

# Social Robots in Service Contexts: Design, Personalization, and Real-World Applications

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## ABSTRACT

Social robots (SRs) interact with humans using speech, motion, and affective behavior, and are used in retail, education, healthcare, and disability services. Advances in big data, machine learning, and generative artificial intelligence have enhanced the responsiveness of SRs. However, real-world adoption remains inconsistent, and key human-robot interaction (HRI) dynamics, such as adaptability, personalization, emotional modeling, and robot ‘personality,’ are underexplored. This narrative review synthesizes cross-sector evidence to identify patterns, limitations, and emerging design principles. SRs are most effective when integrated into existing workflows and tailored to context. Socially expressive SRs enhance engagement in hospitality, whereas emotionally responsive designs are more effective for children with autism. In healthcare, SRs are more readily accepted as complementary team members, rather than human substitutes. Overall, effectiveness depends on alignment between system design and user context. Persistent challenges, including novelty effects, ethical concerns, and limited long-term validation, constrain scalability, highlighting the need for human-centered, interdisciplinary development.

**Keywords:** Social Robots; AI in Service; Human-Robot Interaction; Personalized Robots

## INTRODUCTION

Social robots (SRs), which interact with humans through speech, motion, and affective behavior, are increasingly used in retail, education, healthcare, and disability services (1-3). This growth is fueled by a shift from early rule-based robotic prototypes to systems capable of interactive behavior with humans (4). Breakthroughs in large language models (LLM) and Artificial Intelligence (AI) are expected to further transform SRs by enhancing reasoning and adaptive

responses, enabling human-like interactions (5). The supportive presence and emotional expressiveness of SRs have made them relevant in clinical contexts and as learning companions (5). HRI, a multidisciplinary field, examines how humans and robots communicate, interact, and adapt to one another in shared environments (5).

The evolution of SRs provides context for understanding current limitations and capabilities. SR development started with primitive sensory feedback-based models, such as Walter’s tortoises, Elmer and Elsie in 1940s (6). Later research incorporated stigmergy (passive communication through environmental cues) and swarm intelligence were incorporated to explore group-based robot dynamics (7). A pivotal shift occurred in the early 2000s with Kismet, a robot developed at Massachusetts Institute of Technology, that pioneered use of facial expressions and over 15 servo motors to

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enable intuitive communication, vocal turn-taking, and affective feedback, transforming HRI (8). This shift in design moved SRs from passive systems to socially adaptive robots, which paved the way for their use in daily human environments.

Subsequently, a taxonomy distinguishing SRs by interaction complexity, ranging from socially evocative to receptive and adaptive systems was created, laying the foundation for contemporary SRs with pet-like designs (9, 10). In the 2010s, robots like Nao and Keepon brought SRs from research settings into real-world applications, focusing on personalized adaptation (5, 11-13). More recently, humanoid robots like Sophia have gained increased recognition, demonstrating how zoomorphic and anthropomorphic interactive designs can enhance user trust and engagement (10, 14-15). However, overly human-like appearances can trigger the uncanny valley effect, where users feel discomfort with SRs that resemble humans but behave in non-human ways, a challenge that is being addressed by SR developers (4). These historical milestones highlight a broader shift toward context-aware and emotionally intelligent systems, with integration of generative artificial intelligence (gen-AI) and LLMs, transforming HRI (16-18). Despite these advancements, gaps remain in understanding the complexity of HRI, including long-term engagement, trust, and sustainability. One such example is that enthusiasm toward SRs declines after initial interaction but tends to recover if they are perceived as useful and adaptive (2). Moreover, barriers like privacy concerns, overreliance, and unequal access continue to remain (19, 20).

This narrative review aims to critically synthesize evidence on SRs across four key service sectors: retail, education, healthcare, and disability services – through the unified HRI lens. Specifically, the review addresses central themes: (1) how SR design features such as personalization, emotional modeling, and adaptability influence user engagement; (2) how effectiveness and acceptance vary across domains; and (3) what barriers limit sustained, real-world adoption. These sectors were selected due to their practical applicability, diverse user populations, and availability of evolving evidence. This review integrates findings to identify cross-sector patterns and emerging design principles.

## **SERVICE SECTIONS**

### **SRs in Retail and Hospitality**

SRs are increasingly used as customer-facing agents and service assistants, enhancing user experiences

through personalization. For example, humanoid SR, Sophia, has been used for brand engagement (Figure 1A) (15). Analysis of Instagram reactions to Sophia revealed that happy or surprised expressions led to positive emotional connections, while sad expressions led to less favorable responses. This suggests that affective feedback, through supportive gestures and empathetic expression can influence customer satisfaction.

Similarly, SR named Pepper, equipped with speech recognition and gesture tracking, is now deployed in airports and banks to greet customers and answer questions (13). In hospitality, a hotel delivery SR named Relay, autonomously transports toiletries and snacks, reducing delivery times by 30% and boosting guest satisfaction scores by 8-12% (21-23). At Hilton Hotels, Connie, an AI-powered concierge, offers customized local recommendations, demonstrating acceptance of humanoid SRs in retail settings (23). Together, these examples demonstrate the ability of SRs to facilitate tasks and interact with customers, thereby improving customer satisfaction and brand modernization.

The success of SR use in retail settings highlights the importance of context-specific deployment strategies. For example, two tele-operated SRs were introduced in Japanese bakeries - one as a greeter to attract customers and the other as a recommendation assistant to guide purchasing choices (24). Sales were boosted, mostly driven by the recommendation SR, and the collaboration between SR and human clerks increased the likelihood of customers wishing to return, compared to human clerks alone (24).

Behavior modeling also plays a role in SR engagement. In a study in a shopping mall, SR Sota's behavior was evaluated by comparing active greeter engagement, passive-positive display (dancing), and passive-negative behavior (acting confused or curious) across 65,000 engagements and pedestrians (25). Surprisingly, passive-negative behavior generated the highest engagement. This finding underscores the interaction between human curiosity and non-intrusive SR behaviors in shaping HRI.

Highlighting the importance of trust and gradual adaptation, a study on customer attitudes toward Nao, a tele-operated humanoid SR deployed alongside a human barista in a Polish café, revealed that initial interactions were often neutral or insecure (26). However, as interactions progressed, customers expressed greater acceptance, highlighting the importance of gradual building of trust in hospitality environments (26). Another study based on an analysis of 4000 online hotel reviews in China identified that performance efficiency

(using the Service Robot Integration Willingness scale) was the most positively cited factor influencing customer acceptance of SRs, followed by human-like traits (27).

Collectively, these studies suggest that SR's effectiveness in retail is not driven by human-likeness alone, but by alignment between behavior and context. Across studies, performance efficiency and role clarity outweigh anthropomorphic features in predicting user acceptance. Emotional expressiveness enhances engagement in branding contexts, while non-intrusive or even ambiguous behaviors may increase curiosity-driven interaction in public spaces (28). Importantly, hybrid human-robot collaboration appears to strengthen trust and return intention, indicating that SRs function most effectively as augmentative service agents rather than replacements.

### **SRs in Education**

SRs have demonstrated measurable impacts on both affective and cognitive learning outcomes, though their effectiveness varies by context and design, just like the retail sector. A meta-analysis of 101 studies reported moderate-to-large effect sizes (Cohen's  $d \sim 0.70$  for cognitive and  $\sim 0.59$  for affective outcomes), suggesting that SR-assisted learning can outperform traditional instruction in certain settings (5, 29, 30). These gains are partly driven by the physical presence of SRs, which enhances attention and engagement, particularly in early education.

SRs such as Nao and Keepon have been used as tutors in 50-85% of studies, as peers in around 10%, and as learners in 1% (13, 31). Social cues, such as eye contact, can improve learning, but excessive social interaction may distract learners when cognitive load is high. When combined with humanoid features such as gestures and emotion (LLaMa 3.2 from Meta), empathetic SRs improved students' learning outcomes, including memory recall (32). These findings suggest that emotionally intelligent SRs can enhance engagement, though their effectiveness depends on appropriate calibration of social behaviors and cognitive demands of the learning environment. The sample size for empathetic SRs is very small with limited generalizability. An elementary pilot with fourth-grade students (ages 9-10 years) evaluated a personalized SR-tutor using performance data and student feedback (32). The SR group showed an 8% greater improvement and academic motivation levels compared to baseline, suggesting that data-driven, affective customization can boost learning. Similarly, in middle school settings, SR-facilitated comprehensive sex

education increased student comfort in asking sensitive questions due to the SR's non-judgmental demeanor, highlighting the value of SRs in psychologically sensitive learning environments (33).

In a university setting, an SR-facilitated exam tutor preparation resulted in stronger motivation and better grades, compared with non-participants (who did not use any tutor) (34). However, in a separate study, the non-adaptive SR version had similar outcomes to the adaptive SR version, suggesting that increased system adaptability may not always translate to improved performance (35). Notably, this study was a cross-sectional and subject to recall-bias, limiting interpretation.

Another study on vocabulary learning among 120 individuals aged 18-60 years, in a group learning format, found that adaptive SR guidance supported cognitive gains but decreased on-task enjoyment (36). This indicates a potential trade-off between autonomy and user engagement in adaptive systems; however the wide age range may have influenced the findings, as variability in digital familiarity and motivational priorities can shape perceived effort differently.

Researchers also evaluated an empathetic SR in group learning over short- and long-term periods (37). In short-term sessions, students interacting with empathetic-SR engaged in more meaningful discussions compared to those using non-empathetic SR or no SR. However, in a two-month intervention, learning gains plateaued, suggesting that initial benefits may be influenced by early novelty effects. In addition, technical limitations such as speech recognition and gesture interpretation may further limit the widespread adoption of empathetic-SRs (37). Overall, SRs can enhance learning, particularly during early interactions when novelty is high, but their long-term effectiveness remains inconsistent across settings, underscoring the need for sustained and adaptive design strategies.

Collectively, SR effectiveness in education depends on emotional engagement, cognitive load, and personalization. Although meta-analyses show moderate-to-large gains, effects are context-dependent and decline over time due to loss of novelty. Increased adaptability yields diminishing returns, and a trade-off between autonomy and enjoyment persists. Overall, SRs perform best in short-term settings, with long-term scalability limited by technical and engagement constraints.

### **SRs in Healthcare**

SRs are increasingly integrated into healthcare, with studies showing their potential to improve patient

engagement, treatment delivery, and adherence. However, considerations related to privacy, ethics, and personalization persist.

A  $3 \times 3 \times 3$  experimental design (human-likeness, task type, and context) evaluated factors influencing perceptions of privacy and utility with hospital check-in, patient mobility support, and in-home rehabilitation (19). The study found that the task type and context were stronger determinants of patient perception than human-likeness, suggesting that functional design outweighs appearance in clinical settings. Another study combined a national survey (n=1,000 participants) and a single-site emergency department cohort (n=40 participants) and found that 93% participants rated SR-based triage comparable to human-led triage, supporting their role in front-line clinical workflows, potentially reducing staff burden and improving efficiency, with improved patient satisfaction (38).

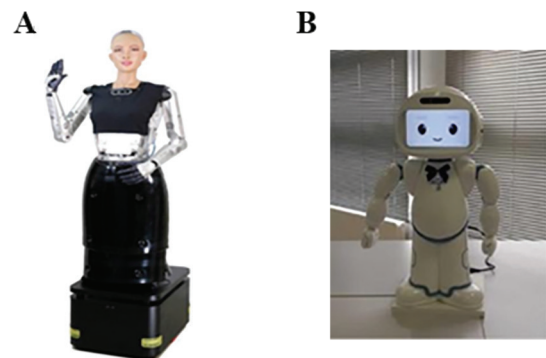
Several studies evaluated the role of SRs in pediatric care, where emotional distress is common, and resource gaps exist. SR-assisted interventions in waiting areas, procedures, and inpatient settings consistently demonstrated reduced stress and pain. For example, in a randomized clinical trial in a pediatric emergency department waiting area (n=109, ages 3-10 years), children in the SR-assisted group experienced lower cortisol and anxiety levels (39). Similarly, SR-assisted blood draws and dental procedures resulted in lower pain and anxiety levels compared to standard care (40, 41). In hospitalized setting, an interactive co-present “huggable” SR elicited higher physical and verbal engagement compared to plush toys or virtual avatars, suggesting that embodiment enhances interaction quality (42).

Collectively, these findings indicate that SRs are particularly effective as emotional support tools in high-anxiety pediatric contexts. These findings warrant caution due to small samples, short durations, and controlled settings that may not reflect real-world clinical complexity.

Despite high reported acceptance, long-term adherence and trust remain underexplored, and heterogeneity in design, populations, and outcomes limits generalizability. Large-scale, longitudinal studies are needed to establish the clinical and operational value of SRs.

### SRs in Disability Services

SRs have also been studied in populations with autism spectrum disorders, physical disabilities, and sensory impairments. In these settings, Pepper and Qtrobot (Figure 1B) were perceived as more effective for emotional support in individuals with autism spectrum when compared to tablet-based therapy, however, long-term acceptance as a reliable companion was variable (43). Importantly, multiple studies highlight that SRs function best as complementary tools rather than standalone interventions (44). For example, another pilot study using Qtrobot, human educator involvement was essential to sustain attention, emphasizing human-SR collaboration, particularly among children with autism (45). Similarly, online platforms using Nao (Figure 2),



**Figure 1.** Humanoid social robots used across service contexts: (A) Sophia for customer interaction and brand engagement in retail settings; (B) Qtrobot for educational and therapeutic use in children with autism (15, 45).



**Figure 2.** Nao humanoid social robot deployed in service environments (e.g., cafés) to assist with customer interaction and task execution (57).

SR communicated with children with autism and helped stratify emotional well-being levels, but girls had a higher opinion of SR as a confidante when compared to boys (46). One possible reason might be that girls may feel more socially secure with SRs, especially in emotionally stressful situations.

Pepper was used to conduct pediatric audiometry assessments in children with hearing disabilities during the COVID-19 pandemic despite mask-related barriers, with children remaining engaged, demonstrating its feasibility and utility in hearing assessments (47).

Recent studies show that SRs can support adults with physical, cognitive, and neurological impairments. A South Korean study of 26 adults with neurological disabilities demonstrated improvements in physical function over eight weeks using a home-based SR-guided rehabilitation program, with caregivers reporting reduced care-related burden (48). The Stretch system, a mobile SR-guided exercise system, used in adults with Parkinson's disease helped improve both physical and cognitive stimulation (49). Another exploratory study of older adults found in-home companionship using Lovot (Figure 3A) was preferred over pets due to lower caregiving demands (50). Similarly, company of SRs like Paro, Lovot, and Aibo (Figure 3B) were associated with reduced loneliness and dementia in elderly individuals (51-53).

Across studies, SRs show benefits in structured rehabilitation and short-term companionship, especially with human support. However, long-term engagement is inconsistent and depends on user characteristics. Ethical concerns, including infantilization and privacy limit scalability, supporting their role as complementary rather than autonomous tools. (54-56). These findings highlight the need for policy-guided integration of SRs into human workflow.

## FUTURE DIRECTION

Building on these findings, future research should prioritize sustainability, supporting meaningful, long-term human engagement. This requires longitudinal studies evaluating adaptability and emotional intelligence, and user-trust across real-world contexts. Ethical governance frameworks, particularly in healthcare and disability settings, are essential to address data protection and preservation of autonomy. Advances in real-time affective feedback systems for personalization must be in alignment with user needs. Additionally, inclusive design that accounts for diverse cognitive, cultural, and accessibility factors will be critical for scalability. Overall, SR development is shifting from novelty-driven use to a sustained, context aware, and human-centered design.

## CONCLUSION

SRs have evolved from simple prototypes to advanced systems capable of meaningful human interaction. Early robots relied on basic sensory feedback, but advances in adaptive behavior, along with integration of gen-AI and LLMs have enabled SRs to respond in real time. Despite these advances, several limitations persist across service sectors and while short-term benefits are evident, long-term engagement is limited by novelty effects, technical constraints, and variability in real-world implementation. Key barriers include limitations in speech and gesture recognition, insufficient contextual awareness, and concerns such as loss of privacy, infantilization, and reduced human interaction. Hybrid human-robot models consistently yield higher acceptance and outcomes, supporting the role of SRs as complementary tools

A



B



**Figure 3.** Companion social robots used in care settings: (A) Lovot, a humanoid robot providing emotional support for elderly individuals; (B) Aibo, a zoomorphic robot used for companionship in dementia care (51, 53).

rather than replacements. Addressing these gaps through longitudinal research, ethical frameworks, and inclusive, context-specific design will be essential for scalability. Ultimately, SRs must function as trustworthy, adaptive partners that enhance, rather than replace human interaction.

## CONFLICT OF INTEREST

The authors do not have any conflicts that influenced the research or the interpretation. The authors did not receive any funding for this work.

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