器人在封闭环境中与人类用户进行体育锻炼监督的交互进行的。开发一个包含三个因子的理论模型，该模型最初将 11 个变量分组，以获得人机交互的评估指标。为了收集这些信息，记录了用户与虚拟机器人在监督界面中的交互视频，并呈现给一组参与者。然后，他们使用李克特量表完成了一项调查，对每个变量进行评分，其中还包括两个开放式问题，旨在确定改进的想法，以提出未来的研究。验证性因子分析的应用使我们得出结论，用于测量界面可用性的模型由一个将 10 个变量分组的因子组成。此外，未来的研究应侧重于使人机交互更加自然。

关键词：因素分析、人机界面、可用性、虚拟机器人、深度学习

1. Introduction

Assistive systems for robotic interaction have many applications, from group identification in social environments [1] to assistance in production environments or manufacturing processes [2]. Works such as the one presented in [3] identify the need to include the user in aspects such as conditioning of the human-robot workspace. Therefore, it is necessary to establish and measure interaction capabilities in this type of environment and in cases such as collaborative manipulation [4] or robotic control by gestures [5-7]. However, these interaction aspects are usually evaluated only against the functionality of robotic interaction techniques and algorithms.

While developments in human-robot interfaces have focused on human safety [8, 9], the need for a cognitive model that also projects the robot as a friend in collaborative interaction is now envisioned [10]. With capabilities such as tolerating changes in the environment in which it operates [11] and that direct interaction with humans provides the necessary confidence, for example, when moving an elderly person's position is the task [12], or when identifying a sign of fatigue supports the performance of a task to the user [13].

Although there are multiple developments in human-robot interfaces and robots that evaluate the form of interaction [14], safety [15], and decision making [16], few investigations have evaluated the model from the user's perspective. In [17], this type of evaluation was presented, where a questionnaire measured on a Likert scale [18] generated questions to quantify the user's perception of the collaborative work model without relying on a specific model for measuring parameters.

Based on the analysis of the state-of-the-art presented in the development of human-robot interfaces and the interaction with collaborative robots, the interaction model needs to be evaluated from the user's perspective. Models that have been identified as necessary in the development of previous works based on the design of human-machine interaction systems, such as [19-21]. Although the functionality at the engineering level did not contemplate the user's perception, it was necessary to foresee the basic aspects in the design phase to improve the user experience, from what a user perceives as pleasant, beyond the functionality achieved.

A model for measuring the usability of human-robot interfaces is proposed, supported by Likert-scale questionnaires. In this case, the model was applied and validated using a virtual robot assistant with exercise routines oriented to residential environments.

This article is divided into four sections, starting with an introductory analysis of the state of the art. This is followed by section two with the presentation of the methodology that gives rise to the model, section three which exposes the results achieved, and finally section four which concludes the use of the model.

2. Methodology

The communication interface to be evaluated (Figure 1) corresponds to that of a virtual robotic system for the supervision of physical training exercises in a closed environment, which was trained using deep learning algorithms such as convolutional neural networks (CNN) and short- and long-term memory (LSTM), based on the previous work presented in [21]. These networks are used for the recognition of voice commands and physical actions captured by the video of the user, seeking a natural interaction for which a predefined dialog script is developed to guide the training of the user in the execution of exercises: chest flexion, abdominal, jump, or squat.

The starting point is the theoretical model proposed in [22], which suggests three independent usability factors, each with observed variables, to which the variables are added: command interpretation, command sufficiency, and expected response, associated with the factors of effectiveness, efficiency, and user satisfaction, respectively.

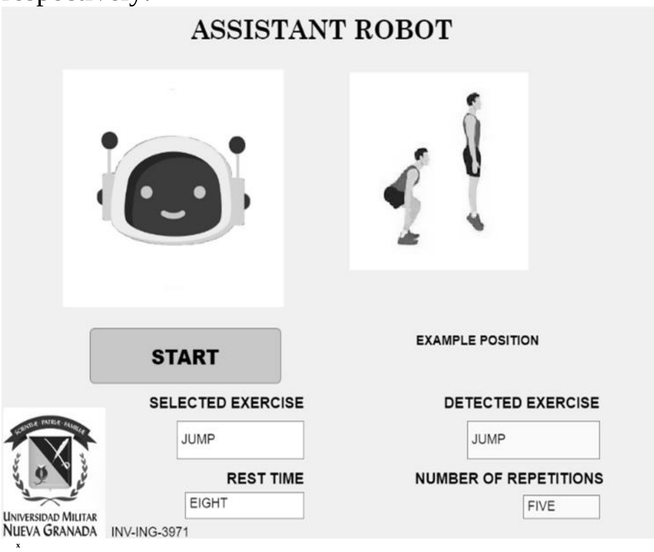

Figure 1. Human-robot interaction interface (Source: [21])

The hypothesis to be evaluated is the verification of the extended theoretical model, presented in Figure 2, where there are three factors *(F_i)* each with three or four completely independent variables *(Xj)* and the error representation *(e_j)*.

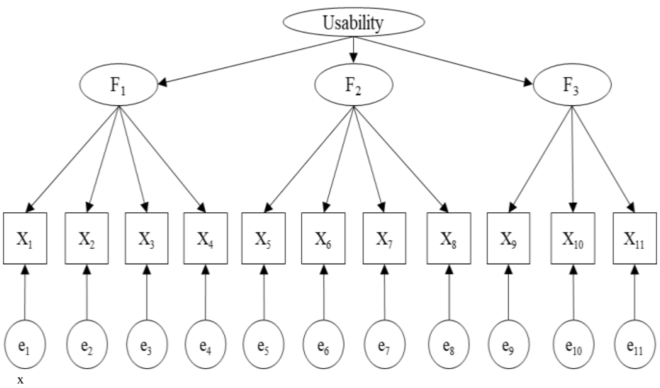

Figure 2. Initial Path Diagram (Source: developed by the authors)

Using a mixed methodology, this study seeks to identify the perceptions of potential users regarding the usability of the proposed interface. For the analysis, a survey of 11 questions was designed (in Google form) that included informed consent and the 11 variables to be assessed using a Likert scale from 1 to 5. Two final questions (12 and 13) were included to identify opportunities for improving the interaction between the user and the virtual robot, and the application of the virtual robot, in order to guide future research, so the latter will have a differential treatment.

Table 1 shows the number of questions, with the factors *(F_i)*, their denomination in the model *(Xj)* to be analyzed with Confirmatory Factor Analysis (CFA), the variables, and their identification with the theoretical model.

Table 1. List of questions, factors and variables (Source: developed by the authors)

# ask	Factor	Variable/Subject
1	Efficiency (F_2)	Clarity (X_5)
2	Effectiveness (F_1)	Assertiveness (X_1)
3	User satisfaction (F_3)	Naturalness (X_9)
4	Effectiveness (F_1)	Effectiveness (X_2)
5	User satisfaction (F_3)	Satisfaction (X_{10})
6	Efficiency (F_2)	Ease (X_6)
7	Effectiveness (F_1)	Utility (X_3)
8	Efficiency (F_2)	Learning (X_7)
9	User satisfaction (F_3)	Expected response (X_{11})
10	Effectiveness (F_1)	Command interpretation (X_4)
11	Efficiency (F_2)	Command sufficiency (X_8)
12	Does not apply	Improvement idea for the interaction between user and virtual robot
13	Does not apply	Improvement idea for the application of the virtual robot

For data collection, a video was recorded where one of the members of the research team interacted with the virtual robot, which was observed by 334 potential users who agreed to participate in the test by means of their respective informed consent and subsequently answered the questionnaire between May 8 and September 26, 2024. This methodology of consultation using videos to investigate robot perceptions in HRI research presents antecedents, as reported in [23-25]. Video-based studies make participants have an observational role with minimal risk [26], in this particular case, without requiring them to make the physical effort of the exercise involved.

First, the data collected for the closed questions were studied quantitatively by means of descriptive statistical analysis, followed by a test to determine the type of behavior (normality with Kolmogorov-Smirnov for samples greater than 50), which makes it possible to determine the type of subsequent analysis: parametric or non-parametric.

Factor analysis was used to ratify the relationships that exist between the 11 observed theoretical variables and the three latent factors.

Starting from a pre-structured model, CFA is adequate for studying the dependence relationships between variables. Confirmatory factor analysis was performed using the SPSS software.

Finally, the results of Questions 12 and 13 were qualitatively studied using content analysis.

3. Results

Table 2 presents the descriptive statistics analysis for questions 1 to 11, with the mean, variance, and kurtosis, while questions 3 and 11 present a negative kurtosis because they have outliers that are less concentrated around the mean. Therefore, they have lighter tails, while the rest of the questions present a positive kurtosis, indicating that the data are closer to the mean. With the measures of central tendency, we have that the mean varies between 3.5120 and 4.1407, the median and mode coincide in the value of 4, the variance having low values indicates that the dispersion of the data is close to the mean of each variable allowing statistical measures to be reliable and facilitating forecasts based on this information.

Table 2. Descriptive statistics (Source: developed by the authors with SPSS)

# ask	Mean	Variance	Kurtosis
1	4.0329	0.98993331	2.3214
2	4.1407	0.92930008	2.8808
3	3.5569	1.33658432	-0.4009
4	4.0898	0.93205206	2.1648
5	3.8383	1.07565707	0.8396
6	4.0988	1.07107641	1.9375
7	3.9671	1.09172971	1.2291
8	3.8503	1.11531428	0.7357
9	4.0120	1.03578472	1.6867
10	4.0868	0.94156298	2.2820
11	3.5120	1.45943741	-0.5057

The Kolmogorov-Smirnov normality test [27] was run because there were more than 50 data points, from which it was observed that for all questions, there was a significance of less than 0.05, as shown in Table 3, concluding that none of the variables followed a normal distribution so that non-parametric tests could be performed.

Table 3. Kolmogorov-Smirnov (Source: developed by the authors with SPSS)

# ask	Statistical	gl	Sig.
1	0.316	334	0.000
2	0.307	334	0.000
3	0.233	334	0.000
4	0.301	334	0.000
5	0.274	334	0.000
6	0.294	334	0.000
7	0.297	334	0.000
8	0.281	334	0.000
9	0.295	334	0.000
10	0.306	334	0.000
11	0.229	334	0.000

The sample adequacy measures were calculated with a KMO of 0.959 and Bartlett's test of sphericity with a significance of 0.000, which were used to test the relationship between variables and to show the validity and appropriateness of the responses, indicating that there is a correlation between the variables, so the factor analysis is relevant [28].

Using SPSS, CFA was performed, as indicated in [29], which uses the principal component and maximum likelihood methods to obtain similar results.

Initially, the analysis was carried out taking into account the pre-structured three-factor model; its anti-image matrix (Table 4) shows data on the diagonal with values very close to one (greater than 0.948). Therefore, it is concluded that there is a correlation between the variables, and none of them generates noise, indicating that the factorial model is adjusted.

Table 4. Anti-image correlation (Source: developed by the authors with SPSS)

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1	0.950	-0.413	-0.049	-0.158	-0.145	-0.115	-0.036	0.081	-0.080	0.029	-0.085
2	-0.413	0.950	-0.030	-0.245	-0.010	-0.081	-0.054	0.008	-0.124	-0.116	-0.020
3	-0.049	-0.030	0.959	-0.079	-0.281	0.082	-0.155	-0.120	-0.028	0.058	-0.120
4	-0.158	-0.245	-0.079	0.967	-0.076	-0.085	-0.050	-0.113	-0.127	-0.189	0.067
5	-0.145	-0.010	-0.281	-0.076	0.952	-0.255	-0.226	-0.131	-0.007	0.062	-0.008
6	-0.115	-0.081	0.082	-0.085	-0.255	0.965	-0.151	-0.052	-0.038	-0.236	-0.024
7	-0.036	-0.054	-0.155	-0.050	-0.226	-0.151	0.966	-0.223	-0.111	-0.017	0.044
8	0.081	0.008	-0.120	-0.113	-0.131	-0.052	-0.223	0.967	-0.088	-0.182	-0.075
9	-0.080	-0.124	-0.028	-0.127	-0.007	-0.038	-0.111	-0.088	0.965	-0.339	-0.010
10	0.029	-0.116	0.058	-0.189	0.062	-0.236	-0.017	-0.182	-0.339	0.948	-0.064
11	-0.085	-0.020	-0.120	0.067	-0.008	-0.024	0.044	-0.075	-0.010	-0.064	0.964

The results in Table 5 show that most of the extraction values were greater than 0.57, except for question 11, which had a value of 0.179, suggesting that this variable should be removed from the model.

Table 5. Communalities (Source: developed by the authors with SPSS)

# ask	Initial	Extraction
1	1.000	0.752
2	1.000	0.792
3	1.000	0.571
4	1.000	0.811
5	1.000	0.759
6	1.000	0.774
7	1.000	0.761
8	1.000	0.700
9	1.000	0.761
10	1.000	0.751

11	1.000	0.179

Because components 2 and 3 present eigenvalues lower than 1, it is recommended that they be attached to another variable with a higher eigenvalue. Table 6 shows that the only factor that met this condition was variable, with a total explained variance of 69.186%.

Table 6. Total variance explained (Source: developed by the authors with SPSS)

Component	Initial Eigenvalues		
	Total	% of variance	Cumulative %
1	7.610	69.186	69.186
2	0.853	7.752	76.938
3	0.570	5.182	82.120

This analysis shows that Factor 1 is composed of eight of the 11 questions with a percentage of 72.72%, while Factor 2 has two questions with 18.18% of the questions, and Factor 3 has only one question with 9.01%, as shown in Table 7.

Because Factors 2 and 3 have few components and with the results obtained for the total variance explained, it is recommended to perform a new analysis to find a better model fit [30].

Table 7. Rotated component matrix (Source: developed by the authors with SPSS)

	Component		
# ask	1	2	3
10	0.857	0.250	0.158
2	0.828	0.340	0.147
9	0.828	0.312	0.135
4	0.815	0.397	0.102
6	0.786	0.393	0.128
1	0.774	0.372	0.170
7	0.645	0.608	0.084
8	0.627	0.546	0.148
3	0.307	0.871	0.169
5	0.595	0.669	0.117
11	0.173	0.149	0.972

Therefore, a second analysis was performed that allowed SPSS to define the model factors, excluding variable 11, whose anti-image matrix (Table 8) presented values close to 1 (greater than 0.947) in its diagonal, indicating that this second model was adjusted.

Table 8. Second model. Anti-image correlation (Source: developed by the authors with SPSS)

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	0.949	-0.417	-0.059	-0.154	-0.146	-0.117	-0.032	0.075	-0.082	0.023
2	-0.417	0.948	-0.033	-0.244	-0.010	-0.081	-0.054	0.007	-0.124	-0.118
3	-0.059	-0.033	0.961	-0.071	-0.284	0.080	-0.151	-0.130	-0.029	0.051
4	-0.154	-0.244	-0.071	0.969	-0.075	-0.084	-0.053	-0.108	-0.126	-0.186
5	-0.146	-0.010	-0.284	-0.075	0.951	-0.256	-0.226	-0.132	-0.007	0.062
6	-0.117	-0.081	0.080	-0.084	-0.256	0.964	-0.150	-0.054	-0.038	-0.238
7	-0.032	-0.054	-0.151	-0.053	-0.226	-0.150	0.967	-0.221	-0.111	-0.014
8	0.075	0.007	-0.130	-0.108	-0.132	-0.054	-0.221	0.967	-0.089	-0.188
9	-0.082	-0.124	-0.029	-0.126	-0.007	-0.038	-0.111	-0.089	0.964	-0.340
10	0.023	-0.118	0.051	-0.186	0.062	-0.238	-0.014	-0.188	-0.340	0.947

In the communalities matrix (Table 9), it was found that the extraction values were equal to or greater than 0.568, although question 3 had the lowest extraction value.

Table 9. Second model. Communalities (Source: developed by the authors with SPSS)

# ask	Initial	Extraction
1	1.000	0.752
2	1.000	0.792
3	1.000	0.571
4	1.000	0.811
5	1.000	0.759
6	1.000	0.774
7	1.000	0.761
8	1.000	0.700
9	1.000	0.761
10	1.000	0.751
11	1.000	0.179

In the second model, the total explained variance corresponds to 74.516%, as shown in Table 10. When comparing the accumulated variance of the two analyses, it was observed that with only one factor, its value increased by 5.33%, which is favorable in terms of model accuracy.

Table 10. Second model total variance explained (Source: developed by the authors with SPSS)

Component	Initial Eigenvalues		
	Total	% of variance	Cumulative %
1	7.452	74.516	74.516
2	0.575	5.751	5.751
3	0.425	4.248	4.248

It was concluded that the most convenient model had a factor with 10 variables; for a better fit, question 11, which generated noise and negatively affected the accumulated explained variance, was excluded. The final proposed model is presented in Figure 3, where there is one factor with ten completely independent variables.

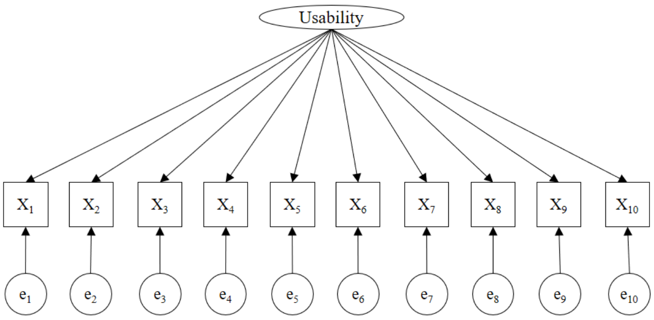

Figure 3. Final Path Diagram (Source: developed by the authors)

The analysis of questions 12 and 13 shows a practical and user-centered approach. The information collected corresponds to unstructured data, which allows defining future research that would benefit the application developers and end users in terms of improvement opportunities related to interaction and application. The 100 most-used words in the natural language of the interviewees in questions 12 and 13, representing 21.85% (73 participants) and 16.77% (56 participants) of the sample, are shown in Figures 4 and 5, respectively.

Figure 4. Cloud of the 100 most used words in the answers to question 12 (Source: developed by the authors with Voyant tools)

Figure 5. Cloud of the 100 most used words in the answers to question 13 (Source: developed by the authors with Voyant tools)

From the analysis of the answers to question 12, whose list of terms is shown in Figure 6, it can be seen that the proposals revolve around making human-robot interaction more natural and fluid, suggesting replacing the voice used with a more human one and making the interface friendlier, which can help users feel more comfortable. However, these proposals did not consider the possible diversity of users. Overall, continuous improvement in the human-robot interaction interface is essential, and a critical approach can guide the development of more effective and humane solutions.

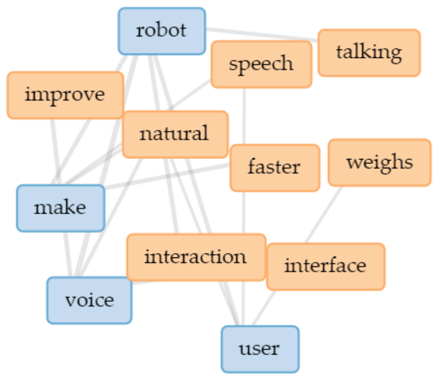

Figure 6. List of terms of opportunities for improvement of the virtual human-robot interaction (Source: developed by the authors with Voyant tools)

With respect to the answers to question 13, whose list of terms is shown in Figure 7, it can be seen that some participants in the survey made suggestions for improving the application, highlighting the idea of making the application more visually attractive and more interactive to maintain user interest and encourage physical activity. In addition, including a stopwatch and the ability to track repetitions and rest times are relevant and practical for exercise optimization.

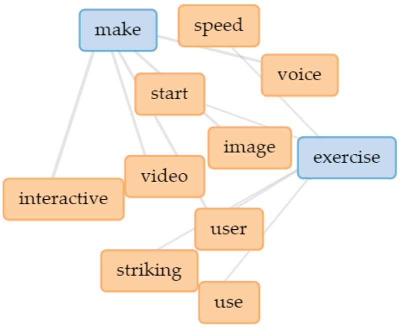

Figure 7. List of terms of opportunities for improvement of the virtual robot application (Source: developed by the authors with Voyant tools)

In general, future research should focus on the need for a more dynamic design, a more natural voice, and an intuitive interface, which may lead to the creation of a more personalized and effective experience with additions such as timer, orientation videos, and number of series. Their implementation depends on a cost–benefit analysis and an evaluation of the possible limitations in the implementation of the suggestions.

4. Conclusion

The descriptive statistical analysis allowed us to conclude that the data were homogeneously distributed because the dispersion was low. In addition, it was observed that the questions coincided with their modes and medians. Having a symmetrical frequency distribution provides reliability to the statistical tests performed and facilitates forecasting.

When performing the Kolmogorov-Smirnov normality test for each variable, it was observed that none of them presented a normal distribution, which allowed us to conclude that non-parametric CFA tests must be performed to evaluate the model that determines the relationship between the latent variables and their indicators.

The study concludes that the extended theoretical model initially presented changed and was reduced to one single factor with 10 variables that allow obtaining a cumulative variance explained of 74.516%, which is a sufficient value; thus, it is possible to apply this model to assess the Human-Robot Interface Usability, which allows the collection of valuable information without putting the participants at risk in environments where virtual robots are used.

From the text analysis of questions 12 and 13, we conclude that the main need is to define the naturalization of human-robot interaction in voice and language fluency in future research.

From the statistical analysis obtained, it is recommended that the reader use a high number of surveys that provide evidence of the key trends of the evaluation, developing simple questions about the user's experience in the robot's work but with multiple options (at least five), which helps to avoid biases in the model. This applies and limits its use in punctual interactions, as in the assumed example case. A general interactive environment can be segmented into interaction scenarios to facilitate identification of improvement actions.

Declarations

Author Contributions

Conceptualization, J.M.R., and E.C.A.; methodology, E.C.A.; validation, E.C.A., and R.C.E.; formal analysis, E.C.A. and R.C.E.; investigation, E.C.A., and R.C.E.; data curation, R.C.E.; writing—original draft preparation, E.C.A.; writing—review and editing, J.M.R.; visualization, R.C.E.; supervision, J.M.R.; project administration, J.M.R.; funding acquisition, J.M.R. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of the Universidad Militar Nueva Granada (project INV-ING-3971, date of approval: 18/01/2024).

Informed Consent Statement

Informed consent was obtained from all the subjects involved in the study.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this manuscript. In addition, ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies, have been completely observed by the authors.

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