Human-Like Social Robots in Retail: Investigating Perceived Similarity and Physiological Responses in AI-Driven Recommendations

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Abstract

AI-powered social robots are increasingly discussed as a way to improve the in-store customer experience, but the effects of similarity-based personalization remain unclear. This study examines whether language-based similarity features in a retail recommendation dialogue improve user comfort, trust, and intention to use. In a controlled laboratory experiment, participants interacted with the social robot Furhat either in a basic "good sales assistant" or in an adaptive, similarity-based variant (speech rate, volume, pitch and similarity statements). Questionnaire data and continuous electrodermal activity (EDA) were combined to capture both self-reported and physiological responses. Using robust mean comparisons (Yuen tests), structural equation modeling (SEM) and EDA analyses, no significant differences between conditions in terms of comfort, trust or intention to use were found. However, SEM revealed stable internal mechanisms: rapport strongly predicted comfort, usefulness strongly predicted trust and comfort predicted intention to use. These results suggest that the specific similarity cues implemented in this study do not reliably improve user responses in early retail robot interactions. In retail sales consulting, it seems sensible to leave robot behavior unadjusted and to base it on a generally good sales consultant. Improvement through personalization is not generally advantageous but it depends heavily on the context.

CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**; **Empirical studies in HCI**; • **Information systems → Personalization**.

Keywords

Human–robot interaction, social robots, personalization, perceived similarity, trust, comfort, intention to use, electrodermal activity, retail services

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1 Introduction

Retailers face growing pressure from online competition, rising costs, and omnichannel expectations, which is driving demand for high-quality in-store interactions. AI-powered social robots are a promising option because they can support customer decision-making as social interfaces [10, 29]. Yet acceptance remains limited: first encounters often create uncertainty and strongly shape comfort, trust and intention to use [12, 15, 16, 25, 26]. Trust and comfort are particularly fragile at this early stage. From a research method perspective, a further challenge is measurement, since self-reports mainly capture conscious evaluations; combining questionnaires with physiological measures is therefore recommended [30]. Prior HRI research and Similarity Attraction Theory suggest that perceived similarity can strengthen social connection and trust [6, 19]. However, conversational-agent research indicates clear boundary conditions: even with successful personality manipulation, matching users and agents by personality did not significantly increase communication satisfaction across introvert, ambivert, and extravert subgroups [1]. This suggests that similarity cues are not universally beneficial. Against this background, this study examines whether similarity cues, which are implemented through the robot's conversational behavior, in a retail recommendation dialogue influence comfort and trust. In a between-subjects study using the social robot Furhat, a basic "good sales assistant" variant is compared with an adaptive similarity-focused variant, combining questionnaire data with electrodermal activity (EDA) measures to derive design implications.

2 Theory and conceptual framing

This research is grounded on the Similarity Attraction Theory (SAT), which was justified by Byrne [7]. According to the theory people are generally more attracted to individuals who share similar attitudes and beliefs [22]. Studies show that the acceptance of AI and robots is higher when they are adapted to the users' characteristics [2, 3, 9, 11]]. SAT distinguishes between two primary dimensions of interpersonal similarity. The first dimension, surface-level similarity, focuses on visible demographic attributes including gender and ethnic background [11, 31, 32]. The second dimension, deep-level similarity, refers to psychological compatibility through shared attitudes, beliefs and personal viewpoints [2, 11, 32]. In total, research indicates that both surface-level and deep-level similarities play a significant role. Trust and comfort are key determinants of users' willingness to accept and use social robots in service settings, ultimately shaping intention to use [2, 8, 16, 17, 33]. Comfort can be understood as a state of feeling at ease (low distress) that is influenced by contextual and personal factors. The robot's design and interaction behavior act as salient environmental cues [4, 16, 21, 24, 28]. Trust reflects a positive expectation that the robot will competently support users' goals [12, 16, 33]. Building on the insight that comfort promotes trust and that both factors predict behavioral intentions [5, 16, 23], these constructs are supplemented by a conversation recommendation perspective using the CRS-Que framework [14, 20]. The aim is to capture users' perceptions of the quality of the conversation (attentiveness, positivity, coordination, rapport) and usefulness as precursors to attitudes and intentions. In line with previous work on factors of robot sociality [30], this study focuses on communication and language as the primary design lever and operationalizes similarity through adaptive speech characteristics and expressions of agreement. Given conflicting previous findings on similarity effects, the study examines whether language-based similarity cues improve user responses in HRI encounters in retail settings. The following research question is addressed: *Do similarity cues in a retail recommendation dialogue affect users' comfort, trust and intention to use compared with a basic non-adaptive robot variant?*

2.1 Study design and method

A controlled between-subjects laboratory experiment was conducted. Participants were randomly assigned to a basic condition (robot as a good sales assistant) or a similarity condition (robot as a good sales assistant with adaptive conversational behavior). In both conditions, the social robot delivered a running-shoe recommendation. In the similarity condition, it additionally adapted speech rate, volume, and pitch based on early user responses and used an agreement statement highlighting a similarity between the robot's preferences and the user's clothing. The agreement statement is generated by analyzing an image of the user, captured at the beginning of the conversation, using a local multimodal large language model. Both dialogue variants were implemented using OpenAI cloud text-to-speech. In addition, a manipulation check was included in the post-interaction questionnaire to assess whether participants perceived the robot as similar to themselves. To capture explicit and implicit responses, post-interaction questionnaires were combined with continuous electrodermal activity (EDA). EDA was recorded from the ring finger of the non-dominant hand (1–10 Hz), including a 2-minute neutral baseline [30]. Interaction milestones (B, R, V, I, E) were time-marked for segmentation. EDA was decomposed into tonic (SCL) and phasic (SCR) components, and NeuroKit2 [18] was used to extract interval-based arousal features (SCR frequency, mean phasic amplitude, sympathetic index, tonic variability) [13, 23, 30].

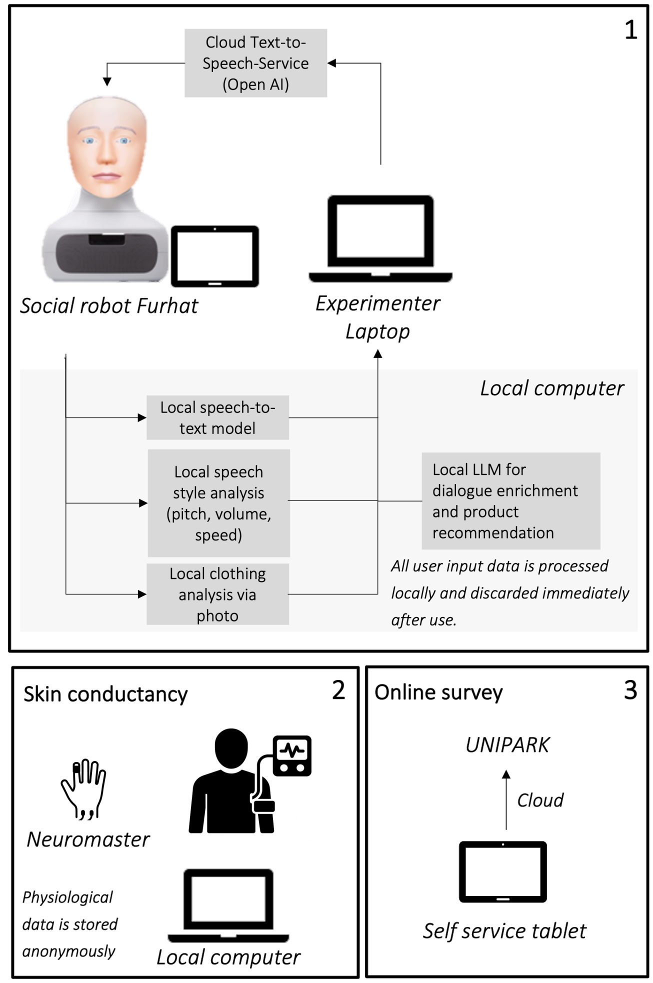

Figure 1: Technical setup of the experiment

2.2 Results

The final sample was N = 124 (basic: 61; similarity: 63). Both groups are comparable on demographics and prior robot experience. Most participants have little prior experience with robots (maximum 1-3 times or never: 73%) and the sample is predominantly young (86% for 18-25 years) and female (77%). The results of the manipulation check revealed no significant difference between the basic and similarity conditions ($p > .05$), indicating that the implemented similarity cues were not reliably perceived by participants. Because several constructs deviated from normality, Yuen tests (20% trimmed means) are used [27]. Descriptively, both variants were evaluated positively on a scale of 1 (disagree) to 7 (strongly agree) (Table 1). The basic variant showed higher means for most constructs (CUI Rapport, Comfort, Trust, and Usage Intention), while only CUI Usefulness was slightly higher in the similarity variant. However, none of these differences reached statistical significance (all $p > .05$).

Thus, the similarity-based variant did not significantly improve comfort, trust, or usage intention compared with the basic variant.

Table 1: Mean differences between conditions (selected constructs).

Construct	Basic (M)	Similarity (M)	Δ (B–S)	p (Yuen)
CUI Rapport	4.505	4.003	0.502	0.062
CUI Usefulness	4.918	5.048	-0.130	0.688
Comfort	5.621	5.371	0.250	0.370
Trust	4.954	4.690	0.263	0.160
Usage Intention	4.798	4.524	0.274	0.410

To assess latent relationships beyond group mean comparisons, a structural equation model (SEM) was estimated. Results indicate that CUI Rapport strongly predicts Comfort ($\beta = 0.565, p < .001$) and positively predicts Trust ($\beta = 0.201, p = .002$). CUI Usefulness strongly predicts Trust ($\beta = 0.709, p < .001$), while Comfort predicts Intention to Use ($\beta = 0.400, p < .001$). The path from CUI Usefulness to Comfort was not significant ($\beta = 0.133, p = .146$). Multigroup and moderation analyses further showed no reliable variant-specific differences in these relationships. Overall, the findings suggest stable internal mechanisms of user evaluation, but no measurable advantage of similarity cues at the group level.

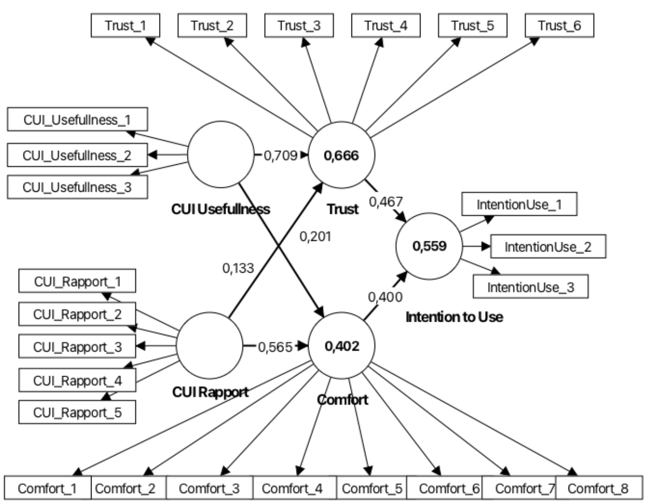

Figure 2: SmartPLS structural equation model

After preprocessing and quality control, the physiological dataset includes n = 119 (basic: 58; similarity: 61). The Yuen tests show no significant differences for central arousal indicators, including the number of phasic peaks per minute (SCR frequency), the mean phasic amplitude (SCR Amplitude Mean), the sympathetic activation index (EDA Sympathetic) and the tonic variability (EDA Tonic SD) (all p > .05). These measures capture complementary aspects of physiological arousal and emotional activation during the interaction. The absence of significant differences suggests that the similarity cues did not measurably affect participants' physiological engagement. Taken together, these findings answer the research question: in this retail HRI setting, speech-based similarity cues did not significantly improve comfort, trust or intention to use compared with the basic non-adaptive variant.

2.3 Conclusion

The study consistently shows across questionnaire, SEM and EDA analyses that the implemented similarity cues in this retail setting had no significant influence on comfort, trust or intention to use. Instead, conversation quality, especially rapport, emerged as a key driver of comfort and trust, and thereby indirectly of intention to use. However, no moderation by robot variant was found. This interpretation is supported by prior research: even with a successful personality manipulation, similarity matching (e.g., introvert user with introvert bot) did not produce significant gains in communication satisfaction within personality-based subgroups. A notable share of users even preferred an opposing style [1]. Practically, this suggests that personalization is not always beneficial when implemented as static similarity matching. In retail sales consulting, it seems sensible to leave the robot's behavior unchanged and align it with that of a generally good sales consultant. Improvement through personalization is not generally beneficial but depends heavily on the context. However, several limitations should be considered when interpreting these findings. Since several similarity cues were implemented simultaneously, the study cannot isolate the effect of individual cues. In addition, the findings should be interpreted in the context of short first-time interactions with a relatively young participant sample.

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