Human-robot interaction enhanced by a Large Language Model (LLM): analysis of the acceptability and usability of a social robot in a geriatric care institution.

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Abstract

Background: Socially assistive robots offer promising opportunities to support older adults in healthcare settings by enhancing communication, reducing loneliness, and promoting emotional well-being. Beyond direct patient interaction, socially assistive robots may also assist healthcare professionals by facilitating information delivery, relieving workload, and improving the organization of care activities. However, ensuring that these systems are both acceptable and usable by older adults and healthcare staff remains a critical challenge, particularly in dynamic hospital environments.

Objective: This study aims to evaluate the acceptability and usability of a social robot in a geriatric day care hospital among patients and their informal caregivers and to identify facilitators and barriers to the adoption of social robots in healthcare settings.

Methods: Tests were conducted between May 2023 and July 2024, involving 97 participants, including patients (n=65) and informal caregivers (n=32), across three experiments, called waves. The ARI robot, developed by PAL Robotics, was used in this study. Participants were invited to interact spontaneously with the robot as long as they wished, after which they completed usability and acceptability standardized questionnaires. They were administered orally and complemented by open-comments.

Results: Quantitative analysis showed a significant increase in usability and acceptability scores across the three experimental waves. and qualitative analysis revealed similar improvements and participants reported greater comfort and satisfaction, particularly after the integration of a large language model.

Conclusions: Successive upgrades of the social assistive robot, driven by large-language-model integration, led to significant increases in acceptability and usability scores across the three experimental waves, both in patients and caregivers. Introducing the LLM enabled the robot to engage in dialogues that were more natural, coherent, and context-sensitive. These findings show the value of an iterative, user-centred refinement process when integrating social robots in geriatric care. Clinical Trial: The study was approved by the French national ethics committee: “Comité de Protection des Personnes, CPP Ouest II, Maison de la

Recherche Clinique-CHU Angers" (IRB: 2021/20) and was compliant with the General Data Protection Regulation (GDPR) (DPO: 20210114153645, AP-HP register).

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Human-robot interaction enhanced by a Large Language Model (LLM): analysis of the acceptability and usability of a social robot in a geriatric care institution.

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Abstract

Background: Socially assistive robots hold promise for supporting older adults in hospital settings by promoting social engagement, reducing loneliness, and enhancing emotional well-being. They may also assist healthcare professionals by delivering information, managing routines, and alleviating workload. However, their acceptability and usability remain major challenges, particularly in dynamic real-world care environments.

Objective: To evaluate the acceptability and usability of a socially assistive robot in a geriatric day care hospital and to identify key factors influencing its adoption by older adults and their informal caregivers.

Methods: Over the course of one year, 97 participants (65 older adults patients and 32 informal caregivers) took part in a mixed-methods evaluation of ARI, a socially assistive humanoid robot developed by PAL Robotics. ARI was deployed in the waiting area of a geriatric day care robot in Paris (France), where it interacted with users through voice-based dialogue. After each session, participants completed two standardized assessments : the Acceptability E-scale and the System Usability Scale, administered orally to ensure accessibility. Open-ended qualitative feedback was also collected to capture subjective experiences and contextual perceptions.

Results: Acceptability scores significantly increased across waves (Wave 1: 15.4/30; Wave 2: 20.9/30; Wave 3: 22.5/30; P<.001). Usability scores also improved (Wave 1: 47.9/100; Wave 2: 57.4/100; Wave 3: 69.3/100; P<.001). A strong positive correlation was observed between

acceptability and usability scores (r=0.664; P<.001). Qualitative findings indicated improved ease of use, clarity, and user satisfaction over time, particularly following the integration of a large language model in Wave 2, leading to more coherent, natural, and context-aware interactions.
Conclusions: Successive system enhancements, most notably the integration of a large language model, led to measurable gains in usability and acceptability among patients and informal caregivers. These findings underscore the importance of iterative, user-centered design in deploying socially assistive robots in geriatric care environments.
Trial registration: This study was approved by the French national ethics committee (CPP Ouest II, IRB: 2021/20). As it did not involve randomization or clinical intervention.

Keywords: Socially assistive robots; Hospital environment; Gerontology; Older adults; Informal caregivers; Acceptability; Usability; Large Language Model; Human-robot interaction.

Introduction

The rapid aging of the global population is one of the major demographic challenges of the 21st century. According to United Nations projections, the number of people aged 65 and over worldwide is expected to increase from 727 million in 2020 to over 1.5 billion by 2050 [1]. This demographic evolution is accompanied by a growing need for long-term care and increased use of specialized services, particularly in geriatric institutions [2]. Consequently, geriatric institutions will face significant challenges in managing a rising number of residents, many of whom present multiple chronic conditions that require comprehensive and personalized care [3]. In response to this societal challenge, the adoption of innovative technologies and, in particular, socially assistive robots (SARs), is increasingly considered a complementary solution to improve the well-being and autonomy of older adults (OAs) [4,5]. SARs are robotic entities designed to interact with humans in socially and emotionally engaging ways. According to Dautenhahn [6], a SAR is “a robot that can interact with humans in a social context, while possessing communication and learning capabilities that mimic, to some extent, human behaviors”. These robots integrate artificial intelligence (AI) and natural language processing to a certain extent, enabling them to interact more naturally with users, leading to enhanced engagement and adaptation to different social contexts [7]. Within geriatric institutions, SARs have the potential to alleviate caregiver workloads, provide cognitive and social stimulation for patients, and assist with daily tasks [8]. However, for these innovations to be successfully implemented and fully beneficial, two critical ergonomic dimensions must be addressed: their acceptability and their usability in human-robot interaction (HRI).

The effectiveness of SARs in geriatric institutions largely depends on the quality of HRI [9,5]. Acceptability refers to how willing users - including patients, their informal caregivers, and healthcare professionals - are to adopt these new tools. This willingness is shaped by their beliefs, needs, and trust in the system [10,11]. Usability, in this context, refers to the extent to which a system supports users in accomplishing their tasks effectively, efficiently, and with satisfaction, within a defined environment. Beyond the system’s ergonomic characteristics, such as interface layout, feedback modalities, and physical interaction, it also encompasses aspects like learnability, error tolerance, and cognitive demand, which are particularly critical when designing for OA populations. [12,13, 14].

Despite their potential, SARs still face significant limitations regarding the quality of human-robot interaction and user engagement with the technology. Studies highlight that SARs often struggle to convey emotions effectively, understand context, and predict users’ behaviors accurately [15-17]. These shortcomings can lead to rigid and unnatural communication, hindering the robot’s ability to interpret human intentions and emotions [18]. Additionally, SARs often lack adaptability to

individual preferences, which can result in a gradual decline in user's interest and engagement [19]. These challenges highlight the importance of designing HRIs that are intuitive, customizable and aligned with the expectations of OAs to enhance both acceptability and successful integration into geriatric institutions. For example, OAs expect robots to use clear, slow speech, maintain a polite, emotionally supportive tone, minimize technical vocabulary, and favor voice-based over touchscreen-based interaction, all of which have been repeatedly identified as essential for promoting acceptance and usability among OAs [5, 19-23].

To overcome these limitations, recent research explored the integration of large language models (LLMs) into SARs to enhance their communication and interaction capabilities [24-26]. LLMs allow for greater conversational flexibility, improved comprehension of complex requests, and enhanced contextual coherence in responses [27, 28]. However, these advancements also introduce new challenges, including biases in generated responses, lack of transparency in robot decision-making, and difficulties in real-time interaction management [29,30].

Given the cognitive and physical limitations often present in OAs, SARs must feature intuitive and user-centered HRIs to maximize their effectiveness [20]. SARs acceptability does not only encompass perceived ease of use but also alignment with user needs, including preferences related to communication style, autonomy, affective support and interaction dynamics [10 ,31-35]. Among OAs, factors such as low digital literacy, distrust of technology, and sensory or cognitive impairments can influence acceptance [21, 36]. Barriers to adoption may include reluctance regarding the robot's appearance, communication style, or ethical concerns about reduced human interaction [11].

Simultaneously, usability focuses on how efficiently, effectively, and satisfactorily a system can be used to perform expected tasks [13, 14]. In geriatric institutions, usability considerations extend to physical ergonomics (e.g., size, weight, tactile interfaces, voice interaction), user safety, and emotional comfort [37]. Evaluating SAR usability through standardized methods, such as the System Usability Scale (SUS), helps identify insights about adoption barriers, assess ease of operation, and guide iterative technological improvements [38, 12].These aspects emphasize the necessity of a user-centered approach tailored to the specific needs of elderly users [20].

Several studies have investigated the acceptability and usability of SARs by OAs in real-world contexts, including institutional settings such as nursing homes and hospitals [19, 37, 39]. However, many of these evaluations rely on scripted interactions, or exclude contextual constraints found in routine care environments. While increasing attention has been paid to the perceptions of professional caregivers, relatively few studies have examined the opinions of informal caregivers (family or friends), despite their role in healthcare decision-making and daily care activities [21, 36]. These gaps highlight the need for in-situ evaluations that incorporate the perspectives of both patients and informal caregivers, while considering institutional realities.

To tackle these challenges, empirical research is essential to assess the acceptability and usability of SARs in real-world conditions. This study aims to evaluate the performance, acceptability and usability of a SAR among patients and their informal caregivers in a geriatric day care hospital (DCH) in Paris (France). It also aims to identify the factors that facilitate or hinder SAR adoption in geriatric institutions. The findings will provide deeper insights into the expectations and concerns of OAs and their informal caregivers regarding the use of SAR in healthcare while offering a set of recommendations to guide future technological and ergonomic advancements in this field.

Methods

Participants

This study involved two populations: OAs patients attending consultations at a geriatric day care hospital (DCH) and their informal caregivers.

Inclusion criteria for patients were: being ≥60 years older, having a Mini-Mental State Examination (MMSE) score above 10 (indicating absence of severe cognitive impairment, based on standard thresholds with scores of 25–30 are considered normal, 21–24 as mild, 10–20 as moderate, and below 10 as severe)[40], not exhibiting symptoms of altered reality and understanding and speaking french fluently. Informal caregivers were family members or friends (primarily spouses or children) aged ≥18 years, accompanying the patient and speaking french fluently.
No *exclusion criteria* were applied based on gender, socio-professional background or ethnicity.

Recruitment of participants

Recruitment was carried out using the DCH database, and participants were pre-screened prior to enrollment, contacted by phone and invited to participate in the study the day of their next consultation. An information letter was sent by post and informed consent was collected on-site.

Setting

The study was conducted between May 2023 and July 2024 in the geriatric DCH of the French Memory Clinic of a geriatric hospital in Paris, France. The DCH provides specialized outpatient care for OAs with physical and/or cognitive impairments, offering a wide range of consultations, including neurology, oncology, cardiology, psychiatry, and memory assessments. Three waves of data collection were carried out during this period, with a different sample of participants included in each iteration.

Study design

A mixed-method design was used, combining qualitative and quantitative methods to provide an in-depth understanding of the acceptability and usability of a SAR in a geriatric institution. Mixed methods are particularly suited to exploring complex phenomena in the health and social sciences, as they enable the integration of complementary perspectives and strengthen the validity of results [41, 42]. By combining quantitative rating scales with semi-structured interviews, this approach identifies both general trends and nuances specific to users' perceptions [43, 44]. Mixed methods enable data triangulation, essential for understanding factors that influence SAR adoption in real-world contexts [45]. This approach, widely recognized in health services evaluation, guarantees a richer, contextualized analysis of the dynamics at play [46, 47].

Material

ARI robot

The SAR used in this study was ARI, developed by PAL Robotics (Spain)[48]. The robot is 1.65 m (5 ft 5 in) tall and weighs 50 kg. The robot moves by rolling and is equipped with articulated arms that are not designed for load-bearing. Its interface includes a touch screen for dialogue transcription located on the torso, animated eyes with a gaze-tracking module, luminous ears, and an emergency stop button on the back of the robot. ARI supports autonomous operation for 8 to 12 hours prior to recharging. It is equipped with wired and wireless connectivity capabilities, for flexible integration into a variety of environments. For visualization, ARI is equipped with 3 wide-angle cameras positioned on the head, chest and back, giving it a wide and versatile view of its surroundings. In terms of audio, the robot features four microphones, facilitating voice recognition and the efficient

capture of ambient sounds.

For this study, the ARI robot was programmed with a set of modules explicitly developed as part of the European H2020 SPRING project, described in Alameda-Pineda et al. (2024) [49]. Among these modules, the conversational system was initially developed, before recent LLM advances (such as ChatGPT), relying on a ‘traditional’ modular architecture that combines retrieval-based responses, rule-based intent handling, and open-domain generation [50] (Wave 1). In order to take advantage of LLMs abilities for solving complex language-related tasks the conversational systems was redeveloped (Wave 2) and refined (Wave 3) with an LLM-based architecture, based on the a Vicuna model with 13 billion parameters (Vicuna-13b-v1.5 [51]). For deployment in hospital settings, it was adapted to function offline and integrated with a custom prompt targeting healthcare-related scenarios in French. This design ensured safe use without requiring an internet connection, while enabling more coherent and context-sensitive interactions with patients and informal caregivers.

At the time of the study, ARI had not yet been commercially deployed in hospitals or long-term care institutions beyond the scope of research projects. Its use in this evaluation should therefore be considered as part of an exploratory, pre-commercial experimentation phase within controlled healthcare settings.

Figure 1. Photos of ARI robot, front and side (Photo credit: Pal robotics)

Introduction of ARI’s capabilities

The SAR was deployed in the waiting area of a geriatric DCH, to welcome and assist patients and their informal caregivers. Although participants were free to interact spontaneously with the robot, the researcher introduced five illustrative use cases at the beginning of the session to showcase the robot’s potential functionalities: (1) greeting and welcoming the user; (2) recalling hygiene and infection prevention procedures; (3) providing information on the consultation procedure; (4) offering orientation and guidance about hospital services and (5) providing entertainment activities. These examples were intended to guide participants' understanding of the robot's capabilities, without restricting the content of their interactions.

Ethical approval and compliance with data protection regulations

The study was approved by the French national ethics committee: “Comité de Protection des Personnes, CPP Ouest II, Maison de la Recherche Clinique-CHU Angers” (IRB: 2021/20) and was

compliant with the General Data Protection Regulation (GDPR) (DPO: 20210114153645, AP-HP register).

Assessment scales

To assess the acceptability and usability of the ARI robot in a DCH, we used two standardized scales.

(a) *Acceptability*: Assessed using the Acceptability E-scale (AES), french version [52]. Acceptability is defined as the psychological determinants that shape an individual's intention to use a technology prior to any direct experience with the system. The AES scale comprises six items rated on a 5-point Likert scale, yielding a total score ranging from 6 to 30. For marketable products, the scale's acceptability threshold is set at 25.81/30. The adapted version of the scale used in this study is provided in Multimedia Appendix 1.

(b) *Usability*: Assessed using the System Usability Scale (SUS) [53, 54]. Usability refers to the degree to which a system can be used by specified users to achieve specific goals with effectiveness, efficiency, and satisfaction in a specified context of use. Ease of use influences user performance and satisfaction, while acceptability determines actual usage [55]. The SUS consists of a 10-item scale designed to assess the overall usability of a system, generating an overall score out of 100, where a higher score reflects better usability. For this scale, experimenters are asked to respond to statements on a 5-point likert scale ranging from "strongly disagree" to "strongly agree". The usability threshold for marketable products is 72/100 for this scale. The adapted version of the scale used in this study is provided in Multimedia Appendix 1.

For each of the scales, participants were invited to comment on their choices in a discussion with the researcher.

Assessment Procedure

Each session (~45 minutes) took place in a dedicated room. After free interaction with the robot, participants completed two validated instruments: the Acceptability E Scale (AES) and the System Usability Scale (SUS). Both were administered orally and supported by open-ended discussion to elicit qualitative data. Finally, participants were accompanied back to the waiting area.

Data analysis

To ensure a comprehensive understanding of the research topic, both qualitative and quantitative data were collected. Each session was audio-recorded and subsequently transcribed for analysis.

Descriptive statistics (means, standard deviations and percentages) were used to describe the sample characteristics and the scores obtained on the AES and SUS scales.

To assess statistical differences between waves and between groups, several statistical tests were performed. First, Kruskal-Wallis tests were used to compare multiple groups and Mann-Whitney tests were used to compare two scores or two groups. Shapiro-Wilk tests were used for normality assumption.

When significant differences were found, Tukey's post-hoc tests were conducted to further explore the data. A p-value less than 0.05 was considered statistically significant in all analyses.

Qualitative data were analyzed using inductive thematic analysis [56], allowing themes to emerge from the transcripts of the interviews with the researcher.

System evolution for each experimental wave

In order to evaluate the evolution of the ARI robotic system, with the help of feedback from participants, we carried out system updates. Over the evaluation period, the ARI robot received two updates, resulting in 3 waves of experimentation. Table 1 shows the overall differences in system performance over the three test waves and the full list is described in SPRING Deliverable D1.6 [57].

Table 1. System evolution based on participants' feedback

Aspect	Wave 1 (May - July 2023)	Wave 2 (Sept. - Dec. 2023)	Wave 3 (March - May 2024)
Robustness of robot 's responses	Basic diagnostic tools to prevent operational failures; first version of a modular dialogue system.	Improved diagnostic tools accuracy; reduced memory/computational load for vision modules; integration of an extended LLM.	Enhanced general system stability; improved speech recognition robustness.
Features display and interactive functionalities	Display of dialogues transcription on the robot screen.	Optimized display output; improved display model for transcribed speech	Conversation start/end display; operator speech control; refined LLM prompt tailored to hospital context.
Perception and tracking	Depth estimation of the environment, person tracking, and facial identification modules.	Integration of a module for associating vocal input to individual users (Ecapa model); optimization of facial recognition processing time.	Addition of head movements enabling the robot to follow participants' gaze; optimization of gaze estimation; improved audio-visual tracking; enhanced speaker identification (Ecapa2 model); improved Voice Activity Detector.

Results

Participants - Socio-demographic data

Descriptive statistics

Over the three experimental waves, one hundred and ten participants (n=110) agreed to take part in the study. Of these, only ninety-seven (n=97) completed the experiment. Incomplete robot assessment sessions occurred when participants were called away for their scheduled medical appointments.. The results presented below reflect the feedback from these ninety-seven participants (n=97) across the 3 experimental waves (Wave 1=14 participants; Wave 2=43 participants; Wave 3=40 participants). Table 2 shows the socio-demographic data for these participants in each wave. Participants are categorized as patients (P) or informal caregivers (IC).

Table 2. Socio-demographic data for each experimental wave.

Wave n	Profile n (%)	Gender n (%)	Age years (± SD)	Education years (± SD)	MMSE score (± SD)
Wave 1 14	P: 11 (79%)	M: 2 (18%); F: 9 (82%)	78.4 ± 7.1	13.6 ± 2.1	27.8 ± 1.9
	IC: 3 (21%)	M: 1 (33%); F: 2 (67%)	75.3 ± 11.6	12 ± 3	N/A
Wave 2 43	P: 30 (70%)	M: 9 (30%); F: 21 (70%)	78.3 ± 6.6	12.9 ± 3.5	25.2 ± 4.5
	IC: 13 (30%)	M: 5 (39%); F: 8 (61%)	63.9 ± 19.4	15.0 ± 00	N/A
Wave 3 40	P: 24 (60%)	M: 6 (25%); F: 18 (75%)	81.2 ± 6.4	11.4 ± 3.6	25.5 ± 3.9
	IC: 16 (40%)	M: 9 (56%); F: 7 (44%)	67.9 ± 12.9	13.2 ± 4.1	N/A
Total 97	P: 65 (67%)	M: 17 (26%); F: 48 (74%)	79.4 ± 6.7	12.5 ± 3.4	25.7 ± 4.1
	IC: 32 (33%)	M: 15 (47%); F: 17 (53%)	67 ± 15.7	13.8 ± 3.2	N/A

Socio-demographic data analysis using non-parametric tests (justified by significant Shapiro-Wilk tests indicating non-normal distributions: $P<.001$ for socio-educational level, $P=.008$ for MMSE scores, and $P\leq0.003$ for age across waves 2 and 3) revealed no significant difference in terms of age across the three waves ($\chi^2(2)=.388$, $P=.824$), no significant difference in socio-educational level ($\chi^2(2)=3.330$, $P=.189$), suggesting a relatively homogeneous distribution of these characteristics among the groups. Furthermore, no significant difference was observed regarding the MMSE scores of patients across waves ($\chi^2(2)=4.064$, $P=.131$).

A correlation analysis was carried out between the AES and the SUS scores in order to explore the consistency of participant's responses across the two scales. The results reveal a strong positive correlation between the two variables ($r=0.664$, $P<.001$), indicating that higher acceptability scores were associated with higher usability scores.

Figure 2. Illustration of experiments

Acceptability E-Scale (AES)

AES results over the three waves of observation showed a positive progression between waves: 15.4/30 (SD=5.81) for Wave 1, 20.9/30 (SD=5.25) for Wave 2, and 22.5/30 (SD=4.23) for wave 3, indicating a steady increase over time. Using the Kruskal-Wallis test, the mean scores for AES show a significant increase in scores between waves ($\chi^2(2)=13,4$; $P<.001$). The Mann-Whitney test revealed no significant differences in AES scores between male and female participants (U=960, P=.705), nor between patients and informal caregivers (U=905, P=.567).

Analysis of the AES scores across the three experimental waves showed a significant difference between Wave 1 and Wave 2 ($P<.01$) as well as between Wave 1 and Wave 3 ($P<.001$). Additionally, no significant difference was observed between Wave 2 and Wave 3.

Based on these findings, an item-by-item analysis was conducted to identify specific differences across the themes related to system acceptability. Tukey post hoc tests revealed significant differences in four of the six items: robot usability, robot's perceived usefulness in the hospital setting, robot's response time, and overall satisfaction with the robot.

Regarding satisfaction with the robot, a significant mean difference of –0.956 was observed between Waves 1 and 2 (P=.018), and a difference of –1.336 between Waves 1 and 3 (P<.001). With respect to the robot's perceived usefulness in the hospital, a significant mean difference of –1.289 was found between Waves 1 and 3 (P=.004). The robot's response time showed a significant difference of -1.86 between Waves 1 and 2, and a significant difference of -2.079 between Waves 1 and 3 ($P<.001$). Finally, on overall robot satisfaction, a mean difference of -0.815 was observed between Waves 1 and 2 ($P=.042$), as well as a mean difference of -1.246 between Waves 1 and 3 ($P<.001$).

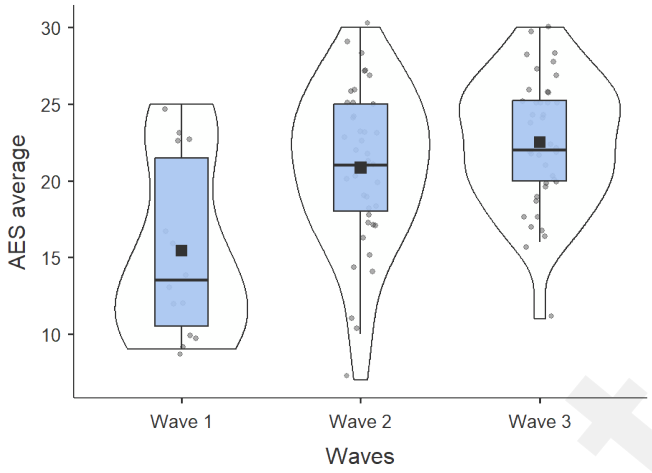

Figure 3. AES scores across the three experimental waves

System Usability Scale (SUS)

SUS results over the three waves of observation showed a positive progression between waves: 47.9/100 (SD=24.18) for Wave 1, 57.4/100 (SD=22.46) for Wave 2, and 69.3/100 (SD=16.03) for Wave 3, indicating a steady increase over time. Using the Kruskal-Wallis test, the mean scores for SUS show a significant increase in scores between waves ($\chi^2(2)=11,4$; $P<.001$). Mann-Withney test revealed that no significant differences were observed in SUS between the results for men and women (U=848, $P=.141$) and for patients and those of informal caregivers (U=855, $P=.189$).

Analysis of SUS scores across the three experimental waves revealed significant differences between Wave 1 and Wave 3 (P<.01), and between Wave 2 and Wave 3 (P<.05). No significant difference was found between Wave 1 and Wave 2 (P>.05).

Based on these findings, an item-by-item analysis was conducted to examine specific differences in responses related to system usability. Tukey post hoc tests revealed significant differences in five of the ten items: conversation complexity, assistance, inconsistency, ease of use, and user confidence.

On the complexity of conversations, a significant difference of -1.089 was observed between Waves 1 and Wave 3 ($P=.014$). Regarding the assistance required to interact with the robot, a significant difference of -1.182 was observed between Waves 1 and 3 ($P=.023$). Regarding the design of the robot's functionality, a significant difference of -1.039 was observed between Waves 1 and 3 ($P=.005$) as well as a mean difference of -0.569 between Waves 2 and 3 ($P=.039$). Robot inconsistencies showed a significant difference of -1.28 between Waves 1 and 2 ($P=.003$) and of -1.632 between Waves 1 and 3 ($P<.001$). Finally, for confidence using the robot, a significant difference -1.050 was observed between Waves 1 and 3 ($P=.014$).

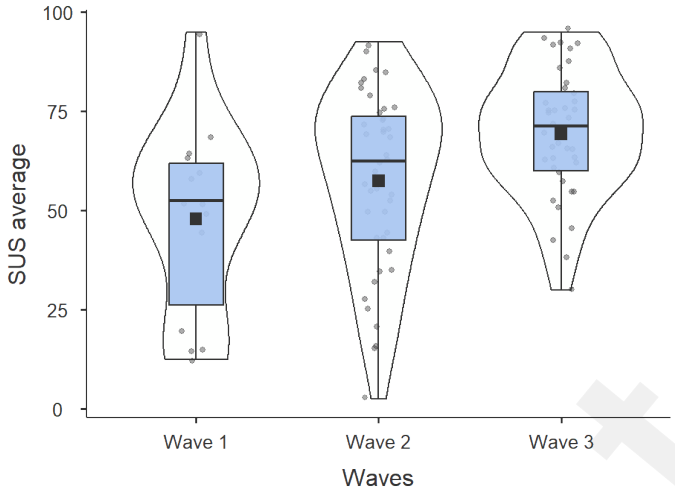

Figure 4. SUS scores across the three experimental waves

Qualitative data

Thematic qualitative analysis

A thematic qualitative analysis of participants' feedback was conducted to explore perceptions of the ARI robot's acceptability and usability. Verbatim responses from patients and informal caregivers were reviewed and categorized into five themes representing key aspects of user experience: (1) ease of use, (2) comprehension of the robot responses, (3) perceived usefulness of the robot in a hospital setting, (4) quality of interaction, and (5) overall system satisfaction. These themes correspond to established dimensions of acceptability (e.g., perceived usefulness, satisfaction) and usability (e.g., ease of use, comprehension, efficiency). Each theme is illustrated with representative quotes translated from French to English.

Ease of use

The robot's ease of use, an essential component of acceptability, was progressively enhanced throughout the study. While its physical ergonomics remained constant, updates to the dialogue system facilitated more fluid and coherent interactions. These improvements contributed to users' perceptions of the robot as simpler and more intuitive to operate. Several participants pointed out that the novelty of the robot could, at first, generate a certain amount of reluctance, suggesting that perceived ease of use also depended on experience acquired through interaction. For example, in Wave 1, some found the voice interface practical: "*The voice is helpful because I can't see well* [referring to the transcript on the robot's screen]*. You just have to ask it a question.*" (IC-Wave1), while others found it unintuitive: *"Not at all* [easy to use]*!"* (P-Wave1). However, some participants pointed out the limit of novelty when faced with a robot: "*I mean, we're not used to it. When you're used to it, it's easy, but not the first time. It's a bit confusing. You have to get used to it.*" (P-Wave1). This need for an adaptation period was most prominent in Wave 1, when the system was less refined, but it also emerged in a few cases in Waves 2 and 3. This suggests that while improved usability facilitated smoother interactions, user familiarity remained a factor influencing initial comfort in engaging with the robot.

As waves progressed, more participants acknowledged the simplicity of interacting with the robot: *"It's easy, you just need to ask questions, and if the question is relevant, it answers."* (P-Wave2). However, some participants reported challenges in formulating their questions appropriately: "*I had*

to force myself to phrase my questions differently from how I would naturally say them." (IC-Wave3).

Understanding the robot's response

Although voice synthesis remained consistent, updates to the dialogue system, particularly the integration of a LLM facilitated clearer and more coherent exchanges. While participants generally found the language comprehensible, some reported mismatches between their questions and the robot's responses, suggesting that perceived comprehension remained sensitive to the contextual specificity of the interactions. In Wave 1, participants' opinions ranged from finding the robot's speech fully understandable, *"They were completely understandable and easy."* (P-Wave1), to report inconsistencies in comprehension. In Wave 2, many agreed that the robot spoke clearly: *"It was perfectly understandable."* (P-Wave2), although some responses were off-topic: *"Its explanations are clear, but some responses were off the mark."* (IC-Wave2). In Wave 3, while participants generally found the language clear: *"I found it very clear and precise."* (P-Wave3), some noted occasional mismatches between their questions and the robot's responses: *"Not entirely understandable, because it made me ask the same question multiple times."* (P-Wave 3).

Perceived usefulness of the robot in hospital settings

Perceptions of the robot's usefulness evolved over the three waves. While some participants found it useful for providing basic information, others expected a more interactive experience. Over time, the focus shifted to the accuracy of the robot's responses, with some seeing it as a "glimpse into the future", while others emphasized its current limitations. In Wave 1, some found it practical for basic information: *"Just telling me* [the location needed] *it's next door was enough for me."* (IC-Wave1), while others expected a more interactive experience: *"If it* [the robot] *had come with me* [to show me the path]*, it would have been better."* (P-Wave1). In Wave 2, usefulness was conditional on the accuracy of responses: *"Plenty useful, but only if it understood the question and answered it correctly."* (IC-Wave2), "*It did the job, but a good signpost could do it too."* (IC-Wave2). By Wave 3, opinions remained divided, with some participants perceiving the robot as indicative of future technological developments: *"It's an opening into something futuristic. So, it's useful to me."* (IC-Wave3), while for others opinions remained mixed with respect to the robot. *"Well, it annoyed me quite a bit* [...] *Every time I ask it a question, it tells me to go to the reception."* (IC-Wave3). However, some participants highlighted its efficiency: *"It answered all those questions 100%."* (IC-Wave3), and its consistency compared to human interactions: *"Even if some people might find a human more pleasant, humans can get tired or irritated—whereas ARI* [the robot] *never does."* (IC-Wave3).

Quality of interaction

Throughout the study, updates to the robot enhanced the fluidity of interactions and the quality of user feedback—two factors critical to its acceptability. These improvements, particularly in response speed, interruption management, and response richness, were reflected in participants' feedback. During Wave 1, the robot demonstrated inconsistent response patterns, as reported by participants *"I asked a question, but it* [the robot] *responded with something completely unrelated—it was totally incoherent."* (P-Wave1), and some participants also perceived that the robot had a limited range of programmed responses: *"I have the impression that it is programmed only to answer certain questions."* (P-Wave1). Additionally, participants noted that the robot often repeated suggestions unrelated to their queries: *"But it does offer to go to lunch a lot."* (P-Wave1). In Wave 3, some participants noted that the robot responded promptly. *"You ask the question, and it answers almost immediately."* (IC-Wave3), whereas others reported challenges in interrupting the robot] while it was

delivering a response. *"You can't interrupt it, and that bothered me a bit."* (IC-Wave3). Furthermore, some participants expressed a preference for the robot's responses over those provided by human receptionists: *"I prefer your robot's answers to those of the ladies at the reception."* (P-Wave3), *"There are humans who aren't as direct and precise* [...] *I'm surprised."* (P-Wave3).

General satisfaction

Overall satisfaction with the experimentation of the robot reflected growing acceptance in terms of both functional effectiveness and ease of use, with clear progression observed from the first to the final wave. In Wave 1, some participants appreciated the robot's novelty: *"I think it is really nice. I think it's fun and funny."* (IC-Wave1), *"I like it—it's nice. Really nice. It's great to see a robot. But a human is still nicer."* (IC-Wave1). Conversely, some participants expressed dissatisfaction: "*I'm sorry if I sound upset, but I didn't feel any satisfaction."* (P-Wave1), *"I didn't get any satisfaction—the robot didn't help me at all. It's actually a bit scary."* (P-Wave1). In Wave 2, reactions remained mixed; some participants found the robot engaging and entertaining. *"I find it amazing, it's super."* (P-Wave2), "*It's impressive, it's the first time it's happened to me, I didn't know robots at all before today and it's impressive to see a machine that you ask questions to, that answers you.*" (P-Wave2), while others highlighted its limitations: "*I'm sure the robot has potential, but at the moment, it's not performing well." (*IC-Wave2). In Wave 3, participant feedback was generally more favorable. Participants described the robot as *"very interesting, very instructive because it's very knowledgeable. It answered me perfectly well."* (P-Wave3) and declared that *"it's funny because you don't expect to find something like this, and it does have quite a lot of answers."* (IC-Wave3). Others expressed an overall appreciation: *"Oh, I like it a lot. I think it's nice, it has beautiful eyes."* (P-Wave3), *"I like this thing."* (P-Wave3).

Discussion

Synthesis of results

This study provides one of the first in-situ evaluations of a SAR equipped with a LLM in geriatric hospital setting. Quantitative data showed a significant increase in both acceptability and usability of the ARI robot, corroborating the qualitative findings. Participants reported improved ease of use, comprehension, and perceived usefulness across experimental waves, as reflected in the significant increases in AES and SUS scores. Acceptability scores increased from 15.4/30 in Wave 1 to 22.5/30 in Wave 3 ($P < .001$), while usability scores rose from 47.9/100 to 69.3/100 ($P = .003$). Verbatim feedback reflected a growing appreciation for the robot's functionality and ease of interaction, aligning with observed improvements in satisfaction and perceived usefulness. These improvements are largely attributable to technical upgrades, most notably the integration of a LLM, which enhanced the naturalness, contextual relevance, and consistency of interactions. The experimental conversational system, developed collaboratively within the H2020 SPRING project [58], consists of an audio-visual perception pipeline that captures speech and behavioral cues, processed by a dialogue system powered by a LLM to synthesize responses into sound. Collectively, these developments contributed to a more fluid, engaging, and user-centered experience with the robot.

Although the ARI robot is commercially available, the conversational system developed in this study remains experimental. Final scores did not meet established thresholds for acceptability (AES>25.81) and usability (SUS>72), underscoring the need for further refinement prior to large-scale hospital implementation, such as transitioning to full-duplex communication, adding multilingual support, and incorporating non-verbal feedback. Nonetheless, the upward trajectory of these scores is encouraging, suggesting strong potential for future clinical deployment as

performance approaches benchmark criteria.

Limitations

This study presents several limitations related to both the experimental design and the technical capabilities of the robotic system.

From a methodological perspective, the study was conducted at a single site within an innovation-friendly clinical environment. While this facilitated implementation, it may limit the generalizability of the findings to institutions with different organizational structures or cultural contexts. Moreover, the recruitment strategy relied on voluntary participation, introducing a potential self-selection bias.

Another limitation concerns the ecological validity of the experimental conditions. Although the robot was deployed in a hospital setting, the interactions took place in a quiet, controlled room rather than in a dynamic waiting area. This may have minimized external distractions and reduced communication challenges typically present in real-world hospital contexts. In addition, the interaction occurred only once per participant. As a result, the findings largely reflect first impressions and do not capture how user perceptions evolve with repeated exposures or long-term use. Longitudinal studies are needed to assess the durability of engagement and trust over time.

On a technical dimension, while the integration of a LLM improved conversational coherence, the system remained prone to occasional misinterpretations or generic responses, especially when confronted with vague or ambiguous input. This limitation is consistent with known issues in LLM-based dialogue systems, which often struggle with generating contextually appropriate and non-generic responses when input is vague or underspecified [59]. Furthermore, the robot's speech recognition system showed sensitivity to user-specific features such as accent, speech rate, and background noise. Finally, the absence of multilingual support reduced inclusiveness for non-French-speaking users, an important consideration in multicultural healthcare environments.

Comparison with prior work

Our findings align with existing literature showing that AI-powered SARs can significantly enhance user engagement when interactions are intuitive and socially appropriate [5, 19, 26]. The integration of a LLM between Wave 1 and Wave 2 notably improved the robot’s conversational fluency and contextual relevance, features widely recognized as essential for effective human-robot interaction [1,2]. Although natural language processing has long been identified as a key component of user engagement, very few studies have directly captured the impact of integrating an LLM into SARs in a healthcare context. Most prior evaluations were conducted either before the emergence of transformer-based language models (pre-2019) or focus on single-instance deployments with fixed systems. Moreover, while most existing studies on SARs have been conducted in controlled environments such as laboratories or nursing homes [3,4], few have examined how real-time system refinements affect user perceptions over successive implementation phases. The present study addresses this gap by documenting how progressive improvements to the LLM-based dialogue system influenced usability and acceptability in situ, over three successive waves.

Future systems should integrate multimodal strategies, (e.g., gesture recognition, facial expression analysis, affective cues), to support more natural and empathetic communication in healthcare environments [49, 16].

Our results also align with previous research advocating for voice-based interaction as particularly suitable for older adults, especially in contexts where digital literacy may vary [22, 23]. Participants consistently favored spoken communication over touchscreen input. Furthermore, the inclusion of

real-time transcription improved accessibility, confirming prior findings on the value of combining auditory and visual cues for inclusive design [60].

Confidence in using the system was closely linked to interaction quality as while Wave 3 participants, who received consistent and context-aware responses, gained confidence, those in earlier waves, confronted with erratic outputs, voiced concerns about the robot's reliability. Interestingly, some participants also blamed themselves, reflecting a well-documented phenomenon in HRI literature, automation bias, where users tend to overestimate the capabilities of intelligent systems and assume personal responsibility for communication failures [61, 62]. These findings underscore the critical role of transparency and predictability in AI-driven behaviors as key determinants of user confidence, reinforcing prior research in human-robot interaction [16, 63, 64].

Finally, our results reaffirm the need for user familiarization with voice-based robotic interaction in healthcare contexts. For the majority of participants, this study marked their first direct interaction with a SAR, and many indicated the need for a period of adjustment. Initial hesitation often gave way to positive engagement, echoing previous research showing that structured onboarding and repeated exposure are key to long-term acceptability [11].

Recommendations

Drawing on the empirical findings of this study, the following recommendations are intended to inform the design and implementation of SARs tailored to the specific interactional needs of OAs in geriatric care settings. These evidence-based insights aim to guide researchers and industry stakeholders in developing socially assistive technologies that are both user-centered and contextually appropriate within healthcare environments.

Improve natural language processing, speech recognition, and multilingual support

To enhance the quality of HRI in geriatric care, it is recommended that future SARs integrate more advanced natural language processing capabilities than those available in current open models to ensure greater coherence and contextual relevance in responses. Speech recognition systems should be optimized to account for prosodic variation, regional accents, and articulation differences (such as slower speech rate, reduced vocal intensity, hesitations, or imprecise consonant production) commonly observed among OAs due to age-related changes in respiratory and orofacial motor control [65]. In addition, the incorporation of multilingual functionality is essential to accommodate the linguistic diversity of users in healthcare settings and to promote equitable access to robotic services.

Develop clear onboarding protocols and autonomous robot self-presentation

To facilitate user engagement and support initial interaction, it is recommended that future deployments of SARs include a structured onboarding protocol. This may involve brief demonstrations or the distribution of printed materials (e.g., leaflets with example questions) to familiarize users with the robot's capabilities. However, recognizing that real-world hospital settings may not consistently offer human assistance at the point of interaction, SARs should also be equipped with a robust self-introduction feature. This feature should autonomously guide users through the robot's purpose, functionalities, and appropriate use cases, clarifying when and how to engage, and what types of questions it can address. Such improvements are essential for promoting user autonomy, reducing uncertainty, and improving the perceived usefulness of SARs in healthcare environments.

Such improvements are essential for OAs, who often face reduced digital literacy, cognitive decline or impairments, or heightened anxiety when interacting with unfamiliar technologies. Study has shown that guided introductions, whether verbal or visual, enhance initial confidence, reduce hesitation, and support sustained engagement [66, 67].

Ensure compliance with privacy, ethical, and regulatory standards

It is essential that the development and deployment of SARs in healthcare settings align with existing ethical guidelines and data protection regulations. Particular attention must be given to the collection, processing, and storage of sensitive health-related information. Developers and implementers should establish clear protocols for obtaining informed consent, ensuring transparency regarding data usage, and enabling users to understand the scope and limitations of data handling. Additionally, SARs should be designed to support confidential interactions, especially when used with vulnerable populations such as OAs, by incorporating features that safeguard user privacy and uphold professional standards of care. Early integration of ethical and legal considerations will be critical to building trust and ensuring responsible implementation.

Enhance interruption management and conversational fluidity

Participants highlighted the difficulty of interrupting the robot while it was speaking, a limitation that disrupted the natural flow of dialogue. To address this issue, future iterations of SARs should improve turn-taking mechanisms and enable responsive interruption handling, especially in multi-party or fast-paced care environments. These refinements are essential for supporting user-led interaction, minimizing frustration, and improving conversational naturalness.

Enable autonomous navigation and spatial guidance

Several participants expressed the desire for the robot to not only provide verbal instructions but also to physically accompany them to their destination. Incorporating autonomous navigation capabilities would expand the robot's role from an informational assistant to an active guide, offering greater support to users with mobility or orientation difficulties in complex care environments such as hospitals. To ensure safe and effective guidance, particular attention should be paid to obstacle detection and navigation in dynamic environments, as well as to adapting the robot's speed to the walking pace of OAs.

Conclusions

This study shows that SAR, when iteratively enhanced and evaluated in real-world conditions, can reach growing levels of acceptability and usability among OAs and their informal caregivers. The integration of a LLM was a turning point in improving the robot's ability to engage in meaningful, coherent interactions. These findings suggest that SARs, when designed with user needs in mind, hold strong potential for supporting care delivery in geriatric hospital settings.

Looking ahead, future work should focus on further leveraging the capabilities of LLMs to enable adaptive, personalized interactions that respond to individual users' communication styles, memory, and emotional cues. Additionally, the integration of multimodal communication features, such as gaze tracking, gesture and facial expression recognition, and targeted dialogue strategies, will be essential to enhancing the robot's relevance, trustworthiness, and effectiveness in complex healthcare environments.

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Conflicts of Interest

None declared

Abbreviations

AES: acceptability e-scale
AI: artificial intelligence
IC: informal caregiver(s)
MMSE: mini-mental state examination
OA: older adult(s)
SAR: socially assistive robot(s)
SUS: system usability scale

Data Availability

Requests to access the datasets should be sent to anne-sophie.rigaud@aphp.fr.

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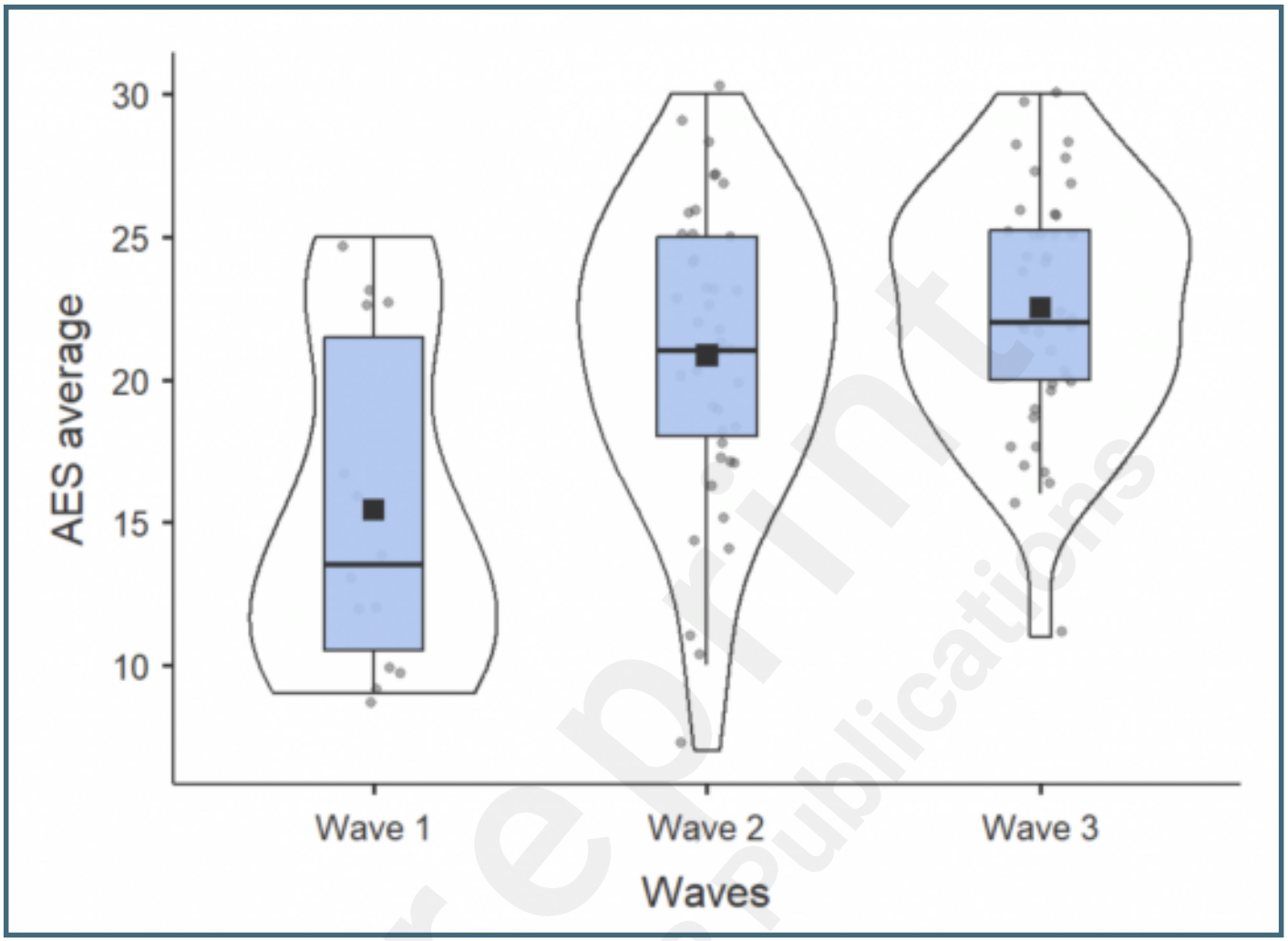
Supplementary Files

Figures

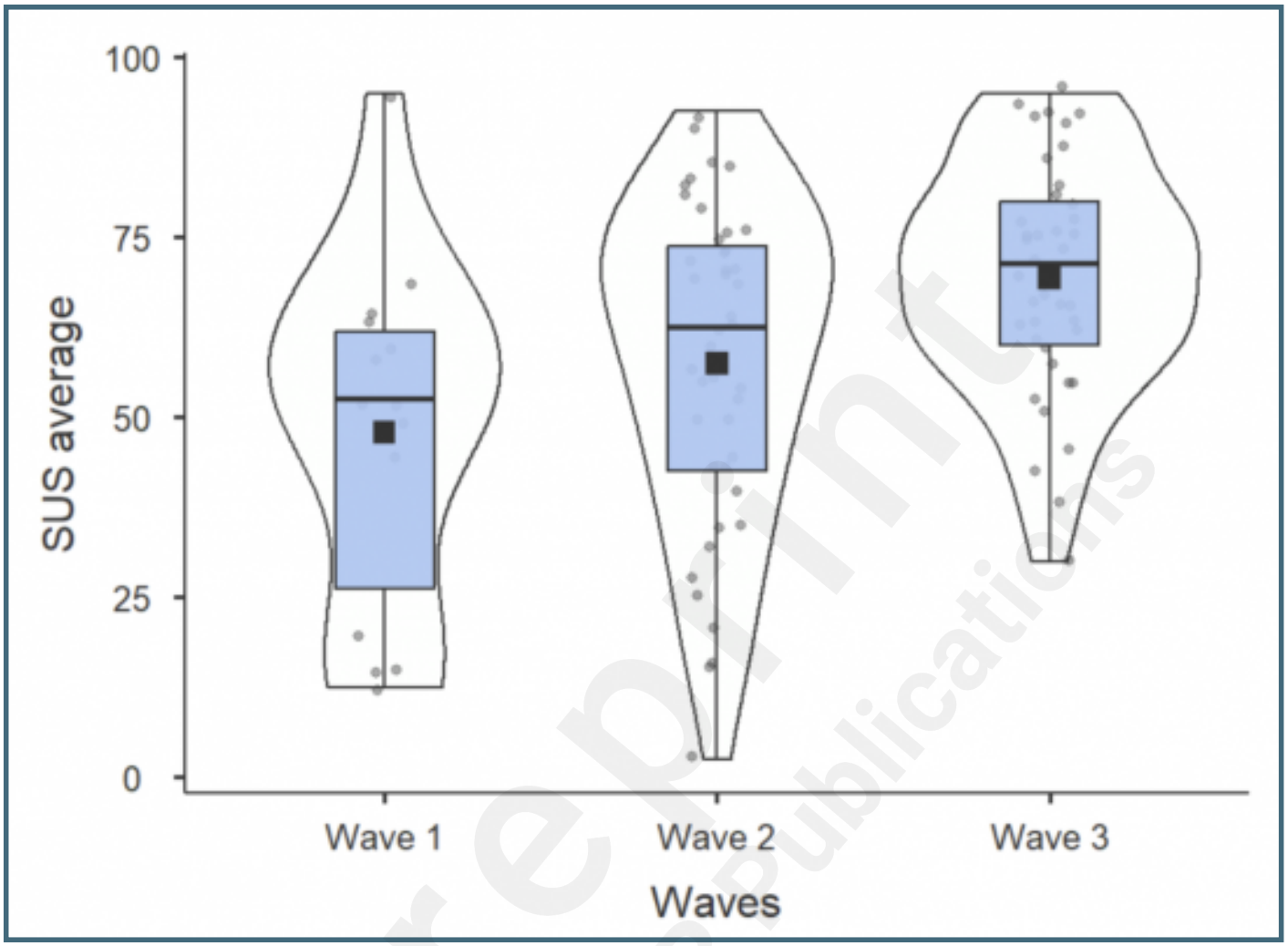
Photos of ARI robot, front and side (Photo credit: Pal robotics).

Illustration of experiments.

AES scores across the three experimental waves.



SUS scores across the three experimental waves.



Multimedia Appendixes

Evaluation scale “AES” & “SUS” (Translated from French).
URL: http://asset.jmir.pub/assets/98a1f52fd1623b94400c15e0a5f3a115.docx