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Master Thesis

Human Resource Management

The Influence of a Robot's Level of Humanness on People's Acceptance Towards Interacting with Robots in Job Interviews

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Abstract

This paper investigates to what extent a robot's level of humanness affects people's acceptance towards interacting with a robot in job interviews. It was hypothesized that a robot's level of humanness would positively predict four acceptance factors (perceived usefulness, perceived enjoyment, perceived trust, and perceived sociability) and the acceptance towards interacting with a robot in job interviews. Furthermore, it was hypothesized that these acceptance factors would affect the relationship between a robot's level of humanness and robot acceptance. A survey-based vignette study has been conducted to estimate the differences between two research groups regarding their perceptions and their behavioural intention towards interacting with a humanlike robot in the first group versus interacting with a machinelike robot in the second group in job interviews. Also, the impact of the acceptance factors on the relationship between a robot's level of humanness and the behavioural intention was estimated. Data of 151 participants were analysed conducting an independent t-test and a mediation analysis. We found significant mean differences in all variables between the groups. Higher levels of robotic humanness predicted higher perceived enjoyment, trust, sociability, humanness, and behavioural intention but lower perceived usefulness. Furthermore, perceived enjoyment significantly strengthened and perceived usefulness significantly weakened the relationship between a robot's level of humanness and the behavioural intention. This study provides initial empirical evidence for the importance of robotic humanness on people's behavioural intention to interact with a robot in job interviews. This new knowledge may help managers to not just improve human-robot interactions in job interviews but also to improve recruitment processes and to hire a qualified workforce.

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1. Introduction

The automation of the workplace is one of many consequences of the constantly evolving technology in the world. With the development of the industry 4.0, which refers to the ongoing automation of work processes by using modern smart technology, futuristic robots tend to be intelligent, multifunctional, and collaborative (Du et al., 2018). According to literature (Vysocky and Novak, 2016), the advantages of work robots in comparison to humans are that they complete tasks faster, with better quality and are more cost-efficient. However, humans are still needed to adapt operations to actual conditions as machines are limited by their programming (Vysocky & Novak, 2016). Therefore, human-robot interactions (HRI) and their implication for businesses have become a hot topic in manufacturing, laboratory, and even in more complex human working environments such as offices, hospitals, and the outer space (Bauer et al., 2008).

Not only work processes are being automated but also in management, activities are increasingly automated. In particular, in human resource management (HRM), artificial intelligence (AI) is expected to take over most of the HRM processes in the future (Siavathanu & Pillaim, 2018). Some of the HRM practices in which automation has the most impact are recruitment and selection (van Esch & Black, 2019). For instance, social robots are beginning to be used to perform job interviews (Nørskov et al., 2020). Therefore, it is important to enable a desirable HRI in the context of job interviews. In this paper, we focus on the exploration of robotic features that can improve candidates' perceptions of the robots and, in return, enhance their acceptance towards interacting with robots in job interviews. Subsequently, their attitudes related to the selection procedure and the recruiting company in general can be reinforced in order to ensure a positive reputation of the hiring company and good chances of hiring a qualified workforce. This is crucial in order to maintain or even increase the organizational performance of the company (Nørskov et al., 2020).

Therefore, the goal of this research is to investigate to what extent a robot's level of humanness affects people's acceptance towards interacting with a robot in job interviews. In this case, humanness involves the characteristics a robot obtains that resemble a human (Złotowski et al., 2014). The relevance of robotic humanness in the context of human-robot job interviews is emphasized as they are social interactions that demand of a robot to display humanlike characteristics and skills in order to be accepted and used by humans (Breazeal et al., 2008). Our research model builds on The Technology of Acceptance Model (TAM) (Davis, 1989), the theory of perceived enjoyment in technology (Shin & Choo, 2011), and the Service

Robot Acceptance Model (sRAM) (Wirtz et al., 2018). We expect that a robot's level of humanness affects certain acceptance factors and the acceptance towards interacting with a robot itself. Accordingly, the research question this study aims to answer is:

To what extent does a robot's level of humanness affect people's acceptance towards interacting with a robot in job interviews?

This study provides two main theoretical contributions. First of all, it advances our understanding of robot acceptance and provides a grounding for future research on the interaction between humans and robots in management. By robot acceptance, we hereinafter refer to the acceptance towards interacting with a robot (Beer et al., 2011). In particular, the investigation of people's perceptions of a robot's level of humanness in relation to their acceptance towards interacting with a robot in job interviews has, to our knowledge, not been conducted yet in prior empirical research. It, therefore, fills a gap with regard to the implications of this relationship for important HRM practices, in this case, job interviews. Particularly job interviews have been chosen because studies indicate that robots can perform better hiring decisions than HR professionals, avoid biases, and raise fairness perceptions of job candidates related to the selection procedure (McAllister & Haak, 2019; Nørskov et al., 2020). Furthermore, technologically advanced interviews were found to increase candidates' honesty during job interviews. As candidates in regular job interviews tend to present themselves better than they are, human-robot job interviews, in contrast, may reveal their *"true colors"* (Langer et al., 2020, p. 272). Therefore, this paper gains insights into how robotic humanness may reinforce the HRI in desirable ways in order to enable these advantages over human interactions in return. Second, the theories on technology acceptance are expanded by this study since different existing models and theories are combined into a new constellation (Davis, 1989; Shin & Choo, 2011; Wirtz et al., 2018). This constellation of different constructs allows us to gain multiple insights into the causal mechanisms underlying the relationship between a robot's level of humanness and people's acceptance towards interacting with a robot.

Next to the scientific relevance, two practical contributions are provided. First, we aim to estimate the relevance of robotic humanness on people's acceptance of robots in job interviews. This new knowledge may, then, help managers to improve HRI in job interviews. For example, in case of high relevance, they should take certain human features and characteristics into consideration when designing a robot for a desirable interaction between robot and human. Second, the findings may help the hiring company and its managers to improve recruitment processes and, thereby, to establish a positive reputation of the company. As a consequence, good chances of hiring a qualified workforce can be ensured which is important for the organizational success of the company.

This paper starts with the theoretical framework and a review of relevant literature. Then, the method used to collect data followed by the findings are examined. Lastly, the findings in light of the existing literature are discussed and concluded with implications, limitations, and directions for further research.

2. Theoretical Framework

2.1 Human-robot interaction

Human-robot-interaction (HRI) is defined as *"a challenging research field at the intersection of psychology, cognitive science, the social sciences, artificial intelligence, computer science, robotics, engineering and human-computer interaction"* (Dautenhahn, 2007, p. 103). The field of HRI addresses the design, understanding, and evaluation of robots and involves humans and robots interacting through communication (Murphy et al., 2010). The main objective of HRI is to empower robots with many competencies that will improve their interactions with humans (Billard & Grollmann, 2012). HRI can be divided into four areas of application (Sheridan, 2016):

1. The human supervisory control of robots performing routine tasks. This includes, for example, handling of parts on manufacturing assembly lines and accessing. These so-called telerobots are capable of carrying out a limited series of actions automatically based on a computer programme, thereby, sensing its environment and its own joint positions, and communicating such information back to a human operator who updates their computer instructions.

2. The remote control of space, terrestrial, airborne, and undersea vehicles for non-routine missions in inaccessible or dangerous environments. These so-called teleoperators perform manipulation and mobility tasks in the distant physical environment in correspondence to continuous control movements by the human.

3. Automated vehicles in which the human is a passenger, including automated highway, rail vehicles, and commercial aircraft.

4. Human-robot social interaction, including robot devices to provide entertainment, teaching, comfort, and assistance for mostly children and elderly, autistic, and handicapped people (Sheridan, 2016). In this research, we will focus on human-robot social interactions because job interviews require a social exchange between the interviewer and the candidate in order for the interviewer to determine the candidate's suitability for the particular job. In the case of human-robot job interviews, a social robot interviews a human candidate.

Human-robot social interaction

Social robots are autonomous, mostly physically embodied robots that interact and communicate by following social behaviours and rules attached to their role (Breazeal et al., 2008). They are designed to interact with people in a natural and interpersonal manner, mostly to achieve socio-emotional goals in diverse application fields such as health, education, quality of life, entertainment, communication, and collaboration (Breazeal et al., 2008). One famous example of a social robot is MIT's Kismet. It is an expressive robot head with 'social intelligence' developed in 1998. By processing the face and voice of a person, Kismet makes appropriate gestures in return. Hence, it is one of the first robots able to demonstrate social and emotional interactions with humans (Sheridan, 2016).

The long-term objective of creating social robots that are capable partners for humans is a challenging task. To be accepted in a human environment, robots must adopt social behaviours by communicating naturally with people using both verbal and nonverbal signals. Additionally, they should obtain socio-cognitive skills and a theory of mind to understand human behaviour and to be naturally understood by humans (Breazeal et al., 2008). In other words, they need to engage humans not only on a cognitive level but on an emotional level as well. Considering the richness of human behaviour and the complexity of human environments, many social robots are among the most sophisticated, articulate, behaviourally rich, and intelligent robots nowadays (Breazeal et al., 2008). Two types of robots have been designed for social interaction: zoomorphic robots and anthropomorphic robots. Zoomorphic robots are toys with the appearance of dogs or cats. Anthropomorphic robots are more dedicated to social interaction and therefore, need to be able to express their internal emotional states, goals, and their desires (Toumi & Zidani, 2014). Expressing emotions is an important aspect of social robots, particularly when they operate within the HRM context – which will be discussed next.

2.2 HRI in the HRM context

To our knowledge, there is not much literature about HRI in the context of HRM as it is a relatively new research field. HRM in the industry 4.0 context is also referred to as E-HRM (Bondarouk & Brewster, 2016), smart HR, or SHR (Sivathanu & Pillai, 2018). Siavathanu and Pillai (2018) claim that emerging technologies will automate most of the HR processes in the future. Therefore, HR departments need to adopt and incorporate novel technologies such as Artificial Intelligence (AI) in their work in order to stay competitive. Russell and Norvig (1995) defined AI as *"anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors"* (as cited in Van Esch et al., 2019, p. 216). There are different forms of AI being used in E-HRM: some take shape as a software system, others as chatbots, and yet others are embodied in physical robots (Jia et al., 2018). One example of a typical robotic function in E-HRM that facilitates HR professionals' work is data analysis as robots can crunch huge amounts of data much faster than humans. As a result, HR professionals have a considerable amount of time spared that they can dedicate to more strategic and nuanced issues (McAllister & Haak, 2019).

According to Libert et al. (2020), organizations have to work on more complex HRM practices such as recruitment processes, performance assessment, promoting leadership, empowering the workforce, and creating incentives in order to ensure the success of the organizational change. Ultimately, (future) employees should be prepared and developed through the whole implementation process and be aware of the possible consequences related to the robot. Therefore, there is a need to adapt HRM practices to the type of technology implemented (Libert et al., 2020). In the next two subsections, we focus on robots applied in the HRM practice recruitment.

AI in recruitment processes

Considering the rising technological development in the world, companies who want to attract and recruit talent have to do this in the digital space with digital technologies and tools (van Esch & Black, 2019). Electronic recruitment refers to *"the use of communications technologies, such as websites and social media, to find and attract potential job applicants, to keep them interested in the organization during the selection processes, and to influence their job choice decisions"* (Chapman & Godollei, 2017 as cited in Johnson et al., 2020). The use of e-recruitment has, in fact, several advantages over traditional recruitment processes. When applicants apply for a job, websites have the potential to use AI filters, determine, and match the most suitable candidate with the available job (van Esch et al., 2019). For example, AI can use behavioural and physiological characteristics (e.g., biometrics) as part of the selection process (van Esch et al., 2019). Another e-recruitment method is the use of AI cognitive insight capabilities that help to identify the characteristics of high performing employees to develop targeted recruitment messages that can motivate similar applicants to apply for jobs (Johnson et al., 2020, p. 4). Moreover, the digitalization of job information, both information from candidates to companies and from companies to candidates, has increased the number of applicants per position. To keep up with the screening and evaluations of these increases in applications, a company needs to use AI-enabled tools to screen the job applicants as they operate much faster than humans (van Esch & Black, 2019). Thus, AI-enabled tools have improved to the point where they are superior to humans in terms of both efficiency and effectiveness (van Esch & Black, 2019).

Social robots in job interviews

Utilizing social robots in job interviews is still under research (Nørskov et al., 2020). One of the first interview robots to exist is the Swedish AI-robot ‘Tengai’, which launched in 2019 (*TNG’s Physical and Social AI-Robot’s First Job Interview*, 2019). An interview robot’s tasks are to hold automatic job interviews with candidates, to assess their performance, and afterwards, to contribute to the hiring decision (Langer et al., 2019). At lower levels of automation, the robot may automatically rank candidates based on their performance and present this ranking to HR managers. At higher levels of automation, the robot may even decide itself which candidate proceeds to the next selection stage (Langer et al., 2019).

Studies already show that robots like ‘Tengai’ can perform better hiring decisions than HR professionals because data is all that matters to them (McAllister & Haak, 2019). More specifically, they are supposed to avoid biases (towards body size, ethnicity, race, etc.) that can occur during the interviews as well as reinforce candidates’ fairness perceptions related to the selection procedure that can influence their attitudes and behavioural intentions towards the company (Nørskov et al., 2020). Furthermore, Langer et al. (2020) found that candidates engage in less impression management, such as lying about past work experience, during technologically advanced interviews. Similarly, candidates were unfamiliar with how to positively influence their evaluations when realizing that their interview answers will be analysed automatically (Langer et al., 2020). Consequently, human-robot job interviews may increase the validity of interviews by revealing the real capabilities of candidates instead of their ability to use impression management.

However, technology-enhanced interviews can then also evoke negative candidates’ reactions as they see less potential to present themselves in the best light which may cause them to leave the application pool (Langer et al., 2020). Other related problems with human-robot job interviews are that robots are restricted to their programming; they cannot acquire new knowledge from previous interactions and apply it to current situations, they are constrained to a set of possible responses and cannot tailor an interaction to a specific individual (Fox & Gambino, 2021). These limitations of a robot’s social capabilities may have implications for the effectiveness of HRI in job interviews. Furthermore, job interviews are special HRI due to the power imbalance between the interviewer and the candidate; the interview robot has the ‘power’ over the candidate who has a lot on the line (Jiang, 2013). This power imbalance emphasizes the need for the robot to make the candidate feel comfortable and to account for their nervousness (Das, 2021). To reduce these problems related to the robot and to enable a comfortable environment for the candidate, it is important to ensure a desirable HRI in job interviews.

Desirable human-robot job interviews could be achieved by considering the robotic design. Nørskov et al. (2020) propose that the design of a robotic agent for candidate selection does not only affect the candidates’ perception of the robot but also of the company in question. This is because the robot is, in a way, an organizational representative and may, therefore, influence the candidates’ perceptions of the company’s attraction. In general, interviewer characteristics that have a positive influence on applicant attraction to the company and job acceptance intentions were found to be, for instance, empathy, friendliness, positive affect, and showing interest in the candidate (Carless & Imber, 2007). Consequently, companies need to consider how the features of a robot may reinforce the HRI in desirable ways (Nørskov et al., 2020).

One particular robotic feature that this research focuses on is humanness. The dictionary defines humanness as *“the quality of being human” (*American Heritage, n.d.*)*. Thereby, the level of humanness of a robot can be determined by the presence or absence of specific robotic characteristics that resemble a human such as embodiment, movement, verbal communication, emotions, and gestures (Złotowski et al., 2014). Robotic humanness seems especially relevant in the context of job interviews because they are social interactions that demand of a robot to display humanlike skills in order to be accepted by humans (Breazeal et al., 2008). User acceptance is further very important to the successful implementation of any technology (Taherdoost, 2019). Therefore, we are interested to realize the factors that drive people’s acceptance or rejection of a technology. In the following, we will draw on the TAM and the sRAM model to study how a robot’s level of humanness is connected to robot acceptance in job interviews.

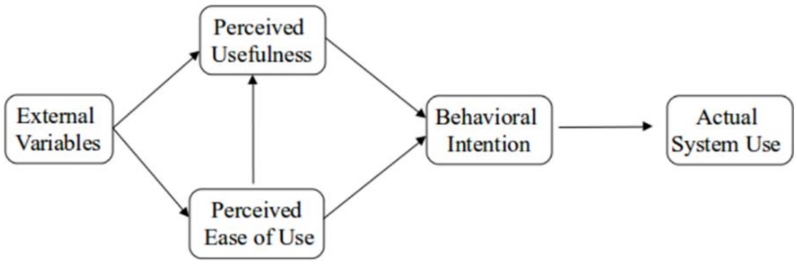
2.3 The Technology of Acceptance Model (TAM)

Dillon and Morris (1998) defined technology acceptance as *“the demonstrable willingness within a user group to employ information technology for the tasks it was designed to support”* (as cited in Shroff et al., 2011, p. 603). In the context of social robots, it was found that acceptance increases the more similar a robot becomes to a human up to a specific point where the ratio between ‘humanness’ and ‘machine-likeness’ becomes uncomfortable to humans. This effect is called the uncanny valley (Rosenthal-Von Der Pütten & Krämer, 2014). Similarly, Pelau et al. (2021) found that a human perception of a robot increases robot acceptance in different service situations. Recent evidence showed that people have a strong tendency to look for humanlike facial features in social robots because, in the process of facial recognition, the fusiform area of a face plays an important role in systematically detecting and processing facial information (Song & Luximon, 2020). The assigning of human characteristics to nonhuman entities is also called anthropomorphism (Daily et al., 2017). This phenomenon can be explained by people’s need to control their environment; anthropomorphizing a social robot helps them to explain, control, and predict the robot’s behaviour (Graaf & Allouch, 2013). Consequently, social robots that look humanlike as well as being able to imitate human behaviour and display humanlike faces may improve the overall interaction experience in HRI (Song & Luximon). However, so far it remains open why and to what extent the humanness of a robot affects robot acceptance. In this study, we suggest that a robot’s level of humanness is evaluated based on certain perceptions.

The original Technology of Acceptance Model (TAM) introduced by Davis (1989) consists of the predictors ‘perceived usefulness’ and the ‘perceived ease of use’ of variables of technology, in this case, a social robot. These predictors are supposed to affect the behavioural intention (acceptance) and ultimately lead to the actual system use (see Figure 1). Therefore, we call them acceptance factors. In this study, the variable ‘perceived usefulness’ is directly adopted but ‘perceived ease of use’ is replaced with ‘perceived enjoyment’. This is because the human’s feelings of enjoyment within an HRI appear more context-relevant than the perception of ease of use of a robot (Shin & Choo, 2011). In return, it is suggested that a robotic feature, in this case, a robot’s level of humanness, affects these perceptions. In the next sub-sections, the predictors of the behavioural intention are explained in detail and connected to the robotic characteristic ‘humanness’.

Figure 1

The Technology of Acceptance Model



Perceived usefulness

In general, perceived usefulness is defined as the degree to which an individual believes that using a particular system would enhance his or her job performance (Chuttur, 2009). In the context of robots, usefulness is defined as the user's belief that using the robot would improve their daily activities (Graaf & Allouch, 2013). Both information systems and robotics research indicate that perceived usefulness influences usefulness, use attitude, use intention, and actual use. As a consequence, people expect a robot to look and act appropriately given the circumstances (Goetz et al., 2003; Graaf & Allouch, 2013). Accordingly, if a robot is designed for the social interaction with humans, the robot should project humanness so that the user feels comfortable enough to socially engage with the robot (Graaf & Allouch, 2013). For example, Shin and Choo (2011) found that user perception of usefulness depends on how much a robot can adapt to changing environments. The adaptability of the robot is defined as *"the perceived ability of the system to be adaptive to the changing needs of the user"* (Graaf & Allouch, 2013, p. 5). Therefore, a robot's humanlike ability to adapt its behaviour to the user's preferences and personality may enhance perceived usefulness. Considering that a robot's level of humanness may affect people's perceived usefulness of the robot in a job interview, the following hypothesis was formulated:

H1: *In a job interview, people's perceived usefulness is higher of a humanlike robot than of a machinelike robot.*

Perceived enjoyment

The original TAM model by Davis (1989) includes 'perceived ease of use' next to 'perceived usability' as the basis for predicting behavioural intention. It is defined as the degree to which an individual believes that using a particular technology, in this case, a robot, would be free from physical and mental effort (Chuttur, 2009). In this study, the perceived ease of use is replaced with perceived enjoyment, which has been widely applied in emerging technologies including robot studies (Shin & Choo, 2011). In fact, in a study by Venkatesh and Morris (2000), enjoyment is conceptualized as an antecedent of perceived ease of use, suggesting that the variables are highly correlated. As this study focuses on the social interaction between humans and robots, the human's feelings of enjoyment appear more relevant than the perception of ease of use of a robot. Therefore, only the variable 'perceived usefulness' is kept as a functional aspect of utility in this research. Enjoyment is defined as the extent to which the activity of using a system, in this case, a robot, is perceived to be personally enjoyable (Shin & Choo, 2011). According to Wirtz et al. (2018), an enjoyable HRI may be one in which the robot is friendly and caring, for example, by expressing emotional responses. As discussed earlier, robots demonstrating socio-emotional skills are crucial for a desirable HRI (Breazeal et al., 2008). Considering that socio-emotional skills are typical human skills, it is suggested that a robot's level of humanness may affect the perceived enjoyment of the robot. This leads to the following hypothesis:

H2: *In a job interview, people's perceived enjoyment is higher of a humanlike robot than of a machinelike robot.*

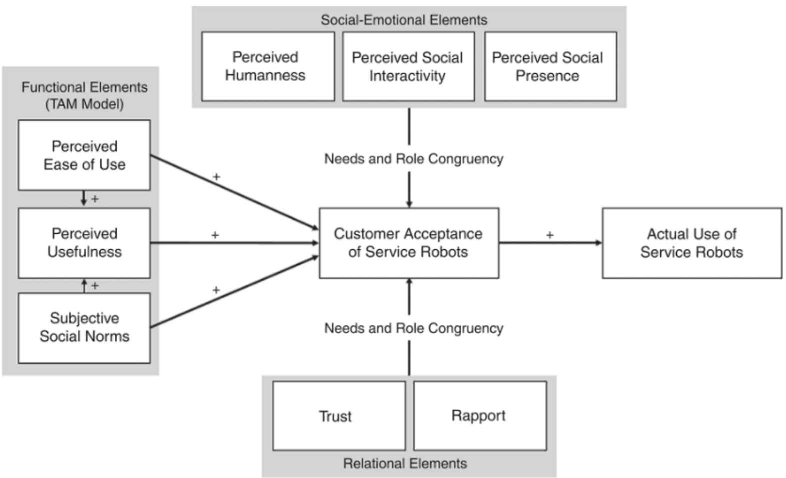
In the next section, we will draw on the sRAM model, which includes two other relevant predictors of robot acceptance for this research: perceived trust and perceived sociability. Perceived trust considers the need for a robot to be trusted in order to be accepted by humans (Oksanen et al., 2020). The latter predictor takes into account the need for a robot to obtain social abilities in order to be accepted (Breazeal et al., 2008).

2.4 The Service Robot Acceptance Model (sRAM)

Additional to the two constructs described, one relational and two socio-emotional elements are included. The relational one, 'trust', was found to be the main determinant of users' attitudes and behavioural intention to use and accept robots next to the perceived usefulness and ease of use (Glikson & Woolley, 2020). Furthermore, the socio-emotional elements 'perceived social interactivity' and 'perceived social presence' were included as this study emphasizes the human-robot *social* interaction in the context of job interviews. These elements stem from the Service Robot Acceptance Model (sRAM) developed by Wirtz et al. (2018) (see Figure 2). It aims to examine consumer perceptions, beliefs, and behavioural intentions as related to robot-delivered services (Shin & Choo, 2011). However, it is suggested that the model also works in different contexts such as for HRM practices in this case. For the sake of simplifying this study, the socio-emotional elements are summarized to the term 'perceived sociability' since there are high similarities in how people evaluate social interactivity and presence based on robotic features (Shin & Choo, 2011). Also, next to 'perceived social interactivity' and 'perceived social presence', 'perceived humanness' is another socio-emotional element of the model. However, this factor refers directly to the robotic quality studied in this research and is, therefore, not included as a predictor of the behavioural intention. Furthermore, next to 'trust', 'rapport' is a relational element originally included in the model. However, in this study, it is left out as well since its definition is very close to 'perceived enjoyment'. In the next subsection, the 'perceived trust' and the 'perceived sociability' predicting the behavioural intention are explained in detail and connected to the robotic characteristic 'humanness'.

Figure 2

The Service Robot Acceptance Model (sRAM)



Perceived trust

Trust is defined 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 important to the trustor, irrespective of the ability to monitor or control that other party."* (Mayer et al., 1995, as cited in Glikson & Woolley, 2020, p. 9). In the context of robots, perceived trust refers to the extent to which an individual is willing to place trust in a robot (Oksanen et al., 2020). Several studies such as the one by Fernandes and Oliviera (2021) found that the level of trust is strongly related the behavioural intention to use a robot. Oksanen et al. (2020) propose that people show higher trust when certain anthropomorphic features such as gestures, expressions, or even typical physical characteristics are included. For example, artificial skin helps to hide the metal skeleton which may look distressing to some humans (Bauer et al., 2008). Considering that a robot's level of humanness may affect people's perceived trust in the robot in a job interview, the following hypothesis was formulated:

H3: *In a job interview, people's perceived trust is higher in a humanlike robot than in a machinelike robot.*

Perceived sociability

Perceived social interactivity can be defined as the perception that the robot displays appropriate actions and emotions in line with societal norms. If the robot interacts socially and displays social abilities, its social attractiveness may increase which would motivate users to engage with the technology (Fernandes & Oliveira, 2021). In fact, it is argued that the social abilities of robots are among the most significant determinants for accepting and using robots (Shin & Choo, 2011). Therefore, it is suggested that humanlike social cues and communication modalities such as voice, conversation, and fulfilment of traditional human roles may have a positive influence on the perceived social interactivity (Fernandes & Oliveira, 2021; Shin & Choo, 2011).

Perceived social presence can be described as the extent to which the robot makes individuals feel as if they are in the presence of another social entity (Fernandes & Oliveira, 2021). While interacting with the robot, humans may believe that the robot is really present, which may influence the way it is perceived and accepted. Shin and Choo (2011) argue that there is a close connection between social abilities and the sense of presence. Therefore, it is proposed that language-based communication skills evoke a sense of social presence (Fernandes & Oliveira, 2021).

To summarize, the factor of communication may influence both social elements. Considering the emphasis on the need for communication to be social and humanlike, it is suggested that, once again, a robot's level of humanness may affect the perceived sociability of the robot in a job interview. This leads to the following hypothesis:

H4: *In a job interview, people's perceived sociability is higher of a humanlike robot than of a machinelike robot.*

2.5 A robot's level of humanness in connection to robot acceptance

In the final section, we will further elaborate on a robot's level of humanness in connection to robot acceptance and the role of the acceptance factors in this relationship.

Behavioural intention

Generally, behavioural intention is defined as *"a measure of strength of one's intention to perform a specified behavior"* (Phua et al., 2012, p. 181). In reference to robots, intention to use refers to the indication of the user's readiness to use the robot (Graaf & Allouch, 2013). It is often described as the acceptance of the system which is determined by people's perceptions of the external variables such as the robotic characteristic 'humanness' in this case (Graaf & Allouch, 2013). Positive user's intentions to use the robots are, therefore, the basis for an effective HRI. We firstly propose that a robot's level of humanness alone affects the behavioural intention to interact with a robot because humanlike robotic features were found to directly affect robot acceptance (Graaf & Allouch, 2013). Incidentally, instead of referring to behavioural intentions *to use* a robot, the term *to interact* with a robot is used in this research as in job interviews, there is communication between the human and the robot rather than collaboration. This leads to the following hypothesis:

H5: *In a job interview, people's behavioural intention to interact with the robot is higher of a humanlike robot than of a machinelike robot.*

Secondly, according to the TAM and the sRAM model, the perceptions of a technology predict the behavioural intention to use, or in this case, to interact with a robot (Davis, 1989; Wirtz et al., 2018). Therefore, we propose that the perceptions affect the relationship between a robot's level of humanness and people's behavioural intention to interact with a robot, in that the relationship becomes stronger when the perceptions, also referred to as acceptance factors, are included. This leads to the following hypothesis:

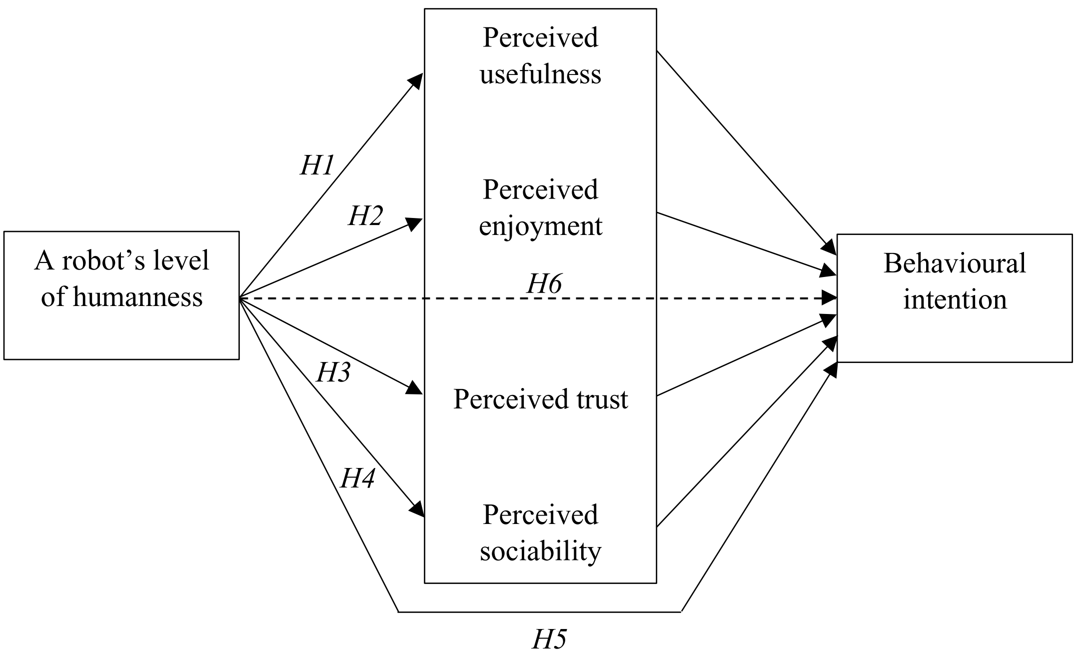
H6: *People's perceptions of a robot partially mediate the relationship between a robot's level of humanness and people's behavioural intention to interact with the robot in a job interview.*

3. Research Framework

In summary, our research framework of this study is an integration of the TAM model (Davis, 1989), the theory of perceived enjoyment in technology (Shin & Choo, 2011), and the sRAM model (Wirtz et al., 2018). The independent variable is a robot's level of humanness, which forms a dummy variable (humanlike = 1, machinelike = 0). Thereby, robotic humanness aims to represent different humanlike features: Adaptability, the capability to express emotions, a human appearance, and natural language and motions. The independent variable is, first of all, on its own expected to predict the dependent variable, which is the behavioural intention (H5). Furthermore, there are four mediator variables in total: perceived usefulness, perceived enjoyment, perceived trust, and perceived sociability. These perceptions are expected to mediate the relationship between a robot's level of humanness and people's behavioural intention to interact with the robot (H6). This means that the independent variable affects the mediator variables too (H1-H4) and the mediator variables, in return, affect the dependent variable. The technology this study will investigate is smart intelligent technology; more specifically, social robots. The context of this study is job interviews, meaning that the HRI takes place in a job interview, in which the social robot interviews the human.

Figure 3

Research Model



4. Methods

The research question of this study was investigated by conducting a quantitative research approach using a survey-based vignette study. A vignette study contains short descriptions of situations or people that are shown to the participants. Subsequently, participants fill in surveys that are constructed around these scenarios (Atzmüller & Steiner, 2010). Particularly in mixed designs, different groups get different vignettes but within each group, each participant receives the same vignettes for judgment (Atzmüller & Steiner, 2010). In this study, the participants were randomly assigned to one of two experimental research groups. In both groups, almost the same scenario was presented to the participants. The difference between the two groups was the robot they were presented to. More specifically, in the first group, the robot had a humanlike appearance and humanlike characteristics. In the second group, the robot had a machinelike appearance and machinelike characteristics. In other words, the first group was exposed to the robot that was expected to be evaluated positively, whilst the second group was exposed to the robot that was expected to be evaluated negatively. For detailed information on the types of robots, see the materials section.

This research method was chosen for several reasons. Vignette studies allow us to construct realistic scenarios and to manipulate and control independent variables; thereby, enhancing both internal and external validity (Aguinis & Bradley, 2014). Validity enables us to generalize the outcomes of this study and to draw conclusions on a broader population. Furthermore, since vignette studies entail participants' judgments on specific situations, they allow for detailed investigation on underlying attitudes, behavioural intentions, and reasons. As the goal of this research is to investigate the relationship between a robot's level of humanness and people's acceptance towards interacting with robots in job interviews, a vignette approach seems appropriate. By designing two experimental vignettes using a mixed design approach, we can explore the differences between the groups with regard to the participant's perceptions of the robots as well as the participant's robot acceptance in the context of job interviews.

In the following, the design of this study and the measurement of all variables are defined. Then, the materials used in this study are described. After that, the data collection and finally, the analysis of the data is discussed.

4.1 Design

A two-group research design has been used to estimate the differences between the groups with regard to the participants' perceptions of the robots and their behavioural intention. The study is a between-subject design since the differences in the levels of perceptions and behavioural intention were measured *between* the two groups (Atzmüller & Steiner, 2010). Furthermore, a robot's level of humanness (independent variables) was expected to have an impact on people's perceptions of the robot (mediator variables) and their behavioural intention to interact with a robot (dependent variable). Thereby, the perceptions of the robot were expected to partially mediate the relationship between the independent and dependent variable, in that the relationship becomes stronger when the perceptions are included.

A robot's level of humanness was illustrated using a dummy variable with two nominal levels: humanlike (1) and machinelike (0). In contrast to the other variables of this study, this variable cannot be tested with items but is represented by the manipulation through the two different experimental vignettes. The effectiveness of the manipulation will be tested with a manipulation check by including the variable 'perceived humanness'.

The Faculty of Behavioural Sciences Ethics Committee of the University of Twente gave ethical approval for conducting the study.

4.2 Measures

Perceived usefulness

The perceived usefulness of the participants was measured using the TAM scales created by Venkatesh and Davis (2000). However, the items were adjusted to the context of this study. More specifically, the items were rephrased into a conditional mood considering that the participants of this study were asked to imagine a scenario. Also, the phrase 'to use the robot' was exchanged with 'to interact with the robot' considering the emphasis on an HRI in this study. Furthermore, the original items did not fit the job interview context and therefore, the content was slightly changed (e.g., *"**Interacting** with the robot **would** improve my **interview** performance."*). These changes also apply to the other metric variables of this study. The scale consisted of four items. They are rated on a 7-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7), meaning that higher scores reflect positive perceived usefulness and lower scores reflect negative perceived usefulness.

Psychometric evaluations of the TAM scales found evidence for adequate reliability and construct validity (Venkatesh & Davis, 2000). In this study, the internal consistency between the items estimating the perceived usefulness was excellent (α = .93).

Perceived enjoyment

The perceived enjoyment was measured using the three-item scale developed by Heerink et al. (2008) and Heijden (2004), which was adopted from the paper by Shin and Choo (2011). The scale consisted of four items (e.g., *"I think I would enjoy being interviewed by this robot."*). They are rated on a 7-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7), meaning that higher scores reflect positive perceived enjoyment and lower scores reflect negative perceived enjoyment.

Psychometric evaluations of the three-item scale found evidence for adequate reliability, convergent validity, and discriminant validity (Shin & Choo, 2011). In this study, the internal consistency between the items estimating the perceived enjoyment was excellent (α = .93).

Perceived trust

The perceived trust was measured using the Trust in Technology scale created by Jian et al. (2000). Two items indicate positive perceived trust (e.g., *"I think the robot would be reliable."*) and two items indicate negative perceived trust (e.g., *"I would be suspicious of the robot's intent, action, or output.").* They are rated on a 7-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7), meaning that higher scores reflect positive perceived trust and lower scores reflect negative perceived trust. The scores of items indicating negative perceived trust were reversed so that higher agreements with statements reflecting negative perceived trust are translated into lower scores and lower agreements with these statements are translated into higher scores.

Psychometric evaluations of the Trust in Technology scale were not discussed in the paper by Jian et al. (2000). In this study, the internal consistency between the items estimating the perceived trust was acceptable (α = .75).

Perceived sociability

The perceived sociability was measured using two-items scales adopted from the paper by Fernandes and Oliveira (2021). Two items indicate a positive perceived social interactivity (e.g., *"I think this robot would understand me."*) and two items indicate a positive perceived social presence (e.g., *"When interacting with the robot, it would feel like talking to a real person."*). They are rated on a 7-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7), meaning that higher scores reflect positive perceived sociability and lower scores reflect negative perceived sociability.

Psychometric evaluations found evidence for adequate reliability, convergent, and discriminant validity of the two-items scale (Fernandes & Oliveira, 2021). In this study, the internal consistency between the items estimating the perceived sociability was good (α = .81).

Behavioural intention

The behavioural intention to interact with a robot was measured using the TAM scales by Venkatesh and Davis (2000). The scale consisted of four items (e.g., *"Assuming I have the opportunity to interact with a robot in a job interview, I intend to do it."*). They are rated on a 7-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7), meaning that higher scores reflect a high behavioural intention and lower scores reflect a low behavioural intention. The internal consistency between the items estimating the behavioural intention was good (α = .82).

Perceived humanness

The perceived humanness was measured using the two-item scale adopted from the paper by Fernandes and Oliveira (2021). Two items indicate a positive perceived humanness (e.g., *"I can imagine the robot to be a living creature."*). They are rated on a 7-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7), meaning that higher scores reflect positive perceived humanness and lower scores reflect negative perceived humanness. The internal consistency between the items estimating the perceived humanness was good (α = .86).

Factor analysis of the scales

To test the validity of the scales, a confirmatory factor analysis (CFA) was run with the programme 'IBM SPSS Amos 26 Graphics'. To estimate the goodness of model fit, we assessed the chi-squared test (X^2), the comparative fit index (CFI), the standardised root mean square residual (SRMR), and the root mean square error of approximation (RMSEA) as proposed by Kline (2010). The values indicated a good fit between the model and the unobserved data (X^2 (174, N = 151) = 447.7, p = .00; CFI = .89; SRMR = .1; RMSEA = .00), except for the value of the SRMR which is above the recommended threshold of .08 (Kline, 2010). Based on these values, we decided to not make any modifications.

Next, we looked at the factor loadings of each component. The items measuring the behavioural intention (item 1, 2, and 3) loaded strongly on the first component (all loadings > .65). Similarly, the items measuring the perceived usefulness (item 4, 5, 6, and 7) loaded strongly on the second component (all loadings > .81). The same applied to the items measuring the perceived enjoyment (item 8, 9, 10, and 11) that loaded strongly on the third component (all loadings > .8). Three items measuring the perceived trust (item 13, 14, 15) loaded at least moderately strong on the fourth component (all loadings > .58). However, item 12 loaded weakly on the fourth component (.36). The items measuring the perceived sociability (item 16, 17, 18, and 19) loaded, once again, strongly on the fifth component (all loadings > .60). Lastly, the items measuring the perceived humanness (item 20 and 21) loaded strongly on the sixth component (all loadings >.87).

These loadings show that the scales, for a great part, measured what they were supposed to measure. Accordingly, we can assume high validity of the constructs and, consequently, of the findings of this study. Only item 12, which stems from the Trust in Technology scale (Jian et al., 2000), loaded weakly on its component. However, there was no good reason to delete the item from the construct as the internal consistency of the scale without this item does not significantly increase. Therefore, item 12 was kept.

4.3 Control variables

Attitude

People's general perceptions towards a technology influence how they evaluate its impact on society and their understanding of the technology (Graaf & Allouch, 2013). In this line of reasoning, people's general attitudes towards social robots may influence their behaviour when confronted with a robot and their acceptance of it within society (Graaf & Allouch, 2013). Therefore, we include this concept to control for the general attitude towards interacting with a robot on the variables studied in this research.

Attitude was measured using the TAM scales by Venkatesh and Davis (2000). The attitude scale consisted of four items but in this case, only one item has been selected (*"I like the idea of interacting with a robot")*. It is rated on a 7-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7), meaning that higher scores reflect a positive attitude and lower scores reflect a negative attitude.

Participants' characteristics

Further control variables included in this study were age and gender. The influence of age has been confirmed in several studies in human-robot interactions (Graaf & Allouch, 2013). Age differences have been found to impact abilities, attitudes, behaviours, and the willingness to use new technologies (Graaf & Allouch, 2013). Older people, as compared to younger people, show more negative emotions towards robots, and have lower intentions to use a robot (Graaf & Allouch, 2013; Heerink, 2011). However, they are more likely to enjoy using and to anthropomorphize a robot than young people (Graaf & Allouch, 2013).

Furthermore, gender has been suggested to be an important variable in human-robot interactions too, which may be caused by the differences between male and female social behaviours and their social roles in society (Graaf & Allouch, 2013). Thereby, men perceive robots as more useful, show higher intention to use them in the future, and are more willing to accept these robots in their daily lives compared to females (Graaf & Allouch, 2013; Heerink, 2011; Oksanen et al., 2020). This may be because men tend to anthropomorphize a robot more as they perceive a robot as an autonomous person. In contrast, females feel more comfortable with zoomorphic robots (Graaf & Allouch, 2013).

These results indicate both age and gender differences in the perceptions of social robots and should, therefore, be considered in the data analysis.

4.4 Materials

Before measuring the variables, a video of either a humanlike robot or a video of a machinelike robot was shown depending on the group the participant was assigned to. The humanlike robot was introduced in a talk show, while the machinelike robot interviewed a celebrity. Additionally, a brief description of the most crucial robotic features and a photo of either robot was included in order to ensure that the participants were aware of the robot's characteristics when filling out the questions afterwards. The concepts that were used to operationalize humanness were adaptability, the capability to express emotions, a human appearance, and natural language and motion.

Accordingly, the humanlike robot aimed to appear adaptable, to be able to express emotions, to have a human experience, to use natural language, and to move naturally. In particular, high adaptability was achieved by presenting the robot in the video as funny, social, and talkative which fit the talk show environment. Also, the description pointed out that the robot can recognize its conversation partner's needs and tries to find ways to achieve goals with them. The robot was further able to express emotions as it could visibly make facial expressions and also communicate them to its conversation partner. A human appearance was ensured as the robot obtained humanlike physical features such as lifelike skin, a humanlike head with eyes, a nose, ears, a mouth, a female-shaped body with arms and legs, etc. Moreover, it was described as being able to follow faces, to sustain eye contact, and to recognize individuals. Finally, the robot used natural language and motions in the video which was described as allowing it to have meaningful conversations with people. Also, it could visibly move its head, arms, legs, and the whole body while talking. Next to these concepts, we used subjective personal pronouns ('she/ her') for the humanlike robot and called it by its human name ('Sophia').

In contrast, the machinelike robot was aimed to appear inflexible, to be incapable of expressing emotions, to have a machinelike appearance, to use artificial language, and to not move at all. In particular, the inflexibility of the robot was achieved by describing it as static and limited in its interpersonal skills. A machinelike appearance was enabled by comparing the robot's appearance to a camera which was also visible in the video. The incapability to express and recognize the emotions of its conversation partner was emphasized in the description. Lastly, the robot used artificial language in the video which was elaborated in the description by pointing out the limitation in its communication skills. Next to these concepts, we used objective personal pronouns ('it') for the machinelike robot and gave it a robotic name ('Robo Bot'.

After the presentation of the robots, a scenario thematizing a human-robot job interview was presented to the participants (see Appendix B).

4.5 Procedure

The survey was created in 2021 with the online survey software Qualtrics (see Appendix B). From 05.05.21 to 24.05.21, data was gathered from the participants. The recruitment of participants was carried out through snowball sampling, which provided a heterogeneous convenience sample of students from the close environment of the researcher. The participants were recruited via personal invitation by the researcher (WhatsApp and in-person) and via public social media posts (Facebook, Instagram, and Snapchat). Furthermore, the test subject platform of the University of Twente, Sona Systems, which provides credits for students of the Behavioural and Management Sciences (BMS) department for participating in research projects, served as a mean to recruit participants. More precisely, the survey with a short description was uploaded in Sona Systems, whereupon students of the BMS department had the chance to sign up for it and further participate in the study. Afterwards, a settled number of credits was being granted to the student by the researcher for completing the survey.

For the sake of providing information about the study to the participants before their participation, a short overview was given on the topic of the study, its purpose as well as the expected time frame of 15 minutes to complete the survey. As it turned out, it took participants on average 34.2 minutes to complete the survey but the time frame of actively filling out the questionnaire is suggested to be much lower. Then, the participants were notified that the survey took place voluntarily and that they were allowed to withdraw from the study anytime. Further, they were informed that the data will be treated confidential and will only be used for research purposes. Also, it was stated that the ethics committee of BMS gave ethical approval to conduct this study. The participants were, then, able to either provide or refuse informed consent. When they did not give consent, they were directly led to the end of the survey. When they gave consent, the survey continued.

First of all, the participants were randomly assigned to one of the two groups. Subsequently, they had to answer one control question about prior experiences with job interviews and one control question about their general attitudes towards interacting with robots. Next, in the first group, a video, a photo, and an information text about the humanlike robot were shown. In contrast, in the second group, a video, a photo, and an information text about the machinelike robot were shown. After that, almost the same scenario was presented to both groups in which they were asked to imagine that they were interviewed by that same robot for a job they applied to. Then, the participant's behavioural intention to interact with the robot and their perceptions of the robot were assessed by asking them to indicate to what extent they agree with statements about the robot, while keeping the robot and the job interview scenario in mind. Here, the manipulation was checked as well by directly asking the participants a few questions about the perceived humanness of the robot. Lastly, the participants were asked to answer questions about their demographic characteristics (e.g., gender, nationality).

The questionnaire ended with an acknowledgement for the participation, including the contact mail of the researcher in case of the occurrence of any questions or remarks.

4.6 Data Analysis

The data were tabulated in the statistical programme 'IBM SPSS Statistics 24'. To analyse the demographic characteristics of the study population, descriptive statistics were computed, consisting of the frequency tables, means, and standard deviations. To analyse the variables of this study, means, standard deviations, and the correlations of the variables were computed. To test the assumption of normality of the data, the skewness and kurtosis of the Mean Scores were assessed. Also, histograms of the distribution of the Mean Scores were created. Furthermore, the statistical test Kolmogorov-Smirnov was performed to compare the Mean Scores to a normal distribution. Finally, a CFA was run with the programme 'IBM SPSS Amos 26 Graphics' in order to test the validity of the scales. The Cronbach's alpha estimated a between-score correlation of the set of items, which gave information about the internal consistency. A measure equal to or above .6 indicates acceptable reliability as determined by Nunnally (1978).

To check the manipulation, an independent t-test was conducted. This test compared the means of the two independent groups in order to determine whether there was a statistical difference between the means of these groups. Thereby, the test allowed the relationship to go in both directions. In this context, it aimed at estimating the mean difference between the two groups in terms of their perceived humanness of the robots. For the sake of testing H1 to H4 about the effect of a robot's level of humanness on people's perceptions, another independent samples t-test was conducted. This time, it aimed at estimating the mean differences between the two groups with regard to their perceptions of the robots. For the sake of testing H5 about the effect of a robot's level of humanness on their behavioural intention to interact with the robot, the mean differences between the two independent groups regarding their behavioural intention were estimated. Furthermore, to control for the effect of the general attitude, prior experiences with job interviews, and the demographic characteristics (gender and age) on the perceptions and behavioural intention, the mean differences in terms of these control variables were estimated. Lastly, to test H6 about the influence of the perceptions on the relationship between a robot's level of humanness and behavioural intention, a stepwise regression analysis followed by a mediation analysis using 'PROCESS' as developed by Hayes (2017) was conducted. The significance level used for all analyses was $<.05$.

5. Results

This section presents the results of this study. Descriptive statistics of the study are given, followed by the hypotheses testing. The descriptive results include the demographic characteristics of the sample population, the means, standard deviations, and correlations of the (control) variables, an independent samples t-test to investigate mean differences in terms of the control variables, and normality tests to explore the distribution of the data. Furthermore, the hypotheses testing contained an independent samples t-test of the variables of analysis to investigate the mean differences between the two research groups. Lastly, a stepwise regression analysis followed by a mediation analysis of the variables of analysis were conducted to test the impact of the mediator variables on the relationship between the independent and the dependent variable.

5.1 Descriptive statistics

Demographic characteristics of the sample population

The target group of this study were men and women in all age groups with different nationalities and educational levels for the sake of securing a balance in age, gender, nationality, and educational level to provide a generalizable and non-biased outcome. In total, 27 out of 178 (15.17%) questionnaires were incomplete. They were excluded from further data analysis to increase the validity and reliability of the results. Accordingly, 151 participants have fully completed the survey, of which 75 were in the humanlike robot group and 76 were in the machinelike robot group.

Table 1

Demographic Characteristics of the Sample Population

Variable	*Total*				*Group 1*				*Group 0*			
	N	**%**	**M**	**SD**	**N**	**%**	**M**	**SD**	**N**	**%**	**M**	**SD**
Gender												
Male	53	35.1	1.65	.48	29	38.7	1.61	.49	24	31.6	1.68	.47
Female	98	64.9			46	61.3			52	68.4		

Age												
18-25	111	73.5	22.2	1.62	61	47	22.18	1.6	47	61.8	22.28	1.61
26-35	31	20.5	28.26	2.13	13	18	28.92	4.0	18	23.7	27.78	1.96
36-45	4	2.7	39.5	2.38	1	3	38.0	2.2	3	3.9	40.0	2.64
46-55	3	2.0	52.0	.00	0	3	/	5.0	3	3.9	52.0	.00
56-65	2	1.3	60.0	4.24	0	2	/	/	2	2.6	60.0	4.24
Nationality												
Dutch	41	27.2	2.02	.75	17	22.7	2.03	.68	24	31.6	2.01	.81
German	66	43.7			39	52.0			27	35.5		
Other	44	29.1			19	25.3			25	32.9		
Occupation												
Student	120	79.5	1.27	.67	65	86.7	1.13	.34	55	72.4	1.41	.87
Employed	27	17.9			10	13.3			17	22.4		
Not employed	1	.70			0	/			1	1.3		
Other	3	2.0			0	/			3	3.9		

(1 = humanlike robot group; 0 = machinelike robot group)

In total, 98 participants were female (64.9%) and 53 participants were male (35.1%). The age ranged between 18 and 63 (*M* = 25.01, *SD* = 6.89). Most participants were German (43.71%), followed by other (29.14%), and lastly, Dutch (27.15%). Finally, 120 participants were students (79.47%), 27 participants were employed (17.88%), three participants indicated a different occupation than was listed (1.99%), and one participant was not employed (.66%).

Means, standard deviations, and correlations of the variables

The means, standard deviations, and correlations of the variables of analysis and the control variables have been determined and can be seen in Table 2. We do not find evidence to suggest multicollinearity since the Variance Inflation Factors are between 1.48 and 3.93 and thus far below the recommended threshold of 10 (O'brien, 2007).

Table 2

Means, Standard Deviations, and Correlations of the (Control) Variables

	N	M	SD	1	2	3	4	5	6	JIE	GA	Gender	Age
1. A robot's level of humanness	151	.50	.50							.06	-.07	-.08	-.21**
2. Perceived usefulness	151	3.59	1.39	-.27**						-.02	.32**	-.02	.05
3. Perceived enjoyment	151	3.82	1.58	.35**	.43**					-.02	.47**	-.14	-.04
4. Perceived trust	151	3.97	1.18	.16*	.41**	.51**				.03	.31**	-.15	-.11
5. Perceived sociability	151	2.98	1.30	.16*	.56**	.68**	.61**			.09	.46**	-.06	-.09
6. Behavioural intention	151	5.28	1.23	.17*	.59**	.57**	.44**	.46**		-.07	.24**	.13	-.06
7. Perceived humanness	151	2.27	1.47	.21*	.42**	.52**	.49**	.32**	.76**	.13	.33**	-.08	-.08

**Correlation is significant at the .01 level (2-tailed).
*Correlation is significant at the .05 level (2-tailed).
JIE = Job interview experience; GA = General attitude

Looking at the correlations between the variables of analysis, it is noticeable that there are significant correlations between all of them. The correlations with robotic humanness suggest that higher levels of humanness are related to more positive perceptions of the robot and a higher behavioural intention, except for perceived usefulness. In this case, higher levels of humanness are related to more negative perceived usefulness of the robot. Another indication is that positive perceptions of the robot are associated with a higher behavioural intention to interact with the robot in a job interview. Moreover, the Mean Scores of the behavioural intention are by far the highest with a value above 5. Accordingly, this may indicate high robot acceptance in both groups. In contrast, the Mean Scores of the perceptions are roughly between 2 and 4, suggesting more neutral and even negative evaluations of the robots. The worst scored the perceived humanness which tested the effectiveness of the manipulation with a mean below 2.5. This finding indicates that the robots have not been evaluated as very human.

Furthermore, looking at the correlations between the variables of analysis and the control variables, it is noticeable that there are significant correlations between the mediator/ dependent variables and the control variable of the general attitude. These significant correlations suggest that people's general attitude towards interacting with a robot is positively related to perceptions and the behavioural intention towards the robot that was presented to them in this study. In contrast, job interview experience, age, and gender are not significantly related to the research variables, except for the relationship between the independent variable and age. In this case, higher levels of humanness are negatively related to age, meaning that participants in the machinelike robot group were on average coincidently older than participants in the humanlike robot group.

Independent samples t-test of the control variables

As the next step, the Mean Scores of male and female participants were compared to each other. The independent samples t-test showed that all mean differences were insignificant. Age was controlled for by dividing the sample into participants under 30 and equal/ above 30 years. The analysis found no significant mean differences. The same applied to prior job interview experience. In contrast, regarding the general attitude towards interacting with a robot, the analysis found significant mean differences in all variables (see Appendix A). Accordingly, participants with a more positive general attitude towards interacting with robots also had more positive perceptions and a higher behavioural intention towards interacting with the robot in a job interview than participants with a neutral or negative general attitude. These findings are in line with the Pearson correlations in Table 2.

Normality tests

Next, the assumption of normality was tested. First, based on the normality plots of the Mean Scores, a few extreme outliers have been erased to increase normality and therefore, the validity and reliability of the results. The skewness and kurtosis of the Mean Scores are almost all in-between -1 and 1, assuming a normal distribution (see Appendix A). Based on the histograms, the Mean Scores of perceived usefulness, perceived enjoyment, and perceived trust are normally distributed. In contrast, the Mean Scores of the behavioural intention are right-skewed and the Mean Scores of perceived sociability and perceived humanness are left-skewed. However, Piovesana and Senior (2018) found that sample sizes of greater than 85 generate stable means and standard deviations regardless of the level of skewness. Lastly, the Kolmogorov-Smirnov Test suggested that almost all Mean Scores are not normally distributed as the p-values are low (see Appendix A). To conclude, the distribution of the Mean Scores is not clearly determinable but there is a tendency towards non-normal. Nevertheless, due to the high sample size, results can likely still be regarded as reliable.

5.2 Hypotheses

Independent Samples T-Test of the variables among the two research groups

To answer H1-H5 about the mean differences in the perceptions and behavioural intention towards interacting with the robot in a job interview between the two research groups, an independent samples t-test was conducted for each variable.

Table 3

Mean Differences of Each Variable Between the Two Groups

	Group	M	Mean difference	SD	Sig. (2-tailed)	Cohen's d	N
Perceived	1	2.57	.60	1.72	.01	.42	75
humanness	0	1.97		1.08			76
Perceived	1	3.59	.74	1.52	.00	.55	75
usefulness	0	4.33		1.14			76
Perceived	1	4.37	1.1	1.67	.00	.74	75
enjoyment	0	3.27		1.27			76
Perceived	1	4.17	.39	1.24	.04	.33	75
trust	0	3.78		1.09			76
Perceived	1	3.19	.42	1.50	.05	.33	75
sociability	0	2.77		1.04			76
Behavioural	1	5.49	.41	1.12	.04	.34	75
intention	0	5.08		1.29			76

1 = humanlike robot group; 0 = machinelike robot group

The analysis found significant differences in all Mean Scores between the two research groups. More specifically, there was a significant, small-sized mean difference in perceived humanness between the two groups found [$t(149) = 2.56$, $p = .01$, $d = .42$]. The humanlike robot was evaluated as more human than the machinelike robot (see Table 3), meaning that the manipulation can be regarded as successful.

Moreover, there was a significant, medium-sized mean difference in perceived usefulness between the two groups found [$t(149) = -3.38$, $p = .00$, $d = .55$]. H1 stated that people would evaluate the humanlike robot as more useful than the machinelike robot. However, the analysis indicated that participants believed that the machinelike robot was more useful (see Table 3). Given this finding, H1 is rejected.

Next, there was a significant, medium-sized mean difference in perceived enjoyment between the two groups found [t(149) = 4.56, *p* = .00, *d* = .74]. H2 stated that people would evaluate the humanlike robot as more enjoyable than the machinelike robot. The analysis could confirm this expectation (see Table 3). Thus, H2 is accepted.

Further, there was a significant, small-sized mean difference in perceived trust between the two groups found [t(149) = 2.04, *p* = .04, *d* = .33]. H2 stated that people would trust the humanlike robot more than the machinelike robot. Indeed, the analysis found that participants trusted the humanlike robot more than the machinelike robot (see Table 3). Given this finding, H3 is accepted.

Subsequently, there was a significant, small-sized mean difference in perceived sociability between the two groups found [t(149) = 1.98, *p* = .05, *d* = .33]. H3 stated that people would evaluate the humanlike robot as more sociable than the machinelike robot which the analysis could confirm (see Table 3). Thus, H4 is accepted.

Lastly, there was a significant, small-sized mean difference in the behavioural intention between the two groups found [t(149) = 2.06, *p* = .04, *d* = .34]. H4 stated that people would have a higher behavioural intention towards the humanlike robot than towards the machinelike robot (see Table 3). Indeed, the analysis indicated that participants showed a higher behavioural intention towards the humanlike robot than towards the machinelike robot. Given this finding, H5 is accepted.

Stepwise regression analysis and mediation analysis of the variables

To test H6 about the impact of the acceptance factors on the relationship between a robot's level of humanness and people's behavioural intention, a stepwise regression analysis followed by a mediation analysis using 'PROCESS' as developed by Hayes (2017) have been conducted.

Table 4

Summary of Stepwise Regression Analysis for Variables Predicting the Behavioural Intention

	Model 1			Model 2			Model 3		
	B	*SE B*	*ß*	*B*	*SE B*	*ß*	*B*	*SE B*	*ß*
Control variables									
Job interview experience	-.34	.30	-.11	-.43	.30	-.21	-.21	.22	-.06
General attitude	.19	.06	.25**	.20	.06	.27**	-.03	.05	-.04
Gender	.03	.21	.01	.08	.21	.03	.18	.15	.07

Age	-.01	.01	-.08	-.01	.02	-.04	-.01	.01	-.03
Independent variable									
A robot's level of humanness				.45	.20	.19*	.58	.19	.24**
Mediator variables									
Perceived usefulness							.50	.07	.57**
Perceived enjoyment							.23	.07	.29**
Perceived trust							.13	.08	.13
Perceived sociability							-.06	.11	-.06
Manipulation check									
Perceived humanness							-.10	.08	-.12
R^2		.07			.10			.54	
F for change in R^2		2.8*			3.3**			16.0**	

**Correlation is significant at the .01 level (2-tailed).
*Correlation is significant at the .05 level (2-tailed).

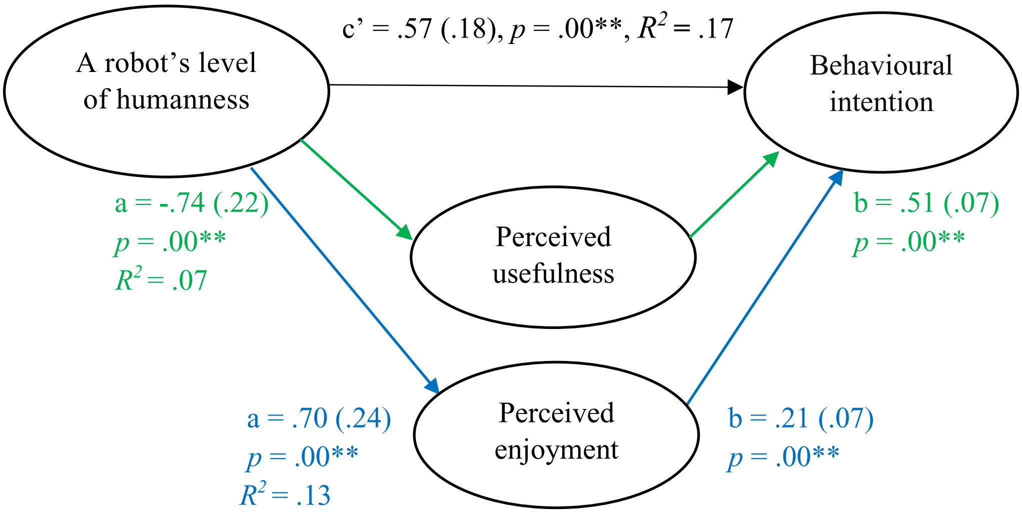
Before starting with the mediation analysis, it was tested whether the control variables, the independent variable, the mediator variables, and the perceived humanness, which checked the effectiveness of the manipulation, significantly predicted the behavioural intention by running a stepwise regression analysis.

In the first step, we only included the control variables. Correspondingly with the findings of the Pearson correlations (see Table 2), only the general attitude towards interacting with a robot significantly predicted the dependent variable [B = .19, SE = .06, p = .00, R^2 = .07]. In the next step, we included the control variables and the independent variable. The findings suggested that only the general attitude [B = .20, SE = .06, p = .00, R^2 = .10] and a robot's level of humanness [B = .45, SE = .20, p = .02, R^2 = .1] significantly predicted the dependent variable. The latter was the basic criterion for conducting the mediation analysis later on. In the third and last step, we included the control variables, the independent variable, the mediator variables, and the perceived humanness. Here, the effect of the general attitude on the dependent variable became insignificant [B = -.03, SE = .05, p = .50, R^2 = .54]. A robot's level of humanness, in contrast, still significantly predicted the dependent variable [B = .58, SE = .19, p = .00, R^2 =

.54]. Furthermore, regarding the perceptions, only 'perceived usefulness' [B = .50, SE = .07, p = .00, R^2 = .54] and 'perceived enjoyment' [B = .23, SE = .07, p = .00, R^2 = .54] significantly predicted the dependent variable. In contrast, 'perceived trust', 'perceived sociability', and 'perceived humanness' were not significantly related to the dependent variable (see Table 4). Consequently, only 'perceived usefulness' and 'perceived enjoyment' were included in the mediation analysis.

Figure 4

Mediation Model with 'Perceived Usefulness' and 'Perceived Enjoyment' Mediating the Relationship Between 'a Robot's Level of Humanness' and 'Behavioural Intention'



Subsequently, it was tested whether a robot's level of humanness significantly predicted the prospective mediator 'perceived usefulness'. Indeed, the analysis confirmed this expectation [B(4.03, 4.64) = -.74, SE = .22, p = .00, R^2 = .07] (see Figure 4). The negative coefficient indicates that higher levels of humanness predict lower perceived usefulness, which is consistent with the findings of H1 (see Table 3). Moreover, it was tested whether the potential mediator 'perceived usefulness' had a significant effect on the dependent variable. This effect was found to be significant [B (.37, .65) = .51, SE = .07, p = .00], which is consistent with the findings of the stepwise regression analysis (see Table 4).

Furthermore, it was tested whether a robot's level of humanness significantly predicted the prospective mediator 'perceived enjoyment'. The analysis confirmed this expectation as well [B(2.94, 3.61) = .70, SE = .24, p = .00, R^2 = .13] (see Figure 4). The positive coefficient indicates that higher levels of humanness predict higher perceived enjoyment, which is consistent with the findings of H2 (see Table 3). Moreover, it was tested whether the potential mediator 'perceived enjoyment' had a significant effect on the dependent variable. This effect was found to be significant [*B*(.08, .35) = .21, *SE* = .07, *p* = .00], which is consistent with the findings of the stepwise regression analysis too (see Table 4).

Table 5

Results of the Indirect Effects of a Robot's Level of Humanness Over the Hypothesized Mediators on Behavioural Intention

Model	IE_{med}	SE_{Boot}	95% confidence interval
Complete indirect effect			
A robot's level of humanness → Perceived usefulness → Behavioural intention	-.36	.11	[-.59, -.15]
A robot's level of humanness → Perceived enjoyment → Behavioural intention	.21	.09	[.06, .40]

IE_{med} = completely standardized indirect effect of the mediation
SE_{Boot} = standard error of the bootstrapped effect sizes

The total effect between the independent and the dependent variable was found to be significant [*B*(.03, .82) = .43, *SE* = .20, *p* = .03, R^2 = .17] as was their direct relationship [*B*(.23, .92) = .57, *SE* = .17, *p* = .00] (see Figure 4). Further, the indirect relationship between the independent and the dependent variable that is mediated by 'perceived usefulness' was significant [*B*(-.59, -.15) = -.36] as was the indirect relationship between the independent and the dependent variable that is mediated by 'perceived enjoyment' [*B*(.06, .40) = .21] (see Table 5). This is because the confidence levels do not include zero (Agler & De Boeck, 2017).

Note that the direct relationship was larger than the total effect. This is likely to be explained by the negative coefficient of the indirect relationship that is mediated by 'perceived usefulness'. In this case, literature speaks about an inconsistent mediation in which the direct and the indirect relationship have opposite signs (MacKinnon et al., 2007). Accordingly, 'perceived usefulness' and 'perceived enjoyment' partially mediate the relationship between the independent and the dependent variable, in that the relationship becomes stronger when 'perceived enjoyment' is included but the relationship becomes, in fact, weaker when 'perceived usefulness' is included. The weakening effect of the mediator 'perceived usefulness' on the positive relationship between the independent and the dependent variables is consistent with the findings of H1 and the linear regression analysis; higher levels of humanness predict lower perceived usefulness, but perceived usefulness positively predicts the behavioural intention.

Although the stepwise regression analysis indicated that the effects of ‘perceived trust’, ‘perceived sociability’, and ‘perceived humanness’ on the dependent variable were insignificant, we still tested their effects in a post-hoc mediation analysis. As was foreseeable, the mediation effects of these perceptions were insignificant. Thus, ‘perceived trust’, ‘perceived sociability’, and ‘perceived humanness’ do not significantly mediate the relationship between the independent and the dependent variable.

Given the findings of the mediation analysis, H6 is only partially accepted.

6. Discussion

Prior research has outlined that in HRM, AI is expected to take over many HRM processes in the future (Siavathanu & Pillaim, 2018). One of these processes includes job interviews in which social robots will interview human candidates (Nørskov et al., 2020). Studies showed that there are several advantages of human-robot compared to regular job interviews such as better hiring decisions, the avoidance of biases, and candidates' increased honesty during the interview (Langer et al., 2020; McAllister & Haak, 2019; Nørskov et al., 2020). At the same time, robots were found to be limited in their social capabilities, which may have implications for the effectiveness of HRI in job interviews (Fox & Gambino, 2021). Furthermore, job interviews create a power imbalance between the interview robot and the candidate, in which the robot has the 'power' to decide over the candidate (Das, 2021). Consequently, it will be of a hiring company's interest to reduce these problems related to the robot and to enable a desirable HRI in job interviews. This may be achieved by designing the robot in a way that positively affects candidates' perceptions of the robot and their robot acceptance in the job interview context. Subsequently, their attitudes related to the selection procedure and the hiring company in general could be reinforced in order to ensure a positive reputation of the company and good chances of hiring a qualified workforce. Ultimately, this is crucial in order to maintain or even increase the organizational performance of the company (Nørskov et al., 2020).

As literature showed that robots displaying humanlike characteristics and behaviour is related to robot acceptance in social interactions, we suggested that the level of robotic humanness influences candidates' perceptions and behavioural intention to interact with the robot in job interviews (Breazeal et al., 2008). Therefore, this research aimed to investigate to what extent a robot's level of humanness affects people's acceptance towards interacting with a robot in job interviews. This study provides initial empirical evidence for the importance of robotic humanness on technology acceptance and behavioural intention to interact with a robot in job interviews – supporting theories and assumptions of earlier studies (Breazeal et al., 2008; Graaf & Allouch, 2013; Shin & Choo, 2011; Song & Luximon, 2020). We will now discuss the main results and the theoretical and practical implications. Afterwards, limitations of this research are presented and recommendations for future research are given. We will end the paper with a conclusion.

6.1 Main results

To answer the research question, the research had two objectives. The first one was to test whether a robot's level of humanness predicts certain acceptance factors and robot acceptance itself. The second one was to test whether the acceptance factors affect the relationship between a robot's level of humanness and robot acceptance. It was hypothesized that a humanlike robot would be perceived as more positive and consequently, more accepted compared to a machinelike robot. Furthermore, it was hypothesized that the acceptance factors would mediate the relationship between a robot's level of humanness and people's behavioural intention towards interacting with the robot in a job interview, in that the relationship becomes stronger when the acceptance factors are included.

The effectiveness of the manipulation

By equipping the humanlike robot with humanlike characteristics and skills as opposed to the machinelike robot, we tried to create a drastic contrast between the two robots. Additionally, by using subjective personal pronouns for the humanlike robot and calling it by its human name, whilst using objective personal pronouns for the machinelike robot and giving it a robotic name, we tried to create an even stronger contrast. Since participants' perceived humanness was higher of a humanlike robot than of a machinelike robot, the manipulation was considered successful. However, it is worth mentioning that neither robot has been evaluated as very human. In fact, both mean values of perceived humanness were rather low (humanlike robot group: $M = 2.58$; machinelike robot group: $M = 1.99$). Fernandes and Oliviera (2021), from whose paper we adopted the perceived humanness scale, came to the same conclusion. This finding may be explained by the effect of partial anthropomorphism: it occurs when people see objects as having some human traits but do not consider them human as a whole (Fernandes & Oliviera, 2021). Therefore, participants might have evaluated the humanlike robot more as an object with humanlike features than a human itself.

The relationship between a robot's level of humanness and people's perceptions of a robot/ robot acceptance

First of all, we found significant mean differences in all variables of analysis and the manipulator variable. More specifically, the means of 'perceived humanness', 'perceived enjoyment', 'perceived trust', 'perceived sociability', and 'behavioural intention' were, as expected, higher of the humanlike robot group than of the machinelike robot group. In other words, participants' perceived humanness, enjoyment, trust, sociability, and behavioural intention of a humanlike robot were evaluated at higher levels than of a machinelike robot. However, the mean of 'perceived usefulness' was, unexpectedly, higher of the machinelike robot group than of the humanlike robot group. In other words, participants' perceived usefulness of a machinelike robot was evaluated at higher levels than of a humanlike robot. Consequently, H2-H5, which stated that people's perceived enjoyment, trust, sociability, and behavioural intention would be higher of a humanlike robot than of a machinelike robot, were accepted. In contrast, H1, which stated that people's perceived usefulness would be higher of a humanlike robot than of a machinelike robot, was rejected.

The results of H2-H5 are in line with the literature. With regard to perceived enjoyment, Wirtz et al. (2018) suggested that people enjoy HRI in which the robot is sympathetic and caring by, for example, expressing emotional responses. According to Breazeal et al. (2008), robots demonstrating such socio-emotional skills are, therefore, crucial for a desirable HRI. Since socio-emotional skills are typical human skills, the humanlike robot was presented as being capable of expressing emotions, whilst the humanlike robot was presented as being incapable of expressing emotions. This contrast can explain the difference in participants' perceived enjoyment between the humanlike and the machinelike robot group.

Several studies such as the one by Wu et al. (2011) found that next to perceived usefulness and ease of use, the level of trust is strongly related to both attitude and behavioural intention to use a robot. Oksanen et al. (2020) proposed that people show higher trust when certain anthropomorphic features such as gestures, expressions, or physical characteristics are included. Therefore, the humanlike robot obtained humanlike physical features such as lifelike skin, eyes, a nose, ears, and a mouth, a female-shaped body with arms and legs, etc. Furthermore, it was described as being able to follow faces, to sustain eye contact, and to emulate more than 60 facial expressions. These physical features and abilities made its appearance more human than the machinelike robot, which, in contrast, was described as looking like a camera. This contrast can again explain the difference in participants' perceived trust between the humanlike and the machinelike robot group.

Regarding perceived sociability, Shin and Choo (2011) proposed that the social abilities of robots are amongst the most significant determinants for accepting and using robots. According to Fernandes and Oliveira (2021), (language-based) communication skills of a robot including voice, conversation, and fulfilment of traditional human roles contribute to its social abilities. Therefore, the humanlike robot was able to use natural language and motions that allowed it to have meaningful conversations with people. In contrast, the machinelike robot used artificial language, was limited in its communication skills as it could not answer abstract counterquestions, and it did not move. This contrast may once again explain the difference in participants' perceived trust between the humanlike and the machinelike robot group.

The more positive effect of the machinelike robot on participants' perceived usefulness in comparison to the humanlike robot, however, contradicts our expectations. This is because literature found that user perception of usefulness depends on how much a robot can adapt to a changing environment (Graaf & Allouch, 2013; Shin & Choo, 2011). Therefore, the humanlike robot was presented as adaptable to its environment/ conversation partner; it cannot only sense the mood of its environment but it can also recognize its conversation partner's changing needs and tries to find ways to achieve goals with them. In contrast, the machinelike robot was presented as very limited in interpersonal skills. One possible explanation for a more positive perceived usefulness of the machinelike robot in comparison to the humanlike robot is the uncanny valley effect, referring to the humanlike robot (Fernandes & Oliviera, 2021). Interacting with a very humanlike robot could lead people to experience anxiety and discomfort, especially when they are inexperienced with HRI (Fernandes & Oliviera, 2021). According to Rose and Fogarty (2006), technology discomfort is a direct predictor of perceived usefulness which would explain the more negative evaluations of the humanlike robot regarding perceived usefulness. Another explanation could be the aspect of perceived ease of use that predicts perceived usefulness in the original TAM model (Davis, 1989). In this line of reasoning, participants might have perceived the machinelike robot as simpler and less complicated than the humanlike robot due to its simplicity in communication and output. Maybe for tasks like a job interview, a simpler, straightforward robot fits better. After all, it remains open why participants perceived the machinelike robot as more useful which should be given more attention to in further research by, for example, including technology discomfort and perceived ease of use as direct antecedents of perceived usefulness.

Now that we understood the relationship between robotic humanness and people's perceptions/ acceptance of a robot in a job interview better, the next step was to investigate the role of people's perceptions of a robot in the relationship between robotic humanness and robot acceptance in the context of a job interview.

The impact of people's perceptions of a robot on the relationship between a robot's level of humanness and robot acceptance

Regarding the impact of the acceptance factors on the relationship between robotic humanness and people's behavioural intention to interact with the robot, we found that only 'perceived usefulness' and 'perceived enjoyment' significantly predicted behavioural intention. Therefore, the mediation analysis was run with only these acceptance factors. As it turned out, 'perceived usefulness' and 'perceived enjoyment', indeed, partially mediated the relationship between a robot's level of humanness and behavioural intention, in that the relationship became stronger when perceived enjoyment was included but it became, in fact, weaker when perceived usefulness was included. Therefore, H6, which stated that people's perceptions of a robot would partially mediate the relationship between the independent and the dependent variable was only partially accepted. This is because the other two acceptance factors 'perceived trust' and 'perceived sociability' did not significantly predict the dependent variable. Also, perceived usefulness had a weakening effect on the relationship instead of a strengthening one.

The existence of a mediation effect of perceived usefulness and perceived enjoyment on the relationship between robotic humanness and robot acceptance is in accordance with the TAM model (Davis, 1989). It suggests that perceived usefulness and perceived ease of use of a technology, which is the equivalent to perceived enjoyment (Shin & Choo, 2011) in this study, form acceptance factors that predict the technology acceptance. Thereby, the negative mediation effect of perceived usefulness on the positive relationship between a robot's level of humanness and the behavioural intention is consistent with the findings of H1 and the linear regression analysis; higher levels of humanness are related to lower perceived usefulness and vice versa, but perceived usefulness positively predicts the behavioural intention. Interestingly, perceived trust, perceived sociability, and perceived humanness did not significantly predict behavioural intention and did, thus, not mediate the relationship. In other words, our findings suggest that these acceptance factors do not play a role in predicting candidates' robot acceptance in a job interview.

In contrast to the scientific evidence (Fernandes & Oliviera, 2021; Oksanen et al., 2020; Wu et al., 2011), we did not find support for the importance of trust on robot acceptance. There are multiple possible explanations. For example, the scale consisted of two reversed items. According to Suárez Álvarez et al. (2018), when combinations of positive/ regular and reversed items are used in the same scale, the measurement precision of the scale is flawed and the one-dimensionality of the scale is threatened by secondary variance. The CFA showed that one of the reversed items correlated weakly with the other items of the scale, even though the scale showed acceptable internal consistency overall. This may be an indication that the reversed items' reliability, indeed, was flawed. After all, we still believe that perceived trust is a significant predictor of robot acceptance due to the strong scientific evidence (Fernandes & Oliviera, 2021; Oksanen et al., 2020; Wu et al., 2011).

Next, the non-significant effect of perceived sociability on robot acceptance is partially in line with the findings by Fernandes and Oliviera (2021). Namely, ‘perceived social interactivity’, which is part of the perceived sociability in this study, did not significantly predict robot acceptance. Fernandes and Oliviera (2021) argue that social interactivity only affects technology acceptance if it helps users to perceive the technology as a ‘real’ person or a social entity. Too much social dialogue may produce mixed results: although it may lead to perceptions of social attractiveness, it may also be viewed as the robot making ‘fake’ attempts to be human. As the perceived humanness was generally low, this may explain the insignificant relationship between perceived sociability and robot acceptance.

Lastly, the non-significant effect of perceived humanness on robot acceptance is again in line with the findings by Fernandes and Oliviera (2021). As discussed before, both robots have not been evaluated as very human due to the absence of humanness in the machinelike robot and a potential partial anthropomorphism of the humanlike robot (Fernandes & Oliviera, 2021). Therefore, the effect of perceived humanness might have not been strong enough to predict robot acceptance, especially in combination with the other perceptions.

When looking at the mean values of the variables of analysis, it was noticeable that the mean values of the behavioural intention were high for both groups, while the mean values of the perceptions were rather low or neutral. Furthermore, the findings showed that the R-squared was relatively low, meaning that there is a lot of unexplained variance. This may imply that there are other predictors affecting the behavioural intention. For example, participants’ characteristics towards social robots might have affected their behavioural intention to interact with a robot in a job interview. Prior research suggests that behavioural intentions are shaped by candidates’ dispositional factors such as Big Five personality dimensions, cognitive abilities, and core self-evaluations (Merkuvola et al., 2014; McLarty & Whitman, 2016 as cited in Nørskov et al., 2020). This is because people with higher self-beliefs about their abilities to perform well are more likely to form stronger behavioural intentions (Ajzen, 2011 as cited in Nørskov et al., 2020). Further research should, therefore, examine how and why such personal factors influence candidates’ perceptions of a robot in a job interview.

Next to candidates’ characteristics, another potential predictor of behavioural intentions in job interviews is pre-existing attitudes towards social robots – which will be discussed next.

The impact of people's general attitude towards interacting with a robot on their perceptions of the robot and robot acceptance

We additionally controlled for the effect of age, gender, prior job experience, and the general attitude towards interacting with a robot on participants' perceptions of the robot and their behavioural intention to interact with the robot. However, the means of age, gender, and prior experience did not show any significant differences between the two research groups. Accordingly, participants' perceptions and behavioural intention did not differ within younger and older people, males and females, or the presence and absence of prior job experience. Within the level of participants' general attitude towards interacting with a robot, however, their perceptions and behavioural intention did differ. More precisely, the independent t-test showed that participants with a higher general attitude also had more positive perceptions and a higher behavioural intention than participants with a neutral or negative general attitude.

This finding is in line with literature that suggests that people's general attitudes towards social robots influence their behaviour when confronted with a robot and their acceptance of it within society (Graaf & Allouch, 2013). Therefore, it may not only be robotic and candidates' characteristics that affect their perceptions and acceptance of the interviewing robot but also their pre-existing attitudes towards robots. Thus, candidates' pre-existing attitudes towards robots should be given more attention to in HRI research.

6.2 Theoretical implications

This study has three theoretical implications for human-robot job interviews. First, this study advances our understanding of robot acceptance and provides a grounding for future research on the interaction between humans and robots in management. More specifically, earlier studies have mostly focused on collaboration instead of the social interaction between humans and robots so this study adds another dimension to the literature (Bauer et al., 2008; Libert et al., 2020; Vysocky & Novak, 2016). Furthermore, robotic humanness was shown to make a difference in all of the acceptance factors and robot acceptance itself. In particular, higher levels of humanness were found to predict higher perceived enjoyment, trust, sociability, humanness, and behavioural intention. Therefore, this study emphasizes the importance of robotic humanness for positive perceptions and acceptance of the robot in HRI such as job interviews.

Second, our results showed that not just robotic humanness but also several acceptance factors are important in explaining candidates' behavioural intention to interact with a robot in a job interview: namely, perceived usefulness and perceived enjoyment. These have significant effects on people's robot acceptance. These findings are consistent with the existing literature on determinants of robot acceptance (Graaf & Allouch, 2013; Shin & Choo, 2011). Thereby, perceived usefulness and perceived enjoyment partially mediate the relationship between robotic humanness and people's behavioural intention, in that the relationship becomes significantly stronger when perceived enjoyment is included and significantly weaker when perceived usefulness is included. The latter finding suggests that perceived usefulness can only strengthen robot acceptance if the robot's level of humanness is, in fact, low. By including the mediators in the relationship between robotic humanness and robot acceptance, we could provide an explanation for their existence. Thus, this study contributes to the literature on the determinants of robot acceptance.

Third, our results are in line with earlier findings and support theories on technology acceptance with regard to perceived usefulness (Davis, 1989) and perceived enjoyment (Shin & Choo, 2011). We can further expand prior theories on technology acceptance since the acceptance factors have, to our knowledge, not been tested in this constellation and neither in the context of human-robot job interviews before. In contrast, the effects of perceived trust, perceived sociability, and perceived humanness were not significant. Consequently, we cannot support the existence of a relationship between perceived trust, perceived sociability, and perceived humanness, respectively, and behavioural intention in the light of our study. We suggest that the non-existent relationship in the case of the perceived trust could have been caused by statistical flaws (Suárez Álvarez et al., 2018). Regarding the perceived sociability, we propose that sociability may only affect robot acceptance if it helps people to perceive the robot as a 'real' person. Otherwise, it may be viewed as the robot making 'fake' attempts to be human (Fernandes & Oliviera, 2021). Lastly, due to the low mean values of the perceived humanness compared to the other predictors, the effect of perceived humanness on the behavioural intention might have not been strong enough to predict robot acceptance.

Although some acceptance factors did not significantly predict the behavioural intention, they should still be considered in future research. This is because they helped us to estimate the relevance of robotic humanness for a desirable HRI in job interviews – which leads us to practical contributions.

6.3 Practical contributions

This study has three practical contributions. First of all, the TAM model (Davis, 1989), the sRAM model (Wirtz et al., 2018), and the theory of perceived enjoyment in technology (Shin & Choo, 2011) are all applicable to social robots. Accordingly, HRI in job interviews can be created more effectively when keeping these models and theories in mind.

In this study, the models and additional theories were, among others, used to evaluate the relevance of robotic humanness in job interviews. All studied variables were found to differ between the humanlike and the machinelike robot. More specifically, perceived enjoyment, trust, sociability, humanness, and the behavioural intention were significantly higher of the humanlike robot than of the machinelike robot. Consequently, a second practical contribution is that a robot utilized to interview candidates should acquire certain humanlike characteristics and skills that positively influence the perceptions of the robot as well as the robot acceptance such as the capability to express emotions, a human appearance, and natural language and motions. Managers can take these robotic features into account when designing interview robots to enable a desirable HRI in job interviews. However, we also found that perceived usefulness was significantly higher of a machinelike robot than of a humanlike robot. Accordingly, we suggest that the humanlike skill of adaptability that was being linked to the perceived usefulness did not play a role in participants' evaluation of perceived usefulness. Instead, other factors such as technology discomfort or perceived ease of use might have predicted the perceived usefulness. Therefore, the importance of adaptability in increasing robotic humanness in job interviews is still emphasized (Graaf & Allouch, 2013, Shin & Choo, 2011; Tanevska et al., 2020).

Thirdly, a consideration for HR managers to enable a desirable HRI in job interviews is to prepare candidates for the human-robot job interview. As mentioned in the theoretical framework, employees should be prepared and developed through the whole implementation process and be aware of the possible consequences related to the robot (Libert et al., 2020). Since the candidates are not yet employees, they should at least receive general facts about the features of the robot before being interviewed by it. This way, the candidates may perceive higher ease of use and some kind of control over the robot to reduce feelings of anxiety or discomfort resulting from uncanniness (Fernandes & Oliviera, 2021). The perceived humanness in this study was rather low so it is not sure whether uncanniness has played a role but it may do in real-life situations. Furthermore, the general attitude towards interacting with a robot may be increased which was shown to be related to people's perceptions and acceptance of the robot in a job interview. In practice, managers should have an educational talk with the candidates and be open to questions before the human-robot job interview.

By taking these practical contributions into account, the hiring company may be able to not just improve HRI in job interviews but also to improve recruitment processes and to, thereby, establish a positive reputation of the company. Ultimately, good chances of hiring a qualified workforce can be ensured to maintain or even increase the organizational success of the company.

6.4. Limitations and recommendations for further research

Despite the effort to ensure careful analyses and appropriate implications, this study does not come without any limitations. One limitation is the method we used, a Vignette study. In self-reports, response bias can occur, which is the tendency to answer questions on a survey untruthfully, misleading, or inaccurately, for example, due to a disinterest in the survey or participant's tendency to give socially desirable answers ('Response Bias - Biases & Heuristics', 2021). Therefore, the results of this study may lack validity. Further research could address this issue by combining the Vignette study with a qualitative research method like interviews or experiments in order to avoid response biases. Especially the latter may not only reduce response biases but also provide more insights into cause-and-effect by demonstrating what outcome occurs when a particular factor is manipulated. For example, researchers could initiate real-life human-robot job interviews with both humanlike robots and machinelike robots to compare the differences in human behaviour and attitudes. The combination of experiments and self-reports may allow for both observations of participants' behaviour in the scenario and the evaluation of their perceptions and behavioural intention through a survey. This way, we may learn more about actual human behaviour in human-robot job interview scenarios and could compare it to participants' reported perceptions and robot acceptance.

Another problem with the Vignettes is that they were built with written descriptions. Participants had to use their imagination in order to put themselves into the described scenario. Although the manipulation worked, the description of the scenario might have not been convincing enough to do so considering the unusual and novel context. Here, it would once again make sense to initiate real-life human-robot job interviews. The realness of these situations may then lead to more real reactions and therefore, more valid results.

A last issue with the Vignettes may be the presentation of the robots. Due to a lack of resources, the videos of the robots that were shown to the participants represented a different context than the one of a job interview. In particular, the humanlike robot Sophia was introduced in a talk show and the machinelike robot Robo Bot was used to interview a celebrity. A video of an actual human-robot job interview would have given participants a better idea about how it would look like if they were in that situation. In return, it would have likely been easier for the participants to imagine the described scenario. Instead, the different contexts might have been distracting from the actual purpose of bringing across the robots' (non-)human features in a human-robot social interaction. However, adding a photo and a description of the most crucial robotic characteristics was meant to increase participants' understanding of the robot. Further research may rather choose videos of actual human-robot job interview scenarios when building Vignettes to ensure valid results.

Another recommendation for further research has to do with the robotic features. In this study, we have linked the acceptance factors to certain human features such as adaptability and the capability to express emotions. However, we have not studied these features in depth. In further research, it would be valuable to investigate which features make a robot truly human and, thereby, to explore which ones are most important in predicting the behavioural intention. Hereby, it would be valuable to focus on interviewer characteristics that have been shown to positively affect company attraction and job acceptance intentions such as friendliness and empathy (Carless & Imber, 2007).

The last limitation concerns the sample. Through snowball sampling, the sample mostly consisted of female, German students so the sample did not provide the balance in demographic characteristics that was wished for. Especially student populations used in TAM model studies have been criticized for not surrogating the general population (King & He, 2006). Further research could address this by distributing the survey randomly and evenly. Furthermore, data collection could take place in different countries.

6.5. Conclusion

The findings of this research show that a robot's level of humanness directly and positively affects people's acceptance towards interacting with a robot in job interviews. In addition, we have identified one variable, namely, perceived usefulness, that can (partly) explain the positive effect of humanness on acceptance and thereby provide novel insights into the causal mechanism underlying the influence of robotic humanness on acceptance of robots in job interviews. Moreover, the relevance of robotic humanness for a desirable HRI in job interviews is expressed by people's perceived usefulness, enjoyment, trust, sociability, and behavioural intention of the robot. Thereby, higher levels of humanness are related to higher perceived usefulness, trust, sociability, and humanness but lower perceived usefulness. In other words, all acceptance factors (except for the perceived usefulness) and the robot acceptance itself were significantly higher of the humanlike robot than of the machinelike robot. Consequently, for a desirable HRI in job interviews, robots should obtain humanlike characteristics that increase these factors such as the capability to express emotions, a human appearance, and natural language and motion. Even though perceived trust and perceived sociability did not significantly determine robot acceptance in this study, we still believe that they are important factors to consider when aiming for a desirable HRI in job interviews. In contrast, people's perceived usefulness was significantly higher of the machinelike robot than of the humanlike robot. In this case, we suggest that the humanlike skill of adaptability that was being linked to the perceived usefulness did not play a role in participants' evaluation of perceived usefulness but the importance of adaptability in increasing robotic humanness is still emphasized.

With this research, we demonstrate the importance of robotic humanness in human-robot job interviews. However, we also emphasize the contribution of candidates' pre-existing attitudes towards robots and potential personal characteristics on their perceptions and acceptance of a robot in a job interview. In any case, this research is a starting point towards a desirable HRI in job interviews which may follow the improvement of recruitment processes, the reputation of the company, and, in the long run, even the organizational success of the hiring company.

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9. Appendix A- Additional Tables

Descriptive statistics

Table 6

Independent Samples T-Test of the General Attitude

	Attitude	Mean	Mean difference	Std. deviation	Sig. (2-tailed)	N
Perceived usefulness	Positive	4.31	.62	1.54	.00	66
	Neutral/ negative	3.69		1.19		85
Perceived enjoyment	Positive	4.53	1.26	1.65	.00	66
	Neutral/ negative	3.27		1.28		85
Perceived trust	Positive	4.36	.99	1.31	.00	66
	Neutral/ negative	3.37		.97		85
Perceived sociability	Positive	3.53	.98	1.51	.00	66
	Neutral/ negative	2.55		.92		85
Behavioural intention	Positive	5.62	.6	1.19	.00	66
	Neutral/ negative	5.02		1.19		85
Perceived humanness	Positive	2.79	.92	1.79	.00	66
	Neutral/ negative	1.87		.98		85

Table 7

Skewness and Kurtosis of the Mean Scores

	N	Skewness	Kurtosis
Perceived usefulness	151	-.26	-.41
Perceived enjoyment	151	.19	-.63
Perceived trust	151	.21	.00
Perceived sociability	151	1.09	1.35
Behavioural intention	151	-.85	.46
Perceived humanness	151	1.48	1.8

Table 8

Kolmogorov-Smirnov Test of the Mean Scores

	N	Sig. (2-tailed)
Perceived usefulness	151	.01
Perceived enjoyment	151	.01
Perceived trust	151	.24
Perceived sociability	151	.00
Behavioural intention	151	.00
Perceived humanness	151	.00

Appendix B- the Survey

Informed consent

Dear participant,

Thank you for participating in this study! My name is Linda Merkel and this questionnaire is part of my master thesis. The aim of this study is to examine people's perceptions towards human-robot job interviews. Completing the questionnaire will take approximately 15 minutes.

Participation is completely voluntary and you can withdraw from the study at any time, without giving a reason. Your answers remain anonymous and will be treated confidential. The data will only be used for research purposes.

This research has been approved by the ethics board of the faculty of Behavioural, Management, and Social sciences (BMS) at the University of Twente.

Please answer the following question:
I have read and understood the information and agree to what I read. I declare that I have been informed about the method, nature, and purpose of the study.

- I consent
- I do not consent

Control questions

Do you have experiences with job interviews?

- Yes
- No

I would like to know how you think about human-robot interactions in general. How much do you agree with the following statement?

I like the idea of interacting with a robot.

- Strongly disagree
- Disagree
- Somewhat disagree
- Neither agree nor disagree

○ Somewhat agree

○ Agree

○ Strongly agree

Introduction of Sophia with video, description, and photo

Now, you will see a short video fragment. Please watch it carefully.

Here, you see the social robot **Sophia**. Sophia is a **humanoid** robot developed by the Hong Kong-based company Hanson Robotics. She has quite a few remarkable features as you might have noticed in the video.

Cameras within Sophia's eyes combined with computer algorithms allow her to **see**. She can **follow faces**, **sustain eye contact**, and **recognize** individuals.

She does not just have **lifelike skin** and the ability to emulate more than **60 facial expressions** but also has **functional legs** and therefore the ability to **walk**.

Furthermore, she is able to **process speech** and have conversations using **natural language**. Thereby, her eye, head, and body **move naturally** along the conversation.

She can even **estimate** how her conversation partner is **feeling** and tries to find ways to **achieve goals** with them. For example, if you look sad, she will ask you what is wrong and how she could help to cheer you up. She has own **emotions** too that she can **express** by simulating various regions of the human brain.

All in all, her complexity allows her to build **emotional connections** and **meaningful conversations** with people.

Vignette of interview scenario with Sophia

Now, I would like you to imagine the following scenario:

You applied for a job at a company and are pleased to hear that you got invited for a job interview. At the day of your job interview, you approach the company building a bit nervously but mostly excited. You walk to the room the secretary has sent you to and knock on the door. A voice calls you inside. You walk inside and notice a man and a woman. However, something seems off with the woman. She is in fact a robot! The man introduces him as the HR department leader and explains to you that not him but Sophia will interview you for the job. Of course, you are a bit surprised by the situation but you try to remain unbothered. He tells you to just be yourself and pretend as if you are talking to a real person. He leaves the room and lets you alone with Sophia. She welcomes you to the interview and asks you to take a seat.

Introduction of Robo Bot with video, description, and photo

Now, you will see a short video fragment. Please watch it carefully.

Here, you see the robot **Robo Bot**. It is an **AI bot** developed by the Zürich-based company Scandit for the sake of **holding interviews**. It looks like a **camera** attached to a tripod that stands on a table in front of its interviewee, but it can do way more than that.

Through its camera combined with computer algorithms, it can **sense** its environment and therefore, **see** and **recognize** people.

Based on a person's available information, it is able to come up with **questions** that are **tailored** towards this information.

It is further able to verbally **communicate** and **interact** with its interview partner using **artificial language**. It can even respond to counter-questions if they are **not too abstract**. If they are, however, it **cannot give** an **appropriate response**.

Furthermore, when it comes to **expressing** as well as **recognizing** the **emotions** of its interviewee, Robo Bot is **limited** in its capabilities as a computer.

All in all, Robo Bot is an intelligent interview partner with the ability to ask you highly **relevant questions** but with **limited interpersonal qualities**.

Vignette of interview scenario with Robo Bot

You applied for a job at a company and are pleased to hear that you got invited for a job interview. At the day of your job interview, you approach the company building a bit nervously but mostly excited. You walk to the room the secretary has sent you to and knock on the door. A voice calls you inside. You walk inside and notice a man and next to him, something that looks like a camera standing on the table. The man introduces him as the HR department leader and explains to you that not him but Robo Bot, an intelligent robotic interviewer, will interview you for the job. Of course, you are a bit surprised by the situation but you try to remain unbothered. He tells you to just be yourself and pretend as if you are talking to a real person. He leaves the room and lets you alone with Robo Bot. It welcomes you to the interview and asks you to take a seat.

Assessment of participants' behavioural intention and perceptions

Now, I would like to know how you would behave and feel about this situation, keeping Sophia/ Robo Bot and the job interview in mind. How much do you agree with the following statements?

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Assuming I am in this situation, I intend to interact with this robot.							
Given that I had to be in this situation, I predict that I would interact with this robot.							
If I had to be in this situation, I want to interact with this robot.							
Interacting with this robot would improve my interview performance.							
Interacting with this robot would increase my competence during the job interview.							
Interacting with this robot would enhance my effectiveness during the job interview.							
Interacting with this robot would strengthen my ability to provide good answers during the job interview.							
I think I would enjoy talking to this robot.							
I think interacting with this robot would be fun.							
I think I would enjoy being interviewed by this robot.							

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I find this robot enjoyable and fascinating.	○	○	○	○	○	○	○
I think this robot would behave in an unhanded manner.	○	○	○	○	○	○	○
I would be suspicious of this robot's intent, action, or output.	○	○	○	○	○	○	○
I think this robot would be reliable.	○	○	○	○	○	○	○
I would trust this robot.	○	○	○	○	○	○	○
This robot would be pleasant to interact with.	○	○	○	○	○	○	○
I think this robot would understand me.	○	○	○	○	○	○	○
When interacting with this robot, it would feel like talking to a real person.	○	○	○	○	○	○	○
I think this robot could be a real person.	○	○	○	○	○	○	○
This robot seems to have real feelings.	○	○	○	○	○	○	○
I can imagine this robot to be a living creature.	○	○	○	○	○	○	○

Demographic characteristics

Lastly, I would like to ask some general questions.

What is your gender?

○ Male

○ Female

- Not specified
- I do not want to say

What is your age in years?

What is your nationality?

- Dutch
- German
- Other

What describes your current occupation best?

- Student
- Employed
- Not employed
- Retired
- Other

Debriefing

You have reached the end of the questionnaire. Thank you for participating.

If you have any questions, remarks or want to know the outcomes of the study, do not hesitate to write an email to:

l.m.merkel@student.utwente.nl

Linda Merkel

P.S.: Please make sure to click the arrow on the right one more time so your response is recorded.