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Human- or Machine-like Music Assistive Robots

Effects on Fluency and Memory Recall

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ABSTRACT

Assistive robots are expected to contribute to the solution of major societal problems in healthcare, such as the increasing number of elderly who need informal and professional care over a long period of time. Most of the research focuses on the development of human-like robots to facilitate human-robot interaction and strengthen the social, cognitive and affective processes. However, there are some possible downsides of this type of “robot humanizing”, like raising high expectations and causing incorrect mental models of the robots. Machine-like robots, on the other hand, may help to build more realistic mental models and expectations but might bring about less fluent interactions and less pronounced experiences (i.e., less to remember). To test if a human-like robot indeed brings about better interaction fluency and memory recall, we designed two types of robots for a joint human-robot music listening activity: A human-like and a machine-like robot (Pepper). Thirty students participated in the experiment managed by a Wizard-of-Oz set-up. As expected, the human-like robot proved to perform better in terms of fluency and memory recall. Currently, we are preparing a follow-up experiment, consisting of longer sessions with the elderly to see whether this effect persists for this age group and how far the human- or machine-likeness influences the elderly’s understanding and expectations of the robot’s capabilities.

CCS CONCEPTS

• **Human-centered computing → Laboratory experiments**.

KEYWORDS

Robot, Music, Human-like robot, Machine-like robot, Fluency, Memory recall

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1 INTRODUCTION

The population is ageing and people are living longer. According to the United Nations [2], there are 727 million people over the age of 65 in 2020. The significance of elderly care is widely recognised based on these facts [17, 27]. Elderly care providers are under tremendous pressure as a result of the growing elderly population. Robotics may help with some of these issues thanks to its numerous advancements. Social robots could be employed for a range of tasks, including leisure, general assistance, artificial companionship, and healthcare [32]. Most of the social robot research focuses on the development of human-like robots to facilitate "natural" human-robot interaction and strengthen the social, cognitive and affective processes (cf., [7]). However, there are some possible downsides when a robot becomes more human-like: expectations for comprehension and intelligent responses rise as well [29], which may not always be in line with what a robot is actually capable of [36]. In contrast, people won’t assume robots have advanced social cognition if they behave in a machine-like robotic manner. In short, inaccurate or overconfident mental models of robots may cause people to interact with them inappropriately which could be disastrous for a "fluency" human-robot interaction.

In addition to the robotic task support, music has a broad versatile support potential for providing content and ambience of the activities in elderly care [3] that can improve health and well-being. Especially, studies have shown that autobiographical memories can be efficiently sparked by music [4, 20], and as noted by [18], it can help the elderly by connecting them to "others who may no longer be living, and may also validate memories, give meaning to live, and bring a greater sense of spirituality". In conclusion, music-evoked autobiographical memories (MEAMs) are an important aspect of elderly care.

The overall research program aims at an assistive robot that supports older adults in music-enriched meaningful activities. This support should be attuned to the individual competencies, needs and preferences of the adult. Personality is defined as a person’s behaviours, cognition, and emotions, which are influenced by both biological and social factors [16]. Social psychology research has demonstrated that people with different personalities prefer to interact in different ways [5]. Personality is increasingly recognised as a key concept in understanding human behaviour [15, 24]. Moreover, personality characteristics appear to relate to the degree type of self-disclosures of people towards a social robot [26]. The Big 5 personality traits will be used in our research to convey relevant individual differences to address in the support.

This paper presents our first study to test if a human-like robot brings about better interaction fluency and pronounced experiences (i.e., memory recall) than a machine-like robot. These two "robot identities" were designed, implemented in the Pepper robot of Softbank, and evaluated with students in a joint human-robot music listening activity.

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2 ROBOT DESIGN

People's mental models of robots can be influenced by numerous aspects [13, 21, 23]. In this study, we used four primary factors to design the different robot conditions: appearance, behaviour, voice and dialogue.

2.1 Appearance

The user's first impression of the robot is its appearance. Therefore, the appearance of the robot is crucial in helping the user to develop the correct mental model with the robot. In this study, a Pepper robot [33] was employed, the machine-like type robot maintains its original appearance, whereas the human-like type robot dresses in clothing with noticeable "human" traits, such as a tie and a hat.

2.2 Behaviour

The user's perception of the robot's identity during the interaction is heavily influenced by the robot's behaviour, such as the robot's body movements when talking to the user. Specifically, the robot's gaze and gestures have an impact [22, 31]. Likewise, [12] suggested that collaborative robots should show social cues, which may involve the display of emotions. Therefore, in this study, the majority of behaviours are kept the same for both types of robots. The only different behaviour is the dance of the robot. Human-like robot dance has the following characteristics: human-quality motion, flowing, organic, natural, and curved lines, whereas the machine-like robot dance has: precision, control, proximity and safety [1].

2.3 Voice

Hearing is one of the most important human senses, and a robot's voice can also affect the user's perception of its identity. In this study, the voice was adjusted by the built-in voice settings. The *naoenu* setting is a distinctly human voice with tone and emotion which is used for the human-like robot. The *naomnc* setting is apparently a synthesized voice which was typically considered to be machine-like [35] is employed by the machine-like robot.

2.4 Dialogue

Fischer [11] has summarised the literature on the distinctions between human-to-human communication (HHC) and human-computer interaction (HCI) in several aspects. In this study, the dialogue with a machine-like robot with the following features compared to the human-like robot: less polite, with fewer words per conversation, a smaller lexicon, fewer syntactic, more simplification, including a little over-specification, and technical disclosure rather than emotional disclosure. Table 1 shows an example segment of the dialogue. It can be noticed that this machine-like robot has a bit of over-specification and considerable technical disclosure.

Human-like Condition	Machine-like Condition
I am an intelligent social robot, and my name is Robin. I am designed to communicate with people and act like a human, just like you! Please make yourself comfortable. Are you ready to begin?	My name is Tronic, and I am a humanoid robot. I am fully equipped to be able to communicate with humankind in a robot way. I am connected to the Internet. I have sensors and much more. Can you hear me well?

Table 1: Example of the human-robot dialogue

3 EVALUATION METHOD

3.1 Participants

Thirty University students (from the Netherlands) participated in the experiment (recruited through social media advertisements or on-site recruitment). The participants were randomly divided equally into two groups, with 15 being placed in the machine-like robot condition and the other 15 being placed in the human-like robot condition. The average age was 24.8 years old (SD = 4.8).

3.2 Procedure

The set-up of the experiment can be seen in Figure 1. A Wizard of Oz setup was used to control the dialogue. It took roughly 15 minutes to complete the experiment. The experimenter began by giving a brief introduction and asking the participant to sign the informed consent. Then they were instructed to take a seat on the chair (see Figure 2) and informed that the experiment would shortly begin.

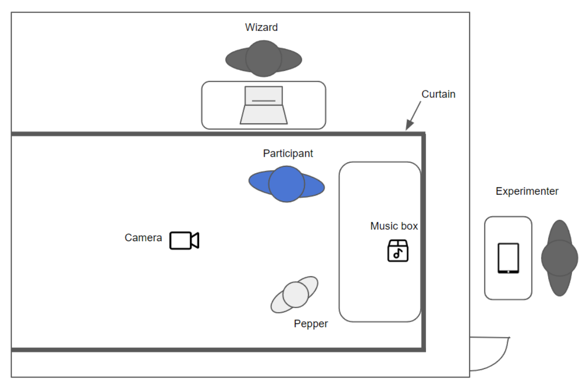

Figure 1: Schematic set-up of the experiment

The experimenter would now activate the robot and launch the experiment, then robot started with an introduction and then asked the participants for their profile information. Once the profile is created, the robot helped the participant choose a song that they know. Once the selection was made, the song was played and the robot started dancing. At the same time, the robot asked general questions about the music. When the dancing stopped, the robot asked for some memories related to the song. The robot would try to ask for more information about memory. If the participant had already been asked twice about memory, the robot would end the conversation. The participants were given a questionnaire once it was completed.

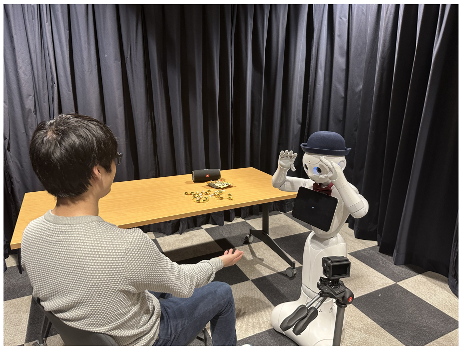

Figure 2: A site photo of the experiment

3.3 Measures

Two forms of data were gathered during the experiment: video records of the experiment and the follow-up questionnaire.

- From the video records, two variables were derived. The *objective fluency* metric is measured by the H-IDLE time ratio (i.e., the percentage of total task time when the human is inactive) [19]. The *TEMPau test score* was widely used to assess autobiographical memory performance [8–10, 28], in this study, it concerns participants' verbal answers to the memory recall questions (see Table 2).
- The questionnaire is divided into two main sections. The *subjective fluency* metrics contain nine questions which are summarized by [19], all of which used a 7-point Likert scale. The *Ten-Item Personality Inventory (TIPI) scoring scale* [14] was used to assess the individuals' Big 5 personality traits.

Score	Example
0	My father.
1	My father used to drink coffee.
2	My father used to drink coffee in the backyard.
3	One morning on a summer vacation in the mountain, my father was not able to find a grocery to buy coffee.
4	One morning on a summer vacation in the mountain, My father was bit nervous without his morning coffee.

Table 2: TEMPau test score example from [9]

4 RESULTS

4.1 Video observations

4.1.1 Objective fluency metrics. The H-IDLE ratio in the human-like condition (Mdn = 0.395, M = 0.393, SD = 0.047) was generally lower than in the machine-like condition (Mdn = 0.446, M = 0.438, SD = 0.049), see Figure 3. The dataset with machine-like conditions failed the normality test. Thus, the Mann-Whitney test was used to analyse the data, and it revealed that the median H-IDLE ratio for the human-like group differs significantly from that of the machine-like group (w = 46, $p < 0.01$).

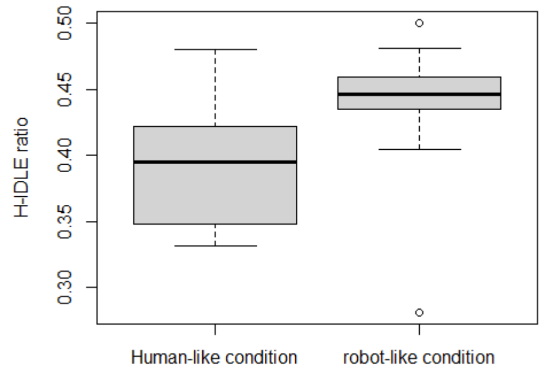

Figure 3: H-IDLE ratio from video observations

4.1.2 Performance of memory recall. The performance of memory recall was determined using the TEMPau test score. The primary experimenter reviewed all of the video data, and to reduce scoring bias, a second independent rater evaluated 20% of the data (N = 6) as well. The results indicated that they have the same viewpoint regarding the assessment with 100% inter-rater reliability. As shown in Figure 4, the TEMPau score of the human-like condition (Mdn = 1, SD = 1.18) is higher than the machine-like condition (Mdn = 1, SD = 0.68). Due to the non-normal distribution of these two datasets, we performed the Mann-Whitney test once more. The results showed that there is a significant difference between the two groups (w = 64, $p < 0.05$).

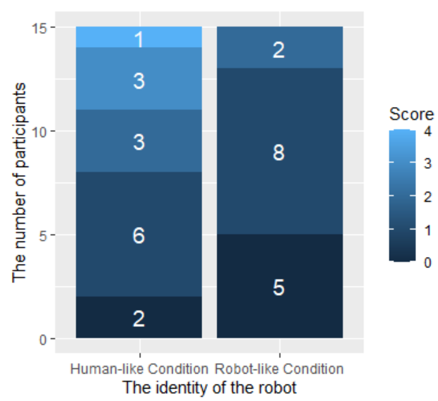

Figure 4: TEMPau test score from video observations (range from 0 to 4)

4.2 Questionnaire

4.2.1 Subjective fluency metrics. The subjective fluency metrics consisted of nine questions, each of which employed a 7-point Likert scale. In order to create a more normal distribution, which may

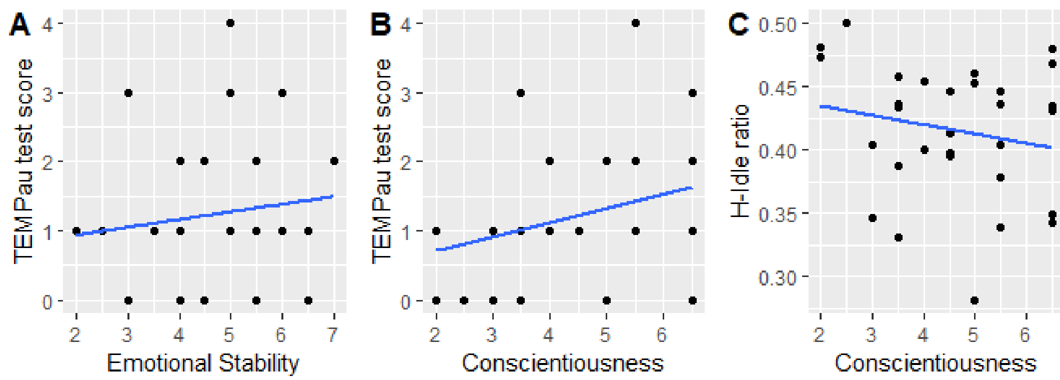

Figure 5: The relationship of personality to the H-IDLE ratio and TEMPau test scores (3 significant results)

be favourable to the t-test, a technique called summed scores was applied [6]. Due to the fact that both datasets passed the normality test, we performed a two-sample, two-tail, equal variance t-test. The findings show no statistically significant differences ($t(28) = -0.036$, $p > 0.05$) between the 15 participants who interacted with the human-like robot ($M = 48.07$, $SD = 5.12$) and the 15 individuals in the machine-like condition ($M = 48.13$, $SD = 4.85$).

Dimension	Average score	TIPI norms
Agreeableness	5.25	5.23
Conscientiousness	4.58	5.4
Emotional stability	4.7	4.83
Extroversion	4.05	4.44
Openness	5.13	5.38

Table 3: Comparison of average scores with TIPI norms

4.2.2 Big 5 personality. Table 3 shows that the average scores of the 30 participants are generally consistent with the TIPI score Norms. The Pearson correlation test was used to determine the relationship between the data. The results of the positive correlational analysis are summarised in Figures 5A and 5B, the TEMPau test scores exhibit a significant but weakly positive correlation to emotional stability ($r(28) = 0.398$, $p < 0.05$) and conscientiousness ($r(28) = 0.41$, $p < 0.05$). Participants with higher scores on the personality traits of emotional stability or conscientiousness expressed a richer memory. This result may be explained by the fact that people with higher emotional stability prefer the human-like robot rather than the machine-like robot [30, 34] and previous studies have demonstrated a positive relationship between conscientiousness and the intention to self-disclose [25].

Figure 5C indicates that the conscientiousness personality trait and the H-IDLE ratio were found to be negatively correlated ($r(28) = -0.34$, $p < 0.05$). In this human-robot interaction task, participants with higher conscientiousness personality trait scores had a lower H-IDLE ratio. The lower H-IDLE ratio means the inactive time ratio of the participant is also lower, which indicates more HRI fluency.

5 CONCLUSION AND FUTURE WORK

In this study, we designed, partly implemented, and evaluated a music assistive robot with two identities. One is attempting to act like a human, which was with intuitive fluid interaction but may provide the user with an inappropriate mental model. The other, who had clear expectations but less intuitively smooth interaction, exhibited machine-like traits. Whereas Neerincx et al. [26] did not find an effect of machine-like versus human-like identity (also for a Pepper robot), our experiment showed that the human-like robot outperforms the machine-like robot in terms of the fluency in the human-robot interaction and MEAMs performance in the music listening activity. Although the individuals did not perceive the human-like robot's fluency improvement subjectively. Furthermore, we discovered that participants prefer to dance with human-like robots during the experiment. Similar to Neerincx et al. [26], we found the effects of personality traits on the "richness" of the answers. However, they discovered a negative correlation between conscientiousness and the degree of self-disclosure, which is an interesting starting point for further personalization of the dialogues.

This research contributes to the development of social robots for elderly care, embedded with music that promotes the health and well-being of older adults. The robot can listen to music with the elderly and talk about music-related memories, which can help them have better mental health. The findings of this research may aid in understanding why more and more social robots are being developed to resemble humans since the human-like robot in the experiment performed better. In this first experiment, the robot was tested with young adults. Currently, we are preparing a follow-up experiment, consisting of longer sessions with the elderly to see whether the positive effect of "human-likeness" persists for this age group and how far the robot's identity influences the elderly's understanding and expectations of the robot's capabilities. This study may in general serve as a good point for the long-term application of social robots, because the music service can be repeatedly used. The elderly can benefit from the music activity by having a wide range of memories stimulated, which can improve their health and well-being.

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