Not so difficult? Studying the relationship between task complexity and preference for feedback from social robots

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ABSTRACT

Have you wondered if social robots are better communicators than humans? Can they grasp the important aspects of interaction while improving the accuracy of the message they want to communicate? And more important how does it feel to interact with a social robot? Nowadays technology is rapidly improving therefore, the academic world has to keep enriching the literature regarding cutting-edge technology products such as social robots.

This paper aims to investigate human attitudes towards social robots in the context of feedback in order to figure out in which cases do people prefer to receive feedback from social robots. The key tool in this experimental study is Furhat. Furhat will assist participants into their journey of completing tasks and interact with them in order to assess their performance.

The paper includes an introduction of the key concepts studied in this research: feedback, preference, task complexity, openness to experience and social robots. These key concepts are studied from an academic point of view through literature review and further they are investigated through experiments with Furhat. The findings of the research are proposing an interesting relationship between the concepts studied and the paper is highlighting further aspects regarding the interaction between humans and social robots.

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1. INTRODUCTION

Feedback is the information about the reaction to a product or to someone's performance (Hattie & Timperley, 2007). Nowadays, people are provided with feedback in multiple manners throughout their day from various entities factors such as teachers, parents, friends, and even your phone is weekly reminding you how much time you spent on your social media accounts last week.

Currently, the agents who provide feedback in a systematic and controlled way in different environments are teachers, employers, trainers, etc. Moreover, the feedback is provided based on the provider's own understanding of a performance rather than from the data gathered. In the paper by David A. Davis, MD Paul E. Mazmanian, PhD Michael Fordis, MD R. Van Harrison, PhD Kevin E. Thorpe, MMath Laure Perrier, MEd, MLIS (2006) it is found that the self-assessment made by a physician was different than the assessment made by a specially designed machine or another physician. This could suggest that feedback may as well be more accurate if it is based on data or it does not involve subjective feelings as self-assessment does. Moreover, the form in which someone provides feedback has a significant influence towards the way in which the feedback is received. In the book by Boud and Molloy (2013), it is mentioned that the way feedback is perceived can be influenced by the provider, moreover they write about how students are not satisfied with the feedback they receive from teachers due to problems of shared meaning. The problem of shared meaning refers to an individual's beliefs and attitudes that can influence how the feedback is perceived. Therefore, a considerable amount of literature is discussing how feedback should be provided and what aspects should be taken into account in order to achieve a better understanding and overall attitude towards feedback. This suggests that the academic and practical world did not yet find the appropriate feedback provider method. An appropriate feedback provider method should overcome the current challenges.

In order to rule out problems that arise in the process of providing feedback, technology turned its focus to social robots. Social robots are robots that can interact with humans or other robots. These robots are created with the purpose of simulating human to human interaction (Caic et al., 2019, page 463). Moreover, they have artificial intelligence incorporated that helps the robots to interact (Paul Formosa, 2021). Patrick van Esch and J. Stewart Black (2019) describe how AI can be integrated in the recruitment process and what are the challenges that AI still has to overcome in order to fully digitalize business processes such as recruiting. However, recruiting processes are currently handled in a hybrid version.

would be interesting to investigate whether the process of providing feedback can follow a similar path towards a digitalization journey.

Thus, in this paper, the researcher will investigate the attitude towards receiving feedback from social robots in different cases. The researcher wants to tackle the issue of attitudes towards feedback provided by social robots because digitalizing the process of providing feedback can bring a few advantages and close the gap found in the learning process named feedback. One of the advantages of digitalizing the process of providing feedback is cutting costs on training personnel in companies.

However, in order to digitalize this process, it is first needed to study the attitude "preference" towards a new feedback tool. Preference represents a positive attitude towards a concept or object (Ritu Agarwal and Jayesh Prasad ,1999).

One example of such a feedback tool – which is the key focus of the current study – is Furhat.

Furhat is a social robot who can execute applications such as different kinds of human-robot interactions (Furhat Robotics, 2020). For example, it can run the application "meeting Furhat" and the robot will take the individual on an introductory journey or "telling jokes" and Furhat will try to make the user laugh. It is believed that one of the functionalities of Furhat will be to build long-term social relationships with other people (Furhat Robotics). This indicates that Furhat could take the role of a couple's counselor robot that promotes positive communication behavior in romantic couples, a robot that functions as a public speaking coach or a facilitator for business meetings (Furhat Robotics). Moreover, this technology edge product might represent an opportunity to revolutionize feedback: Can we avoid the emotional reactions that feedback is arising in people by providing the feedback through a robot such as Furhat? Can a robot like Furhat provide feedback in a more systematic way and can it help us implement feedback in our daily tasks?

In order to compare the attitude of an individual in different scenarios in which the social robot provides feedback task complexity is used. This is because feedback is measuring someone's performance of a task and the task performance and performance needs are influenced by task characteristics (Belkin et al. 1982 and Ingwersen, 1992 and Mick et al., 1980). Complexity is measuring the level of complexity of a task based on a set of characteristics, such as: repetitivity, analyzability, a priori determinability, the number of alternative paths of task performance, outcome novelty, number of goals and conflicting dependencies among them, uncertainties between performance and goals, number of inputs, cognitive and skill requirements (Byström & Järvelin, 1995). Thus, by using task complexity different characteristics of the tasks can be measured which will help draw conclusions regarding the cases in which social robots could be used to provide feedback.

Moreover, the researcher will investigate the presence of a moderator variable in the research equation. The moderator variable is named openness to experience. The reason for believing that openness to experience is a dimension that should be taken into account is the fact that social robots are created based on cutting edge technology. Thus, interacting with a social robot can be considered a new experience for most people. Further,

To sum up, the objectives of this paper are to investigate to what extent the complexity of a task can be a factor that contributes to the preference of receiving feedback from social robots. The indicator task complexity is a way of characterizing the different scenarios in which individuals receive feedback. To investigate whether an individual's level of openness to experience is another factor that contributes to the individual's overall preference to receiving feedback from social robots. The research paper will answer the empirical question: To what extent does task complexity influence the preference of an individual to receive feedback from social robots?

The theoretical implications of this research are enriching the literature regarding social robots and their functionalities and the literature regarding process of providing feedback and how to improve it. As for the practical implications, the findings of this study could seriously decrease costs and labor hours in organizations that will decide to provide feedback through social robots.

In the following chapter of the paper, the theoretical framework that lays at the base of this research will be presented. The literature is divided in a few subsections: literature concerning social robots and in specific Furhat, theories regarding task

complexity, literature about one of the big five personality traits which is openness to experience and literature regarding attitudes and in specific preference. Further, the paper will continue with the methodology chapter in which the research design, data collection and data analysis are presented. To continue, the results of the statistical tests will be presented and discussed in the discussion chapter. The last chapters of the paper will discuss limitations and recommendations for future research and it will sum up the research paper with a conclusion.

1. THEORETICAL FRAMEWORK

1.1 Feedback

According to Susan M. Brookhart (2017), feedback is part of the "formative assessment". The formative assessment is a method of benchmarking someone's performance to the goals of the task. In other words, feedback can help an individual assess his performance and benchmark it with a previous performance. In this paper, it is mentioned that in order to conduct an effective feedback session, the feedback provider has to take into account the feedback content. The feedback content has a focus, a comparison, function, valence, clarity, specificity and tone. Moreover, besides these aspects the time of the delivery of the, the mode and the audience are all factors that influence how the feedback will be perceived.

According to Rick Bommelje (2012), the Situation Behavior Impact is a model of providing feedback that feedback is formulated in a clear and non-defensive manner. Feedback constructed by following this model is focused and relevant.

Therefore, the environment in which Furhat will provide feedback will be kept unchanged. Both the lasagna recipe and dish brush will be placed exactly in the same location for each participant. Moreover, the feedback will include an overall score of the performance, a comparison with what was supposed to be achieved and what was actually achieved by the participant. The valence will be mentioned during the feedback as well (positive/negative) and the tone of Furhat will be friendly and playful.

2. THEORETICAL FRAMEWORK

2.1 Social robots

According to Breazeal C., Takanishi A., Kobayashi T (2008) "social robots are robots that can interact with humans or other robots." The purpose of these robots is to imitate humans (Breazeal C., Takanishi A., Kobayashi T. , 2008,1349-1350). In other words, social robots were created in order to interact with humans and other robots. Human Robot Interaction is a field that "analyzes, designs, models, implements and evaluates robots for human use "(Yong Cui, Xiao Song, Qinglei Hu, Yang Li, Pavika Sharma, Shailesh Khapre, 2022, 1) . Therefore, this field is studying the challenges and advantages that the interaction between human and robot present. The social robot that will be referred to the most in this paper is Furhat. Furhat is a cutting-edge technology social robot that can interact with humans. It has a customizable appearance and the user can choose the gender, age and human likeness. It allows the user to choose the language and the tone of the voice and it also expresses facial expressions in order to facilitate nonverbal communication (Furhat Robotics).

Furhat has an interesting functionality which is called Blockly. Blockly is a program that allows anyone to program Furhat without having to own knowledge about other programming languages. This is possible by building algorithmic blocks with commands that Furhat will execute. These commands can be speaking commands, or facial expression commands or even listening commands. Therefore, the researcher can use Furhat's functionality "Blockly" to provide feedback based on certain predefined goals and requirements and thus simulate an interaction between human and robot. (Furhat Robotics)

The predefined commands work as an algorithm. "An algorithm is an abstract mathematical structure that has been implemented into a system for analysis of tasks in a particular analytic domain". (Rosanna Nagtegaal,2021) Thus, an algorithmic block programmed in Blockly is a logical sequence of commands that will be executed by Furhat and that can be conditioned by the interaction with an individual. In other words, the commands can also be conditioned on an individual's reaction to the previous commands.

This suggests that by programming Furhat through Blockly the social robot does not use a machine learning in order to interact. Thus, the interaction is not based on data gathered by the artificial intelligence and it is predefined.

The functionalities that are critical for someone to provide feedback are its ability to let an individual know what they have done that reached a required standard in order for them to be able to repeat the behavior and what they have done that did not reach a certain standard in order for them to improve. (Russell, 1998) Thus, Furhat will be programed to interact with the individual for whom he is providing feedback by offering an explanation of the feedback, based on the goals and requirements of a task

2.1 Task complexity

The goal of this research is to investigate in which cases people would prefer to receive feedback from social robots. Feedback is an information seeking process and according to Belkin et al. (1982) and Ingwersen, 1992 and Mick et al., 1980 information needs and information seeking processes depend on an individual's task. In other words, the feedback is modeled based on task characteristics to cover the information seeking needs. Moreover, Ingwersen (1992) argues that "an effective information retrieval is based on the understanding of an individual's task". Therefore, the dimension task is used in order to define the cases in which Furhat could potentially provide feedback on task performance. Further, the dimension task is characterized by literature.

The characteristics of a task that can be used to measure the task complexity are "repetitivity, analyzability, a priori determinability, the number of alternative paths of task performance, outcome novelty, number of goals and conflicting dependencies among them, uncertainties between performance and goals, number of inputs, cognitive and skill requirements." (Byström & Järvelin, 1995). Task complexity plays a key role in the research equation because it provides a complete and complex overview about different scenarios in which social robots could take over the responsibility of providing feedback. However, in this research Furhat, is providing feedback based on predefined commands, this means that the input, process and outcomes have to be priorly determined. Thus, in this paper the tasks will be characterized by repetitivity, analyzability, a priori determinability, the number of alternative paths of task performance, and outcome novelty. The repetitivity of a task measures how tedious and predictable a task is. For example, placing products on shelves in stores is a repetitive task, because it requires the same movement of the hand. The analyzability of a task is the characteristic of a task to decompose. The a priori determinability of a task refers to the level of knowledge regarding the scope of a task. The number of alternative paths

refers to the number of ways of completing the task. Outcome novelty refers to the level of predictability of the outcome of a task. So, the more intuitive the outcome of a task is the lower the level of novelty of the task.

The tasks with a low complexity are tasks with priori knowledge, in other words tasks that are repetitive, analyzable, priori determined, it has just one or two alternative paths for task performance and have a low level of outcome novelty (Byström & Järvelin, 1995). The tasks with high complexity are tasks for which there is no priori knowledge, in other words tasks that are not repetitive, analyzable, not priori determined, it has multiple alternative paths for task performance and have a novel outcome (Byström & Järvelin, 1995). Furhat is providing feedback based on predefined commands thus, it is expected that in the case of complex tasks, which can not be priorly determined, that individuals will not prefer feedback from Furhat.Moreover, according to Dale L. Goodhue and Ronald L. Thompson (1995) task-technology fit is an important aspect that affects the performance. Thus, if the technology does not fit the tasks then the experience of receiving feedback will be affected in a negative way.

In the paper "Task Complexity as a Moderator of Goal Effects: A Meta-Analysis" it is mentioned that there is empirical evidence that specific challenging goals lead to a higher task performance (Locke, Shaw, Saari, & Latham, 1981; Pinder, 1984) and according to Byström & Järvelin (1995) task complexity is characterized by many aspects, including the type of goals the task has. Thus, there is reason to believe that task complexity is an indicator that can help to find the right direction for future research regarding cases in which social robots could provide feedback.

H1: If the complexity of a task increases then the preference for receiving feedback from social robots decreases.

2.2 Openness to experience

In order to figure out in which cases people prefer to receive feedback from social robots, the researcher will study the presence of a moderator variable, openness to experience.

Each individual has certain personality traits that influence their attitudes. Gowan & Lepak (2010) For instance, if a person is an introvert, he will most likely feel uncomfortable carrying on long and important presentations. Another example would be a person who is not open to new experiences will most likely be skeptical of technological innovations. In fields such as human resources, it is very important to identify and understand an applicant's personality trait in the selection process because this will influence the way the candidate will interact with tasks and other people. Moreover, the fact that social robots simulate human interaction suggests that personality traits influence the way the candidate will interact with social robots as well.

The Big Five Approach is categorizing the personality traits into 5 big dimensions: extraversion, agreeableness, conscientiousness, emotional stability and openness to experience (Gowan & Lepak, 2010). The personality trait that is influencing the way people perceive the interaction with cutting edge technology is openness to experience.

According to Gowan & Lepak (2010) openness to experience refers to "an individual's degree of intellectual curiosity, creativity and preference for novelty". Moreover, openness is defined as "fundamentally an intrapsychic variable, associated with such esoteric phenomena as chills in response to sudden beauty, the experience of déjà vu, and homesickness for the unknown." (McCrae, R. R., & Sutin, A. R. ,2009).

In other words, openness to experience is best represented by a hunger for the unknown.

The reason for studying the openness to experience concept is that social robots are a cutting-edge technology product and most people did not interact with one yet, which means that in order to implement such a technology into people's everyday life they first have to go through a learning curve. The learning curve shows that before mastering the knowledge there is a dip in the curve. According to Barrick Mount (1991) the dimension openness to experience is positively correlated with someone's motivation to learn. Thus, it is necessary to take into account this concept when one wants to analyze the preference of people towards receiving feedback from social robots. Moreover, McCrae (2009) states that these characteristics are affecting the social behavior of an individual.

Therefore, because someone's personality trait influences its attitudes and beliefs, it is interesting to investigate how someone's attitude towards experience might affect the relationship between task complexity and preference.

H2: If an individual is open to experience then the negative relationship between the task complexity and the individual's preference towards receiving feedback from social robots becomes weaker.

If an individual is not open to experience then the negative relationship between the task complexity and the individual's preference towards receiving feedback from social robots becomes stronger.

2.3 Preference

In order to implement social robots as a feedback tool the researcher wants to analyze people's attitude towards receiving feedback from social robots. Attitudes are learned predispositions to respond in a particular way towards a concept or object (Doob, 1947). In other words, an individual's attitude is a habitual reaction towards a concept or object. Preference represents a positive attitude towards a concept or object (Ritu Agarwal and Jayesh Prasad ,1999). Preference represents a positive attitude towards a concept or object (Ritu Agarwal and Jayesh Prasad ,1999). The variable preference, which represents someone's attitude towards receiving feedback from social robots, was conceptualized in the survey in a number of statements written according to Ritu Agarwal and Jayesh Prasad (1999). "The cognitive component is what came to be known as beliefs, while the affective component alone comprises attitude; this conceptualization of attitude underlies the theory of reasoned action (Fishbein & Ajzen, 1975), and subsequently, TAM." (Ritu Agarwal and Jayesh Prasad, 1999) The attitude is defined as the affective component underlying the Theory of Reasoned Action. The Theory of Reasoned Action states that there is a relationship between beliefs and attitudes and an individual's behavior can be predicted based on precedent attitudes and internal beliefs (Fishbein & Ajzen, 1975). The scale used for his method is a 7-point scale with values from strongly disagree to strongly agree. (Appedinx 9.2) Therefore, the researcher is studying human's attitudes towards receiving feedback from social robots by investigating their level of preference because if an individual prefers to receive feedback from social robots then they will also be open to implement this practice in their life. According to James N. Druckman and Arthur Lupia (2000) "the objects between a preference are those that a person can imagine as substitutable. "This means that a person would prefer a substitute over the old product if they can imagine themselves using the substitute.

In the paper "comparison effects of preference construction" by Ravi Dhar, Stephen M. Nowlis and Steven J. Sherman it is explained that the user preference is correlated with the individual's ability to make feature-based comparisons within alternatives on the market. In general, in order to implement a

cutting-edge technology product such as Furhat for example, the model Technology Acceptance Model is used to find solutions of integrating the technology in the market. (Doob, 1947) However, this research is not investigating how to force implementing social robots in the feedback process rather study if one functionality of social robots could be providing feedback.
Figure 1 is a visual representation of the research equation and the influence the variables have on each other. To sum up, it is assumed that task complexity is negatively influencing the preference of an individual towards receiving feedback from social robots. Moreover, this relationship is affected by the individual's personality trait, openness to experience.

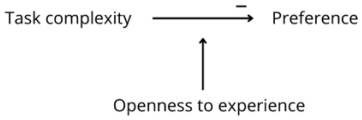

Figure1. Research equation

3. METHODOLOGY

3.1 Research design and data collection

3.1.1 Cause, effect and causal relationship

In order to find out if there is a negative relationship between task complexity and attitude towards feedback from Furhat, candidates were invited to conduct experiments. "Experiments are the study in which intervention is purposely introduced with the scope to observe an effect." Campbell, D. T., Cook, T. D., & Shadish, W. R. (2001). Thus, in the case of this research, the researcher used an experiment with different treatments in a controlled environment with the scope of measuring their preference to feedback from Furhat. The different treatments were defined by the diverse tasks that Furhat asked the participant to complete. Therefore, the participants were randomly assigned to one of the two tasks that the research prepared for the experiments.
The cause-effect relationship that was observed in this paper is task complexity and attitude towards feedback received from a social robot. The hypothesis that was tested is: If the task complexity increases then the preference for receiving feedback from social robots decreases. Further, the causal explanation that is described in Figure 1 indicated the existence of a confound. The moderator variable "openness to experience" ruled out the bias of internal factors such as personality traits that predefine the attitude towards receiving feedback from Furhat. Thus, the second hypothesis that was tested is: If an individual is not open to experience then the relationship between the task complexity and the individual's preference towards receiving feedback from social robots becomes stronger.

3.1.2 Method and dependent variable

The type of experiment that suits the limitations and conditions of this research is the random experiments. The sample included students and teachers who are studying or working at the University of Twente. Thus, the participants were randomly assigned to one of the tasks, which had different levels of task complexity. The first task, which is a task with low level of complexity was to identify all the ingredients out of a lasagna recipe. The lasagna recipe was the same for all the participants and it was printed on a paper which was placed on the table in front of the participant. The participant was asked by Furhat to pick up the paper and read the ingredients out loud. The second task, which is a task with high level of complexity was to deliver a one-minute pitch in which the participant has to convince Furhat to buy a red dish washer without mentioning that the object can be used for washing dishes. The red object was placed on the table in front of the participant.
After the participant finished the task, Furhat provided feedback by mentioning the overall performance (negative, positive, very positive) and mentioning if the goal of the task was achieved by the participant while the requirements were respected.
The feedback that was provided by Furhat was modeled according to indications of the Situation Behavior Impact model and the literature written by Susan M. Brookhart (2017) regarding "how to give effective feedback to students".
The participant could ask Furhat for an elaboration of the feedback and Furhat explained again to the participant about the scoring method it used in order to provide feedback. The dependent variable was measured at the end of the experiment by completing a survey that tests the attitude towards receiving feedback from Furhat. The survey included questions about the individual's attitude after receiving feedback in order to compare if the individual's attitude was more positive in the cases with low complexity. The scale used for his method is a 7 point scale with values from strongly disagree to strongly agree.

3.1.3 Variable for task complexity

The level of complexity was monitored by the task characteristics: repetitivity, analyzability, a priori determinability, the number of alternative paths of task performance, and outcome novelty. Thus, the tasks with low complexity that the participants had to complete were tasks which met the characteristics related to a priori determinability of a task and the ones with high complexity met the characteristics related to the extent of task (Byström & Järvelin, 1995). For example, a representative for low complexity tasks was to identify ingredients in a recipe and for high complexity tasks was to give a one-minute selling pitch. Identifying ingredients from a recipe is a repetitive and analyzable task, it has a prior determinability and it does not have a novel outcome or multiple alternative paths of completion. Whereas, sustaining a one-minute selling pitch with the goal of selling a dishwasher without mentioning that it can be used for dishes is a task with multiple and interdependent goals and uncertainties, it requires the use of different skills and it has multiple inputs.
The variables from the research equation were task complexity, preference and openness to experience. Task complexity was created as a nominal variable with values "identify ingredients" and "1 minute pitch". The first value is representative for tasks with low complexity. Thus, it was recoded into a different variable with values "0" for "identify ingredients" and "1" for "1 minute pitch".

3.1.4 Moderator variable

The variable openness to experience was conceptualized in the survey in a number of statements with answers from totally disagree to totally agree. The method used to measure this variable is the" Big Five Inventory " by John, O. P., & Srivastava, S. (1999). This is due to the fact that Statements 5,10,15,20,25,30,35R,40,41R,44 are related to someone's openness to experience.
The scale used for his method is a 5 point scale with values from totally disagree to totally agree. (Appendix 9.1)

3.1.5 Sample

The sample of participants consisted of people who currently live in the Overijssel region and are a part of the University of Twente

community as well as outside. The community has approximately 12514 (reference) people, who are either students or teachers. In order to calculate the size of the sample it was taken into account a 95% confidence interval and an error margin of 8%. Thus, the sample size should have been 150 participants. However, due to the research's limitations and the research scope a sample of approximately 65 participants was used.

3.2 Data analysis

3.2.1 Reversed values

Further, the negative variables were reversed in the following manner:
1->5; 2->4; 3->3; 4->2; 5->1 and
1-2->7;2-3->6; 3-4->5; 4->4; 4-5->3; 5-6->2; 6-7->1

3.2.2 Computed variables

Moreover, the variables preference and openness to experience were computed based on the score for the correspondent statements from the survey.
Preference= (IlikeusingFurhat+ Furhatisfuntouse+ IdislikeusingFurhatR+Furhatprovidesanattractiveworkingenvironment)/4
Openness to experience= (Isoriginalcomesupwithnewideas + Iscuriousaboutmanydifferentthings
+Isingeniousadeepthinker+Hasanactiveimagination
+Isinventive+PrefersworkthatisroutineR+Likestoreflectplaywithideas+HasfewartisticinterestsSelfReportMeasuresforLoveandCompassionR+Issophisticatedinartmusicorliterarture)/10
Moreover, the interaction between task complexity and openness to experience was computed by multiplying the two variables. The interaction variable is named "interaction" in SPSS.
Interaction= Whichtaskdidyoucomplete* Opennesstoexperience

3.2.3 Regression Analysis

To begin with, the statistical test used in order to study the relationship between task complexity and preference is a linear regression. The reason for choosing this statistical test is that the researcher wants to test the interaction between the variable task complexity and preference and also whether there is a linear relationship between the two variables. The linear regression test is offering information about the relationship between the variables and moreover it also offers the regression equation of the variable preference.
To continue with, the statistical test used in order to investigate the effect of the moderator variable on the relationship between task complexity and preference, the researcher used a multiple linear regression. The reason that lays behind this choice is that this test offers information about the interaction of the moderator variable, which is the aspect that the paper is investigating.

4. RESULTS

4.1 Descriptive statistics

The descriptive statistics table is presenting an overview of the answers given by each participant, the mean of the answers per each question, the minimum and maximum that was scored for each question and the standard deviation.
Table 1 (Appendix 9.4) offers a summary of all the variables in the research model.
The mean of the variables is relatively high which means that most of the answers were positive. Thus, also the variable preference and openness to experience will have a high mean.

Table 2. Descriptive statistics computed variables

Variables	N	Minimum	Maximum	Mean	Standard deviation
Preference	63	3.1	4.9	3.901	.39411
Openness to experience	63	2.13	7	5.720	1.053
Valid N (listwise)	62				

In Table 2 it can be observed that the mean for the computed variable preference is 3.901 and a standard deviation of .394. The computed variable Openness to experience has a mean of 5.720 and a standard deviation of 1.053.
To begin with, the means of the answers are high, in general above the median value. This is a positive sign because it suggests that most of the participant agreed with the statements included in the survey. Therefore, this is the first clue that the attitude towards Furhat is a positive one. To continue, some of the items have a minimum of 0 even though the scale for preference is from 1 to 7 and the scale of openness to experience is from 1 to 5 because the researcher declared the missing values as 0.

4.2 Reliability analysis

The researcher conducted a reliability analysis in order to test the scale for preference. In Figure 4 it is presented that there were four items in the scale and the Cronbach's Alpha based on standardized items is 0.850 and Cronbach's Alpha is 0.848.

Table 4 Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardize d Items	N of Items
.848	.850	4

Further, a reliability analysis was also conducted for the scale openness to experience. In Figure 5 it is presented that there were ten items in the scale and the Cronbach's Alpha based on standardized items is 0.646 and Cronbach's Alpha is 0.565.

Table 5 Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardize d Items	N of Items
.565	.646	10

4.3 Regression analysis

The researcher conducted a linear regression between the independent variable, task complexity, and the dependent variable, preference in SPSS.

The mean of the variable preference is 5.7202 and the standard deviation is 1.053. The B value of task complexity is .037 and the constant is 5.692.
The adjusted R square is -0.016. The adjusted R square value explains 1.6 % of the variance of the preference in this model. This is a significant low percentage. Moreover, the p-value is 0.887 which is higher than alpha (alpha=0.05). This means that the null hypothesis is rejected. Thus, there is not enough evidence to state that there is a negative relationship between task complexity and preference.
Further, the multiple regression between task complexity, openness to experience and preference was conducted. The B values of the variables are: -8.945 for task complexity -.892 for openness to experience and 2.341 for interaction and the constant is 9.216. The means of the variables are: 2.054 for interaction variable, 3.901 for openness to experience and 5.720 for preference and 0.55 for task complexity. The standard deviations of the variables are: 2.030 for interaction, .394 for openness to experience, 1.053 for preference and 0.532 for task complexity.
The adjusted R square of the module is 0.165. The adjusted R square explains 16.5% of the variance of the preference in this model.
The P-values are: <0.001 for task complexity, .044 for openness to experience and <0.001 for interaction. The P-value is lower than alpha=0.05 in all three cases thus, we do not reject the null hypothesis. The P-value of task complexity is <0.001. This value is lower than alpha (alpha=0.05) which means that the null hypothesis is not rejected. So, there is a significant relationship between task complexity and preference. The P-value of openness to experience is .044. This value is lower than alpha (alpha=0.05) which means that the null hypothesis is not rejected. So, there is a significant relationship between openness to experience and preference.
The P-value of task complexity is <0.001. This value is lower than alpha (alpha=0.05) which means that the null hypothesis is not rejected. So, there is a significant relationship between the interaction variable and preference

5. DISCUSSION

This study aims to contribute to the process of introducing social robots as feedback provider into human's lives. This is because the current method of providing feedback has some issues.

5.1 Reliability analysis of scales

In order to test the reliability level of the scale preference and openness to experience, the researcher conducted a reliability analysis using Cronbach's Alpha. The reason for choosing to analyze the reliability, Cronbach's alpha is that the variables are constructed with a Linkert scale. The aim of this test is to investigate the internal consistency of the scale. There is a continuous discussion regarding the minimum value that the coefficient can have in order to assume that the scale is reliable enough. However, it is agreed that above 0.8 suggests that the scale is reliable and above 0.5 suggests that the scale is reliable enough. ("Cronbach's Alpha in SPSS Statistics - procedure, output and interpretation of the output using a relevant example | Laerd Statistics.", 2022). The Cronbach's alpha for preference is 0.848 which suggests that the scale is reliable enough.
However, for the variable openness to experience the result is not so optimistic. Cronbach's alpha is 0.565. This represents a low value, however it does not mean that the scale is not reliable enough but rather that there might be some statements that test the same concept which is often the case for questions that reflect different underlying personal qualities such as openness to experience. (https://statistics.laerd.com/spss-tutorials/cronbachs-alpha-using-spss-statistics.php)

5.2 Assumptions

In order to conduct the statistical tests, the researcher has to check if the assumptions for linear regression tests are met by the data collected.

5.2.1 Quantitative variables

All the variables that participate in a linear regression have to be quantitative variables. (Pascal van Gils, 2022) The variables preference and openness to experience are quantitative variables as well as the dummy variable, task complexity.

5.2.2 Linearity Assumption

The linearity assumption suggest that the results have to show a linear relationship between the dependent and independent variables. In order to test this assumption a normal P-Plot test was conducted in SPSS. (Pascal van Gils, 2022)
The P-Plot figure of the regression standardized residuals suggests that there is a linear relationship between task complexity and preference and between openness to experience and preference. Figure 2 is the visual representation of the P-Plot test which is showing the linearity.

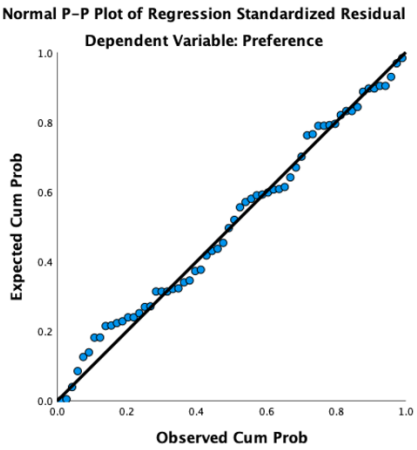

Figure 2 P-Plot Figure

5.2.3 Homoscedasticity

The homoscedasticity assumption suggests that the group of people who were assigned to perform the task with low complexity has an equal variance with the variance of the group of people who were assigned to perform the task with high complexity. In order to test this assumption a scatterplot of the residuals was created in SPSS. (Pascal van Gils, 2022)
The scatterplot shows if there are equal variances between the group of people who conducted the low complexity task and group of people who conducted the high complexity task. Thus, the visual representation of the scatterplot of the residuals in Figure 3 is indicating that the two groups have an equal variance.

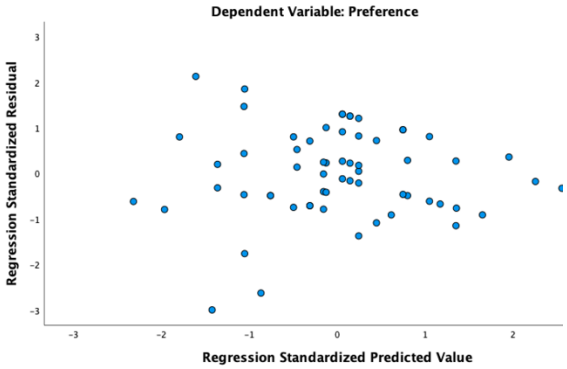

Figure 3 Scatterplot of residuals

5.2.4 Independence

Table 3 Collinearity Statistics

Tolerance	VIF
.933	1.072
.933	1.072

This assumption suggests that the variables are not multicollinear. In order to test this assumption a Collinearity analysis test was conducted (Pascal van Gils, 2022). The collinearity analysis checks the presence of multicollinearity using VIF values. It is obvious that the VIF values are below 10 thus it can be assumed that the variables are not multicollinear.

5.2.5 Normality

This assumption suggests that the residuals are normally distributed. In order to test this assumption, the researcher created a scatterplot of the residuals (Pascal van Gils, 2022). The fourth assumption investigated the degree of normality by creating a normal probability plot. In order to test this assumption Figure 3 is observed. The figure does not show any drastic deviations from the normality line thus it can be assumed that the data is checking the normality assumption.

In conclusion, all the assumptions for a linear regression test are met and further, the researcher could conduct the appropriate analysis in order to investigate the hypothesis formulated in the theoretical framework.

5.3 Hypothesis 1

In order to test the first hypothesis, the researcher did a linear regression in SPSS.

The adjusted R square value explains 1.6 % of the variance of the preference in this model. This is a significant low percentage. This coefficient is pointing out that the variable task complexity is most probably not influencing the variable preference.

The linear regression equation is preference= 5.692+0.37*task complexity.

However, the p-value is 0.887 which is higher than alpha (alpha=0.05). Thus, we can reject the null hypothesis. This means that there is not enough evidence to reject the null hypothesis.

This suggests that there is no clear negative relationship between task complexity and preference. This result is different than it expected. The first hypothesis was formulated based on the literature review: according to Belkin et al.,(1982) and Ingwersen, (1992) and Mick et al., (1980) the feedback needs and processes are related with the individual's understanding of the task. However, in the literature review the model chosen to define task complexity was the one suggested by Byström & Järvelin (1995) in which the task characteristics: repetitivity, analyzability, a priori determinability, the number of alternative paths of task performance, outcome novelty, number of goals and conflicting dependencies among them, uncertainties between performance and goals, number of inputs, cognitive and skill requirements were analyzed. Thus, a more complex overview from different perspectives over task complexity can be an interesting topic for future research.

Moreover, according to Dale L. Goodhue and Ronald L. Thompson (1995) if the technology does not fit the tasks then the experience of receiving feedback will be affected in a negative way. Thus, the lack of enough scientific data to prove that there is a negative relationship between task complexity and preference can be explained by the limitation of the program used to write the predefine commands in the form of an algorithm instead of using the full potential of the AI. However, moving to the second hypothesis, the results suggest that the presence of a moderator variable can strengthen the negative relationship between task complexity and preference.

5.4 Hypothesis 2

In order to test the second hypothesis, the researcher did a multiple regression in SPSS.

Table 6 Model Summary

Model	R	R square	Adjusted R Square	Std.Error of Estimates
1	.018	.000	-.016	1.06821
2	.079	.006	-.027	1.07406
3	.454	.206	.165	.96811

The adjusted R square explains 9.8% of the variance of the preference in this model. This coefficient is pointing out that the variable openness to experience is most probably influencing the relationship between task complexity and preference. Thus, by taking into account openness to experience the relationship between task complexity and preference is stronger.

Table 8 Coefficients

		Unstandardized Coefficients					Collinearity Statistics	
Model		B	Standard Error	Standardized Coeffcients Beta	t	Sig.	Tolerance	VIF
1	(Constant)	5.692	.192		29.614	<.001		

	Task complexity	.037	.256	.018	.143	.887	1	1
2	(Constant)	4.845	1.449		3.343	.001		
	Task complexity	.077	.266	.039	.29	.773	.933	1.072
	Openness to experience	.212	.359	.079	.589	.558	.933	1.072
3	(Constant)	9.216	1.736		5.309	<.001		
	Task complexity	-8.945	2.372	-4.013	-3.772	<.001	.010	104.644
	Openness to experience	-.892	.434	-.334	-2.056	.044	.520	1.924
	Task complexity & Openness to experience	2.341	.612	4.486	3.824	<0.001	.010	100.562

The regression equation fort this model is preference= 9.216-8.945*task complexity-0.892*openness to experience+ 2.341*moderator. In other words, if the score of openness increases with one, the absolute value of the variable preference increases with 0.892.

The P-values for each variable are significant enough to reject the null hypothesis, thus this indicates that the second assumption is true. An individual's level of openness to experience is play an important role in the relationship between task complexity and preference.

The results found by carrying out statistical tests suggests that the moderator variable, openness to experience, is strengthening the negative relationship between task complexity and preference. In other words, when an individual's level of openness to experience is high the relationship between task complexity and preference is weaker. This relationship is represented in Figure 4 (Appendix 9.11) where it is shown that when people are open to experience the relationship between the independent variable and preference is weaker than when the people are not open to experience.

The results of this regression were expected to be significant enough to prove the hypothesis. The reason the researcher assumed that this hypothesis is true is because according to the literature, openness to experience and preference represent someone's attitude towards something, thus it is logical that someone's attitudes are aligned as they arise from the personality of respective person.

According to Ritu Agarwal and Jayesh Prasad (1999), preference is a positive attitude towards something over something else. Thus, this study suggests that in environments where people have a high level of openness to experience the tasks carried out can have different levels of complexity. Whereas, in environments where people have a low level of openness to experience, the level of complexity of tasks has to be low so that people would prefer to receive feedback from social robots rather than other traditional methods.

5.5 Practical and Academic Implications

In the practical scene, these findings suggest that social robots could be implemented in environments where most of the population is open to experience. For example, in academic institutions such as schools or universities or even in the entrepreneurial world to help organizations shift their learning processes into a more efficient and modern method.

Moreover, as stated in the literature, according to Furhat Robotics, Furhat is able to change its voice, face and even gestures. All these functionalities can be adapted to make Furhat an even better communicator for people from different backgrounds.

In the academic scene, the findings of this paper suggest that there is potential to implement social robots as feedback provider and it opens the door for other studies related to social robots used in learning processes. Thus, this research can be used in different academic fields where researchers could continue the study of social robots on different topics such as, education. Since people who are open to experience prefer feedback from Furhat, researchers could study if the feedback from Furhat can be used in order to improve academic assignments. This type of research would require changing the standard environment in which Furhat is professing and studying how does Furhat interact with humans in open spaces with many stimuluses, such as a classroom.

6. LIMITATIONS AND FUTURE RESEARCH

6.1 Limitations

The research did not find enough support for the relationship between task complexity and preference. However, the results were more optimistic when the moderator variable, openness to experience was taken into account.

The limitations of this research are mainly due to technical issues with the social robot used and time constraints.

To begin with, Furhat, the social robot used in this research had to be coded in the programming language Kotlin in order to access the full potential of the AI (Furhat Robotics). However, the researcher does not have expertise in coding thus it was opted to program the social robot with commands. Programming the social robot with commands can be done in a new function created by Furhat Robotics, "blockly". In this function, commands such as "say" or "ask" or "smile" were used in order to program the robot to explain the goals and requirements of the tasks and provide a predefined feedback. The predefined feedback was divided into 3 options of feedback: negative feedback, positive feedback and very positive feedback.

Due to this limitation, Furhat could provide only three options of feedback that were repeated for each participant, thus decreasing the variability of the feedback. Because of this the feedback could not be personalized for each participant and this decreased the value of the feedback.

Time constraint represented a challenge and a limitation of the research. The time frame in which the research was conducted is

ten weeks. Moreover, due to the availability of Furhat, the data collection was made in a time frame of three weeks. Thus, the optimal number of participants was not achieved and the sample contained only 64 participants.
Another constraint of the research was that during the experiment some of the participants were not yet accustomed to interacting with a social robot. Therefore, the interaction was slow sometimes and even needed one of the researchers to intervene and explain certain constraints of Furhat.
Furhat has certain limitations as well. The social robot, Furhat, is still not produced in a commercial manner, thus the technology is still sensitive to the environment and it malfunctions when it is used for a long period of time.
Moreover, another limitation of the research is the scales used during the data collection phase. In order to standardize the scale for preference was adjusted to a scale from 1 to 5 and after the data was collected it was converted into a scale from 1 to 7 by using mathematical expressions. The implication that it has on the study is not significant enough to show an internal inconsistency of the data as the reliability test shows.

6.2 Future research

As for future research, this paper represents the base for further studies on social robots to be conducted. The findings related to the cases in which Furhat could be preferred as a feedback provider opens up the door for further research that includes other variables that could increase the preference, such as cultural values. Moreover, this study had certain technical limitations, thus it would be interesting to repeat the study by using the social robot's machine learning. This would also require a different analysis of the concept task complexity and it opens up possibilities of providing feedback based on data captured during an individual's task performance.
In the paper "Engaging students in peer review: feedback as learning "by Catherine Moore and Susan Teather, feedback is described as a learning tool. This is an important aspect because it suggests that the environment in which the feedback is provided can be considered a learning environment.

Andrew S. Sense (2007) is proposing a theoretical framework of five sociological elements that have to be taken into account when someone is analyzing the learning environment. The aim of these elements is to create a social infrastructure that supports the learning process. The first element is cognitive style. "this element is capturing someone's preferred method of gathering, processing and interpreting information." (Andrew S. Sense, 2007). This suggests that the first element that has to be investigated is someone's preference towards receiving feedback from social robots. In this paper, feedback was considered a learning experience, however the researcher did not include the literature to support this assumption. Thus, the researcher is recommending that the academic world should conceptualize feedback by using the framework proposed by Catherine Moore and Susan Teather.

7. CONCLUSION

This study examined human attitude towards receiving feedback from social robots. The robot used in this study, Furhat, was manufactured by Furhat Robotics and bought by University of Twente for research scopes. The research question of this paper was, to what extent does task complexity influence the preference of an individual to receive feedback from social robots?
The findings of the research are in favor of choosing social robots as feedback provider in certain environments. This fact is enriching the academic gap in the literature related to learning processes and cutting-edge technology products such as Furhat. Moreover, this research contributes to the process of finding out the opportunities and possibilities that social robots bring and answers bigger questions such as how does it feel to interact with a social robot?

8. REFERENCES

AGARWAL, R., & PRASAD, J. (1999). ARE INDIVIDUAL DIFFERENCES GERMANE TOTHE ACCEPTANCE OF NEW INFORMATION TECHNOLOGIES?. *DECISION SCIENCES*, *30*(2), 361-391.
https://doi.org/10.1111/j.1540-5915.1999.tb01614.x

Barnes, J., FakhrHosseini, M., Jeon, M., Park, C.-H., & Howard, A. (2017). The Influence of Robot Design on Acceptance of Social Robots. https://ieeexplore.ieee.org/document/7992883-

BELKIN, N.J., ODDY, R.N. and BROOKS, H.M. (1982), "ASK FOR INFORMATION RETRIEVAL: PART I. BACKGROUND AND THEORY", *Journal of Documentation*, Vol. 38 No. 2, pp. 61-71. https://doi.org/10.1108/eb026722

Breazeal C., Takanishi A., Kobayashi T. (2008) Social Robots that Interact with People. In: Siciliano B., Khatib O. (eds) Springer Handbook of Robotics. Springer, Berlin, Heidelberg. https://doi-org.ezproxy2.utwente.nl/10.1007/978-3-540-30301-5_59

Boud, D., & Molloy, E. (2013). Deep Reinforcement Learning with Interactive Feedback in a Human–Robot Environment. https://books.google.nl/books?id=PZJbBAAAQBAJ&printsec=frontcover&source=gbs_ge_summary_r&cad=0#v=onepage&q&f=false

Brookhart, S. M. (2017). *How to Give Effective Feedback to Your Students*. ASCD. https://books.google.nl/books?hl=en&lr=&id=uttODgAAQBAJ&oi=fnd&pg=PA1&dq=Feedback+That+Works:+How+to+Build+and+Deliver+Your+Message+english&ots=PSQjmu7J1N&sig=VvphcpwuuSB2qH3EmXr9gU68RP0&redir_esc=y#v=onepage&q&f=false

Byström, K., & Järvelin, K. (1995). Task complexity affects information seeking and use. *Information Processing & Management*, 191-213. https://www-sciencedirect-com.ezproxy2.utwente.nl/science/article/pii/030645739580035R

Caic, M., Mahr, D., & Oderkerken-Schröder, G. (2019, June 18). Value of social robots in services: social cognition perspective. https://www.emerald.com/insight/content/doi/10.1108/JSM-02-2018-0080/full/html#sec001-

Campbell, D. T., Cook, T. D., & Shadish, W. R. (2001). EXPERIMENTAL AND QUASI-EXPERIMENTAL DESIGNS FOR GENERALIZED CAUSAL INFERENCE. Boston, Massachusetts, United States: Cengage Learning.

Cronbach's Alpha in SPSS Statistics - procedure, output and interpretation of the output using a relevant example | Laerd Statistics.. Statistics.laerd.com. (2022). Retrieved 26 June 2022, from https://statistics.laerd.com/spss-tutorials/cronbachs-alpha-using-spss-statistics.php.

Davis, D., Mazmanian, P., Fordis, M., Van Harrison, R., Thorpe, K., & Perrier, L. (2006). Accuracy of Physician Self-assessment Compared With Observed Measures of Competence. *JAMA*, *296*(9), 1094. https://doi.org/10.1001/jama.296.9.1094

Dhar, R., Nowlis, S., & Sherman, S. (1999). Comparison Effects on Preference Construction. *Journal Of Consumer Research*, *26*(3), 293-306. https://doi.org/10.1086/209564

Druckman, J. (2000). Preference formation. *Annual Review of Political Science*, *3*(1). 10.1146/annurev.polisci.3.1.1

F Cascio, W., & Montealegre, R. (2016). How Technology Is Changing Work and Organizations. *Annual Review of Organizational Psychology and Organizational Behavior*, 350.

Formosa, P. (2021). Robot Autonomy vs. Human Autonomy: Social Robots, Artificial Intellgience (AI), and the Nature of Autonomy. Minds& Machines 21, 595-616

Furhat Robotics. (2020). *Robot Owner Guide*.

Furhat Robotics. (n.d.). *Furhat Robotics*. Furhat Robotics: The world's most advanced social robot. Retrieved April 2, 2022, from https://furhatrobotics.com/

Gowan, M., & Lepak, D. (2010). *Human Resource Management*. Pearson/Prentice Hall.

Hattie, J., & Timperley, H. (2007). The power of feedback. *American Educational Research Association*, *77*(1), 81.

I Ajzen (1975A Bayesian analysis of attribution processes. Psychological Bulletin 82(2),261

Ingwersen, P. (1992) Information and Information Science in Context 99-135 https://doi.org/10.1515/libr.1992.42.2.99

John, O. P., & Srivastava, S. (1999). The Big-Five trait taxonomy: History, measurement, and theoretical perspectives. In L. A. Pervin & O. P. John (Eds.), Handbook of personality: Theory and research (Vol. 2, pp. 102–138). New York: Guilford Press.

Leite, I. (2013, January 25). Social Robots for Long-Term Interaction: A Survey. https://link.springer.com/article/10.1007/s12369-013-0178-y

LW Doob(1947) The behavior of attitudes. Psychological Review 54(3),135 0033-295X 10.1037/h0058371

McCrae, R. R., & Sutin, A. R. (2009). Openness to Experience. In M. R. Leary and R. H. Hoyle (Eds.), Handbook of Individual Differences in Social Behavior (pp. 257-273). New York: Guilford.

Nagtegaal, R. (2021). The impact of using algorithms for managerial decisions on public employees' procedural justice. *Government Information Quarterly*, *38*(1), 101536. https://doi.org/10.1016/j.giq.2020.101536

Patrick van Esch, J. Stewart Black. (2019). Factors that influence new generation candidates to engage with and complete digital, AI-enabled recruiting. *Business Horizons*, *62*(6), 729-739. https://doi.org/10.1016/j.bushor.2019.07.004

R Bommelje (2012) The listening circle: Using the SBI model to enhance peer feedback International Journal of Listening 26(2),67

RE Wood(1987) Task complexity as a moderator of goal effects: A meta-analysis. Journal of Applied Psychology 72(3), 416 10.1037/0021-9010.72.3.416

Russell, T. (1998). *Effective Feedback Skills*. Kogan Page.

Sense, A. (2007). Structuring the project environment for learning. *International Journal Of Project Management*, *25*(4), 405-412. https://doi.org/10.1016/j.ijproman.2007.01.013

Straub, E. T. (2017, January 10). Understanding Technology Adoption: Theory and Future Directions for Informal Learning. https://journals.sagepub.com/doi/full/10.3102/0034654308325896

Taylor & Francis (2012)1090-4018 10.1080/10904018.2012.677667

van gILS, P. (2022). Essay.utwente.nl. Retrieved 25 June 2022, from https://essay.utwente.nl/90535/1/van%20Gils_BA_BMS.pdf.

Yong Cui, Xiao Song, Qinglei Hu, Yang Li, Pavika Sharma, Shailesh Khapre, (2022) Human-robot interaction in higher education for predicting student engagement, Computers and Electrical Engineering,ISSN 0045-7906, https://doi.org/10.1016/j.compeleceng.2022.107827.

9. APPENDIX

9.1 Research equation

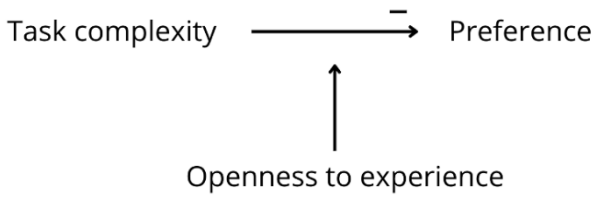

Figure1. Research equation

9.2 Attitude

1. I like using Furhat.
2. Furhat is fun to use.
3. *I dislike using Furhat .
4. Furhat provides an attractive working environment

9.3 Openness to experience

5. Is original, comes up with new ideas
10. Is curious about many different things
15. Is ingenious, a deep thinker
20. Has an active imagination
25. Is inventive
35. *Prefers work that is routine
40. Likes to reflect, play with ideas
41. * Has few artistic interests Self Report Measures for Love and Compassion Research: Personality
44. Is sophisticated in art, music, or literarture

*- reverse-score items

9.4 Descriptive Statistics

Table1. Descriptive Statistics

Variables	N	Minimum	Maximum	Mean	Standard deviation
Is original comes up	64	1	5	4.02	.882

with new ideas					
Is curious about many different things	64	3	5	4.37	.549
Is ingenious a deep thinker	64	2	5	4.16	.761
Is inventive	64	2	5	3.84	.801
Has an active imaginatio n	64	2	5	4.27	.718
Values artistic aesthetic experience s	64	2	5	4.27	.821
Prefers work that is routine R	63	0	5	3.14	1.202
Likes to reflect play with ideas	64	2	5	4.3	.659
Has few artistic interests R	64	1	5	3.14	1.180
Is sophisticat ed in art music or literature	64	1	5	3.58	.940
Task complexity	64	0	1	.55	.532
What was the feedback you received fromFurhat	64	1	3	2.41	.684
I like using Furhat	64	1	7	5.641	1.273
Furhat is fun to use	64	1	7	5.852	1.157
I dislike using Furhat R	63	1	7	6	1.307
Furhat provides an attractive feedback	64	2.5	7	5.312	1.375
Valid N (listwise)	62				

9.5 Descriptive Statistics computed variables

Table 2. Descriptive statistics computed variables

Variables	N	Minim um	Maxi mum	Mean	Standar d deviatio n

Preference	63	3.1	4.9	3.901	.39411
Openness to experience	63	2.13	7	5.720	1.053
Valid N (listwise)	62				

9.6 Normal P-Plot

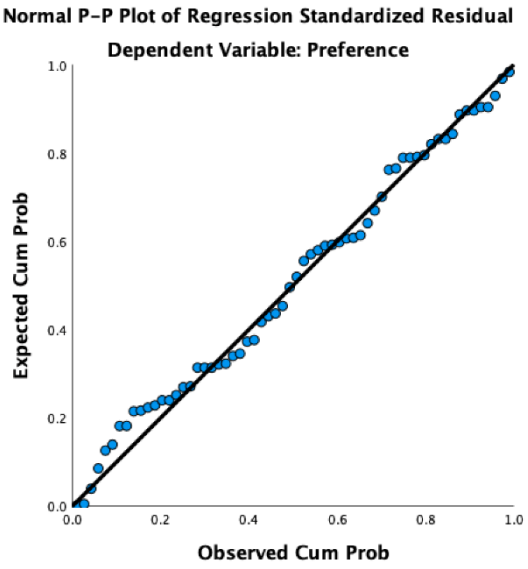

Figure 2 P-Plot Figure

9.7 Scatterplot of residuals

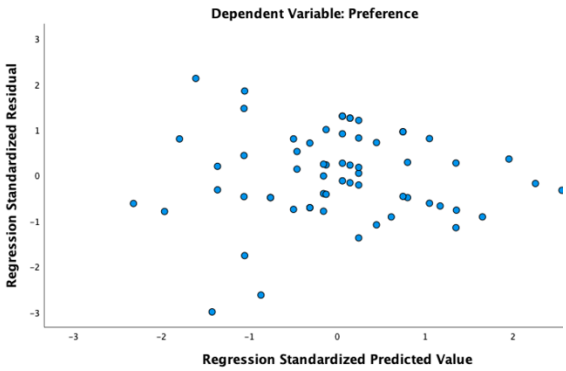

Figure 3 Scatterplot of residuals

9.8 Collinearity analysis

Table 3 Collinearity Statistics

Tolerance	VIF

.933	1.072
.933	1.072

9.9 Reliability analysis

Table 4 Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardize d Items	N of Items
.848	.850	4

Table 5 Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardize d Items	N of Items
.565	.646	10

9.10 Regression analysis

Table 6 Model Summary

Model	R	R square	Adjusted R Square	Std.Error of Estimates
1	.018[a]	.000	-.016	1.06821
2	.079[b]	.006	-.027	1.07406
3	.454[c]	.206	.165	.96811

Tabel 7 ANOVA

Model		Sum of Squares	df	Mean Sqaure	F	Sig
1	Regression	.023	1	.023	.021	.887
	Residual	68.464	60	1.141		
	Total	68.487	61			
2	Regression	.424	2	.212	.184	.832

	Residual	68.063	59	1.154		
	Total	68.487	61			
3	Regression	14.128	3	4.709	5.025	.004
	Residual	54.359	58	.937		
	Total	68.487	61			

Table 8 Coefficients

		Unstandardized Coefficients					Collinearity Statistics	
Model		B	Standard Error	Standardized Coeffcients Beta	t	Sig.	Tolerance	VIF
1	(Constant)	5.692	.192		29.614	<.001		
	Task complexity	.037	.256	.018	.143	.887	1	1
2	(Constant)	4.845	1.449		3.343	.001		
	Task complexity	.077	.266	.039	.29	.773	.933	1.072
	Openness to experience	.212	.359	.079	.589	.558	.933	1.072
3	(Constant)	9.216	1.736		5.309	<.001		
	Which task did you complete?	-8.945	2.372	-4.013	-3.772	<.001	.010	104.644
	Openness to experience	-.892	.434	-.334	-2.056	.044	.520	1.924
	Task Complexity x Openness to experience	2.341	.612	4.486	3.824	<0.001	.010	100.562

9.11 Visual representation of relationship between variables

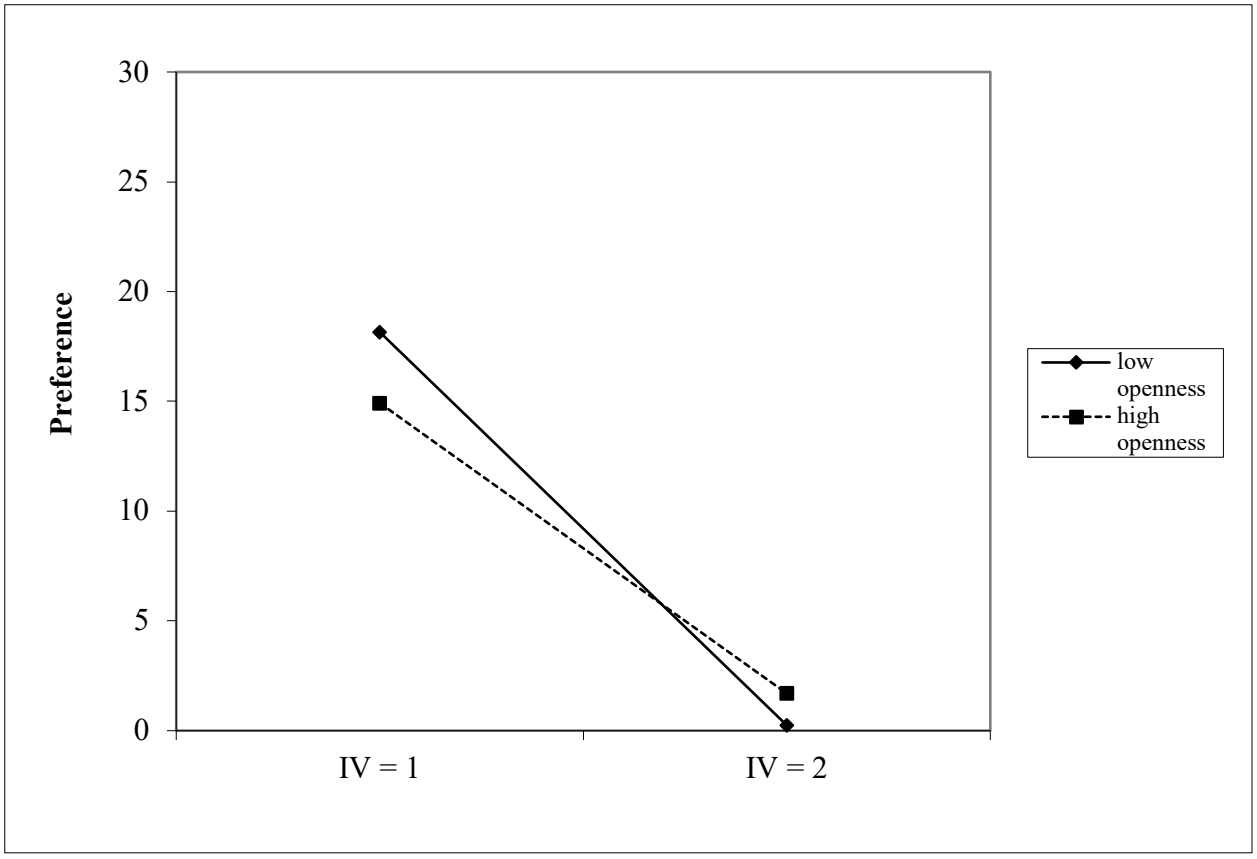

Figure 4 Visual representation of relationship between variables

9.12 Person's correlation

Table 9
Correlations

		Task complexity	Preference	Openness to experience
Task complexity	Pearson Correlation	1	.025	-.250
	Sig.		.843	.049
	N	64	63	63
Preference	Pearson Correlation	0.025	1	.069
	Sig.	.843		.594
	N	63	63	62
Openness to experience	Pearson Correlation	-.250	.069	1
	Sig.	.049	.594	
	N	63	62	63