DOCTORAL THESIS

Acceptance of Guide Robots in Organizations Through User Self-Efficacy, Robot Nonverbal Behaviour, and Workflow Integration

Kristel Marmor

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Declaration:
I hereby declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology, has not been submitted for a doctoral or equivalent academic degree at any other university or institution.

Kristel Marmor

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TALLINNA TEHNIKAÜLIKOOL
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48/2026

Juhtrobotite aktsepteerimine organisatsioonides: kasutajate enesetõhusus, roboti mitteverbaalne käitumine ja integratsioon organisatsiooni töövoogu

KRISTEL MARMOR

TALTECH
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Contents

List of Publications

List of the author’s publications on which the thesis has been prepared:

I Marmor, K., Leoste, J., & Heidmets, M. (2026). Guide robots’ acceptance in organizations: User’s self-efficacy and robots’ organizational value. *Frontiers in Robotics and AI*, 13, 1842941. https://doi.org/10.3389/frobt.2026.1842941

II Leoste, J., Marmor, K., & Heidmets, M. (2024). Nonverbal behavior of service robots in social interactions – A survey on recent studies. *IxD&A Interaction Design & Architecture(s)*, 61, 164–192. https://doi.org/10.55612/s-5002-061-006

III Marmor, K., Leoste, J., Heidmets, M., Kangur, K., Rebane, M., Pöial, J., & Kasuk, T. (2024). Keeping social distance in a classroom while interacting via a telepresence robot: A pilot study. *Frontiers in Neurorobotics*, 18, 1339000. https://doi.org/10.3389/fnbot.2024.1339000

IV Leoste, J., Marmor, K., Hollstein, T., Hinkelmann, H., & Leoste, L. B. (2024). Enhancing university visitor satisfaction: A human–robot interaction study on the design and perception of a guiding robot assistant. In R. Balogh, D. Obdržálek, & M. Fislake (Eds.), *Robotics in Education. RiE 2024*, 1084, 223–234. Springer, Cham. https://doi.org/10.1007/978-3-031-67059-6_20

V Leoste, J., Marmor, K., Rodríguez-Piñero, P. T., Raie, A., Leoste, L. B., & Beatty, K. (in press). User perceptions of social service robot guidance in an academic library. In *Proceedings of the Social Robotics + Art: 18th International Conference on Social Robotics, ICSR 2026, London, UK, July 1–4, 2026*.

VI Marmor, K., Leoste, J., & Rodríguez-Piñero, P. T. (2026). Enhancing human–robot interaction through nonverbal communication and user self-efficacy. In M. Staffa, J.-J. Cabibihan, B. Siciliano, S. S. Ge, L. Bodenhagen, A. Tapus, ... H. He (Eds.), *Social Robotics + AI*, 16133, 289–299. Springer, Singapore. https://doi.org/10.1007/978-981-95-2398-6_20

Author’s Contribution to the Publications

Contributions to the papers included in this thesis are:

I In this article, I am the lead author. I contributed to the conceptual development of the study, the formulation of the research design, the structuring of the analytical chapter, and the integration of the theoretical and empirical parts into a unified framework. I led the writing of the manuscript and the synthesis of the findings related to user self-efficacy, robot value, and organizational integration. I also coordinated revisions of the text based on co-author and supervisor feedback.

II In this article, I am the second author and contributed substantially to the review design, the analysis of the literature, the structuring of the thematic categories, and the interpretation of the findings. I contributed to the writing and revision of the manuscript, especially in sections related to nonverbal communication, behavioural expectations, and implications for human–robot interaction.

III In this article, I am the lead author. I contributed to the study design, data collection, data analysis, and interpretation of findings related to spatial behaviour and behavioural realism in telepresence robot interaction. I led the drafting of the manuscript, prepared the reporting structure of the study, and integrated co-author feedback into the final version.

IV In this article, I am the second author and made a major contribution to the study design, the analysis of the empirical data, and the interpretation of the results. I contributed to the writing of the manuscript, particularly to the sections related to user perceptions, interaction quality, and the role of robot behaviour in public-space guidance. I also supported the refinement of the final manuscript during the revision process.

V In this article, I am the second author and contributed substantially to the development of the research focus, the empirical analysis, and the interpretation of the findings. I contributed to drafting and revising the manuscript, especially in relation to user acceptance, interaction clarity, robot embodiment, and the role of handover in guide robot interaction.

VI In this article, I am the lead author. I contributed to the conceptual framing of the study, the analysis of the relationship between nonverbal communication and user self-efficacy, and the synthesis of the findings into the broader argument of the dissertation. I led the writing of the manuscript and was responsible for integrating the study into the thesis-level research logic concerning robot behaviour and user acceptance.

Introduction

Social service robots are increasingly discussed as technologies that may support public-facing services in healthcare, education, libraries, hospitality, retail, and other organizational environments. Their relevance is connected to advances in artificial intelligence and machine learning, the growing pressure on service organizations, labour shortages, and the need to provide more consistent, accessible, and responsive services. Within this wider field, guide robots represent a specific functional role of social service robots. They support users in orientation, information access, and navigation in physical environments; for example, by helping visitors find a destination, understand a spatial layout, or move through an unfamiliar building.

Despite the increasing technical maturity of social service robots, their adoption in real organizational settings remains limited and often fragile. Many deployments remain short-term pilots, demonstrations, or publicity-oriented experiments rather than becoming integrated parts of everyday workflow. This gap between technological potential and sustainable organizational use forms the starting point of the present thesis. The topic was selected because guide robots make this adoption problem especially visible. A guide robot must move through a shared public space, communicate its intentions, maintain a socially acceptable distance, provide understandable cues, and hand the task back to the user at the right moment. At the same time, it must fit into existing organizational routines, staff responsibilities, infrastructure, and service expectations. Therefore, guide robot acceptance cannot be explained by technical performance alone. It depends on the alignment between users, robot behaviour, and organizational conditions.

The central issue investigated in this thesis is how guide robots can move from isolated pilots toward a routine organizational use. The thesis asks under what socio-technical conditions such a transition becomes possible. More specifically, it examines how users' self-efficacy shapes guide robot acceptance, which nonverbal and spatial behaviour capabilities make robot guidance understandable and manageable, and which organizational conditions enable guide robots to become part of routine workflow rather than remain isolated experiments. The thesis therefore approaches guide robot adoption as a socio-technical problem involving three interrelated actors: the user, the robot, and the deploying organization.

The purpose of the thesis is to explain how guide robots can be integrated into organizational workflows in ways that support meaningful, acceptable, and sustainable use. To achieve this purpose, the thesis performs several connected tasks. First, it positions guide robots within the broader typology of service robots and social service robots. Second, it develops a theoretical and analytical framework for studying guide robot acceptance by drawing on self-efficacy theory, human–robot interaction research, technology acceptance research, socio-technical theory, and actor–network theory as a sensitizing perspective. Third, it operationalizes guide-robot-specific user self-efficacy through the Guide Robot User Self-Efficacy Scale (GRUSES). Fourth, it examines how nonverbal and spatial robot behaviour, including movement, proxemics, orientation, stopping, and handover cues, influences users' interpretation of the robot. Fifth, it analyses organizational barriers and enabling conditions related to guide robot deployment. Finally, it synthesizes these findings into a socio-technical model of guide robot adoption and translates the results into practical recommendations for organizations, manufacturers and distributors, and for users.

Methodologically, the thesis follows an article-based and cumulatively built research design. It combines conceptual work, review-based synthesis, instrument development, controlled and field-based empirical studies, and qualitative stakeholder inquiry. The empirical programme includes a questionnaire-based study of guide robot user self-efficacy, pilot and field studies with guide robots in organizational environments, a PRISMA-informed review of nonverbal behaviour in service robot interaction, an experiment on telepresence robot proxemics, an academic library field study, and semi-structured stakeholder interviews on deployment barriers and organizational conditions. Quantitative and qualitative evidence are used side by side because the research problem cannot be adequately addressed through a single method or dataset. The baseline information used in the thesis consists of previous theoretical and empirical research on social service robots, self-efficacy, nonverbal behaviour, technology acceptance, and organizational implementation, together with empirical data collected across the six included studies.

The theoretical novelty of the thesis lies in bringing together three dimensions that are often studied separately: users' perceived capability to interact with robots, the behavioural intelligibility of robot guidance, and organizational readiness for deployment. By linking these dimensions within a single guide-robot-specific analytical framework, the thesis shows that acceptance is not a single user attitude but a relational configuration shaped by users, robot behaviour, and organizational arrangements. The methodological novelty lies especially in the development and iterative use of GRUSES as an instrument for assessing users' perceived capability to interact with guide robots in controlled and real-life settings. The practical novelty lies in translating the socio-technical model into implementation-oriented recommendations that address role clarity, onboarding, workflow fit, environmental readiness, maintenance, behavioural readability, and user support.

The outcomes of the thesis have been approbated through six publications that form the basis of the dissertation. These include a published article on guide robot acceptance in organizations, a published review article on nonverbal behaviour of service robots in social interactions, a published pilot study on telepresence robot proxemics, a conference publication on the design and perception of a guiding robot assistant in a university environment, an accepted study on user perceptions of social service robot guidance in an academic library, and a published integrative article on nonverbal communication and user self-efficacy in human–robot interaction. Together, these publications provide the theoretical, methodological, and empirical foundation for the thesis. The full texts of the publications are included in the appendices, and the final GRUSES instrument is presented separately as an appendix.

The thesis is structured as follows. Chapter 1 introduces the background, robot typology, problem statement, research questions, methodology, contributions, and included publications. Chapter 2 develops the theoretical background and previous related research. Chapter 3 synthesizes the empirical studies according to the three main research dimensions: user self-efficacy, guide robot behaviour, and organizational deployment. Chapter 4 answers the research questions, presents the empirically supported conceptual model, and discusses the contributions, limitations, and implications of the thesis. Chapter 5 translates the findings into practical recommendations for organizations adopting guide robots, for manufacturers and distributors, and for users.

Abbreviations

AI	Artificial Intelligence
ANT	Actor–Network Theory
GR	Guide Robot, understood in this thesis as a functional role performed by a social service robot
GRUSES	Guide Robot User Self-Efficacy Scale
HRI	Human–Robot Interaction
HRIES	Human–Robot Interaction Evaluation Scale
SAR	Socially Assistive Robot, used in the literature especially in care and rehabilitation contexts
SPRS	Social Perception of Robots Scale
SR	Service Robot
SSR	Social Service Robot
TAM	Technology Acceptance Model
TPR	Telepresence Robot
UTAUT	Unified Theory of Acceptance and Use of Technology

Explanations of abbreviations used in the thesis.

1 Research Context, Aim, and Design of the Thesis

1.1 Historical Background

The history of robots is not only a history of machines but also a history of how humans have imagined delegating action to artificial agents. Long before modern electronics, automata were designed as self-acting mechanical devices that imitated service, movement, performance, or simple decision-like sequences. These early devices were not intelligent in the modern sense, but they already expressed a durable ambition: to make an artificial body act in a human environment. The modern term *robot* entered the public realm through Karel Capek's play *R.U.R.* in 1920, where robots were presented as artificial workers and as part of a wider social and economic order [1]. Accordingly, robots in the contemporary meaning of the term are not purely technical objects. For a century, the term has raised questions about labour, control, usefulness, replacement, and human dependence on artificial systems. Figure 1 illustrates the history of the evolution of contemporary robotic technologies since the invention of the first automata in Ancient Greek.

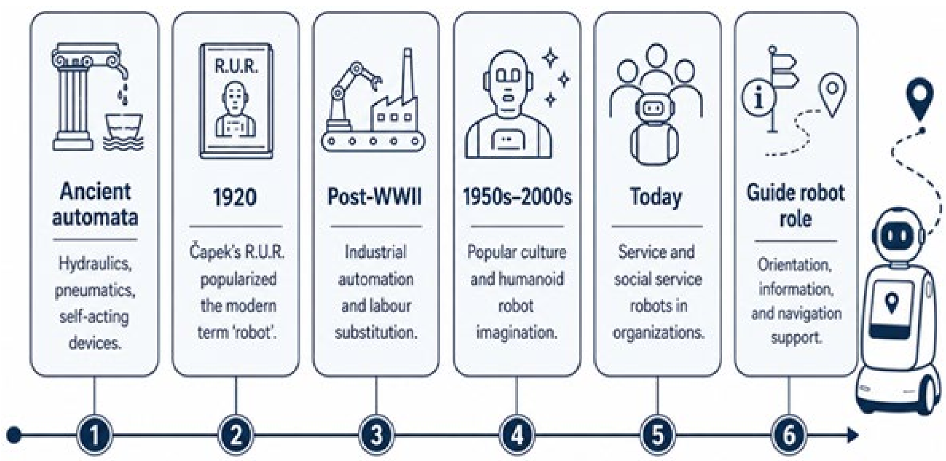

Figure 1. Historical pathway from automata to guide robots.

In the aftermath of the World War II, robotics developed primarily through industrial automation, where robots were used to perform repetitive, precise, or physically demanding tasks. At the same time, humanoid robots in popular culture shaped public expectations of robots as human-like, autonomous, and socially meaningful beings. These cultural images still affect how people interpret robots, even when contemporary service robots are far more limited and task specific. Complexities and dilemmas related to a robot powered by artificial intelligence have, for example, been vividly described in another, more recent, literary work – Kazuo Ishiguro's novel *Klara and the Sun* [2].

The current thesis focuses on a later development in this trajectory: guide robots as embodied service technologies used to support orientation, information access, and navigation in organizational environments. The relevant historical shift is therefore from mechanical imitation and industrial automation toward socially situated service tasks. Guide robots are not considered here as futuristic humanoids but as service technologies whose value depends on robots' understandable behaviour, users' confidence and their perceived ability to interact with robots, and robots' integration in organizations that use them [3, 4].

1.2 Typology of Robots

There is no single universally agreed upon unified typology of robotic equipment available that would allow neatly mapping hundreds of different types of robots. As the field remains heterogeneous, every typology depends on the needs of a specific study. For the purposes of the current study, robots are mapped along two interrelated but analytically distinct dimensions: (1) *morphology*, referring to the robot's external form, and (2) *function*, referring to the task, role, or service purpose the robot fulfils in a particular context. In terms of morphology, robots carrying a social function (social robots) may be described as anthropomorphic, humanoid, animal-like or zoomorphic, or functional/non-biomimetic. Anthropomorphic robots use human-like cues, such as facial expressions, eye shapes, voice, gestures, or social signals, but they do not necessarily represent the full human body. Humanoid robots are more explicitly modelled according to the structural features of the human body, typically including a head, torso, arms, and/or legs, as ASIMO. Animal-like or zoomorphic robots draw on the appearance or behaviour of animals, whereas functional or non-biomimetic robots are shaped primarily by the task they perform rather than by resemblance to humans or animals. Such robots' morphology allows connecting the appearance of technology to user expectations in terms of the perceived sociality and interaction style. Still, morphology alone does not define the robot's actual functional purpose [5, 6].

Functionally, robots are often distinguished as industrial robots and service robots. Industrial robots are primarily associated with automation in production and manufacturing, whereas service robots serve or support humans outside of traditional industrial environments. Service robots may be further divided into professional service robots, used in organizational or institutional settings, and personal service robots, used in private or everyday environments. Within professional service settings, a narrower group of robots can be described as *social service robots*: embodied service robots that communicate with people and support service-oriented interactions through information provision, communication, orientation, guidance, or navigation. These systems are not merely technical tools, as their effectiveness depends, among others, on their capacity to enter socially meaningful interaction with their users [4, 6].

The current work focuses on robots that within this functional typology can be broadly described as *social service robots* (SSRs). These are embodied service robots used in public or organizational service environments to provide users with information, reception, guidance, navigation, and communication support. SSRs are generally understood as autonomous or semi-autonomous systems designed to perform useful tasks for humans outside industrial production settings, while social robots are more specifically defined through their capacity to communicate with humans, use socially meaningful cues, and participate in interaction as embodied agents [4, 6, 7, 8, 9]. They enter already structured routines, such as reception work, visitor guidance, patient support, library services, or educational assistance, where their value depends not only on what they can do technically, but also on whether their conduct is understandable and compatible with the surrounding service process [4, 9].

According to this typology, the specific sub-category of the robots used in our research programme – *the guide robot* – does not appear as a distinct morphological type, but rather indicates a specific role attributed to or a function performed by a particular social service robot. A guide robot may, therefore, for its outlook appear as anthropomorphic, even humanoid, or merely functional. What defines it is not its physical shape but the fact that it assists users functionally in orienting themselves in and moving through space and accessing services or information. Such distinction is central for the purposes of the current thesis, as its focus is not on one specific morphological robot type but on the social acceptance of robots that perform the role of guidance in service- and healthcare-related environments. Figure 2 offers a typology of the robotic technologies underpinning the current thesis.

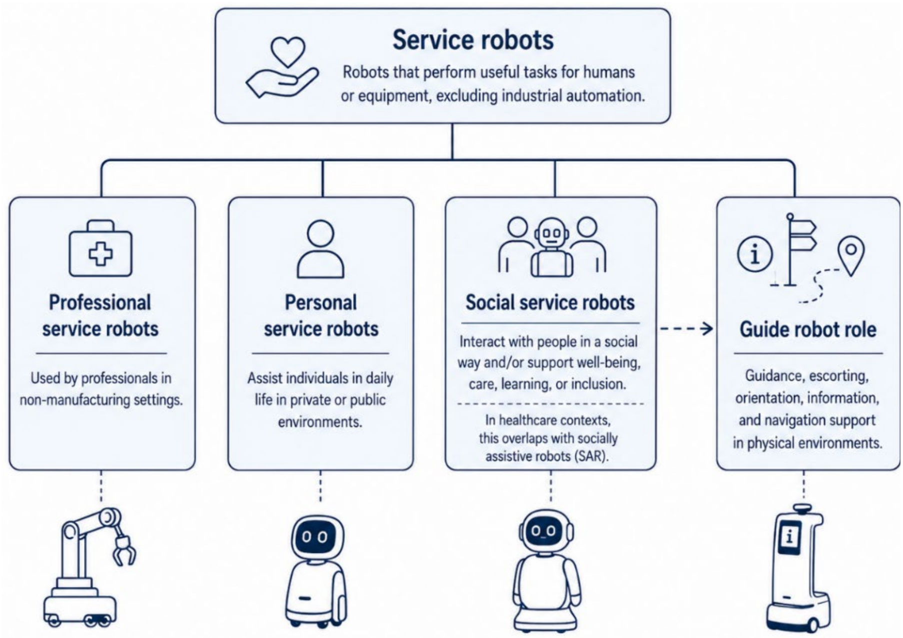

Figure 2. Functional position of social service robots and the guide robot role.

In healthcare and care contexts, the term *social service robot* overlaps with that of *socially assistive robots*, the latter also describing a contextualised function of a robot. Socially assistive robotics refers to systems that support users primarily through social interaction rather than through physical manipulation or direct bodily assistance [3]. In elderly care and healthcare research, socially assistive robots have been associated with roles such as guidance, motivation, reassurance, companionship, cognitive stimulation, and communication support [10]. For this reason, the term *socially assistive robot* is seen in this thesis as a closely related, context-specific synonym for a social service robot when the robot's primary purpose is to assist users through social interaction, orientation, guidance, or communicative support in healthcare-related settings. However, as in our case we focus on the robot's guiding function, we mostly use the term *guide robots* (GRs). It should, however, be remembered that all these terms are at least partially overlapping and that no single widely accepted typology of robotic technologies exists. GRs have been previously studied in museums, hospitals, hotels, airports, libraries, and university settings, where users need help finding destinations or understanding spatial layouts. Across these settings, their value lies in combining route completion with socially intelligible interaction. A guide robot must not only reach the correct location but also communicate its intentions clearly enough for users to follow the interaction and understand when robot-led guidance has ended and independent action should begin [11, 12, 13].

1.3 Problem Statement and the Aim of the Thesis

Due to their increasing AI- and machine-learning supported capabilities, SSRs are expected to rely more on their cumulating learning experience and act less following strict algorithms, and as a result – participate in increasingly complex interactions [14, 15]. This has widened robots' relevance in many applied settings. For example, robots such as Pepper and NAO have been used in educational contexts to support learner engagement [16], while service and assistive robots have been explored in elderly care and independent living contexts [17, 18, 19, 20].

These developments have increased interest in SSRs in sectors affected by labour shortages and rising service demands, including healthcare, education, hospitality, retail, and personal assistance. In such settings, SSRs may support guidance, provide information, offer companionship, and engage in routine service interactions that require both functional efficiency and interactional clarity [9, 19, 20]. Their appeal lies not only in productivity gains or service consistency but also in their potential to reduce routine work and improve service quality by supporting more responsive service environments [9, 21, 22].

At the same time, rapidly increasing technical capabilities of SSRs have not yet translated into their widespread adoption in service organizations, supported by adequately modified work routines. The core challenge addressed in this thesis concerns the still limited integration of SSRs in real-life organizational environments. While robots have proven useful in structured settings, their integration into publicly accessible and interactionally dynamic organizations remains limited [4, 14]. In such settings, interactions are less predictable, workflows that relay on human presence are already well established, and, accordingly, the superficial insertion of a robot is more likely to disrupt the operation rather than bring benefit in terms of a reduced human effort or increased quality of service. Thus, despite growing expectations for SSRs, their practical areas of use remain limited when organizations try embedding them into everyday workflows, reaching hardly beyond short-term pilots or demonstrations. Many releases of robotic technologies remain short-lived, pilot-based, dependent on carefully crafted experimental conditions, often serving publicity purposes rather than real-life innovation, and ending as soon as the funding for the laboratory stage of the technology development ends [24]. This gap between the technical potential of the emerging social service robotics and its conservative, if any at all, organizational use [17, 24, 25] forms the starting point of the present thesis.

A part of this challenge concerns the users. Even when a robot is technically capable, people may hesitate to engage if they do not feel confident in their ability to understand, follow, or manage the interaction. Low self-efficacy, uncertainty, or anxiety can weaken acceptance, especially in dynamic or unsupervised environments [22, 26, 27].

Another element concerns the organization-robot interaction design. Organizations may underestimate the amount of preparation required for effective deployment, including training, role clarity, workflow redesign, and local support. At the same time, the robot's nonverbal behaviour remains comparatively underexplored, even though gaze, proxemics, movement, and other expressive cues shape emotional response, social presence, and interactional comfort [11, 28, 29]. A robot that violates the expected social norms may therefore alienate users, even when its technical functioning remains faultless.

These dimensions have been usually studied in isolation from each other. The current work advances a paradigmatic shift, suggesting a model in which robot users' characteristics, features of the robot's nonverbal behaviour, and the depth of the robot's organizational adoption are integrated. Accordingly, these variables combined are seen as shaping a meaningful and effective routinization of SSRs in organizational workflows. The thesis aims to explain how guide robots can be integrated into organizational workflows in ways that support their becoming an integral part of everyday organizational practices. More specifically, it examines which factors strengthen users' self-efficacy in guide robot interaction, which behavioural and organizational conditions support acceptance and workflow integration, and how these insights can be translated into practical recommendations for organizations adopting guide robots, for manufacturers and distributors, and for guide robot users. A central premise of the study is that successful guide robot deployment depends on the interaction between users' perceived capability to manage the encounter with a robot, the robot's behavioural intelligibility, and the organizational conditions supporting the use of robots. To address this aim, the thesis focuses on three analytical dimensions: user self-efficacy in guide robot interaction, guide robot's nonverbal behaviour, and organizational readiness for robotics integration.

1.4 Analytical Framework and Research Questions

Starting from the broader problem that the real-life level of adoption of SSRs remains well below their actual technological potential; the thesis draws on a multi-stage research programme conducted between 2022 and 2025. The study focuses on one specific functional role within the category of SSRs, that of the guide robots that help users navigate physical environments to reach their intended destinations. Accordingly, the thesis examines robot use in particular environmental settings where the interaction unfolds in public space and where the routinization of the task performance entails more than its mere technical completion. This is being done through the lens of the actor–network theory (ANT) as a sensitizing socio-technical perspective. From that viewpoint, guide robot adoption emerges from the relations between heterogeneous human and non-human actors rather than from isolated user attitudes or isolated technical features alone [30, 31, 32]. Users, robot behaviour, organizational routines, physical spaces, and institutional rules jointly determine whether the use of a guide robot becomes workable and repeatable in practice.

The proposed analytical framework appears as a three-actor structure organized around the robot, the users interacting with it, and the organization responsible for deployment. Within this framework, the study foregrounds one focal dimension for each element. For users, the focus is self-efficacy, understood as the perceived capability to manage interaction with the guide robot. For the robot, the focus is nonverbal and spatial behaviour, especially those cues that make guidance readable and socially intelligible. For the organization, the focus is readiness for robots' integration, including role clarity, workflow fit, staff training, infrastructure readiness, and the availability of support. These dimensions have been selected because they help explain why guide robots' use sometimes stabilizes in everyday service work and sometimes discontinues after short-lived pilots. Figure 3 presents the analytical framework used to organize the thesis and to connect the three research questions to the broader problem of guide robot deployment in organizational workflow. The framework is revisited and refined through cumulative evidence in Section 4.2.

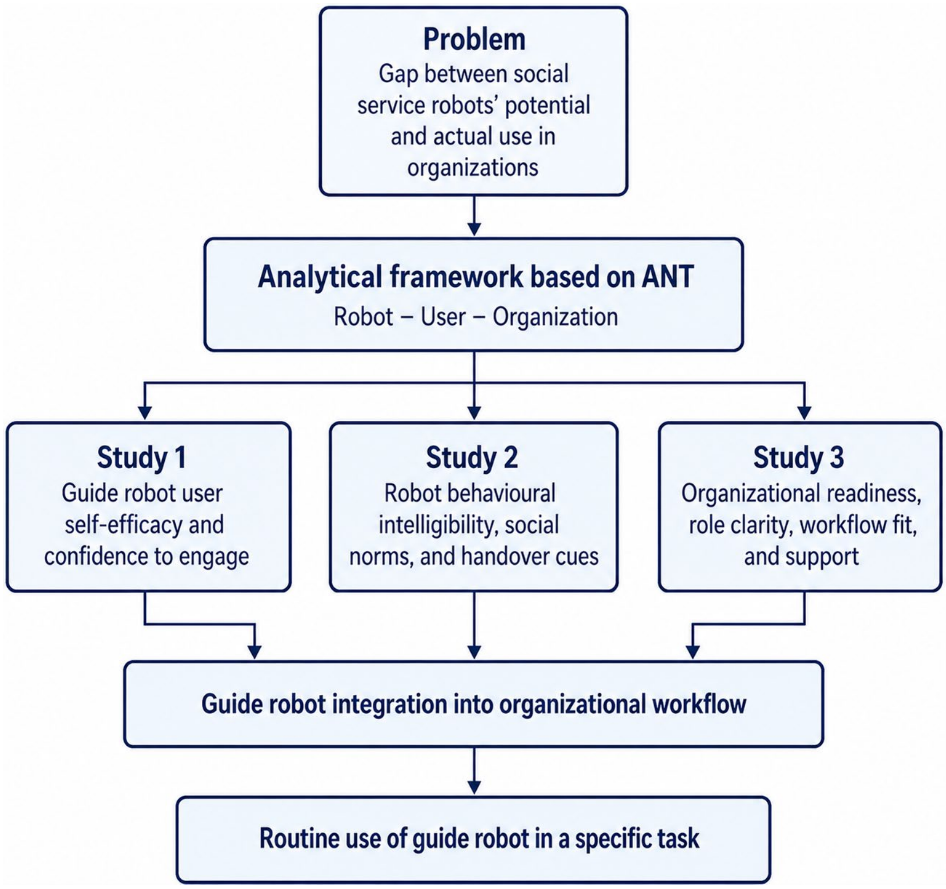

Figure 3. Analytical framework for exploring guide robot acceptance in organizations and its research-question structure.

Building on the analytical framework, the thesis poses one overarching question and three more specific research questions. The main question concerns the socio-technical conditions under which guide robots can move from isolated pilots toward routine organizational use. The three sub-questions examine the respective contributions of user self-efficacy, robot behaviour, and organizational conditions to that process.

Main Research Question: Under what socio-technical conditions can guide robots move from isolated pilots toward routine organizational use?

- *RQ1:* How does user self-efficacy shape the acceptance and practical use of guide robots in organizational contexts?
- *RQ2:* Which nonverbal and spatial behaviour capabilities make guide robot guidance understandable and manageable in organizational contexts?
- *RQ3:* Which organizational conditions enable guide robots to be deployed as part of routine workflow rather than as isolated experiments?

The cumulative study design and research logic of the dissertation are outlined below. Article 1 provides the main conceptual and empirical backbone, Articles 4 and 5 contribute direct field evidence, Article 3 provides adjacent proxemic evidence relevant to RQ2, Article 6 links behaviour and self-efficacy, and Article 2 provides the review-based foundation for the behavioural perspective.

Publication and evidence pathway. Because the dissertation is article-based and methodologically heterogeneous, the six publications do not contribute identical forms of evidence. Articles 1, 4, and 5 provide the principal direct evidence from GR and organizational deployment contexts. Article 2 provides review-based support for the behavioural dimension. Article 3 provides adjacent proxemic evidence from telepresence interaction and is therefore used to clarify a mechanism relevant to GR guidance rather than as direct evidence of their deployment. Article 6 integrates the strands of user self-efficacy and robot's nonverbal behaviour. The thesis-level answers are produced by synthesizing complementary evidence, as opposed to treating all six publications as parallel replications. Figure 4 maps the contribution of each publication to RQ1–RQ3 and to the main research question.

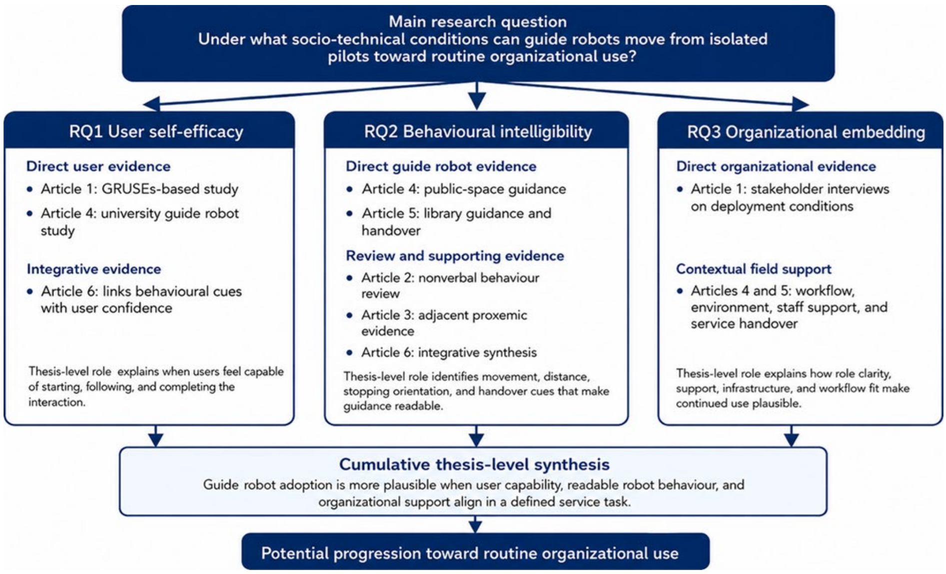

Figure 4. Evidence pathway from the six publications to the thesis level answer.

1.5 Research Methodology and Methods

The thesis follows an article-based, cumulatively built research design that combines conceptual work, review-based synthesis, instrument development, controlled and field-based empirical studies, and qualitative stakeholder inquiry. Rather than being organized as one single linear experiment, the thesis brings together six publications produced between 2023 and 2025 into one research programme. Methodologically, the work would be best described as a heterogeneous mixed-design study with a strong socio-technical orientation: quantitative and qualitative evidence are used side by side, and each publication contributes a different part of the explanation of guide robot adoption in organizations. The research programme evolved in stages. It began with a review of nonverbal behaviour in socially structured human–robot interaction (HRI), clarifying which behavioural dimensions had already been studied and which remained underexplored in the context of SSRs. That review work informed the analytical focus of the study and supported the decision to foreground behavioural intelligibility as one of the three central dimensions of GR adoption. In parallel, the broader research problem was refined around the relationship between users, robot behaviour, and organizational deployment conditions.

1 – User perspective

Research Question 1: How does user self-efficacy shape the acceptance and practical use of guide robots in organizational contexts?

This stage investigates whether users believe they have the capability to manage interactions with a robot, which directly impacts their willingness to engage.

Study and articles	Methods and sample
Study 1.1: GRUSES study (Article 1)	Questionnaire study, n = 226
Study 1.2: University pilot (Articles 4, 6)	Pilot experiment, n = 28

2 – Robot perspective

Research Question 2: Which nonverbal and spatial behaviour capabilities make guide robot guidance understandable and manageable in organizational contexts?

This stage examines how robot cues, such as movement, orientation, and stopping distance, help users interpret the robot's intentions.

Study and articles	Methods and sample
Study 2.1: Nonverbal review (Article 2)	PRISMA literature review, 39 papers
Study 2.2: Telepresence proxemics (Article 3)	Empirical experiment, n = 24
Study 2.3: Library field study (Article 5)	Mixed-method field study, 47 interactions

3 – Organizational integration and synthesis

Research Question 3: Which organizational conditions enable guide robots to be deployed as part of routine workflow?

This stage addresses the overarching question: under what socio-technical conditions can guide robots move from pilots toward routine use?

Study and articles	Methods and sample
Study 3: Stakeholder barriers (Article 1)	Qualitative interviews, n = 26
Final synthesis: Validated socio-technical model	Cumulative research logic across Articles 1–6

Figure 5. Study design and cumulative research logic of the dissertation.

The empirical component then combined several complementary forms of evidence. First, questionnaire-based studies were used to examine users' perceived capability to interact with guide robots and to iteratively develop GRUSES. Second, pilot and field studies were used to observe how robot's behaviour was interpreted in situated interaction, including public-space guidance and robot-mediated communication. Third, semi-structured stakeholder interviews were used to identify barriers, expectations, and enabling conditions related to organizational deployment of robots. This combination made it possible to examine the same overarching problem from the user, behavioural, and organizational angles rather than through a single method or dataset.

Throughout the research programme, the logic of the study was cumulative. The review article provided conceptual grounding, the scale-development and field studies generated GR-specific evidence, the telepresence pilot contributed supporting insight on proxemics and behavioural realism, and the later integrative article helped connect the behavioural and self-efficacy strands more explicitly. Together, the six publications form a connected evidence base that allows the thesis to move from isolated findings toward a broader socio-technical synthesis of guide robot adoption.

Figure 5 summarizes this cumulative study design by demonstrating how the main research question is addressed by means of three interlinked empirical studies and how the evidence from the six articles contribute to the programme-level synthesis.

1.6 Key Contributions

This thesis makes four closely connected contributions to research on guide robot adoption in organizational settings.

First, it develops user self-efficacy into a guide-robot-specific analytical lens and operationalizes it through GRUSES.

Second, it clarifies the role of behavioural intelligibility in guidance tasks, showing that movement, stopping, orientation, and handover cues matter for acceptance as much as technical task completion.

Third, it demonstrates that proxemics and other nonverbal cues shape how users interpret robot competence, social presence, and the manageability of the interaction.

Fourth, it shows that routinized adoption depends on organizational embedding, especially role clarity, onboarding, workflow fit, maintenance support, and communication around the robot's practical purpose.

Together, these contributions position guide robot adoption as a socio-technical alignment problem rather than as a narrow question of usability or attitude alone.

1.7 Overview of the Included Articles

The dissertation draws on six publications that play different roles in the overall argument. Some provide direct evidence on guide robot use in organizational settings, while others contribute theoretical grounding, supporting behavioural insight, or integrative synthesis. The complete texts of the included publications are provided in Appendices 1–6, while Appendix 7 presents the final GRUSES instrument used in the dissertation. Read together, the articles offer a staged research programme in which the later publications refine, test, or extend issues that had emerged in the earlier ones.

1.7.1 Article 1. "Guide Robots' Acceptance in Organizations: User's Self-Efficacy and Robots' Organizational Value"

Article 1 [33] provides the main conceptual and empirical backbone of the dissertation. It presents the broader research problem, outlines the three-actor logic of the study, and integrates earlier research on guide robots, robot users, organizational context, organizational value, and user self-efficacy. Empirically, it reports the two central strands on which much of the dissertation later builds: the GRUSES-based study of user self-efficacy in controlled and real-life settings, and the stakeholder interview study on expectations, barriers, and solutions related to guide robot deployment. Its contribution to the thesis is therefore dual: it clarifies the conceptual architecture of the work and provides direct evidence for both RQ1 and RQ3.

1.7.2 Article 2. "Nonverbal Behavior of Service Robots in Social Interactions – A Survey on Recent Studies"

Article 2 [34] analyses the role of nonverbal communication in HRI by reviewing recent empirical studies on service robots with social capabilities. The article maps which kinds of cues, such as gaze, gestures, posture, and proxemics, have received research attention and what kinds of methodological approaches have been used to study them. Within the dissertation, its main value is theoretical: it establishes the foundation for the behavioural dimension of the thesis and helps justify why nonverbal behaviour should be treated as a central condition of understandable and acceptable guide robot interaction rather than as a secondary design detail.

1.7.3 Article 3. "Keeping Social Distance in a Classroom While Interacting via a Telepresence Robot: A Pilot Study"

Article 3 [35] reports a pilot study on spatial behaviour in telepresence robot interaction in an educational setting. The robot in this study was not a guide robot, and the article does not address organizational guide robot deployment directly. It is nevertheless important for the dissertation because it isolates the proxemic dimension of robot-mediated interaction and shows how interpersonal distance and behavioural realism may shift when communication is conducted through a robot body. In the thesis, the article functions as supporting evidence for RQ2 by strengthening the discussion of spatial norms, user comfort, and the interpretability of robot behaviour.

1.7.4 Article 4. "Enhancing University Visitor Satisfaction: A Human–Robot Interaction Study on the Design and Perception of a Guiding Robot Assistant"

Article 4 [11] reports an empirical study in which a semi-autonomous TEMI v3 robot was used as a guide robot in a university environment. The study focused on the design and perception of verbal and nonverbal guidance behaviour, including greeting, route guidance, comprehensibility, collaboration, and the public visibility of interaction. Although the article used a broader interaction-perception questionnaire rather than the final GRUSES instrument, it is highly relevant to the dissertation because it provides direct field-based evidence on how user experience guides robot interaction in a real organizational setting. It therefore contributes especially to RQ1 while also informing the behavioural interpretation developed under RQ2.

1.7.5 Article 5. "User Perceptions of Social Service Robot Guidance in an Academic Library"

Article 5 [12] presents an exploratory mixed-method field study conducted in an academic library, where visitors could choose between two social service robots for a book-guidance task. This study reaches beyond general acceptance of SSRs and examines which concrete features of the guidance process users actually valued in practice. Its findings show that practical usefulness, precise stopping, readable cues, and a clear handover from robot-led navigation to user-led action mattered more than robot size alone. Within the dissertation, this article provides some of the clearest direct evidence for RQ2 and also sharpens the practical understanding of what makes guide robot deployment workable in public organizational environments.

1.7.6 Article 6. "Enhancing Human–Robot Interaction Through Nonverbal Communication and User Self-efficacy"

Article 6 [36] functions as an integrative article that brings together the dissertation's two closest analytical dimensions, nonverbal communication and user self-efficacy. It synthesizes how behavioural cues influence users' confidence, interpretive ease, and willingness to engage with the robot. Its contribution to the thesis lies in making explicit the bridge between RQ1 and RQ2 and in showing more clearly why behavioural intelligibility and user capability should not be analysed as disconnected issues.

1.7.7 Cumulative Logic of the Included Articles

Together these six articles constitute a cumulative research programme in which guide robot studies are complemented by a review article, an indirect behavioural pilot, and an integrative synthesis. Article 1 provides the main conceptual and empirical backbone, Articles 4 and 5 provide the most direct field evidence on guide robot interaction, Articles 2 and 6 strengthen the behavioural and interpretive explanation, and Article 3 contributes supporting insight on proxemics and behavioural realism. Such cumulative architecture constitutes on its own a part of the dissertation's novelty, as it makes transparent how different types of evidence are mobilized to answer a single unifying problem addressed in the thesis. The next chapter turns from this publication architecture to the broader theoretical framework, after which the empirical synthesis draws the strands together again.

2 Theoretical Background and Previous Related Research

Building on the structure of the thesis as outlined in Chapter 1, this chapter establishes the theoretical foundations on which the current work has been built. Accordingly, we first identify SSRs as organizational service actors whose real-life contribution depends on both their technical capabilities as well as workflow fit. Thereafter, we turn to the user-side conditions of HRI and finally to the organizational arrangements that shape whether GRs adoption efforts remain mere pilots or feed into sustained provision of restructured services.

2.1 Theoretical Framing of Guide Robot Adoptions

As already explained, in this thesis GRs are seen as a functional subtype of SSRs: embodied technological systems used in public or organizational environments to support orientation, navigation, information provision, and interaction. Accordingly, theoretical approaches to GR adoption must reach further than allowing to explain whether a user likes or does not like a particular technological artefact. A GR becomes useful only when its behaviour is understandable to the person receiving guidance, when users feel capable of managing the encounter with a robot, and when the organization has prepared the roles, spaces, and routines into which the technology is expected to fit. The theoretical starting point of this thesis is therefore integrative, combining social cognitive theory and self-efficacy, technology acceptance and post-adoption research, HRI research covering nonverbal and spatial behaviour, and socio-technical approaches to organizational implementation.

From such theoretical starting point, acceptance of robots does not emerge as a monolithic attitude towards technology or as a direct consequence of their technical performance. Technology-acceptance models, therefore, do not fully explain what happens when robots move from controlled studies into real organizational settings. Laboratory research is useful for testing usability, task performance, or interface features, but it often simplifies the social and material conditions that shape robot use in everyday environments. A person may consider robots interesting in general terms but still hesitate to follow one in a hospital corridor, ask it for assistance in public, or rely on it to reach the desired destination. Conversely, even a technically modest robot may be accepted if its role is clear, its behaviour is readable, and the surrounding organization supports its use. In real-life deployments, robots interact not only with their primary user but also with staff members, bystanders, organizational routines, spatial layouts, and local norms. Their practical value emerges through situated coordination rather than through technical performance alone. The relevant theoretical question is therefore how routine use becomes possible when user capability, robot behaviour, and organizational conditions are brought into alignment.

For that reason, the present study complements technology-acceptance perspectives with ANT (actor–network theory) as an interpretive socio-technical lens rather than informing a full formal ANT analysis [32]. ANT treats technology as part of a heterogeneous network made up of human and non-human actors. In this context, these actors include users, robots, software, organizational rules, physical spaces, and cultural expectations. The key question is not which actor matters most in the abstract but how relations between them produce stability, coordination, or breakdown [31, 32]. From this perspective, GR acceptance does not emerge as the result of a single attitude or a single design feature. It is better understood as an effect of alignment between material and social elements in practice. Following Mol [37], this means that hardware, software, language, norms, and expectations all participate in how the robot is enacted in an organizational setting. Used in such a modest way, ANT helps clarify why the same robot may be accepted in one context and remain fragile in another. It directs attention to relations, dependencies, and local arrangements rather than to isolated variables alone. Accordingly, this adopts an ANT-inspired perspective alongside more conventional acceptance models. The aim is not to replace any of these models but to explain how users, robots, and organizations together create or fail to create workable arrangements in practice.

2.1.1 User Self-Efficacy and the Manageability of Robot Interaction

The first proposed theoretical pillar is the robot user's self-efficacy. In Bandura's social cognitive theory, self-efficacy refers to people's beliefs about their capability to organize and carry out actions as required in a specific situation [26, 38, 39]. In practical terms, self-efficacy is therefore not treated here as a fixed personal attribute. It can be intentionally supported through gradual onboarding, simple first tasks, peer modelling, and interaction settings in which users do not feel exposed or judged. This point is particularly relevant for guide robots in operating public or semi-public environments, where visibility and uncertainty may otherwise undermine willingness to engage. Self-efficacy should not be seen as a general skill or objective competence. It concerns whether a person believes that they can manage the task at hand.

Bandura [26] identifies four main pathways through which self-efficacy can be strengthened: mastery experiences, vicarious experiences, social persuasion, and the regulation of emotional arousal. Applied to HRI, this means that successful first encounters, observing how others use the robot successfully, receiving supportive verbal guidance, and low-pressure interaction settings can all strengthen users' confidence in their own ability to engage with the robot. From a social-cognitive perspective, self-efficacy can be strengthened through training, intuitive technological design, and gradual exposure. Unless people believe that their actions can produce the desired effect, they have little incentive to act [40]. In organizational HRI, this means that adoption depends not only on what the robot can do but also on whether users feel capable of using it effectively.

Self-efficacy is both a predictor of future technology acceptance and an outcome of previous positive interaction. Studies increasingly treat robot-specific self-efficacy as an indicator of readiness to engage with robotic systems [27, 41]. Rosenthal-von der Pütten and Bock [27] have, for example, developed the Self-Efficacy in Human–Robot Interaction Scale (SE-HRI) and showed that direct interaction with a robot increased both self-efficacy and willingness to interact with robots in the future. This is especially relevant for guide robots, because users often must decide quickly whether to trust the robot's cues, follow its guidance, and remain engaged through the full-service sequence.

In the GR context, self-efficacy concerns the user's perceived ability to start, understand, follow, and complete an interaction with the robot. A user must be able to recognize what the robot is offering, decide whether to engage, interpret its instructions, follow its movement, recover from unclear moments, and complete the handover from robot-led guidance to independent action. If users feel that they cannot manage these steps, acceptance is likely to remain weak regardless of the robot's technical capability. Prior work on user self-efficacy in robot use and self-efficacy in HRI supports this logic by showing that confidence, perceived competence, and willingness to interact are closely related in robot-use contexts [27, 42, 43].

Self-efficacy is also of relevance as GR encounters often take place in externally observable public or semi-public spaces. Users may worry about appearing incompetent, misunderstanding the robot, blocking other people, or being unable to stop the interaction. Public visibility of the interaction can therefore complicate the otherwise technically simple task. From this perspective, user self-efficacy is not merely an individual psychological variable. Rather, it is shaped by the combination of the robot's behaviour, the clarity of the environment, prior experience with similar technologies, and the availability of human support when the robot fails or becomes difficult to interpret. Higher self-efficacy supports confidence, reduces anxiety, and encourages engagement with a robot. At the same time, self-efficacy is only one part of a broader acceptance process shaped by human, robot-related, and organizational conditions.

In addition to self-efficacy, robot acceptance is shaped by other human, technological, and organizational factors. Sadangharn [44], for instance, groups these into human factors, robot-related factors, and organizational factors. Human factors include prior technological experience, attitudes, and fears; robot-related factors include social capabilities, appearance, reliability, and behavioural traits; and organizational factors include physical environment, managerial support, change management, and training. These categories help position self-efficacy within a broader ecology of robot acceptance rather than treating it as a standalone explanation.

Reaching beyond generic technology-acceptance models, HRI research treats robots as social, embodied agents. Guide robots operate in interactional spaces where speech, gesture, movement, and appearance all matter. According to the Computers Are Social Actors paradigm, people tend to apply social norms to interactive machines and may respond to robots as if they were intentional or even personable partners [45, 46]. Social Presence Theory similarly suggests that the more a robot is experienced as a social being, the more engaging the interaction becomes. At the same time, excessive human likeness can trigger discomfort associated with the uncanny valley phenomenon [47]. Key HRI frameworks therefore pay attention to anthropomorphism, interactivity, expressiveness, warmth, and competence. Dautenhahn [14] outlines several dimensions of socially intelligent robots, while later work shows that users transfer interpersonal judgments such as warmth and competence to robots as well [29, 48]. For guide robots, this means that behavioural design affects not only task success but also whether users feel comfortable and willing to cooperate.

Recent studies have also introduced standardized instruments for assessing how people perceive robots. Mandl et al. [49] developed the Social Perception of Robots Scale (SPRS) and Spatola et al. [29] proposed the Human–Robot Interaction Evaluation Scale (HRIES). Together, these instruments show that robot's social behaviour is not secondary to technical performance; it is one of the main ways in which users evaluate the interaction.

Humans also form mental models of a robot's agency and intentions. When the robot's social behaviour aligns with user expectations, for example by appearing polite, helpful, and respectful of personal space, acceptance tends to be higher [48, 50]. In this sense, users evaluate a guide robot not only as a tool but also as an interaction partner whose conduct must remain legible and socially appropriate. A further consideration is the fit between a robot's appearance and its task. Robots are designed in many forms, from zoomorphic and cartoon-like systems to more distinctly humanoid machines.

Because mental models of such forms are culturally shaped rather than universal, matching appearance to context and task remains especially important in international or culturally diverse environments [51].

2.1.2 Behavioural Intelligibility, Nonverbal Communication, and Spatial Guidance

The second theoretical pillar has been derived from HRI research on nonverbal and spatial behaviour. GRs do not only communicate by means of sound and the information provided on the screen. They also communicate through their movement, orientation, speed, distance, gaze-like cues, gestures, waiting behaviour, and handover signals. These behaviours determine whether users can understand what the robot is doing and what they are expected to do in response. Behavioural intelligibility is therefore a central theoretical concept for this thesis. A robot's behaviour is intelligible when users can read its actions as purposeful, timely, and socially appropriate within the situation.

While a considerable part of HRI research has focused on robots' verbal capabilities, such as speech recognition, dialogue management, and natural language processing [50, 52], nonverbal communication remains equally important for interaction quality. Verbal interaction is undeniably central in service and assistive contexts, but speech alone does not make interaction intuitive. In this thesis, nonverbal behaviour refers to gestures, gaze, posture, proxemics, and expressive signals that shape how users interpret the robot's social presence, intentions, and reliability.

Nonverbal communication has been shown to shape human interpretations of social robots' behaviour, including their perceived competence, social presence, as well as users' own comfort and willingness to continue interaction [28, 29]. Proxemics is particularly important for GRs because guidance is an embodied and spatial task. A GR must position itself close enough to the user to be followed but not so close that it becomes intrusive. It must move at a pace that users can maintain, stop in a way that makes the destination visible, and signal when the task has been completed. Research on proxemic behaviour in human-robot interaction shows that distance, orientation, and spatial positioning influence how people assess and respond to robots [53]. In this sense, nonverbal behaviour is not a decorative layer added to a technical system. It is part of the functional guidance process. A GR that reaches the correct destination but gives unclear movement, stopping, or handover cues may still fail as a service robot because the user experiences the interaction as uncertain or socially awkward.

Human communication relies heavily on nonverbal cues, and this also applies to communication with robots. In HRI research, gestures, gaze, posture, and proxemics are treated as important determinants of user acceptance because they make the robot appear more socially present, intuitive, and trustworthy [28, 29]. For operating GRs in busy public spaces, effective nonverbal communication helps users understand the robot's intentions and feel more at ease during the interaction.

Previous studies have shown that appropriate nonverbal cues can increase a robot's likeability and make the interaction feel more natural [11, 48]. Gestures and expressive motions are particularly relevant in guidance. A GR may point toward a destination, orient its body in the direction of the movement, or use arm movements to invite the user to follow. When such cues are well designed, they support the robot's verbal message and can also compensate for limited verbal explanation [11, 28]. Salem et al. [48] show that gestures aligned with speech make interaction clearer and more engaging. For robots equipped with screens or digital faces, facial expressions and emoji-like displays can also communicate affective tone, for example by signalling welcome, confirmation, or hesitation [29, 54].

Nonverbal communication also contributes to robot's behavioural realism, understood as the perceived naturalness of communication that combines verbal and nonverbal elements. Behavioural realism matters because users respond more fluently when the robot's conduct resembles familiar interactional patterns [58]. The notion was originally created to describe how simulated beings are perceived in mediated environments, but the same principle is relevant in HRI: the closer a communicative display is to recognizable social behaviour, the easier it becomes for users to interpret and respond to it [55, 56].

Adequate nonverbal behaviour also supports trust and self-efficacy. When a robot acts in a manner consistent with familiar social norms, users are more confident that they understand the robot and can anticipate its behaviour. Nonverbal cues enhance the robot's social presence [29] and can increase user confidence and satisfaction [11, 27]. Li et al. [55] similarly found that appropriate facial expressions when users committed errors improved users' confidence in handling the interaction. Cultural adaptation is important here as well because expectations concerning gaze, distance, and expressiveness are shaped by the surrounding social context [11, 56]. By using gaze, gestures, respectful distances, and readable expressive cues, robots can communicate more effectively and reduce social friction during use. For GRs in particular, nonverbal behaviour supports clarity of communication, comfort, and acceptance by complementing technical functionality with socially intelligible conduct [14, 28].

2.1.3 Social Perception, Trust, and Calibrated Anthropomorphism

Thirdly, the next theoretical strand is closely related to the previous one, concerning social perception, trust, and anthropomorphism. Social robots are often interpreted through human social categories even when their actual social abilities are limited. Human-like appearance, voice, movement, or expressive cues can make interaction more intuitive, but they can also create unrealistic expectations about robot's autonomy, intelligence, empathy, or responsibility. Research on anthropomorphism and social attributes in robots shows that users assess robots through a mixture of functional and social criteria, including perceived animacy, likeability, intelligence, warmth, competence, and safety [7, 57, 58].

For GRs, the theoretical issue here is not whether the robot should appear as human-like as possible. The issue is whether its social cues are calibrated to its actual role and technical capability. Trust is useful only when it is appropriately matched to what the robot can reliably do. Excessive anthropomorphic design may encourage users to overestimate the robot, while a purely mechanical presentation may make the interaction harder to initiate or interpret. The most relevant design principle is therefore that of calibrated sociality: the robot should provide enough social and behavioural cues to support a smooth act of guidance but not imply capabilities that the system does not possess. This is especially important in healthcare, educational, and public service environments, where users may be vulnerable, hurried, unfamiliar with the space, or dependent on the accuracy of guidance. Users need to feel that the robot is reliable, safe, and oriented toward their interests.

Building and maintaining trust is therefore a dynamic process shaped by robot performance, transparency, and the ethical framework within which the technology is deployed. In the context of robotic technologies, trust can be understood as the user's willingness to rely on the robot while expecting it to perform correctly and safely. Research on automation shows that users calibrate their trust according to reliability, predictability, and perceived capability of the technology [28, 48]. If trust is too low, users avoid the robot; if it is unrealistically high, they may form expectations that exceed the robot's actual capacities. Lee and See [59] therefore describe trust as something that is adjusted across repeated interaction. Frequent technical failures and erratic behaviour quickly erode trust [60, 61, 62].

HRI studies similarly treat trust as a key mediator between robot attributes and user acceptance. Users are less likely to engage with robots they perceive as unreliable or error-prone [11, 63]. By contrast, competent and predictable performance supports confidence in the system. Hancock et al. [63] found in their meta-analysis that robot performance, understandable interfaces, and even social behaviour all contribute positively to trust in autonomous systems. Transparency and predictability are especially important in guide robot interaction. Users should be able to anticipate what the robot is about to do and understand why it is doing it [28, 48]. In practice, this means that the robot should provide clear verbal or nonverbal cues before moving, turning, stopping, or processing a request. Such cues reduce uncertainty and make the robot's conduct easier to interpret [11, 29].

Beyond merely technical functioning, ethical and social considerations are also crucial for acceptance. Users need confidence not only in what the robot does but also in whether its use is consistent with social norms and values. Privacy is one of the main concerns. GRs rely on cameras and sensors, which raises legitimate questions about data collection, storage, and use. Transparency about these processes is necessary for building trust [63, 64]. Trust and ethics form an inseparable cluster within robot acceptance. Trust must be earned through reliable and readable behaviour, while ethical deployment requires attention to privacy, dignity, safety, and the social consequences of technological change. Organizations that communicate these concerns clearly are better positioned to create a climate in which users are willing to give the robot a fair chance.

2.1.4 Organizational Readiness and Socio-Technical Embedding

The fourth theoretical pillar emerges from socio-technical theory and organizational implementation research. Socio-technical approaches emphasize that technology use depends on the fit between technical systems, human actors, tasks, organizational structures, and the environment in which work takes place [65]. This perspective is essential for guide robots because their adoption is not completed when the device has been merely purchased or placed for example in a lobby. The robot has to be connected in a meaningful manner to a service process. Staff must understand its role, users must know when and how to approach it, physical spaces must allow the robot to move safely, and the organization must be ready to maintain, explain, and adapt the system.

Organizational readiness to accommodate robots includes several practical conditions: role clarity, workflow fit, staff training, communication with users, technical support, infrastructure readiness, data and privacy arrangements, and a realistic understanding of the robot's limitations. Without these conditions being met, the robot is likely to remain a pilot project or a public demonstration rather than becoming part of everyday service work. Change management research also suggests that new technologies are more likely to stabilize when organizations create a shared reason for adoption, prepare people for new roles, and make the change operationally meaningful rather than merely symbolic [66].

Introducing a GR into an organization is not only an issue of technical deployment but also that of organizational change. A robot that functions adequately in a laboratory or is being used in a tightly managed demonstration may still fail in everyday service settings if its role, timing, and interaction logic do not fit the surrounding workflow. For that reason, guide robots are better understood as workflow actors embedded in existing routines, staff practices, and physical environments rather than as standalone devices operating independently of organizational context [4, 14, 67].

The first condition of the successful integration of a robot is the clarity of its role. Organizations need to attribute a distinct service function to the robot, for example greeting visitors, providing directions, leading short tours, or supporting routine information work. When the robot's task is clearly defined, it is easier for staff and users to understand what the robot is for and how it fits alongside humans doing their work. Illustrative studies in libraries and museums show that guide robot acceptance improves when the robot is linked to a recognizable service task rather than being presented as an ill-defined innovation experiment [67, 68].

The second condition is environmental readiness. GRs depend on navigable corridors, accessible thresholds, reliable connectivity, and spatial layouts that do not constantly undermine movement. Features such as narrow passages, stairs, clutter, or poor stopping space can severely limit practical usefulness, which is why successful deployments often require modest infrastructural adaptation in addition to software configuration [69, 70].

The third condition is organizational support to the robot. Staff need opportunities to learn how to hand users over to the robot, intervene when necessary, and respond to breakdowns or stalled interactions. Maintenance, charging, updates, and troubleshooting must also be integrated into the workflow because otherwise technical failure becomes a visible service failure. Research on workplace collaboration with service robots likewise suggests that institutional support, training, and participatory implementation reduce resistance and strengthen willingness to collaborate [14, 60, 62, 63, 71].

Organizations' readiness to adopt robotic technologies depends closely on their attitude towards innovation in general. In the context of GRs, readiness includes material infrastructure such as adequate space, power supply, connectivity, and technical support, but also a culture that is open to experimentation, learning, and adjustment [14, 65]. Staff buy-in is central here: when employees understand the robot's purpose and see it as supporting rather than threatening their work, resistance is more likely to decrease [21, 59].

Diffusion-oriented approaches help explain why some robot deployments stabilize while others stall. Rogers' [67] diffusion of innovations framework emphasizes compatibility with existing values and workflows, manageable complexity, and visible advantage. Within organizations, early adopters or local champions can help demonstrate the robot's usefulness and normalize its presence. HRI research increasingly treats this organizational work as an integral part of adoption, not as a secondary background condition. Top-management support, employee training, and participatory implementation all matter because they shape whether the robot is framed as a credible addition to the workflow or as an imposed disruption [4, 21, 71, 72].

A study by Almokdad and Lee [21] confirms this organizational dimension empirically. By studying employees' willingness to collaborate with service robots, they found that higher job demands increased the perceived workload, which in turn reduced willingness to accept robots, while organizational support mitigated this negative effect. Their findings suggest that a sustainable human–robot collaboration depends on both institutional support and individual readiness rather than on technological capability alone. In organizational contexts, the diffusion of innovations theory is particularly relevant because technologies spread more easily when they offer visible advantages, fit existing values and workflows, and are not experienced as unnecessarily complex [67]. TAM, UTAUT, and innovation-diffusion approaches underline the importance of perceived value, usability, and organizational support in robot adoption.

Organizational change theory also emphasizes communication, feedback, and iteration. Introducing a guide robot often requires adjustments not only to technology but also to routines, responsibilities, and local meanings attached to work. Concepts such as organizational sensemaking are relevant here because employees collectively interpret what the robot means for their own roles and whether it supports or threatens established practices [73]. Viewed through this lens, guide robot deployment is best understood as a managed change process involving communication, gradual rollout, training, and support structures rather than as a one-off technical installation. Over time, this may develop into co-adaptation, in which staff adjust routines around the robot while the robot, especially when supported by AI, is gradually adjusted to better fit local practices [11, 14].

Deployment of robotic technologies is expected to create value for innovating organizations. The adoption of SSRs can create organizational value by improving operational efficiency and user experience. Reported benefits range from higher productivity and more consistent service to reduced routine workload and a clearer division of labour between staff and technology [4, 74]. At the same time, organizational value is not one-dimensional. It must be assessed in relation to the fitness of the technology to the task, service quality, staff experience, and the broader ethical implications of using robots in human-facing environments.

In healthcare and care, value is often tied to the automation of repetitive or physically demanding tasks, leaving human caregivers more time for interaction that requires empathy, judgment, or complex decision-making [75, 76]. At the same time, care contexts show why organizational value cannot be defined narrowly in efficiency terms. Sparrow and Sparrow [77] argue that robots may assist with practical tasks without replacing the social and emotional significance of human care. Their critique is important because it reminds us that organizational value must also be assessed together with ethical, relational, and dignity-related considerations.

In education, value is usually discussed in terms of engagement, motivation, and support for instructional routines. Robots such as Pepper and NAO have been used to support learner participation and to redistribute some routine tasks, although their contribution depends strongly on pedagogical fit rather than on novelty alone [12, 78, 79]. Belpaeme et al. [78] make this point clearly by showing that educational robots are most useful when interaction design is aligned with learning goals, age-appropriate expectations, and realistic technological limits.

In retail and hospitality, organizational value is more often tied to service consistency, visitor guidance, information provision, and support under labour shortage [4, 74, 80]. Here again, the value of the robot appears to depend more on functional contribution than on novelty alone. Odekerken-Schröder et al. [81] found that customers responded positively to the robot’s social presence, but functional value, especially accuracy and efficiency, had the strongest effect on return intentions. Related work also suggests that when robots take over monotonous tasks, employees may experience less routine strain and greater room for higher-value work [82].

Literature supports a cautious conclusion: SSRs can create substantial organizational value but only when technological capability, service design, and organizational preparation are aligned. From the perspective of this thesis, value is not simply a post hoc benefit of adoption. It is one of the conditions that makes continued organizational commitment to guide robot deployment more plausible in the first place.

2.1.5 Technology Acceptance, User Experience, and Barriers

The fifth theoretical pillar addresses the factors influencing technology acceptance, user experience, and robot deployment. Drawing on technology acceptance research, this perspective examines how perceived usefulness, ease of use, trust, and interaction quality influence users' willingness to engage with robots. At the same time, successful robot adoption depends on addressing broader technical, organizational, social, and ethical barriers that may hinder implementation and long-term use.

Multiple theoretical frameworks have been used to analyse the acceptance of robotic technologies. GR acceptance involves cognitive beliefs such as perceived usefulness, affective responses such as trust and anxiety, and contextual conditions such as organizational readiness and peer influence. For these reasons, robot acceptance is better understood through a combination of a variety of perspectives than through any single explanatory model [64, 83, 84, 85]. Classic technology acceptance theories provide a useful starting point for understanding why people adopt new technologies, including robots. TAM proposes that perceived usefulness and perceived ease of use shape users' attitudes and intentions [83]. In the context of GRs, the core implication is straightforward: users are more likely to accept the robot when it clearly helps them achieve their goal and when the interaction is easy to understand. UTAUT extends this perspective by adding social influence and facilitating conditions to the analysis of technology use behaviour [84]. Several such models have been adapted specifically for robotics. Heerink et al. [85] developed the Almere Model to predict older adults' acceptance of assistive social robots, adding variables such as anxiety, trust, and perceived adaptivity. Turja et al. [43] similarly proposed RAM-Care for care robots, emphasizing that attitudes, social norms, and self-efficacy shape intentions to use robots in practical settings. These adaptations of technology acceptance approaches show that robot acceptance cannot be reduced to generic usability beliefs alone.

Previous user experience with a GR is one of the strongest proximate predictors of later acceptance. Users quickly assess whether interacting with the robot is clear, pleasant, helpful, and worth the effort required to complete the task. A positive experience can increase satisfaction and repeated willingness to use the robot, whereas a confusing or awkward encounter can become a barrier to future engagement. Earlier research therefore highlights user-friendliness, responsiveness, multimodal clarity, and intuitive interaction design, including both dialogue and nonverbal cues as central to acceptance [11, 27, 28, 64].

Positive user experience often translates into higher perceived interaction quality and greater satisfaction. From the organizational perspective, this is one of the expected benefits of guide robots because reliable information provision and reduced waiting times can contribute to a more consistent service quality [19, 80]. Empirical studies in service environments support this view. Such findings suggest that acceptance is reinforced when users experience robot-assisted service as both practically useful and interactionally smooth. Despite the generally positive reception of social robots in many contexts, substantial barriers still slow or prevent their wider adoption. Identifying and addressing these barriers is a central theme in HRI research because the benefits of robot-assisted services materialize only when technological, social, and ethical obstacles are managed in practice [14, 65].

Technical barriers are often the most immediate obstacles identified during pilot implementations of robotic technologies. Common problems include hardware failures, software bugs, and navigation difficulties [60, 61]. For example, a guide robot in a public space may suddenly stop functioning due to a sensor error or fail to recognize a glass wall as an obstacle, leading to a collision. Such incidents do not only disrupt the services but also damage user trust and compromise the robot's reputation. Continuous research and development are needed to improve robots' autonomy, robustness, and adaptability to changes in their operational environment. Until this can be reliably ensured, organizations deploying robots must have backup plans in place, including human oversight or service-abort procedures where necessary. Without such preparations, technical breakdowns may easily become an obstacle, causing projects supporting robots' deployment to be scaled back or cancelled [60, 71].

Even when the technology functions as intended, human factors can create additional obstacles. Negative attitudes toward robots and technophobia remain relevant concerns. Some users feel uncomfortable or fearful around robots because of unfamiliarity, uncertainty, or negative media portrayals. Nomura et al. [86] showed that individuals with higher anxiety toward robots assessed their interactions more negatively. Employees may also fear that a robot may replace them and begin to resist its deployment, either actively or passively [14, 21]. Unrealistically high expectations can also become problematic; clear communication about what the robot can and cannot do helps mitigate disappointment and resistance [11].

Manufacturer- and distributor-related barriers may also be significant. A recurring obstacle to wider adoption is limited knowledge about realistic use cases, reference implementations, safety requirements, and the competencies needed to operate robots effectively [87]. Cho and Kwon [88] likewise note that weak technical support and maintenance intensify resistance to adoption. In retail and service environments, acceptance also depends on both functional and emotional aspects of the customer experience. Jeong and Ha [89] show that perceived usefulness and ease of use remain central, while Saari et al. [90] emphasize that different user groups value different aspects of robot usefulness, suggesting that design, communication, and support strategies should be adapted to the intended user group. Addressing these barriers requires a comprehensive strategy. Rigorous testing, gradual deployment, and iterative refinement help identify problems before a full-scale rollout. Involving end users early through participatory design, demonstrations, and trials makes it easier to surface fears, misconceptions, and usability problems while there is still room to adjust the technology and the implementation process [39, 64].

Ethical and policy barriers are often related to privacy and safety. Some individuals may object to robots recording video or tracking movement, and these concerns become especially acute in sensitive environments such as hospitals. From an ethical and legal perspective, organizations must ensure data protection for any information that robots collect [65, 91]. Cybersecurity is part of the same challenge, as a hacked guide robot could become not only an inconvenience but also a safety hazard or a source of data breach.

The lack of clear regulations and liability frameworks also makes organizations more hesitant to adopt robots. In addition, accessibility and fairness remain important concerns. A guide robot must be able to accommodate users with different abilities and communicate appropriately in multilingual and multicultural environments; otherwise, its usefulness remains limited, and it may even be perceived as exclusionary. Ethical guidelines therefore stress that robots should respect human dignity and be designed for the benefit of their users [91, 92]. As compared with purely technical barriers, many user-related and organizational obstacles can be addressed by the adopting organization itself. Lack of familiarity, fear of interaction, limited skills, unclear organizational value, and weak internal competencies do not disappear automatically, but they can be reduced through training, demonstrations of value, and a culture that supports experimentation and learning. Understanding and addressing these barriers systematically is therefore central to the wider diffusion of social robots [11].

2.1.6 Theoretical Synthesis and the Conceptual Model

Together these five theoretical perspectives position GR adoption as a problem of socio-technical alignment. Social cognitive theory explains why users' perceived capability matters. Technology acceptance research explains how perceived usefulness, ease of use, facilitating conditions, and continued use shape adoption. Human–robot interaction research explains why nonverbal and spatial behaviour are central to the practical intelligibility of guidance. Social perception and trust research explain why robot cues must be socially meaningful but carefully calibrated. Socio-technical theory explains why organizational embedding is necessary for moving from isolated pilots to routine use. ANT allows us to see that GR acceptance emerges as a result of a complex interplay between a number of material and social elements in practice.

Various strands of previous research that inform the current thesis can be therefore interpreted as examining different sides of the same adoption problem. Studies of user self-efficacy address whether people feel capable of engaging with guide robots. Studies of nonverbal and spatial behaviour address whether the robot's guidance is readable and manageable in practice. Studies of organizational deployment address whether the robot can be assigned a clear role in real service environments. The central assumption is that GR adoption becomes more plausible when these dimensions support each other: users feel able to interact, the robot behaves in ways that users can understand, and the organization provides the conditions under which the robot's service role makes sense. The emerging analytical framework also clarifies why the thesis focuses on guide robots rather than on social robots in general. The guiding task makes adoption visible, situated, and testable. It requires the robot to move through shared space, communicate a destination, coordinate with a human user, and hand over the task at the right moment. These features make GRs a useful case for studying how service robots become acceptable not only as technological novelties, but as practical components of organizational workflow.

The five theoretical perspectives are used as complementary explanatory lenses rather than competing models. The theory of self-efficacy explains perceived capability; human–robot interaction research explains behavioural intelligibility; trust and social-perception research explain calibrated reliance; socio-technical and organizational theories explain embedding; and technology acceptance research connects usefulness and facilitating conditions to continued use. These perspectives combined offer a mechanism that has been examined through the cumulative evidence: routine guide robot use becomes more plausible when user capability, readable robot behaviour, and organizational support reinforce one another in a defined service task. The conceptual model developed in this thesis allows synthesizing these relationships by proposing that successful GR adoption emerges from the interaction between user-related, robot-related, and organizational factors.

3 Empirical Studies

This chapter synthesizes the evidence by research strand, distinguishing four evidence roles. Direct evidence comes from studies in which guide robots were used, evaluated, or considered for deployment in organizational settings. Supporting evidence comes from adjacent human–robot interaction research that isolates mechanisms relevant to guidance, such as proxemics. Review-based evidence maps the wider research field, while integrative evidence connects findings across the publication set. This distinction is necessary because the publications differ in method, setting, sample, and proximity to the core phenomenon. The purpose is not to claim uniform replication but to show how different forms of evidence jointly support bounded answers to RQ1–RQ3. Table 1 summarizes the six articles included in the dissertation by outlining their evidence role, contribution to the main and specific research questions, principal findings, and key limitations.

Table 1. Contribution of the six articles to the dissertation research questions.

Article	***Main focus of the article***	***Main RQ***	***RQ1: User self-efficacy***	***RQ2: Nonverbal and spatial behaviour***	***RQ3: Organizational conditions / routine workflow***
Article I – Guide robots' acceptance in organizations: user self-efficacy and robots' organizational value	*Examines guide robot acceptance through user self-efficacy, organizational value, and barriers in real organizational contexts.*	*Core article. Directly explains that routine use depends on the alignment between robot capability, user readiness, and organizational readiness.*	*Direct support. Shows that prior robot experience is linked with higher self-efficacy and that self-efficacy drops in uncontrolled real-life settings.*	*Partial support. Connects robot capability and understandable interaction with user confidence.*	*Direct support. Identifies technical, user-related, and organizational barriers and proposes a three-actor framework for deployment.*
Article II – Nonverbal behaviour of service robots in social interactions: a survey on recent studies	*Literature review of nonverbal communication in HRI with social service robots.*	*Conceptual foundation. Shows why technical functionality alone is insufficient; successful adoption also depends on socially understandable interaction.*	*Indirect support. Links nonverbal communication with trust, trustworthiness, and user confidence in HRI.*	*Direct support. Identifies key nonverbal cues such as distance, personal space, gaze, touch, gestures, and embodied communication.*	*Indirect support. Helps justify why organizations need socially capable robots, not only technically functional ones.*
Article III – Keeping social distance in a classroom while	*Pilot study on social distance, proximity, and behavioural realism in*	*Specific socio-spatial evidence. Shows that robot-*	*Indirect support. Suggests that users need practice,*	*Direct support. Provides empirical evidence on proxemics,*	*Partial support. Indicates that training and context-*

Article	*Main focus of the article*	*Main RQ*	*RQ1: User self-efficacy*	*RQ2: Nonverbal and spatial behaviour*	*RQ3: Organizational conditions / routine workflow*
interacting via a telepresence robot	*telepresence robot interaction.*	*mediated interaction becomes more acceptable when spatial behaviour feels realistic and socially manageable.*	*especially in situations requiring greater interpersonal distance.*	*social distance, and behavioural realism.*	*specific practice are needed before routine organizational use.*
Article IV – Enhancing university visitor satisfaction: a human–robot interaction study on the design and perception of a guiding robot assistant	*Controlled study of the TEMI guide robot in a university setting, including greeting, guiding, video calling, destination information, and feedback collection.*	*Pilot-stage evidence. Shows that a guide robot can perform a structured visitor-guidance service but also points to the need for real-world validation.*	*Partial support. Captures users' perceptions of interaction and collaboration with the robot.*	*Direct support. Tests verbal and nonverbal behaviours designed to make the robot appear as a welcoming service provider.*	*Partial support. Demonstrates a possible organizational use case but still mainly as a controlled pilot rather than a routine workflow.*
Article V – User perceptions of social service robot guidance in an academic library	*Field study of two TEMI robots guiding library visitors to book locations.*	*Strong bridge article. Moves from controlled pilot toward real service use by studying voluntary interaction in an operational academic library.*	*Partial support. Shows that users value clarity, usefulness, comfort, and predictable interaction, which support confidence in use.*	*Direct support. Highlights precise stopping, readable text, clear handover, screen height, visibility, and mobility robustness as important for understandable guidance.*	*Direct support. Shows that routine deployment requires narrow, clearly communicated tasks, minimal interaction flow, and integration with actual service needs.*
Article VI – Enhancing human–robot interaction through nonverbal communication and user self-efficacy	*Qualitative study with end users, staff/collaborators, and robot sellers about nonverbal behaviour, self-efficacy, and public-space deployment.*	*Integrative article. Connects nonverbal robot behaviour, user confidence, staff support,*	*Direct support. Shows a drop in self-efficacy when moving from controlled training to real-life use.*	*Direct support. Identifies gaze, eye contact, proxemics, gestures, movement, posture/height, speed, expressiveness,*	*Direct support. Shows that successful integration requires technical proficiency, user support,*

Article	Main focus of the article	Main RQ	RQ1: User self-efficacy	RQ2: Nonverbal and spatial behaviour	RQ3: Organizational conditions / routine workflow
		and real-world deployment challenges.		*and cultural sensitivity as important cues.*	*training, and attention to organizational deployment barriers.*

The research programme combines several complementary sources of evidence: a questionnaire-based self-efficacy study in controlled and real-life settings, a small-sample university guide robot pilot, a PRISMA-informed review of nonverbal behaviour research, a telepresence robot experiment, an exploratory academic library field study, and stakeholder interviews on deployment barriers and enabling conditions. These studies jointly make it possible to examine GR adoption from three linked angles: user capability, robot behaviour, and organizational embedding. Table 2 provides an overview of the empirical components, methods, samples, and procedures on which the cumulative synthesis rests.

Table 2. Overview of empirical components, methods, samples, and procedures.

Study/ component	Article(s)	Method and sample	Core procedure / focus
Study 1.1 *GRUSES study*	*Article 1*	*Questionnaire study in controlled and real-life settings* *N = 226*	*Participants completed structured guide robot tasks with TEMI v3. GRUSES measured comprehensibility, effectiveness, and subjective pleasantness.*
Study 1.2 *University guide robot pilot*	*Article 4*	*Small-sample pilot experiment with post-interaction questionnaire* *N = 28*	*Students and lecturers completed a university guidance sequence with a semi-autonomous TEMI v3. The questionnaire focused on interaction quality, collaboration, bystander attention, and anthropomorphism.*
Study 2.1 *Nonverbal behaviour review*	*Article 2*	*PRISMA-informed literature review* *39 papers, aggregated N = 1,053*	*Database searches in Web of Science, Scopus, and EBSCO were followed by coding of robot types, nonverbal cues, methods, samples, and outcomes in empirical HRI studies.*
Study 2.2	*Article 3*	*Empirical pilot experiment with depth-camera*	*Telepresent and physically present participants interacted via three telepresence robots in simulated*

Study/ component	Article(s)	Method and sample	Core procedure / focus
Telepresence proxemics experiment		*measurements and questionnaires* *N = 24*	*conversations. Analyses focused on interpersonal distance, comfort, and technical suitability.*
Study 2.3 *Academic library guide robot field study*	*Article 5*	*Exploratory mixed-method field study* *47 interactions, 13 observation consents, 8 interviews*	*Visitors freely selected TEMI v3 or TEMI GO for a book-guidance task over five days. Observations and in situ interviews examined interaction clarity, robot size, stopping behaviour, and the handover moment.*
Study 3 *Stakeholder barriers and deployment conditions*	*Article 1*	*Qualitative interview study* *N = 26*	*Semi-structured interviews with users, administrators, and retailers or suppliers were analysed thematically to identify technical limitations, user concerns, training needs, support requirements, and workflow barriers. Article 6 later synthesizes the behavioural and self-efficacy strands without adding a separate standalone sample.*

3.1 Study 1. User Self-Efficacy in Guide Robot Interaction

Study 1 addresses RQ1 by examining how users' self-efficacy shapes the acceptance and practical use of guide robots in organizational contexts. Its main evidence comes from the GRUSES-based study reported in Article 1 and the university guide robot pilot reported in Article 4, while Article 6 later serves as an integrative bridge by linking self-efficacy more explicitly to nonverbal and spatial aspects of interaction. These components allow analysing whether users assess their interaction with guide robots positively as well as determining under which conditions their confidence is strengthened or weakened.

The first empirical component, reported in Article 1, focused on the iterative development and application of the Guide Robot User Self-Efficacy Scale (GRUSES). In this study, 226 participants interacted with a TEMI v3 guide robot in either a controlled or a real-life setting and then evaluated the experience in terms of comprehensibility, effectiveness, and subjective pleasantness. The full text of Article 1 is reproduced in Appendix 1, and the final GRUSES instrument is presented separately in Appendix 2. The results showed overall relatively high self-efficacy, but the scores were significantly higher in controlled settings (M = 5.68) than in real-life settings (M = 5.05), which indicates that the loss of guided support in public environments reduced users' confidence. Prior robot experience was positively associated with self-efficacy, and experienced users reported higher scores (M = 5.69) than inexperienced users (M = 5.09). In contrast, there were no significant differences in self-efficacy between different age groups or between men and women in this sample. It appears that regardless of age or gender, people's confidence in using the GR in controlled settings was uniformly high, but prior hands-on experience did give some participants an edge in confidence. These results suggest that self-efficacy in the use of guide robots is not a fixed personal trait but a context-sensitive condition shaped by experience, demographic background, and practical conditions of use.

The second component of Study 1, reported in Article 4, complemented the GRUSES findings through a small-sample field-like pilot in a university environment. Twenty-eight students and lecturers interacted with a TEMI v3 robot that guided them through a sequence of navigation and communication tasks, including wayfinding, call function, web-page display, and movement to a relaxation area. Users generally found the robot as easy to use, useful, and socially acceptable, which supports the broader finding that guide robots can perform simple repetitive public-service tasks in a technically feasible and interactionally meaningful way. At the same time, the study exposed an important complication that is less visible in controlled settings: around half of the participants reported increased attention from bystanders during the interaction, and this public exposure was associated with discomfort and reduced confidence. The two components of Study 1 show that users are generally open to guide robot use, but that successful organizational adoption depends on how confidently people feel they can manage the interaction in the actual setting in which the robot is deployed.

At the thesis level, Study 1 answers RQ1 by showing that user self-efficacy is a context-sensitive enabling condition rather than a fixed personal trait. The direct evidence is strongest for the effect of interaction conditions and prior experience: confidence was easier to sustain when the encounter was supported, predictable, and easier to interpret. Public visibility and uncertainty could weaken that confidence even when the robot completed the task. Demographic differences should be interpreted only according to the verified statistical output and should not carry more explanatory weight than the evidence supports. These findings indicate that organizations can influence user readiness through onboarding, low-pressure first encounters, clear instructions, and visible recovery support.

3.2 Study 2. Guide Robot Nonverbal Behaviour in Human–Robot Interaction

Study 2 addresses RQ2 by examining which nonverbal and spatial behaviour capabilities make guide robot interaction understandable and manageable in organizational contexts. The evidence base is cumulative: Article 2 provides the review-based foundation on nonverbal behaviour in service-robot interaction, Article 3 contributes focused empirical insight on proxemics and behavioural realism through telepresence robots, Article 5 adds a guide robot field case from an academic library, and Article 6 functions as an integrative article that links behavioural cues more explicitly to user self-efficacy.

The review reported in Article 2 analysed 39 empirical studies involving a total of 1,053 participants and showed that humanoid robots dominated the field, with NAO, iCub, and Pepper appearing most often. The most frequently studied nonverbal cues were gesture and facial expressions, followed by gaze, voice characteristics, affective displays, and proximity or movement behaviour. Across these studies, nonverbal communication was consistently treated as central to trust, naturalness, social presence, engagement, and users' confidence in understanding what the robot was doing. The review also showed, however, that much of the literature is still based on short-term and laboratory-oriented experiments, which leaves open the question of how such cues function in ecologically valid public settings.

That question was explored further in the telepresence robot experiment reported in Article 3 and in the academic library field study reported in Article 5. In the telepresence study, 24 participants interacted through three telepresence robots in a simulated communication task, and the results showed that telepresent participants selected markedly shorter communication distances than physically present participants (67 cm versus 104 cm on average). According to Hall's [93] categories, telepresent users often remained in personal rather than social space, especially women, which suggests that current telepresence interactions still deviate from familiar human proxemic norms and often lack full behavioural realism. In the library field study, by contrast, the central issue was not remote embodiment but public guide robot use. Two social service robots, TEMI v3 and TEMI GO, were deployed over five days in an academic library, where 47 visitors interacted with them, 13 consented to observational use, and 8 took part in short in situ interviews. The findings showed that users valued practical usefulness and interaction clarity more than the robot size itself. Acceptance depended especially on readable movement, precise stopping, clear completion cues, and a well-managed handover from robot-led navigation to user-led action. Article 6 then strengthened this interpretation by showing more explicitly how such nonverbal and spatial cues influence users' confidence in managing the interaction. Taken together, Study 2 shows that behavioural intelligibility is not secondary to technical performance but one of the main conditions through which guide robots become understandable, trustworthy, and practically usable.

At the thesis level, Study 2 answers RQ2 by identifying behavioural intelligibility as the mechanism that makes guide robot interaction manageable. The strongest direct GR evidence concerns readable movement, accurate stopping, orientation, task-completion cues, and the handover from robot-led guidance to user-led action. The literature review and the telepresence experiment support the wider interpretation that distance and nonverbal behaviour shape comfort and social meaning, but they do not provide equivalent direct evidence for guide robot deployment. The cumulative conclusion is therefore bounded: GR does not need broad human-like social sophistication, but it must communicate what it is doing, what the user should do next, and when the service sequence has ended.

3.3 Study 3. Organizational Deployment of Guide Robots

Study 3 addresses RQ3 by focusing on the organizational, technical, and interactional conditions that shape whether guide robots can become part of routine workflow rather than remain isolated experiments. Its primary empirical source is the stakeholder interview study reported in Article 1, while the university and library field cases reported in Articles 4 and 5 provide contextual support for understanding how these deployment issues appear in practice.

For analytical clarity, the thesis distinguishes three related organizational concepts. Organizational readiness refers to the preconditions that allow deployment to begin, including leadership support, staff preparation, infrastructure, privacy arrangements, and technical resources. Workflow integration refers to the concrete embedding of the robot into tasks, responsibilities, handovers, maintenance, and fallback procedures. Organizational value refers to the benefits that are expected, perceived, or realised after use, such as improved access to information, service consistency, or reduced routine workload. Readiness makes deployment possible, integration makes it repeatable, and value helps determine whether the organization has a reason to continue it.

The main empirical component was a qualitative interview study with 26 participants representing three stakeholder groups: guide robot users, including librarians, healthcare workers, and office workers; organizational administrators; and robot retailers or suppliers. The semi-structured interviews addressed technical functionality, nonverbal behaviour, movement speed, interpersonal distance, gaze, organizational support, and workflow integration. The material was transcribed and analysed thematically, with coding focused on technical performance, trust, privacy, training needs, proxemics, gaze, and touch-related interaction issues. Three broad clusters of barriers emerged from the material. First, participants pointed to technical limitations, especially in navigation precision, language support, and operational reliability. Second, they described user-related barriers such as technophobia, discomfort with gaze or proxemic behaviour, and uncertainty about the robot's intentions. Third, they emphasized organizational barriers, including weak role clarity, insufficient training, poor workflow fit, and limited support structures.

Participants also suggested concrete ways of reducing these barriers, such as more culturally appropriate nonverbal behaviour, adjustable proximity settings, stronger maintenance and after-sales support, and clearer organizational communication about the robot's role. Read together with the field cases, the interview data show that organizations are not passive settings for robot use but active participants in whether guide robot deployment becomes meaningful and sustainable. Leadership support, onboarding, role clarity, maintenance arrangements, and practical fit with service routines all shaped whether the robot could be interpreted as a useful part of workflow rather than a fragile novelty. Within the scope of this dissertation, Study 3 therefore supports the broader conclusion that guide robot adoption depends not only on a willing user or a technically functional robot but on organizational arrangements that make continued use plausible in everyday practice.

At the thesis level, Study 3 answers RQ3 by showing that organizations actively produce the conditions of acceptance. The stakeholder interviews provide direct evidence that role clarity, training, maintenance, technical support, environmental readiness, and workflow fit influence whether deployment remains a demonstration or becomes repeatable service work. The university and library cases provide contextual field support by showing how these conditions appear in actual interaction sequences. The evidence does not allow establishing the conditions for successful long-term routinization of robots across all organizations, but it does explain which arrangements make continued use more plausible and which absences cause pilot deployments to remain fragile.

4 Discussion and Conclusions

Building on the empirical synthesis in Chapter 3, this chapter returns to the central problem of the dissertation: the gap between the technical promise of social service robots and their still limited, often fragile use in real organizational environments.

The thesis does not claim one universal causal model of adoption. Instead, it offers a more bounded socio-technical account of guide robot integration, one that is centred on the alignment between user self-efficacy, behavioural intelligibility, and organizational readiness.

4.1 Answers to the Research Questions

The answers below are calibrated to the role and scope of the evidence. In this thesis, 'supported' refers to convergence across direct, supporting, review-based, and integrative evidence. It does not mean that every relationship was tested in one causal model or observed through a long-term organizational deployment. Stronger claims are made where direct GR field evidence is available, while adjacent and review-based findings are used to explain mechanisms and define the limits of transfer.

Within the empirical scope of the thesis, GRs can move from isolated pilots toward routine organizational use when three conditions align around a bounded service task. First, users need sufficient self-efficacy to initiate, follow, and complete the interaction. Second, the robot must behave in ways that make movement, distance, stopping, orientation, and handover understandable. Third, the organization must provide role clarity, workflow fit, staff preparation, technical support, and an environment in which the service sequence can be completed reliably. These are mutually dependent conditions rather than independent predictors. A weakness in any one domain can destabilize the whole deployment, while their alignment creates a plausible pathway from technical feasibility to repeatable use.

The main research question asked under what socio-technical conditions guide robots can move from isolated pilots to performing routine organizational tasks. Across the studies, the answer is consistent: routinization becomes more plausible when users feel capable of managing the interaction, when the robot behaves in readable and socially intelligible ways, and when the organization provides role clarity, onboarding, technical support, and workflow fit. Guide robot adoption therefore depends less on technical feasibility alone and more on whether these three dimensions are aligned in practice [27, 43, 85].

RQ1 asked how user self-efficacy shapes the acceptance and practical use of guide robots in organizational contexts. The studies indicate that self-efficacy functions as a key enabling condition. Higher perceived capability was associated with stronger acceptance, greater comfort, and higher perceived usefulness, yet this capability was shaped by context rather than fixed in advance. Controlled and guided situations supported stronger self-efficacy than more exposed public encounters, where bystander attention, situational uncertainty, and the absence of structured support could reduce confidence. Prior experience and supportive first encounters strengthened self-efficacy, suggesting that user readiness can be actively fostered rather than treated as a static background variable [11, 27, 28].

RQ2 asked which nonverbal and spatial behaviour capabilities make guide robot guidance understandable and manageable in organizational contexts. The answer points less to broad social sophistication and more to behavioural intelligibility. Across the review, the telepresence pilot, the academic library field study, and the integrative article, users responded positively when the robot's movement, distance, orientation, stopping, and handover cues made the service sequence easy to follow. These findings suggest that nonverbal behaviour is one of the core mechanisms through which users interpret robot competence, trustworthiness, and realism. The evidence also indicates that proxemics and other nonverbal expectations are sensitive to setting and, in some cases, to user characteristics, which makes the context-aware design especially important [29, 30, 36].

RQ3 asked which organizational conditions enable guide robots to become part of routine workflow rather than remain isolated experiments. The material points to visible managerial commitment, communication, training, technical support, infrastructural fit, and clear task boundaries. It also shows that organizations need to define realistic use cases and integrate maintenance, fallback procedures, and staff cooperation into everyday practice. In this sense, organizations do not function as passive backdrops for robot use. They actively shape how the robot is framed, supported, and normalized, and they can either reduce or intensify the barriers identified in the empirical material [21, 69, 75].

The answers to the research questions reinforce the central argument of the thesis: GR adoption in organizations is best understood as a socio-technical alignment problem. Users are more likely to engage with a robot when they feel capable of doing it, their confidence is easier to sustain when the robot's behaviour remains readable, and both are more likely to last when organizational support is in place. The next section confirms the analytical framework introduced earlier in the thesis and presents the conceptual model resulting from the current research programme.

4.2 Empirically Supported Socio-Technical Model of Guide Robot Adoption

The model presented in Figure 6 integrates the answers to the research questions into a thesis-level explanation of how guide robot use can become workable in organizations. It is derived from the cumulative evidence of the six publications and is not a causal model estimated from a single dataset. The user domain is supported mainly by the GRUSES study and the university guide robot case. The behavioural domain combines direct field evidence on movement, stopping, and handover with the review-based and adjacent evidence on nonverbal behaviour and proxemics. The organizational domain is supported principally by the stakeholder interviews, with the university and library cases providing contextual evidence of the workflow and environmental conditions. The model therefore represents converging but differently weighted evidence.

Figure 6 should be distinguished from both the analytical framework presented in Figure 3 and the preliminary conceptual model published in Article 1 [33]. Figure 3 organized the research programme and connected its three domains to the research questions. The model in Article 1 provided an initial three-actor account based mainly on the self-efficacy study and stakeholder interviews, with three broad factors specified for each domain. The thesis-level model retains the underlying logic of interaction among the user, robot, and organization, but refines it using evidence from the full publication set. Each domain now contains four factors, the factors are formulated more precisely, and the mechanism linking the domains is made explicit. The model also introduces boundary conditions and uses a more evidence-bounded outcome. These changes represent a cumulative refinement of the published model, not a rejection of its three-actor foundation.

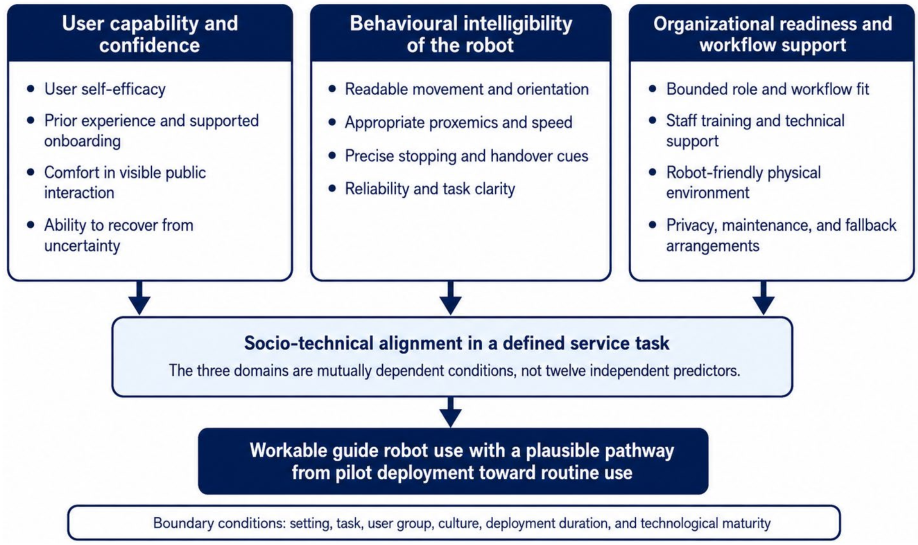

Figure 6. Empirically supported socio-technical model of guide robot adoption.

The first domain, user capability and confidence, comprises user self-efficacy, prior experience and supported onboarding, comfort in visible public interaction, and the ability to recover from uncertainty. User self-efficacy concerns whether users believe that they can initiate, follow, and complete the interaction successfully. Prior experience and supported onboarding can strengthen this confidence by creating familiarity and enabling successful first encounters. Comfort in visible public interaction is included because guide robot use often takes place in public or semi-public spaces, where bystander attention can make an otherwise manageable interaction feel socially exposing. The ability to recover from uncertainty captures whether users know how to proceed when instructions are unclear, the robot pauses or behaves unexpectedly, or human intervention becomes necessary. The evidence is strongest for the context sensitivity of self-efficacy, the role of prior experience, and the effects of supported versus publicly exposed interaction. Recovery from uncertainty is supported more indirectly through repeated findings concerning the importance of clear instructions, accessible assistance, and visible fallback options. Sociodemographic differences identified in the self-efficacy study remain relevant, but they are not treated as a separate core mechanism in the thesis-level model. Age, gender, education, and other user characteristics may influence how interaction is experienced, but the present evidence does not establish these relationships as stable across settings. They are therefore better represented through the user-group boundary condition, which allows future studies to test how the model operates for different populations without treating demographic background as an independent predictor of adoption.

The second domain, behavioural intelligibility of the robot, comprises readable movement and orientation, appropriate proxemics and speed, precise stopping and handover cues, and reliability and task clarity. These factors describe whether the complete guidance sequence can be understood from the user's initial approach to the point at which robot-led navigation ends. Readable movement and orientation help users anticipate where the robot is going and whether they are expected to follow. Appropriate proxemics and speed allow users to maintain a comfortable distance and pace. Precise stopping and handover cues indicate that the destination has been reached and clarify what the user should do next. Reliability and task clarity ensure that the robot performs its bounded function consistently and communicates the purpose and limits of that function. This formulation develops the behavioural dimension beyond a broad category of technological features. The studies did not show that technical sophistication or human-like sociality had value in themselves. Users responded mainly to behaviours that made the robot's actions predictable and the service sequence manageable. The strongest direct guide robot evidence concerns readable movement, accurate stopping, completion cues, and the handover from robot-led guidance to user-led action. The review and telepresence study extend this interpretation by showing how distance, orientation, and other nonverbal behaviours influence comfort and social meaning. Reliability and task clarity connect behavioural intelligibility to the robot's technical performance, while keeping the focus on what the user can observe and understand during the interaction.

The third domain, organizational readiness and workflow support, comprises a bounded role and workflow fit, staff training and technical support, a robot-friendly physical environment, privacy, maintenance, and fallback arrangements. A bounded role specifies the service problem the robot is expected to address, where its responsibility begins and ends, and how its task connects with existing routines. Staff training and technical support ensure that employees can operate the robot, assist users, and respond to common breakdowns. A robot-friendly physical environment supports safe navigation, accessible stopping points, connectivity, charging, and the completion of the intended route. Privacy, maintenance, and fallback arrangements define how data-related concerns, routine servicing, technical failures, and situations requiring human intervention will be managed. The organizational domain operationalizes the broader idea of a supportive organizational culture used in the earlier model. Openness to innovation may facilitate adoption, but the empirical material shows that positive attitudes alone do not create sustainable deployment. Organizational support becomes consequential when it is expressed through assigned responsibilities, training, maintenance, environmental preparation, technical assistance, and recovery procedures. Maintenance and support are therefore positioned primarily within organizational readiness, although their quality also depends on manufacturers and distributors. This reflects the finding that technical problems become organizational service failures when no local responsibility or fallback process has been established.

The twelve factors should be interpreted as mutually dependent conditions, not as twelve independent predictors. Their alignment occurs around a defined service task. Users must feel able to begin, follow, and complete the interaction, including responding to uncertainty. The robot must make its movement, distance, stopping, and handover understandable. The organization must define the task, prepare the setting, support users and staff, and maintain the service process when problems occur. A weakness in one domain can destabilize the complete deployment. Strong user confidence cannot compensate indefinitely for unreliable or unreadable robot behaviour. Readable robot behaviour may still fail to produce continued use when the robot has no clear workflow role. Organizational support cannot make a service sustainable when the robot cannot perform the assigned task reliably.

The immediate outcome of this alignment is a workable approach to GR adoption with a plausible pathway from pilot deployment toward routine use. The pathway, among others, depends on many boundary conditions: the setting, task, user group, culture, deployment duration, and technological maturity. The same robot may be workable in a structured university or library route but less suitable in a crowded hospital, an airport, or another environment involving higher uncertainty and greater consequences of failure. User expectations and interpretations of distance, gaze, movement, and assistance may also vary across populations and cultures. Duration also matters in deployment because short pilot studies cannot demonstrate whether novelty effects disappear, staff routines stabilize, or maintenance demands remain manageable over time. Technological maturity similarly determines whether the robot can perform reliably outside controlled conditions. As an example, Figure 7 offers a visualization of such a practical GR deployment pathway. The pathway, presented here as implementation guidance, not to be interpreted as a longitudinally validated stage model, allows operationalizing the main findings of the thesis.

The formulations offered in this section appear more defensible than treating greater efficiency, improved service quality, or organizational value as directly established outcomes of the present studies. Organizational value remains an important reason for continued investment, but it is likely to emerge only after the service task has become repeatable and integrated into routine practice. The thesis therefore places workable use and progression toward routinization before wider organizational benefits in the proposed sequence.

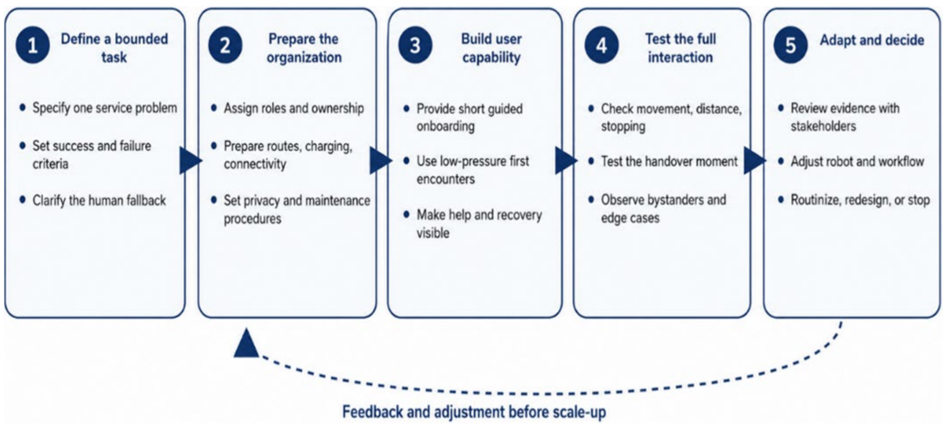

Figure 7. Guide robot deployment pathway with feedback before scale-up.

The model does not replace technology acceptance perspectives based on usefulness, ease of use, trust, or facilitating conditions. It specifies how these broader concepts become observable in guide robot deployment. Ease and perceived capability are reflected in user self-efficacy and recovery from uncertainty. Trust and interpretability are reflected in readable movement, reliable performance, and clear handover. Facilitating conditions are reflected in workflow fit, training, environmental preparation, maintenance, and fallback support. The model is therefore best described as empirically supported and analytically refined, while its individual factors and cross-domain relationships still require longitudinal, comparative, and multi-site testing. It provides the organizing basis for the contributions discussed in the next section and for the implementation recommendations developed in Chapter 5.

4.3 Contributions of the Thesis

The contribution of the thesis lies in making GR adoption more analytically precise and more practically actionable. Rather than treating robot acceptance as a single attitude outcome, the dissertation shows how adoption depends on the interaction between user capability, robot behaviour, and organizational embedding. In that sense, the thesis contributes not only findings about guide robots but also a clearer way of analysing why apparently promising robots still struggle to become routine parts of organizational practice.

Its contributions are best understood at five connected levels:

Differentiating user positions and use situations. A first contribution of the dissertation is that it distinguishes more clearly between occasional visitors, organization-embedded users, and wider stakeholder groups involved in deployment. This helps explain why guide robot acceptance develops differently in public interaction situations and in organizational implementation processes, and why adoption cannot be reduced to one generic user response.

Exploratory operationalization of user self-efficacy. A key methodological contribution is the development and iterative use of GRUSES as a context-specific instrument for studying users' perceived capability to interact with guide robots. The thesis does not present the scale as fully finalized; instead, it shows why guide-robot-specific self-efficacy is analytically useful and how it can be operationalized for further study.

Field-based clarification of behavioural intelligibility in guidance tasks. As a result of the experiments conducted in diverse environments such as various public spaces, as well as an academic library, the dissertation shows that guidance depends not only on route completion but also on readable nonverbal and spatial cues. The emphasis on stopping, orientation, and the handover moment allows sharpening the analysis of human interaction with guide robots in real service environments and links usability more explicitly with visitor satisfaction, comfort, and the manageability of interaction.

Supporting behavioural insight on proxemics and robot-mediated interaction. Through the telepresence pilot, the behavioural review, and the integrative article, the thesis adds supporting evidence that spatial norms, behavioural realism, and nonverbal expectations are central to how robot interaction is interpreted, even beyond strictly guide-robot-specific cases. This broadens the dissertation beyond immediate wayfinding tasks and shows how robot-mediated presence and communication can remain relevant in adjacent organizational and educational use cases as well.

Foregrounding organizational embedding as a condition of routinization. The dissertation shows that guide robot deployment is shaped by role clarity, communication, onboarding, maintenance, workflow fit, and stakeholder expectations. Its practical contribution lies in demonstrating that adoption in organizations depends not only on design and user attitude but also on institutional preparation, leadership support, and everyday coordination.

4.4 Implications for Future Research

GRUSES is presented in this thesis as a context-specific instrument developed and iteratively refined for examining perceived capability in guide robot interaction. It provided a structured basis for comparing supported and real-life encounters and for identifying conditions associated with users' confidence. The present evidence does not establish full validation across populations, organizational settings, or robot types. Further research should therefore test the factor structure, reliability, convergent and discriminant validity, sensitivity to change, and performance in more heterogeneous and longitudinal samples.

Future research should continue to treat guide robot adoption as a socio-technical phenomenon rather than as a question of user attitude or technical performance alone. The findings of this thesis suggest that adoption emerges through the interaction of users, robot behaviour, and organizational conditions. This supports further work that combines insights from technology acceptance research [83, 84] with broader socio-technical perspectives such as ANT [30, 31].

The first priority is to examine these relationships longitudinally and across a wider range of service settings. The present study relied on time-bounded empirical cases, but guide robot adoption is likely to develop over time as users gain experience, organizations adapt workflows, and robots are interpreted less as novelties and more as routine service actors. Future studies should therefore look into how acceptance changes across repeated interaction, organizational normalization, and different types of use environments.

Second priority concerns user self-efficacy. The results indicate that self-efficacy is a central explanatory mechanism in guide robot interaction, but also a context-sensitive one. Future research should examine more closely how self-efficacy is shaped by first encounters, prior technological experience, public visibility, and organizational support, and how it relates to neighbouring constructs such as trust, technology anxiety, and perceived ease of use [26, 27, 90]. As related to this, the GRUSES instrument requires broader validation. Future studies should involve more heterogeneous participant groups, test the scale in additional service contexts, and assess convergent and discriminant validity more systematically. It would also be useful to refine the item pool so that it captures not only successful interaction but also uncertainty, misunderstanding, recovery from errors, and other challenging interaction situations.

Nonverbal and spatial behaviour remains another major research direction. The findings of this thesis suggest that users interpret robot competence and intention through gaze, orientation, movement, proxemics, and task-completion cues. Future work should therefore examine these elements in greater detail, including the handover moment at the end of guidance, culturally variable expectations concerning robot behaviour, and the relationship between behavioural design and users' confidence in managing the interaction [11, 28, 48].

Organizational deployment also requires further study. Future research should include multiple stakeholder groups, such as frontline employees, managers, technical staff, and occasional visitors, and should examine how role clarity, leadership support, training, maintenance arrangements, and workflow fit influence long-term adoption. Comparative and multi-site studies would be especially valuable for understanding which deployment conditions are context-specific and which are more general.

Together, these directions point toward more longitudinal, comparative, and ecologically valid studies that link user experience, behavioural design, and organizational implementation within one analytical framework. It would also be valuable to build more coherent guide-robot-specific datasets across linked sites and repeated deployments so that the same constructs can be compared more directly across organizational contexts. Such work would strengthen both the theoretical explanation and the practical guidance available for the responsible integration of guide robots into organizational settings. Future research should also generate evidence that can inform institutional and policy guidance in areas such as accessibility, privacy, accountability, and the responsible allocation of human and robot roles in public-facing services.

4.5 Limitations and Ethical Considerations

This research has several limitations that define the scope of the conclusions and indicate directions for further work. First, although the distinction between employees and occasional visitors yielded useful analytical insight, it also simplified the social structure of organizations. The study did not examine in greater detail how role, hierarchical position, departmental culture, or task profile may shape guide robot acceptance differently. Future research should therefore include more fine-grained analyses of user groups within organizations, especially because self-efficacy and openness to robot use may vary substantially across work roles and prior technological experience [44].

Second, although the empirical studies were conducted in various public spaces, the variety of environments was still limited. Given the wide variety of the environments in which guide robots can be potentially deployed, expectations toward them may differ considerably. In settings such as museums, hospitals, airports, or retail spaces, the pace of interaction, service norms, and user goals are not necessarily the same as in the settings where the studies reported in the current thesis were conducted [13, 62, 65]. Transferability of the findings should therefore be interpreted with caution, and future research should extend the analysis to a broader range of real-world service environments.

Third, several behavioural recommendations in the thesis are grounded in literature synthesis and focused empirical studies rather than in large comparative experiments. This is particularly relevant for nonverbal behaviour because expectations concerning gaze, distance, orientation, and expressiveness may vary across cultural and organizational settings [48, 56]. Broader cross-cultural validation would strengthen the generalizability of the proposed design implications.

Fourth, the telepresence robot study functioned primarily as a pilot and behavioural precursor to the later guide robot research. Its limited sample and exploratory design restrict the statistical strength and generalizability of the conclusions. Larger multi-site studies are needed to test whether the same patterns of proxemics and behavioural realism emerge across different participant groups and institutional settings.

Fifth, the stakeholder interview study necessarily reflects the perspectives of participants who were already involved in, or at least open to, robot deployment. This may have introduced a positive bias into the material. Future studies should therefore include more sceptical stakeholders as well as organizations that have rejected or discontinued robot adoption, in order to develop a more balanced picture of barriers, resistance, and failed implementation.

Finally, the empirical base of the dissertation is heterogeneous in several respects. Much of the material is qualitative or small-scale, which suits an exploratory research programme but limits the strength of generalization. In addition, not all six included articles provide equally direct evidence on guide robot adoption: some offer conceptual grounding, supporting behavioural insight, or integrative synthesis rather than parallel field evidence. The empirical cases were also time-bounded, which means that routinized use was inferred from converging evidence rather than observed over very long deployment periods. Future work should therefore complement this thesis with larger quantitative studies, more comparable field protocols, longer observational windows, and stronger guide-robot-specific datasets. At the same time, ethical questions concerning privacy, autonomy, accountability, and the responsible distribution of human and machine roles remain central to future guide robot research, particularly in sensitive service settings [65, 91].

These limitations were mitigated in four ways. First, the thesis differentiates direct GR evidence from review-based, adjacent, and integrative evidence, which reduces the risk of treating heterogeneous studies as equivalent. Second, convergence across questionnaires, field observations, interviews, and literature synthesis provides methodological triangulation. Third, the conclusions are framed as bounded and transferable explanations rather than as statistically generalizable laws. Fourth, the proposed model retains the limitations of each evidence strand and identifies the relationships that require longitudinal, multi-site, and psychometric testing. These strategies strengthen the defensibility of the synthesis, although they do not replace the need for broader and longer-term evidence. The limitations do not diminish the value of the present study, but they do clarify its scope. The thesis offers a grounded socio-technical account of GR adoption, while also showing where broader samples, longer time frames, and more varied settings are needed to strengthen the evidence base.

Ethical and data-protection procedures were handled at article level and are consolidated here to make the thesis-level safeguards visible. The doctoral research project “Verbal and Nonverbal Interaction with Social Service Robots in Various Public Areas. Development of a Social Service Robots’ Attitude Scale” received approval from the Tallinn University of Technology Academic Ethics Committee on 26 April 2024. The committee confirmed that ethical and data-protection aspects had been described sufficiently and approved the planned research activities. Before participation, participants were informed about the purpose and procedure of the study, the voluntary nature of participation, their right to withdraw, and the intended use of the collected data. Only data from participants who provided consent for the relevant questionnaire, interview, observation, or measurement were analysed. Personal identifiers were removed or replaced with codes, and the thesis reports only aggregated results or anonymized quotations. Robot cameras and sensors used for navigation were not used for identifiable research recording. Research data were stored as controlled-access research files and paper survey materials, accessible only to the authorized authors / research team. The data were retained only for the period necessary for analysis and publication-related verification. Data that could compromise participant privacy are not openly released.

4.6 Final Conclusion

Guide robot adoption in organizational environments is not determined by technical capability alone. Within the scope of this dissertation, it is best understood as a coordination problem across users, robot behaviour, and organizational arrangements. Deployments remained weak when users could not manage the interaction confidently, when robot behaviour was difficult to interpret, or when organizational support was weak. Conversely, the strongest conditions for routinization emerged when interactional readability, user confidence, and institutional support were aligned in practice. The dissertation therefore argues for a socio-technical understanding of guide robot integration rather than a purely technical or attitude-based one.

At the same time, the thesis offers more than a general socio-technical claim. It provides a guide-robot-specific analytical frame that connects user self-efficacy, behavioural intelligibility, and organizational readiness, and it shows how these dimensions can be studied through cumulative mixed-method evidence. In that sense, the dissertation contributes both conceptual clarification and implementation-oriented guidance for researchers and organizations seeking more realistic, responsible, and sustainable uses of guide robots. In the next chapter, these conclusions are translated into practical recommendations for organizations, providers, and users.

5 Practical Recommendations

Here the findings of the thesis are translated into guide-robot-specific recommendations for the three actor groups that most directly shape routinization: organizations, manufacturers and distributors, and users. The recommendations are not intended as general robotics advice. They are limited to what the dissertation's empirical material supports about guide robot use in organizational settings.

Three recurring findings structure this chapter. First, user self-efficacy was stronger in supported and predictable situations and weaker in socially exposed or ambiguous ones. Second, users evaluated guide robots primarily through behavioural intelligibility, especially movement, stopping, orientation, and the handover from robot-led guidance to user-led action. Third, routinization depended on organizational role clarity, workflow fit, training, and visible technical support. For that reason, each recommendation block is organized at three levels: strategic, operational, and interaction-level. The goal is not necessarily to maximize the number of recommendations, but to make explicit which practical implications follow from which findings. The main actors and their roles are summarized in Table 3.

Table 3. Main actors in guide robot integration and their roles.

Integration partner	***Main role and purpose***
Top management	*Sets strategic goals and ensures organizational commitment to the project.*
Middle managers and process owners	*Align the robot's role with existing workflows.*
IT specialists and engineers	*Ensure technical reliability and infrastructural readiness.*
HR specialists and trainers	*Create onboarding and competence-development programmes.*
Frontline employees	*Act as primary users and co-creators of everyday practices.*
External partners	*Provide customization, maintenance, and ongoing support.*

5.1 Recommendations to Organizations Adopting Guide Robots

5.1.1 Strategic-Level Recommendations

Finding basis: Study 3 showed that weak role clarity, vague organizational value, and uncertainty about the robot's place in the workflow kept deployments at the level of fragile pilots. Organizations should therefore define one narrow service role before wider deployment, communicate that the robot complements rather than replaces staff, and specify in advance where the robot's task begins, where it ends, and what counts as successful use. Guide robot adoption should be treated as workflow design with managerial ownership, not as the placement of a novel device in public space.

5.1.2 Operational-Level Recommendations

Finding basis: Across Studies 1 and 3, confidence and continued use were stronger when interaction was supported and when training and local support were available. Organizations should build onboarding around short, guided mastery experiences, prepare staff for common breakdowns and recovery situations, and make responsibility for maintenance, resetting, and escalation locally visible. Environmental preparation should also be concrete: routes, stopping points, charging, connectivity, signage, and fallback procedures must support one coherent guidance sequence rather than force users to improvise.

5.1.3 Interaction-Level Recommendations

Finding basis: Studies 1 and 2 showed that public exposure, unclear cues, and ambiguous handover moments weakened comfort and acceptance even when the robot technically completed the task. Organizations should therefore stage first encounters in low-pressure situations where possible, provide short start instructions near the robot, and standardize the end of the guidance sequence so that users know exactly when robot-led action ends and what they should do next. In guide robot deployment, following a technically correct route is not enough if the service ends abruptly.

5.2 Recommendations to Guide Robot Manufacturers and Distributors

5.2.1 Strategic-Level Recommendations

Finding basis: Study 3 indicated that adoption weakened when provider narratives exceeded what the robot could reliably do in context, while Study 2 showed that users valued usefulness and clarity more than size or generalized social appeal. Manufacturers and distributors should therefore sell realistic use cases rather than broad innovation promises, and they should describe environmental requirements, task boundaries, and support needs explicitly. Product logic should prioritize guide robot tasks, not abstract social presence.

5.2.2 Operational-Level Recommendations

Finding basis: The empirical material repeatedly identified technical reliability, configurable behaviour, and after-sales support as conditions of sustained use. Providers should make speed, proximity, stopping distance, final positioning, and cue timing configurable enough to fit different sites and user groups, and they should package maintenance, updates, and troubleshooting as part of deployment rather than as an afterthought. Training materials should include short staff-facing scenarios for routine use, stalled interaction, and error recovery, not only technical manuals.

5.2.3 Interaction-Level Recommendations

Finding basis: Study 2 showed that behavioural intelligibility, especially clear movement, readable screen content, precise stopping, and explicit completion cues, mattered more than feature abundance. Manufacturers and distributors should therefore design the handover moment as carefully as the route itself and use movement, orientation, screen prompts, and speech only insofar as they clarify the user's next action. In public guidance, minimal and legible interaction often supports adoption better than richer but less readable behaviour.

5.3 Recommendations to Guide Robot Users

5.3.1 Strategic-Level Recommendations

Finding basis: The studies showed that dissatisfaction often emerged when users approached the robot with inflated or undefined expectations, while self-efficacy strengthened when the task remained understandable and bounded. Users should therefore approach the guide robot as a support tool for a specific wayfinding task, not as a replacement for all forms of human assistance. For employees in particular, repeated low-stakes practice is important because confidence grows through use rather than through abstract explanation alone.

5.3.2 Operational-Level Recommendations

Finding basis: Study 1 showed that self-efficacy is interactionally produced, and Study 3 indicated that onboarding and local support shape whether uncertainty becomes avoidance or learning. Users, especially employees who work alongside the robot, should learn the start, follow, and recovery sequence, know when human help should be called in, and use peer support to normalize early uncertainty. Occasional visitors need shorter support, but even there the principle is the same: the easier the first successful interaction, the more plausible later acceptance becomes.

5.3.3 Interaction-Level Recommendations

Finding basis: Study 2 showed that users interpret the robot's intentions through nonverbal and spatial cues, and the library case identified the handover point as especially decisive. Users should therefore attend not only to speech but also to movement, orientation, stopping behaviour, and screen prompts, because these often indicate what happens next more clearly than verbal output alone. The most useful feedback users can give after interaction is concrete, for example unclear stopping, excessive proximity, unreadable text, or uncertainty at the handover point, because such observations can be acted upon by both organizations and providers.

These recommendations combined reinforce the central argument of the thesis. Guide robot integration becomes more plausible when organizations create role clarity and workflow support, when providers deliver behaviourally readable and supportable systems, and when users are helped to build confidence through understandable first encounters. Therefore, in Chapter 5, the dissertation's socio-technical model is translated into GR-specific implementation guidance rather than into generic claims about robots in general. Across the three stakeholder groups, the first deployment cycle should prioritize three actions. First, the organization should define one bounded guide robot task with explicit success, failure, and human-fallback criteria. Second, it should prepare the physical environment, staff roles, onboarding, maintenance, privacy, and technical support needed for that task. Third, it should test the complete interaction sequence, including approach, movement, stopping, handover, error recovery, and fallback, before considering scale-up. Routine use should follow demonstrated workflow fit, not the novelty of the robot or the technical completion of an isolated route.

List of Figures

List of Tables

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Abstract

Acceptance of Guide Robots in Organizations Through User Self-Efficacy, Robot Nonverbal Behaviour, and Workflow Integration

This doctoral thesis examines the user-related, behavioural, and organizational conditions under which guide robots can be integrated into organizational workflows and become a meaningful part of everyday organizational practice. The study focuses on three interrelated dimensions: users' self-efficacy, guide robot nonverbal behaviour, and organizational readiness for deployment. Its point of departure is the discrepancy between the technical feasibility of social service robots and their still limited, often fragile, use in real organizational settings.

The thesis is based on six publications and follows an article-based, methodologically heterogeneous research design, with the underlying research carried out between 2022 and 2025. Some publications provide direct evidence on guide robot use in field settings, while others contribute theoretical grounding or supporting behavioural insight. The empirical programme combines questionnaire-based studies, pilot and field experiments, and qualitative stakeholder interviews. A central methodological contribution of the dissertation is the development and iterative refinement of the Guide Robot User Self-Efficacy Scale (GRUSES), which was used to assess how confidently users perceive their ability to interact with guide robots in controlled and real-life settings. The research also examines nonverbal and spatial behaviour in robot-mediated interaction, including gaze, proxemics, behavioural realism, and the handover moment at the end of guidance, as well as organizational barriers and enabling conditions affecting practical deployment.

The findings suggest that guide robot acceptance cannot be explained by technical performance alone. Guide robots are integrated more effectively when users feel capable of managing the interaction, when the robot behaves in ways that are socially intelligible and task-wise readable, and when the organization provides clear support structures, role clarity, training, and workflow fit. The results further indicate that user self-efficacy is not a stable personal trait but a situational and interactionally shaped condition that tends to strengthen in supported settings and weaken in more socially exposed public environments. Robot nonverbal behaviour proved central to how users interpreted the robot's intentions, trustworthiness, and task completion, especially at the handover point where robot-led guidance ends and user-led action begins.

The main contribution of the thesis lies in offering a socio-technical account of guide robot adoption in organizations. Its novelty lies in bringing together user self-efficacy, behavioural intelligibility, and organizational embedding within a guide-robot-specific analytical frame rather than treating them as separate questions of acceptance, design, or implementation. By linking users, robot behaviour, and organizational conditions within one analytical framework, the dissertation provides conceptual clarification and practical guidance for designing, evaluating, and implementing guide robot use in organizational settings. It argues that successful integration depends on the alignment of user confidence, behavioural design, and institutional support, and it establishes a foundation for further research and implementation work on social service robots in education, libraries, healthcare, and other service environments.

Lühikokkuvõte

Juhtrobotite aktsepteerimine organisatsioonides: kasutajate enesetõhusus, roboti mitteverbaalne käitumine ja integratsioon organisatsiooni töövoogu

Doktoritöös uuritakse, millistel kasutajate, käitumise ja organisatsiooniga seotud tingimustel on võimalik juhtroboteid organisatsioonide tööprotsessidesse sisulisemalt integreerida ning kujundada neist igapäevase tööpraktika toimiv osa. Uurimus keskendub kolmele omavahel seotud mõõtmele: kasutajate enesetõhususele, roboti mitteverbaalsele käitumisele ja organisatsioonide valmisolekule robotite kasutuselevõtuks. Uurimistöö lähtekohaks on vastuolu sotsiaalsete teenusrobotite tehnilise potentsiaali ja nende endiselt piiratud ning sageli ebastabiilse rakenduse vahel reaalses organisatsioonilises keskkonnas.

Doktoritöö tugineb kuuele publikatsioonile ja lähtub artiklipõhisest ja metodoloogiliselt mitmekesisest uurimisdisainist, mida rakendati aastatel 2022–2025. Osa publikatsioone pakub otsest empiirilist tõendusmaterjali juhtrobotite kasutuse kohta reaalsetes kasutuskeskkondades, samas kui teised loovad teoreetilise raamistiku või annavad täiendava ülevaate kasutajate käitumisest. Empiiriline uurimisprogramm ühendab küsimustikupõhised uuringud, piloot- ja välieksperimendid ning sidusrühmadega läbiviidud kvalitatiivsed intervjuud. Doktoritöö üheks oluliseks metodoloogiliseks panuseks on Guide Robot User Self-Efficacy Scale'i (GRUSES) väljatöötamine ja iteratiivne täiustamine. Skaalat kasutati hindamaks, kui kindlalt tajuvad kasutajad oma võimet juhtrobotitega suhelda nii kontrollitud katsetingimustes kui ka reaalsetes kasutusolukordades. Uurimistöös analüüsitakse ka robotite mitteverbaalset ja ruumilist käitumist, sealhulgas pilgu suunamist, prokseemikat, käitumise realistlikkust ning juhendamisprotsessi lõpus toimuvat üleandmishetke. Samuti analüüsitakse organisatsioonilisi takistusi ja soodustavaid tegureid, mis mõjutavad robotite praktilist kasutuselevõttu.

Uurimistulemused näitavad, et juhtrobotite omaksvõttu ei saa seletada üksnes nende tehnilise toimivusega. Juhtroboteid saab organisatsiooni tööprotsessidesse lõimida edukamalt siis, kui kasutajad tunnevad end suhtluses enesekindlalt, kui roboti käitumine on sotsiaalselt mõistetav ja ülesande täitmise seisukohalt selgelt tõlgendatav ning kui organisatsioon pakub selgeid tugistruktuure, rolliselgust, koolitusi ja töökorralduslikku valmisolekut. Uurimistulemused viitavad ühtlasi sellele, et kasutajate enesetõhusus ei ole püsiv isikuomadus, vaid situatsioonist ja interaktsioonist kujunev seisund, mis tugevneb toetavates tingimustes ning võib nõrgeneda sotsiaalselt nähtavamates avalikes olukordades. Robotite mitteverbaalne käitumine osutus keskseks teguriks selles, kuidas kasutajad tõlgendasid roboti kavatsusi, usaldusväärsust ja ülesande edukat lõpuleviimist, eriti juhendamisprotsessi üleandmisel, kus roboti juhitud tegevus lõpeb ja kasutaja iseseisev tegutsemine algab.

Doktoritöö peamine panus seisneb sotsiotehnilise käsitluse pakkumises juhtrobotite kasutuselevõtu mõtestamiseks organisatsioonides. Töö uudsus seisneb kasutajate enesetõhususe, roboti käitumise mõistetavuse ja organisatsioonilise lõimimise käsitlemises ühtse juhtrobotikeskse analüütilise raamistikuna, mitte eraldiseisvate aktsepteerimise, disaini või rakendamise küsimustena. Sidudes kasutajate enesetõhususe, robotite käitumise ja organisatsioonilised tingimused üheks terviklikuks analüütiliseks raamistikuks, pakub doktoritöö nii kontseptuaalset selgust kui ka praktilisi

suuniseid juhtrobotite kavandamiseks, hindamiseks ja rakendamiseks organisatsioonilistes keskkondades. Töös järeldatakse, et juhtrobotite edukas lõimimine sõltub kasutajate enesekindluse, roboti käitumusliku disaini ja institutsionaalse toe koostoimest. Samuti loob doktoritöö aluse edasisteks uuringuteks ja rakendustegevusteks sotsiaalsete teenusrobotite valdkonnas hariduses, raamatukogudes, tervishoius ja teistes teenuskeskkondades.

Appendix 1

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Guide robots' acceptance in organizations: user self-efficacy and robots' organizational value

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Introduction: This article explores the self-efficacy of guide robot (GR) users and assesses the value of integrating GRs into organizational workflows.
Methods: The study consisted of two stages, both conducted in Estonia. First, we carried out a preliminary quantitative pilot study by applying the newly developed Guide Robot User Self-Efficacy Scale (GRUSES) in controlled and uncontrolled organizational settings. This pilot stage examined users' confidence in using GRs across demographic variables, prior robot experience, and interaction contexts, and generated initial insights for the qualitative stage. In the main stage, we conducted semi-structured interviews with three stakeholder groups: GR end users, organizational administrators, and GR distributors.
Results: The preliminary survey indicated that prior robot experience was associated with higher self-efficacy, whereas age and gender differences were not statistically significant in this sample. Users' self-efficacy was lower in uncontrolled real-life use than in controlled guided scenarios, although this difference should be interpreted cautiously because the groups were not randomly assigned. The qualitative interviews, which form the core of the study, identified technical, user-related, and organizational barriers to integrating GRs into everyday workflows.
Discussion: Based on these findings, we propose an exploratory three-actor framework linking robot capability, user readiness, and organizational readiness. The article also provides recommendations for guide-robot deployment in service organizations. As the GRUSES instrument remains under development, the survey results are interpreted as exploratory and hypothesis-generating.

KEYWORDS
emerging technologies, guide robots, self-efficacy, technology acceptance, technology adoption

1 Introduction

Recent advances in robotics and artificial intelligence (AI) have accelerated the development of social robots (SR) designed to operate alongside human personnel, providing various services of a social nature while interacting in meaningful ways with their users (Lee, 2021). According to (Darling, 2012), a social robot can be defined as "a physically embodied, autonomous agent that communicates and interacts with humans." Human–Robot Interaction (HRI) in the context of social robots has been extensively studied (see e.g., (Arreghini et al., 2024)). A wide range of definitions for robotic technologies with social functionalities exist, and no universally accepted classification has been agreed upon. For example, (Feil-Seifer and Matarić, 2005), refer to categories such as assistive robotics, socially interactive robotics, and socially assistive robotics (the latter lying at the intersection of the first two). For the purposes of internal consistency, we consider Social Service Robots (SSR) as a particular type of SR. As (Wirtz et al., 2018) suggest, SSRs are "system-based autonomous and adaptable interfaces that communicate and provide services to the organization's customers." These robots are equipped with functionalities that allow them to learn from operations and adapt to new situations (Pagallo, 2013), recognize humans and other robots, and engage in social interaction (Latikka et al., 2019).

Adoption of AI-supported machine learning technologies in robotics has increased SSRs' capabilities in HRI, enabling robots to engage in increasingly complex interactions and behave in a more human-like intelligent manner (Romero-C de Vaca et al., 2024; Leite et al., 2013). For example, humanoid robots such as Pepper and NAO have been used in educational settings to support learner engagement (Belpaeme et al., 2018), and the Care-O-bot has been deployed as a home assistant to help older adults and people with disabilities live independently (Asgharian et al., 2022; Bražinová et al., 2024). Because of these benefits, SSRs are being introduced in sectors that suffer from workforce shortages (e.g., healthcare, education, hospitality, and retail) where they provide services such as guidance, information delivery, companionship (Lee, 2021; Fasola et al., 2012), and virtual care (Turja et al., 2019). SSRs can increase organizational efficiency, raise productivity, improve client experience in service organizations, and help alleviate labour shortages (Lee, 2021; Wu et al., 2025; Mukherjee et al., 2021).

Despite successful implementation of robots in controlled environments (e.g., manufacturing), deploying robots in public and organizational spaces remains challenging (Zeller and Dwyer, 2022). Introducing robots into unstructured, real-world workflows often requires overcoming social, technical, and organizational obstacles (Lim et al., 2024). Key variables affecting the adoption of new technology include users' attitudes (Savela et al., 2022), trust in technology (Pinto et al., 2022), and an individual's confidence in their own ability to use the technology–i.e., user self-efficacy (Giger et al., 2025). Self-efficacy was defined by (Bandura, 1986) as an individual's confidence in their ability to perform specific tasks in a specific environment. While SSRs hold great potential for numerous applications, their actual areas of use have so far remained narrow (Vishwakarma et al., 2024; Yoshimitsu et al., 2024). One reason may be the gap between controlled trials and real-world use: previous HRI research has primarily examined user attitudes (Savela et al., 2022), trust (Pinto et al., 2022), and perceptions (Arreghini et al., 2024) in laboratory settings or pilot projects, but there is limited understanding of how self-efficacy manifests in real organizational settings where robot interaction may be mandatory as part of one's job (Zeller and Dwyer, 2022; Lim et al., 2024). This gap is significant because self-efficacy not only shapes individual user experiences but also influences organizational outcomes such as efficiency, employee satisfaction, and willingness to invest in robotics (Kong et al., 2025). By assessing user self-efficacy in both controlled and uncontrolled organizational contexts, the present study addresses these gaps and provides new insights into how confidence in robot use contributes to the successful adoption of guide robots in organizations.

Given the evidence that SSRs have greater potential than their current usage suggests, we undertook a two-part study in 2023–2024. First, we carried out an initial exploratory study focusing on robots' nonverbal behavioural capacities. The results of this study indicated that a robot's nonverbal behaviour expressed by gestures and expressions, is an important factor in improving users' self-efficacy (Leos et al., 2024). Building on those results, in the present research we adopted a more systematic approach to examine additional factors that influence user satisfaction and organizational acceptance of robots, focusing on one type of SSR–the Guide Robot (GR). Person-following and guiding robots (GRs) are defined (Eirale et al., 2025) as having key application domains in healthcare and logistics (e.g., hospitals, warehouses, care facilities), as well as in enclosed public spaces such as museums, airports, and shopping malls. For our purposes, we define a *guide robot* as a subtype of SSR that performs user guidance tasks in socially structured service environments. In our study, a general-purpose robot platform (the TEMI v3 robot) was equipped with custom software to provide GR functionalities.

The present study does not aim to replace established technology-acceptance constructs such as perceived usefulness, perceived ease of use, trust, or attitudes. Instead, it treats user self-efficacy as a complementary explanatory construct. In TAM and UTAUT, perceived usefulness and perceived ease of use describe users' evaluative beliefs about whether a technology improves task performance and whether it is effortful to use, while trust concerns expectations that the technology will behave reliably, safely, and predictably (Pinto et al., 2022; Davis, 1989; Venkatesh et al., 2003). Robot-related self-efficacy operates at a different but related level: it concerns whether users believe they can initiate, maintain, and recover an interaction with the robot in a situated service context. These constructs are therefore likely to interact. A guide robot that is perceived as useful, easy to use, and trustworthy can strengthen users' self-efficacy because the interaction appears more understandable and controllable. Conversely, users with higher self-efficacy may be more willing to explore robot functions, tolerate minor breakdowns, and form more positive judgments of usefulness, ease of use, and trust during situated use (Latikka et al., 2019; Giger et al., 2025).

Such interaction is particularly important for guide robots because users often interact with them publicly, under time constraints, and in physical environments where navigation errors or unclear prompts are immediately visible. In such situations, acceptance depends not only on whether users regard the robot as useful or trustworthy, but also on whether they feel capable of acting competently with it. The link to organizational value follows from this cross-level mechanism. When users feel capable of using the GR, they are more likely to initiate interactions, complete guided tasks, seek assistance from the robot rather than from staff, and recover from minor interaction problems without abandoning the service. Repeated across many service encounters, these individual-level behaviours can contribute to smoother visitor flow, reduced staff interruptions, higher perceived service quality, and stronger organizational justification for continued investment. Accordingly, the contribution of this study is to connect robot-related self-efficacy with organizational value and to examine how this relationship changes when guide-robot use moves from controlled demonstrations to everyday organizational contexts.

To explore GR acceptance in organizations, we employed an exploratory sequential mixed-methods design. We first conducted a quantitative pilot study to gauge GR users' self-efficacy under different conditions, and then a qualitative study as the main component to delve deeper into integration challenges and opportunities. Specifically, we addressed the following research questions (RQs):

- RQ1: How do GR users assess their self-efficacy, and does this assessment depend on their gender, age, and previous experience with robots?
- RQ2: Does users' self-efficacy differ when using a GR in a controlled setting versus an uncontrolled real-life situation?
- RQ3: What are the expectations for GR features, and in what direction should GRs' capabilities, skills, and qualities be developed to ensure better integration into an organization's workflow?
- RQ4: What are the main barriers that currently limit GR users' effectiveness in a workplace context, and what are the users' behavioural expectations for a GR?
- RQ5: What are the potential application areas of GRs in organizations? What tasks could GRs perform, and what roles or jobs could be entrusted to them? How should organizations adjust to this new "workforce" of GRs?

In the following sections, we first review the conceptual background for GR acceptance, then describe our methodology, emphasizing the qualitative approach as the core study and the survey as a preliminary step. Next, we present the results, beginning with the qualitative findings and followed by the survey findings. We conclude with a discussion of the implications of these results and recommendations for both researchers and practitioners.

2 Conceptual model and previous studies

To frame our study, we developed a conceptual model involving three key actors: the robot, the users, and the organizations deploying the robot. Unlike many prior studies that treat organizations as merely the context for HRI (Turja et al., 2020a; Bishop et al., 2019), we conceptualize organizations as active agents that invest in robotic technology and have distinct interests guiding their efforts. Our approach allows assessing GR acceptance from a dual perspective: (i) user self-efficacy (the user's viewpoint) and (ii) organizational value (the organization's viewpoint). By addressing both individual and organizational factors, this dual perspective allows a comprehensive analysis of GR acceptance. We outlined three main dimensions of influence for each actor (robot, user, organization), which determine their roles as either facilitators or barriers in the GR adoption process. Figure 1 presents the conceptual model of guide robot acceptance in organizations.

While much of the existing HRI research focuses on the interactions at the individual level (Bishop et al., 2019), being mostly carried out in controlled experimental settings, relatively few studies have been looking into these interactions within real-life organizational contexts (Zeller and Dwyer, 2022; Lim et al., 2024).

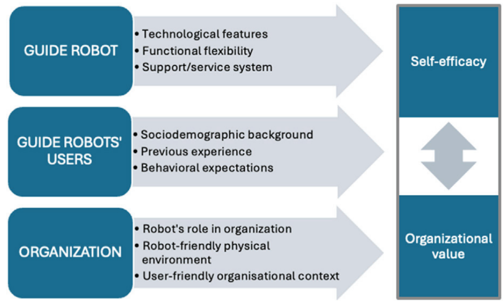

FIGURE 1
Conceptual model of Guide Robot acceptance in organizations.

In the latter case, additional difficulties emerge from the integration of robots in actual workflows. Additional complexities rise from the multi-stakeholder dynamics as well as from possibly diverging organizational goals. At the same time, further development and wider adoption of robots represent a growing opportunity for organizations to innovate and optimize their business processes (Latikka et al., 2019; Yoshimitsu et al., 2024).

Previous research has extensively addressed constructs such as trust, attitudes, and acceptance in HRI (Firmino de Souza et al., 2025). However, one of the less systematically examined factors in organizational contexts is user self-efficacy, despite its central role in Bandura's social cognitive theory (Bandura, 1986; Bandura and Ramachandran, 1997; Bandura et al., 2006). For instance, (Aryati and Armanu, 2023), showed that self-efficacy positively influences employee commitment and ethical behaviour, while (Mustafa et al., 2019) found that organizational structure affects attitudes and behaviour, yet self-efficacy remains underexplored. Similarly, (Seikkula-Leino and Salomaa, 2020), framework highlighted the importance of self-efficacy in organizational development but emphasized the lack of systematic research in this area.

Bandura (Bandura, 1986; Bandura and Ramachandran, 1997; Bandura et al., 2006) emphasized that self-efficacy shapes how people approach challenges, the goals they set, and how persistent they remain when facing obstacles. In organizational HRI settings, employees and visitors with higher robot-related self-efficacy are more likely to interact effectively with robots, adapt to new workflows, and overcome technical or situational barriers. Conversely, low self-efficacy can amplify technophobia, stress, and resistance to change, which can reduce the organizational value of robots.

Although several self-efficacy scales related to robot use have been proposed (e.g., (Turja et al., 2020a; Robinson et al., 2020)), most of these have been validated in laboratory-like conditions or short-term interventions. These settings often lack the complexity of organizational environments where robot interaction may be mandatory and embedded into critical workflows. This represents a significant gap: the translation of self-efficacy from controlled to uncontrolled organizational contexts has not been systematically explored. Furthermore, organizations are still too often treated as passive contexts in HRI studies rather than as active stakeholders with distinct expectations and responsibilities in shaping successful adoption (Turja et al., 2020a; Bishop et al., 2019).

In this article, organizational value refers to the perceived contribution of guide robots to service quality, workflow efficiency, staff workload reduction, user satisfaction, and the organization's capacity to innovate or maintain service continuity. We treat organizational value as a stakeholder-perceived construct rather than as a direct cost-benefit measure. The pairing of user self-efficacy and organizational value is therefore exploratory but theoretically grounded in a socio-technical understanding of technology adoption: guide robots can create value only when robot capability, user capability beliefs, and organizational support structures are aligned. A robot may be technically capable, but if its users do not feel being able to interact with it, or if the organization does not define its role and support routines, the technology may remain underused and fail to produce organizational benefit (Zeller and Dwyer, 2022; Bostrom and Heinen, 1977).

More specifically, our model treats the link between user self-efficacy and organizational value as a conditional cross-level pathway. At the individual level, self-efficacy shapes whether users approach the robot, follow its instructions, persist when prompts are ambiguous, and use recovery options after minor interaction breakdowns. At the interaction level, these behaviours affect task completion, the need for staff intervention, and the perceived smoothness of the service encounter. At the organizational level, the accumulation of successful interactions can be experienced as better service quality, improved workflow efficiency, reduced workload, and greater confidence in further robotics deployment. Low self-efficacy can interrupt this pathway by reducing use, increasing dependence on human staff, or making robot-related problems appear as personal failure. The mechanism is therefore not automatic: organizational value emerges only when individual capability beliefs are supported by reliable robot performance, role clarity, training, and a robot-friendly service environment (Zeller and Dwyer, 2022; Bostrom and Heinen, 1977).

To address these challenges, our study applies the proposed three-actor framework to identify factors that strengthen users' self-efficacy and improve the organizational value of GRs. This approach contributes to filling two interrelated gaps: (i) the lack of empirical evidence on how self-efficacy differs between controlled and real organizational settings, and (ii) the limited treatment of organizations as active agents in HRI research. In doing so, we extend Bandura's theoretical insights into the domain of guide robot adoption, illustrating how individual beliefs about capability and organizational readiness interact to determine successful integration.

Our conceptual model incorporates nine interrelated factors across the three domains of robots, users, and organizations. For GRs themselves, technological features such as navigation, sensors, and interaction capacities determine whether robots can reliably fulfil their guiding functions (Luo et al., 2024). Functional flexibility enhances adaptability across diverse contexts such as hospitals, airports, or museums, thereby increasing organizational value (Chu et al., 2019). A robust support and service system ensures long-term reliability, maintenance, and updates, which are prerequisites for sustained adoption (Cho and Kwon, 2025).

For users, sociodemographic background influences openness to or resistance against robots, with age, education, and cultural expectations shaping acceptance (Chu et al., 2019). Prior experience with technology strongly predicts user confidence, as positive experiences increase willingness to engage with robots while negative ones foster resistance (Chu et al., 2019). Users also bring behavioural expectations to the interaction; when robots meet these expectations through responsiveness, politeness, and smooth motion, interaction quality and satisfaction increase (Chen, 2018).

From the organizational perspective, three factors are critical. First, the robot's role must be clearly defined to ensure effective workflow integration. Second, a robot-friendly physical environment (including space, accessibility, and charging infrastructure) is essential. Finally, a supportive organizational culture that provides training and fosters innovation ensures that both employees and visitors feel confident and motivated to use robots (Cho and Kwon, 2025).

The nine factors depicted in Figure 1 are not intended as nine independently validated predictors. Instead, they are organized into three higher-order socio-technical constructs. First, robot capability includes technological features, functional flexibility, and support/service systems. Second, user readiness includes sociodemographic background, previous experience, and behavioural expectations. Third, organizational readiness includes the robot's role in the workflow, the robot-friendliness of the physical environment, and the user-friendliness of the organizational context. This structure allows the model to move beyond a descriptive list by showing that acceptance depends on alignment among technical capability, user capability beliefs, and organizational support. The model is therefore proposed as an exploratory framework for guide-robot deployment and should be operationalized and tested in future studies rather than interpreted as a validated predictive model.

Our study advances the understanding of GR acceptance by introducing a comprehensive, three-actor framework that simultaneously considers technological, psychological, and organizational factors. By integrating user self-efficacy and organizational value into one model, it bridges individual and institutional perspectives and highlights the interdependence between user confidence, robot capability, and organizational support.

2.1 Social service robots

Recent advancements in AI and machine learning have significantly enhanced SSR capabilities, making them viable in a variety of organizational settings. These include hospitals, universities, libraries, tourist attractions, theme parks, shopping malls, and museums (Adetayo et al., 2023; Iio et al., 2020; Ogle et al., 2019; Shahzad et al., 2024; Gasteiger et al., 2021; Maniscalco et al., 2024). Contemporary SSRs are equipped with sophisticated navigation systems, interactive interfaces, and other functionalities that allow them to become increasingly context-aware and to offer seamless, personalized assistance to users. The future of SSRs appears promising as these technologies continue to evolve, increasing SSRs' usability for different tasks in a variety of environments (QViro, 2024).

Our study focuses on GRs - SSRs configured to assist users in navigating and finding their way in public spaces. The concept of the guide robot dates to the 1970s, when projects such as MELDOG were developed in 1976 to help visually impaired individuals navigate their environment (Tachi et al., 1985). Over the decades, GRs have been utilized in various settings. For example, tour guide robots have been deployed in museums to provide interactive guided tours, and in healthcare facilities to alleviate shortages of guide dogs and human guides (Thrun et al., 2000; Degeurin, 2024).

Despite this growth in SSRs capabilities and applications, including the functionalities that allow them being used in the capacity of GRs, there are still barriers that limit their broader adoption and use, including technical limitations, lack of functional flexibility, and inadequate support and service systems.

Technical barriers are among the most evident challenges to SSR adoption and directly influence HRI and user self-efficacy. Common technical issues include system malfunctions (software or hardware failures) that can be critical in dynamic, unpredictable public spaces. GRs in particular may struggle with navigation in complex environments featuring obstacles such as narrow corridors, uneven flooring, or crowded areas (Mosquera-Maturana et al., 2025; Eirale et al., 2025; Rivero-Ortega et al., 2023). Non-intuitive user interfaces can exacerbate these challenges for people lacking experience with advanced technology, creating accessibility problems and hindering effective HRI (Ogle et al., 2019).

Another barrier to GR adoption is *limited functional flexibility*. Many robots currently available are designed for specific purposes and cannot be easily repurposed for different environments. For example, a robot designed for museum guidance is not immediately suitable for hospital work because it would require different navigation patterns and interaction protocols. To improve flexibility, SSRs need to be customizable for specific tasks and capable of seamlessly navigating complex, uncontrolled environments. Enhancing these abilities would allow social robots to assume different roles across settings, broadening their range of use (Frieske et al., 2024).

A lack of robust support and service systems is also a critical barrier to robot adoption. At present, many distributors and vendors cannot offer comprehensive maintenance, repair, and customer support services–essential components for any organization integrating SSRs into their workflows. Without effective support, organizations face operational risks that can diminish confidence in the technology. Addressing this challenge requires structured after-sales support infrastructure, including regular maintenance services, troubleshooting protocols, and training programs for both end-users and support staff (Sadangharn, 2022; Chen, 2018). Improved collaboration between manufacturers, distributors, and end-users is needed to ensure SSRs remain functional and are aligned with the specific needs of their deployment environments (García et al., 2020).

2.2 Users of social service robots

The typical SSR user is someone who relies on a robot to perform a specific task–for example, navigating to a destination, obtaining information about an exhibit, or scheduling activities in a transit hub (Iio et al., 2020). Data suggest that SSR use is more common among younger individuals, urban residents, and professionals in service sectors, pointing to demographic patterns in robot adoption (Carradore, 2022; González-Anleo et al., 2024). Prior experience with robots is an important factor shaping user interactions - familiarity tends to increase confidence and reduce apprehension (Savela et al., 2022).

User-related issues are among the most complex factors affecting SSR adoption and self-efficacy. These challenges stem from individual perceptions, behaviours, and attitudes toward technology. Unfamiliarity with robots can hinder acceptance and willingness to interact, whereas prior knowledge of robots often leads to greater acceptance (Maj et al., 2023). Job security concerns can also create resistance if employees perceive robots as threats to their roles (Turja et al., 2019). Trust in the robot's reliability is critical: users are less likely to engage with robots they perceive as prone to errors or ineffective at tasks.

Users have also behavioural expectations for robots that influence acceptance. People expect robots to follow certain social and communication norms–for instance, respecting personal space (proxemics), using appropriate gaze and gestures, and generally behaving in a socially acceptable manner (Yi and Park, 2024). Privacy concerns are increasingly relevant as robots collect, store, and process user data. Transparent policies and strong ethical guidelines on data security and respect for user autonomy and dignity are essential for building trust (Vincent et al., 2015).

Nonverbal behaviour is emerging as a critical component of HRI, with growing recognition of its importance in strengthening user engagement, trust, and self-efficacy (Saunderson and Nejat, 2019). Gestures, facial expressions, eye contact, proxemics, and other nonverbal cues significantly improve a robot's perceived social presence and make interactions feel more natural (Spatola et al., 2021). Takayama and Pantofaru (Takayama and Pantofaru, 2009) observed that people are more likely to engage with robots that exhibit human-like proxemic behaviour. A robot's expressions also aid in interpreting its responses and improving coordination–for example, even minimal gaze cues and responsive body language increase a robot's perceived attentiveness (Rifinski et al., 2020). Accompanying verbal instructions with appropriate body and hand gestures enhances communication, making messages clearer and more engaging (Bremner and Leonards, 2016). A robot's expressiveness, for example, richer facial and bodily expressions, can evoke stronger empathetic responses, allowing users to relate emotionally (Konijn and Hoorn, 2020).

Previous studies indicate that appropriate nonverbal cues increase user satisfaction and their confidence in robots (Li et al., 2022). For example, animated facial expressions, smooth movements, and responsive behaviours help users feel more at ease, thereby increasing their willingness to engage with the robot. Also, nonverbal behaviour adjusted according to specific cultural norms and social expectations can further contribute to building trust and comfort, making the interaction more intuitive and natural (Leos et al., 2024; Baxter et al., 2016).

2.3 Organizational context

Organizations are increasingly looking to integrate SSRs into their workflows, motivated by potential gains in efficiency, improved customer service, and an innovative public image (Almokdad and Lee, 2024). SSRs can take on different roles in organizations, often handling routine, repetitive tasks with consistent efficiency and accuracy. These tasks–such as guiding visitors, providing information, or managing simple logistics–can streamline operations and free human staff to focus on more complex responsibilities (Turja et al., 2019; Shahzad et al., 2024; Adetayo et al., 2023). For example, in libraries and hospitals SSRs might reduce administrative burdens while enhancing user experience through intuitive navigation assistance and personalized interactions (Leos et al., 2024; Leoste et al., 2024; Jadad-Garcia and Jadad, 2024; Turja et al., 2019). Beyond functional benefits, integrating robots can signal an innovative and forward-thinking organizational culture (Tanase, 2023; Blaurock et al., 2022).

However, achieving the full potential of SSRs requires overcoming significant organizational barriers. Organizational readiness is critical, including both physical infrastructure and human factors. Infrastructure must often be adjusted to be robot friendly. Physical spaces may need modifications–e.g., wider pathways, ramps instead of stairs, clear signage–to facilitate robot navigation and operation. Environmental features like narrow corridors, door thresholds, stairs, uneven floors, or crowded areas can hinder robots (Gross et al., 2017; Moro et al., 2019; Mosquera-Maturana et al., 2025). Ensuring a robot-friendly physical environment can pose challenges and entail upfront costs.

Equally important is creating a user-friendly organizational context for the introduction of robots (Tan et al., 2016). This includes educating visitors or customers about the robot's functionalities and role, which helps set appropriate expectations and reduce anxiety. It also involves training employees so that staff are prepared to interact with, manage, and maintain the robots. Clearly defining the workflow integration of SSRs is necessary–organizations must specify the robot's role and how human workers should collaborate with it. Robust support systems should be in place, such as maintenance routines and emergency protocols for robot malfunctions or user safety concerns. A proactive approach–actively seeking user and staff feedback and refining processes–can greatly enhance integration (Turja et al., 2020b).

Adapting SSRs to diverse tasks and cultural contexts is another organizational consideration. Robots may need modular design and AI-driven personalization to meet specific needs: assisting older patients in hospitals, guiding multilingual international visitors in museums, etc. When robots display adaptive behaviour and tailored nonverbal communication, user trust and satisfaction tend to grow (Saunderson and Nejat, 2019). Effective use of nonverbal cues like proper distancing and expressive "body language" contributes to more natural human-robot interactions (Takayama and Pantofaru, 2009). Ultimately, the value SSRs bring goes beyond performing tasks–when properly integrated into workflows and aligned with user expectations, they can help transform service models to be more adaptive, efficient, and user-centric.

2.4 User self-efficacy

As robots become increasingly integrated into social environments, it is crucial to assess their design and social impact to achieve productive HRI (Ang et al., 2024). Various criteria have been proposed as bases for such assessments–for instance: anthropomorphism, behavioural realism, sociability, warmth, competence, emotional acceptance, agency, human-likeness, communication quality, and nonverbal behaviour (Mandl et al., 2022; Spatola et al., 2021; Leoste et al., 2024). Other important aspects include attitudes toward technology (Savela et al., 2022), trust in technology in specific contexts (Pinto et al., 2022), and individuals' confidence in their ability to control robotic technologies (Rosenthal-von der Pütten and Bock, 2018), or, in other words, user self-efficacy (Bandura, 1977).

An increasing number of studies are using robot users' self-efficacy as a criterion for assessing readiness to accept robots, e.g., (Lin et al., 2025; Liao et al., 2023). Self-efficacy, defined as an individual's belief in their ability to perform specific tasks in a specific environment (Bandura, 1986), is particularly important for various SSR contexts, where users must feel confident in their ability to interact effectively with robots (Robinson et al., 2020). Unless people believe they can produce desired effects by their actions, they have little incentive to act or to persevere in the face of difficulties (Bandura, 2018). High self-efficacy can lead to greater engagement and persistence, resulting in better performance and satisfaction (Heslin et al., 2006).

In the context of HRI, users with higher self-efficacy are more likely to interact effectively with robots, adapt more quickly to new technologies, and use robots more productively for their tasks. Self-efficacy thus shapes not only users' initial willingness to engage with a robot, but also their long-term adoption, satisfaction, and overall experience with the technology. As (Li et al., 2022) note, *"Self-efficacy helps determine how much effort individuals expend on an activity, how long they persevere when confronting obstacles, and how resilient they are in the face of unfavourable situations."* This applies to HRI by influencing both practical and emotional dimensions of interaction. When users feel efficacious, they are more likely to trust the robot, engage with it, and view it as a helpful tool rather than a source of frustration or threat. Higher self-efficacy can mitigate technophobia and anxiety, highlighting the importance of training programs and design choices that build user confidence (Bandura, 1986).

Prior research provides evidence of self-efficacy's role in HRI. For instance (Robinson et al., 2020), developed a robot self-efficacy scale and found that interactions with a robot instructor increased participants' self-efficacy, agreeableness, and willingness to interact with robots. The influence of the nonverbal behaviour of social robots on user perceptions and self-efficacy was examined by Leos et al. (2024), Leoste et al. (2024), finding that appropriate nonverbal cues can indeed increase user trust and satisfaction. Additionally, studies by (Belpaeme et al., 2018; Kennedy et al., 2017; Mendoza et al., 2024) demonstrate the importance of social feedback and cultural context in HRI across different scenarios.

In our study, we chose to use user self-efficacy as a key indicator for evaluating not only the users' ability to effectively perform tasks with a GR, but also their comfort and confidence during such interactions. By focusing on self-efficacy, we aimed to capture a holistic picture of users' competence, resilience, and satisfaction when using GRs.

3 Methodology

3.1 Research design overview

To meet our objectives of identifying factors that improve users' self-efficacy and increase the organizational value of GRs, we employed a mixed-methods sequential exploratory design. We conceptualized GR acceptance as involving three active agents - the robot, the users, and the organization, and assessed it from both user and organizational perspectives, as described in our conceptual model. Our empirical study was carried out in two stages. First, we conducted a quantitative pilot experiment to measure guide robot users' self-efficacy in two different settings (controlled vs. uncontrolled environments) and across different user characteristics. This initial stage was intended to explore baseline patterns and inform the subsequent inquiry. We then followed up with a qualitative study involving focus-group interviews with key stakeholders, which served as the main study to delve into the barriers, expectations, and opportunities for GR integration in organizational workflows.

The two empirical stages were connected sequentially. The survey stage was used as an exploratory sensitizing step rather than as a standalone validation study. Its findings indicated that prior robot experience mattered for self-efficacy and that self-efficacy was lower in real-life use than in controlled guided use. These findings informed the qualitative interview protocol by directing attention to three issues: how users interpret robot behaviour in less supported situations, what kinds of training or support could strengthen users' confidence, and what organizational arrangements are needed when a guide robot becomes part of a workflow rather than a demonstration object. The qualitative stage then examined these issues from the perspectives of end-users, administrators, and distributors, enabling interpretation of the survey patterns through stakeholder experiences. The adopted sequential approach allowed the findings from the preliminary survey to guide the topics and questions in the interviews. All research activities took place in Estonia and were approved by the relevant institutional review processes. Below, we describe the methodology of each stage in detail.

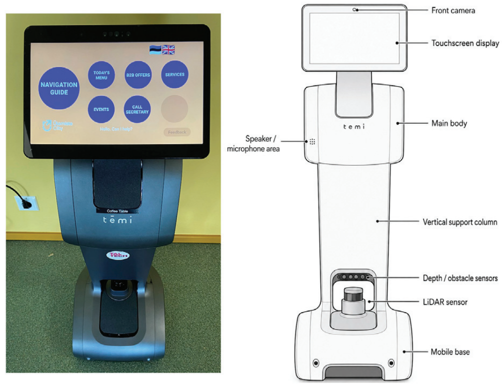

FIGURE 2
TEMI v3 robot's GR interface (left) and the robot's main components (right).

3.2 Participants, robot, and setting

Throughout both stages, we utilized a semi-autonomous social service robot, TEMI v3, configured with guide-robot functionalities (see Figure 2 for the robot's interface and main components). TEMI is an AI-assisted mobile robot equipped with features such as autonomous navigation, pre-mapped location guidance, and human-robot communication capabilities. It can display expressive facial animations on its screen, perform responsive movements, and adhere to proxemic norms (Leos et al., 2024; Leoste et al., 2024). To unlock TEMI's full capabilities (e.g., room mapping, smartphone integration, video calls), we used the TEMI Center Pro service. We also developed custom software for TEMI to enable specific GR behaviours needed for our study. All experiments and interactions took place on the premises of host organizations (e.g., office building, university library, hospital), providing realism while maintaining a controlled scope.

3.3 Study I: interviews with key stakeholders

3.3.1 Research questions

The qualitative stage of the study aimed to identify practical barriers and enablers for integrating guide robots into organizations' everyday workflows. We were particularly interested in understanding stakeholders' experiences and expectations regarding GR behaviour and how organizations might need to adapt to facilitate GR adoption. In line with RQ3, RQ4, and RQ5 (the research questions assigned to this stage), this portion of the research sought to answer: What improvements in GR features and capabilities do users and managers expect for better workflow integration? What are the main barriers currently hindering effective GR use, and what are users' behavioural expectations of GRs? And finally, what potential roles and tasks could GRs take on in organizations, and how should organizations adjust to effectively incorporate GRs as part of their workforce?

3.3.2 Interview instrument

We conducted semi-structured focus group interviews with representatives of three participant groups: (a) End-users of GRs–employees (e.g., library staff, hospital and care facility staff, office workers): who had directly interacted with a guide robot in their workplace; (b) Organizational administrators or managers–individuals responsible for implementing or overseeing the use of robots in their organization; and (c) Distributors/technical support personnel–representatives of companies that sell or rent GRs, who have in-depth knowledge of the robot's functionalities and post-sale support challenges. All interview participants had prior experience with a GR deployed in an organizational setting, where a robot (the TEMI v3) had been used as an in-house guide for at least 1 week.

The interview protocol was designed to explore the role, user-friendliness, and development needs of GRs within organizations. For end-users and administrators, questions prompted participants to reflect on tasks they found GRs suited or not suited for, and to envision future roles for the robot in their organization. Discussions covered how easy or appropriate the robot was for various employees and visitors to use, any concerns users had with current GR models (e.g., technophobia, privacy issues), and suggestions for an "ideal" guide robot that would improve effectiveness and user satisfaction. Participants were asked to describe what an ideal GR would look or behave like, compared to current models, to pinpoint desired improvements.

A second set of questions focused on users' behavioural expectations of the robot, especially regarding the robot's non-verbal behaviour. We asked how aspects such as the robot's body language, movement speed, interaction distance, facial expressions, and gestures influenced participants' confidence and trust. Participants were encouraged to discuss any specific robot behaviours that made them feel comfortable. They also suggested improvements in these behavioural patterns that could strengthen user confidence and cooperation. For instance, we probed which non-verbal cues or interaction styles participants felt would make the robot more "friendly," intuitive, or trustworthy during use.

In the interviews with distributors, we focused on post-deployment experiences and broader adoption factors. We asked about how communication with client organizations occurs after a sale or deployment: What training is provided to new users? What common questions or problems do customers report? What support is available to integrate the GR into specific tasks or environments? Distributors also offered their perspective on how to increase GR adoption in the market–for example, what design improvements or added functionalities are most often requested by customers, and what features might make the robots more understandable and valuable to organizations.

The interview protocol was refined in light of the preliminary survey findings. Because the survey suggested that prior robot experience was associated with higher self-efficacy, participants were asked about training, first encounters with the robot, and the kinds of guidance that would make novice users more confident. Because the survey also suggested lower self-efficacy in uncontrolled real-life settings, the interviews included questions about situations in which users felt uncertain, unsupported, observed by others, or unsure how to recover from interaction problems. These questions later informed the thematic coding of technical reliability, training and support, robot role clarity, proxemics, gaze, and privacy as barriers or facilitators of guide-robot acceptance.

3.3.3 Sample

We conducted semi-structured focus group interviews with representatives of three participant groups: (a) end-users of GRs–employees (e.g., library staff, hospital and care facility staff, office workers): who had directly interacted with a guide robot in their workplace; (b) organizational administrators or managers–individuals responsible for implementing or overseeing the use of robots in their organization; and (c) distributors/technical support personnel–representatives of companies that sell or rent GRs, who have in-depth knowledge of the robot's functionalities and post-sale support challenges. All interview participants had prior experience with a GR deployed in an organizational setting, where a robot (the TEMI v3) had been used as an in-house guide for at least 1 week.

A total of 26 individuals participated in the qualitative interviews, drawn from various organizations that had experience using a social service robot as a guide. This sample included representatives from healthcare (a university hospital and a nursing home), academia (a technological university's IT College and academic library), a smart city office environment (Ülemiste City business campus), and robotics retail companies (e.g., Roborent OÜ, Kinema OÜ, PureSec GmbH). Each focus group was composed of participants with similar roles (e.g., end-users together, managers together, distributors in their own group) to encourage open discussion of shared experiences.

3.3.4 Procedure

The interviews were conducted between June and December 2024. Participants were invited via email with an explanation of the interview's purpose and how the collected data would be used. At the start of each interview, we obtained verbal consent (or written consent, for two participants who opted to give answers in writing) and assured participants of confidentiality. Each focus group session lasted approximately 35–45 min. Most interviews took place in person at a location convenient to the participants; a few were conducted via video conferencing due to availability or distance. With consent, interviews were audio-recorded for accuracy (except for two written-response cases). We used an open-ended interview protocol that allowed participants to freely share experiences, perceptions, and suggestions related to guide robots. Interviewers followed a predefined set of themes aligned with our RQs but also encouraged participants to bring up any relevant issues from their own perspective. After the recorded session, the audio was transcribed. In transcription, we paraphrased where necessary to remove any personally identifying details while preserving the meaning of responses.

3.3.5 Data analysis

We analysed the interview data using thematic analysis (Braun and Clarke, 2006) to systematically identify and interpret patterns in participants' responses. The thematic analysis followed a consensus-based procedure. Two researchers first read the transcripts independently and generated preliminary codes. They then compared the code lists, discussed differences in interpretation, and produced a shared coding structure. The final coding was therefore not the result of a purely independent coding procedure but of negotiated consensus. For this reason, Cohen's kappa was not calculated.

Next, they generated initial codes by highlighting segments of text that captured important concepts or issues raised by participants. These codes were descriptive labels (e.g., "navigation issues," "privacy concern," "needs training") corresponding to recurring ideas in the data. The two coders then compared and refined their codes through discussion, merging similar codes and resolving any discrepancies to ensure consistency.

After coding, we organized the codes into broader themes. Related codes were grouped under candidate themes and sub-themes, which were iteratively reviewed against the data to ensure they accurately reflected participants' views. The coding and theme development process was collaborative: regular meetings between the coders were held to reach consensus on themes and to verify that interpretations were grounded in actual participant quotes. This collaborative approach enhanced the reliability of our qualitative analysis. Ultimately, we identified three overarching thematic categories of barriers and improvement areas: Technical Capabilities, Users' Expectations, and Organizational Arrangements. Within each category, several specific sub-themes were defined (see Table 1 for an overview).

- *Technical Capabilities:* This category focuses on challenges posed by the current design and functionality of GRs. Sub-themes here included Technical Reliability (ensuring the robot operates without malfunctions), Smooth Navigation (the ability to move effectively through various physical environments), Language/Communication Interface (providing a user-friendly, multilingual interaction interface), and Customization to Tasks (the ability to adapt GR functionalities to specific tasks and user needs). These issues represent technical barriers that can hinder GR performance and user confidence.
- *Users' Expectations:* This category captures barriers stemming from user perceptions, needs, and comfort levels. Sub-themes included Privacy (ensuring GR interactions do not infringe on personal data or make users feel observed), Proxemics (maintaining appropriate distance and positioning during interactions), and Gaze (using eye contact or facing users in a way that feels respectful). These aspects reflect what users expect from a robot's social behaviour and how deviations can cause discomfort or distrust.
- *Organizational Arrangements:* Barriers in this category arise from the interplay between GRs and workplace dynamics or processes. Sub-themes included GR's Role in Organizational Workflow (the importance of clearly defining what the robot should do and its responsibilities in processes), Customized Infrastructure (adjusting the physical and IT infrastructure to accommodate GR operations, such as space for the robot to move and integration with organizational systems), and Training and Support (providing adequate training to staff and ongoing support to ensure effective use of the robot). These themes highlight what the organization can do to facilitate or impede successful GR integration.

TABLE 1 Summary of the identified themes and sub-themes with descriptions.

Category	Sub-theme	Description
Technical capabilities	Technical reliability	Ensuring reliable, malfunction-free operation of GRs
	Smooth navigation	Facilitating effective movement through various physical environments
	Language/Communication interface	Providing user-friendly interaction in the preferred language and intuitive interface
	Customization to tasks	Adapting GR functionalities to specific tasks and user needs
User's expectations	Privacy	Ensuring that GR interactions respect personal data and intimacy
	Proxemics	Maintaining appropriate spatial distance and positioning in user interactions
	Gaze	Orienting visual sensors respectfully, making appropriate eye contact
Organizational arrangements	GR role in organizational workflow	Defining clear roles and responsibilities for GRs within workplace processes
	Customized infrastructure	Adjusting the physical setting to accommodate GR operations (e.g., space, signage)
	Training and support	Offering adequate preparation, instruction, and ongoing assistance to users and staff

3.4 Study II: developing robot user's self-efficacy scale

3.4.1 Research questions

In the first, exploratory stage of our research, we focused on assessing users' self-efficacy in operating a guide robot, with attention to basic user characteristics and context effects. This stage addressed RQ1 and RQ2: we asked how users evaluate their own ability to use a GR and whether this evaluation varies by gender, age, or previous experience with robots (RQ1), and whether the context of use–a controlled experimental scenario versus an uncontrolled real-life scenario–affects users' self-efficacy (RQ2).

3.4.2 Research instrument

Various instruments exist to assess perceptions of robots and HRI, such as the Godspeed Questionnaire (Bartneck et al., 2009) and the Robot Social Attribute Scale (RoSAS) (Ca et al., 2017). The Human-Robot Interaction Evaluation Scale (HRIES) (Spatola et al., 2021) measures dimensions like sociability (e.g., "Warm," "Friendly"), animacy (e.g., "Natural," "Human-like"), agency (e.g., "Intelligent," "Intentional"), and disturbance (e.g., "Creepy," "Weird"). Other recent scales include Social Perception of Robots Scale (SPRS) (Mandl et al., 2022) with dimensions of sociability, competence, morality, and anthropomorphism. While these scales gauge general perceptions of robots, our focus was specifically on user self-efficacy in using a guide robot. Some prior instruments measure robot-related self-efficacy (e.g., the RUSH-3 scale (Turja et al., 2020a; Pinto et al., 2022; Rosenthal-von der Pütten and Bock, 2018)), but those were designed largely for laboratory settings or short-term interactions and do not directly apply to GR use in public organizational spaces. Therefore, we constructed a new scale tailored to this context, the Guide Robot User Self-Efficacy Scale (GRUSES), to capture how confident users feel using a GR in an indoor public area of an organization. In developing GRUSES, we followed Bandura's (Bandura et al., 2006) guidelines for creating self-efficacy measures. The scale was constructed following Bandura's recommendation that self-efficacy measures should be task- and context-specific. Bandura advises that self-efficacy scales be context-specific rather than one-size-fits-all, that items should accurately reflect the construct (self-efficacy being a judgment of capability to perform certain actions), and that the scale should be empirically validated through piloting and refinement. Applying these principles, we went through three steps to create and refine GRUSES:

1. Expert panel brainstorming: Three experts in HRI and psychology generated an initial pool of 17 items intended to assess a person's sense of efficacy while using a guide robot. Based on theoretical considerations, the panel anticipated two underlying dimensions: *operational efficacy* (perceived difficulty, clarity, and effectiveness of using the GR for tasks) and *affective efficacy* (the perceived comfort, pleasantness, and sense of safety when interacting with the robot).
2. Pilot testing and refinement: We conducted a pilot survey with as small samples (N = 28). Participants in the pilot trial used the GR in a sample scenario and then answered the draft questionnaire. Based on their feedback and response patterns, we reworded items that were ambiguous or confusing. We also found one important aspect was missing and added an item to cover it. This process resulted in a refined set of items.
3. Survey study: The revised scale, now with 12 items, was administered in the present study's survey (with N = 226 participants; see below for sample details). In the Results section, we report descriptive statistics and evaluate the scale's reliability and validity based on this data.

The final GRUSES instrument (see Supplementary Appendix 1 for the full item list) includes statements that respondents rate on a 7-point Likert scale (1 = "Strongly disagree" to 7 = "Strongly agree"). Example items include assessments of how difficult or easy it was to communicate with the robot, how well the user understood the robot's messages, how secure they felt interacting with it, the robot's reliability as a partner, the pleasantness of the interaction, the user's self-confidence during use, perceived effectiveness and speed of task completion with the robot, and the naturalness of working with the robot. We also collected demographic information (gender, age group) and data on participants' previous experience with using robots, to analyse subgroup differences. GRUSES should be interpreted as an exploratory, context-specific measure developed for the present guide-robot setting.

3.4.3 Study design

We assessed GR users' self-efficacy using the TEMI v3 robot (as depicted in Figure 3) in two distinct settings: a controlled environment and an uncontrolled (real-life) environment. This comparison was designed to reveal any differences in user experience and confidence between a scenario where support and guidance are provided versus one where users must interact with the robot autonomously. Importantly, both the controlled and uncontrolled trials were conducted in authentic public spaces within host organizations (rather than in a laboratory), to increase ecological validity while still distinguishing the level of guidance provided.

- Controlled setting: In the controlled scenario, participants were asked to perform a series of tasks with the robot under the supervision of researchers. We prepared a predefined usage scenario and gave participants step-by-step instructions on how to interact with the robot to complete the tasks. Specifically, participants were told they would use the robot to navigate to various locations and perform simple actions at those locations. The scenario proceeded as follows: the participant approaches the robot and selects a communication language on the touchscreen; they choose a destination from the menu (e.g., a certain office or room); the robot then leads the participant to that destination. Upon arrival, the participant is prompted (by the scenario script) to either place a video call to a "secretary" using the robot's interface or to open the organization's website on the robot's screen (simulating information retrieval). After completing these actions, the participant follows the robot to a final location (e.g., a lobby or relaxation area) to conclude the session. Throughout this controlled session, the researcher stayed nearby, offering guidance or clarifications if the participant seemed confused. The key characteristics of the controlled setting were that participants knew they could rely on help if needed and that using the robot was voluntary and meant to be a "safe" trial–they could always opt out or ask for assistance. This supportive environment was intended to reduce stress and encourage participants to explore the robot's features.
- Uncontrolled setting: In the uncontrolled scenario, the guide robot was deployed as it would be in a real public setting, and participants used it without direct researcher assistance. The robot stood in a public area (for example, an office building lobby or library entrance) and would activate its greeting when someone came within its sensor range. Participants in this condition were asked to approach the robot as if they were regular users or visitors, and to utilize it to reach a destination of their choice. The robot itself initiated interaction by greeting the user with an animated face on its screen and bringing up the user menu. Participants independently navigated the interface–selecting their language and desired destination from the options. Once they made a selection, the robot gave spoken instructions and autonomously guided the participant to the chosen location. Upon reaching the destination, the

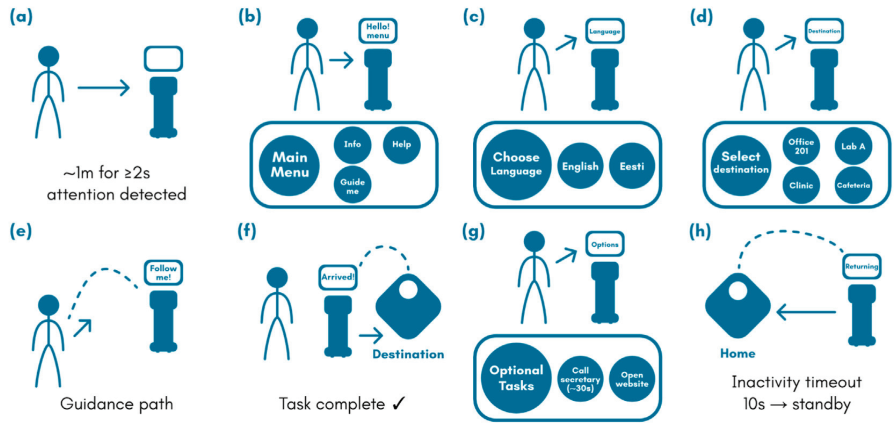

FIGURE 3
Procedure of the experiments. **(a)** User attention is detected when the participant approaches the robot, approximately 1 m for at least 2 s. **(b)** The robot greets the user and displays the main menu. **(c)** The user selects the communication language. **(d)** The user selects the desgnation. **(e)** The robot guides the user along the route. **(f)** The robot announces arrival and task completion. **(g)** Optional follow-up tasks are displayed, including calling a secretary or opening a website. **(h)** After an inactivity timeout of approximately 10 s, the robot returns to its home position and standby mode.

robot announced task completion, bid the participant goodbye, and then returned on its own to its start position to await the next user. In this mode, the additional actions (calling the secretary or viewing the website) were available but not explicitly prompted, to mirror a more natural usage scenario (the participant could choose whether to make a call or get information). The uncontrolled scenario effectively required participants to rely entirely on the robot and their own ability to use it, as if the robot were a permanent service with no human assistant present. After finishing the interaction, participants were approached by the researcher and asked to fill out the feedback questionnaire (GRUSES) if they were willing and had time. The researchers observed quietly from a distance during the interaction to note any issues but did not intervene.

3.4.3.1 Key differences from the user's perspective

The core task (having the robot guide the participant to a location) was the same in both conditions, to allow comparison. However, the *level of guidance and autonomy* was the main difference. In the controlled environment, participants had the safety net of researcher support and knew that using the robot was optional ("for fun" or practice). In the uncontrolled environment, participants were effectively "on their own" with the robot, and the situation simulated a real workflow where using the robot might be necessary to accomplish the task. We anticipated that these differences could affect participants' confidence and stress levels: the controlled condition might make them feel more supported and thus more confident, whereas the uncontrolled condition might reveal challenges that reduce self-efficacy. This dual-context approach allowed us to examine how context influences user self-efficacy, trust, and overall experience with the GR.

3.4.4 Procedure

The pilot experiments were conducted from December 2023 to May 2024 across six different public venues in Estonia. We selected venues relevant to GR use, including: an office building lobby (Ülemiste City business campus), a university administrative floor (the IT College at Tallinn University of Technology), a technology fair (sTARTUp Day in Tartu), a tech conference venue (TalTech Mektory center), a public industry conference (Industry 5.0 conference in Tartu), and a university library (the Academic Library of TalTech). The controlled/uncontrolled comparison should be interpreted as quasi-experimental, as the participants were not randomly assigned to conditions, and the controlled and uncontrolled trials differed in timing and venue. In total, five controlled-environment trials were run between December 2023 and February 2024 (one at each of five venues), and two additional trials in uncontrolled environments took place in May–June 2024 (at the Ülemiste City lobby and the TalTech library).

Each participant in the study went through the following steps, tailored to whether they were in a controlled or uncontrolled trial:

- Step 1: Preparation (controlled trials only). Before a controlled experiment began, a researcher met with the participant individually and provided detailed instructions about what would happen. The participant was briefed on the sequence of actions they would perform with the robot (as outlined in the scenario above). For example, the researcher explained: "You will approach the robot, choose the language and a destination, follow the robot, and when you arrive you will use the robot to call a secretary and also open a webpage, then proceed to a final location." Once the participant indicated they understood and felt ready, the interaction commenced with the participant approaching the robot positioned at its start point in the corridor or lobby.

FIGURE 4
Experimental setup: A snapshot of a participant interacting with the TEMI robot during the controlled experiment, illustrating the user following the robot's guidance.

- Step 2: Interaction. This step was the core human-robot interaction, which was quite similar in both conditions aside from the presence/absence of guidance. The interaction began when the robot's sensors detected the participant approaching (within about 1 m for at least 2 seconds, at a roughly 90-degree field of view). The robot responded by displaying a "curious" facial expression on its screen and greeting the participant, then it activated its main menu. In both settings, the participant then navigated the on-screen menu to select a communication language and a destination (the robot offered multiple preset destinations). In the controlled trials, the researcher might verbally remind the participant of what to do next if they hesitated, whereas in uncontrolled trials the participant relied on the robot's prompts. After the destination was selected, the robot verbally instructed the participant to follow and proceeded to lead the way. The robot provided step-by-step information or cues during navigation (e.g., "Following route to [destination]"). In the controlled scenario, per the script, the robot at some point instructed the participant to initiate a video call (simulated call) and to browse a webpage on the robot's tablet interface (similarly to what is depicted in Figure 4). In uncontrolled scenarios, these additional tasks were optional; the robot could perform them if the participant chose, but it mainly focused on guiding. If at any time in the controlled condition the participant was unsure or took no action for ~10 s, the researcher would step in to assist or the robot would politely terminate the interaction ("say goodbye") and return to standby. In practice, participants generally completed the tasks without needing intervention. In uncontrolled trials, if the participant stopped interacting, the robot itself was programmed to politely end the interaction and return to its base after a short period of inactivity. Overall, this interaction step was designed to simulate real-world use of a GR: the controlled version gave an ideal, well-supported experience, whereas the uncontrolled version introduced more realistic challenges such as the user figuring out the interface alone.
- Step 3: Feedback collection. After each participant finished their interaction with the robot, we collected data via a paper-based or online questionnaire (depending on what was convenient at the venue). The questionnaire included the GRUSES items and demographic questions. A researcher was present to distribute and later collect the questionnaire (or to provide a tablet with the survey if using an online form), but participants filled it out on their own. This step was crucial for quantifying the participant's self-efficacy and experience immediately following the interaction. Once completed, survey responses were digitized (entered into a spreadsheet) for analysis. We also recorded basic observational notes about each participant's interaction (e.g., notable difficulties or behaviours) to contextualize the quantitative data.

3.4.5 Sample

Across all trials, a total of 226 individuals participated in the survey study. The sample included university students and staff, healthcare professionals, and attendees at public tech events–reflecting a diverse mix of potential GR users. Of these participants, 110 identified as men and 106 as women (10 did not specify gender). We categorized participants into three age groups: up to 30 years old (N = 78), 31–50 years old (N = 108), and 51 and older (N = 30). Participants also reported their prior experience with using robots: the majority had no prior experience (N = 103), many had some experience (used a robot a few times; N = 114), and a small subset were frequent users of robots (N = 9). In terms of exposure conditions, 144 participants interacted with the GR in a simulated (controlled) setting, and 82 participants did so in a real-life (uncontrolled) setting. The controlled trials took place between December 2023 and February 2024, whereas the uncontrolled trials took place in May-June 2024.

All empirical work was conducted in Estonia, a relatively technology-oriented national context, and the participating organizations were drawn mainly from education, healthcare, smart-city office environments, technology events, and robotics retail settings. The survey also included relatively few participants aged 51 and older (N = 30), even though older adults and care-sector users are highly relevant for future guide-robot applications. In addition, all deployments used the TEMI v3 platform with custom software. TEMI's tablet-based face, screen-mediated interaction, height, navigation behaviour, and proxemic defaults may have shaped user expectations and responses in ways that would differ from humanoid, voice-first, kiosk-like, or physically assistive guide robots.

3.4.6 Ethics and privacy

All participants received information about the purpose of the study, voluntary participation, confidentiality, and the anonymized use of research data before data collection. Because the study posed minimal risk, involved adult participants, and did not collect personally identifiable data for analysis, the ethics committee waived the requirement for written informed consent for participation. Verbal informed consent was obtained from participants before interviews and survey participation. Two interview participants who provided written responses also provided written consent for those written responses. Interview participants additionally consented to audio recording and to the use of anonymized quotations. All data were anonymized before analysis, and no identifiable images or personal data are presented in the manuscript.

4 Results

4.1 Interview findings

In this section, we present the findings from the qualitative interview study, which form the core of our research contributions. The results are organized around the research questions on GR feature expectations, barriers to GR integration, and potential application areas (RQ3, RQ4, RQ5).

RQ3 (Feature Expectations and Development Directions): Participants across the different stakeholder groups identified numerous areas where guide robots need improvement to fit smoothly into organizational workflows. A frequently mentioned theme was the need for enhanced language support and more open developer tools. As one library employee noted, *"Better language support, improved SDK to control the robot functions, more standards"* [P6]. In our study context (Estonia), having the robot fluently speak the local language was seen as critical; distributors confirmed that *"quite often a customer's wish is that I want a robot attendant that speaks Estonian"* [P2].

Another major expectation was more human-like expressiveness in the robot's behaviour. Participants called for advancements in the robot's facial expressions and gestures to create more engaging interactions. One interviewee suggested, *"Develop robots with a friendlier and more human-like appearance and behaviour, making them more pleasant and less intimidating to* users" [P8]. Others emphasized specific cues: *"A smiley face or a questioning look on the screen helps build trust"* [P20]. Indeed, many users appreciated when the robot attempted eye contact or showed emotion: *"I liked it when the robot moves the screen, so it looks like it is looking at you. It made the interaction feel personal"* [P21]. Figure 5 illustrates the kind of expressive "emotions" displayed by the TEMI robot, which participants found endearing but believed could be expanded further.

FIGURE 5
TEMI displaying facial expressions on its screen, used to convey emotions during interaction.

Appropriate proxemics (the robot's use of personal space) also emerged as important. Users reported discomfort if the robot came too close (within about half a meter) without warning, often causing them to step back instinctively. Conversely, if the robot kept too large a distance, users were sometimes unsure if it was engaging with them. A hospital employee praised the robot's default behaviour: *"It kept a polite distance, not too close, not too far, which made people feel safe interacting"* [P16]. However, there were instances where abrupt movements undermined this comfort. A librarian recounted, *"It kind of did a quick turn without warning–I actually jumped back because I did not expect that"* [P19]. Users suggested that robots clearly indicate their intentions before moving–for example, by giving a verbal cue like "Follow me now" before starting to roll forward. Such a prompt would prepare users and synchronize the robot's verbal and nonverbal signals, preventing surprise or confusion.

Participants also debated the movement speed of the robot. Generally, TEMI's pace was set to a moderate walking speed, which most found acceptable, but context mattered. Some users in busy workplaces wanted a faster response: *"When I'm in a hurry, having to follow the robot feels very time-consuming. It could move at the same pace as me"* [P9], said one corporate office worker. On the other hand, in an elderly care context, a staff member noted, *"The robot needs to move slowly because older people's attention spans are short, and they might not notice the robot moving right away"* [P24]. In fact, if the robot suddenly accelerated, it could startle users: *"The robot suddenly started moving quickly. I did not expect it and thought I had somehow triggered it by mistake"* [P16]. A common suggestion was for the robot to adapt its speed to the user or environment–slowing down in crowded or elder-care environments and having an option to move faster when guiding someone who is clearly in a hurry.

Beyond behaviour and interaction improvements, customization and modularity were highlighted as priorities for future development. Many participants expressed the desire for robots that could be easily tailored to specific organizational needs or personal preferences. *"Users should be able to easily customize the robot's appearance and behaviour. Modular design allows for easy addition or replacement of components,"* explained one tech-savvy participant [P8]. For example, a library administrator imagined adding a module to scan RFID tags on books, whereas a hospital manager thought about integrating a temperature sensor or ID card reader into the robot. Distributors echoed this need: clients often ask if the robot can be modified for the particular tasks. The consensus was that a one-size-fits-all robot is less useful than one that can be configured with the right tools (software or hardware add-ons) for the task at hand.

RQ4 (Barriers to Effective Use and Behavioural Expectations): Participants identified a range of barriers that currently prevent users from being fully effective with GRs. These barriers fell into several categories–aligning with the themes from our analysis.

First, there were technological barriers. Users and managers reported that today's GRs still have "rough edges" in terms of reliability and capabilities. One distributor frankly stated, *"These products are so raw; they are not re*ady" [P2], referring to how immature some commercial robots still are. Frequent malfunctions or errors were noted: lost network connections, freezes, or navigation failures erode user confidence quickly. Limited navigation ability in complex or cluttered environments was a common complaint (e.g., the robot sometimes got stuck or took inefficient routes). Insufficient verbal and nonverbal language support was also seen as a barrier–outside of major languages, the robot's speech and recognition capabilities were lacking, and even in English or Estonian, its tone or inflection sometimes seemed unnatural or hard to hear in noisy environments. A distributor summarized a key issue: *"If the user interfaces and functions of robots are not intuitive, it can lead to frustration for users and reduce motivation to use the robot"* [P8]. Indeed, some end-users criticized the tablet interface design as not very user-friendly for those who are not tech-savvy, creating an accessibility gap.

Turning to user-related barriers, psychological factors like technophobia and low confidence emerged prominently. Some participants observed colleagues or visitors who hesitated to approach or touch the robot: *"Some people have a fear of technology. They are afraid of touching things they do not know*" [P12], a librarian noted. This fear of "breaking something" or making a mistake can prevent people from even attempting to use the robot. Fear of doing something wrong with the robot was mentioned, especially in uncontrolled settings–users worry they might get stuck or not know how to recover if they press the wrong button. Privacy concerns also surfaced repeatedly as a barrier to engagement. People were unsure what the robot's sensors were recording. Some visitors would avoid the robot out of an unease of being watched: *"No, I do not want to interact with it because I do not know who's watching from inside or who's monitoring*" [P9] was a sentiment expressed about camera concerns. Similarly, others questioned, *"How can I be sure I'm not being photographed or filmed by a robot?"* [P18]. Such privacy anxieties can severely limit willingness to use GRs, especially in cultures or contexts where surveillance is sensitive.

Context-dependent proxemics issues were mentioned as well. For tasks that required a person to press the robot's screen or follow closely, participants expected the robot to adjust its distance appropriately. One person gave an example: *"The robot could come closer to allow pressing the screen but kept a greater distance with customers just passing by*" [P24]. In crowded areas, users wanted the robot to be smart about navigating around people and maintaining personal space. *"The robot should be able to quickly assess how to pass a person in a busy space,"* suggested another interviewee [P24]. Additionally, a few participants raised cultural norms as an important consideration: if the robot operates in multicultural settings, it should be aware that personal space and social cues can vary. *"It must be taken into account …it causes discomfort when you have to change your habits, and it limits the use [of the robot],"* one participant [P23] said, implying that if a robot violates local social norms (e.g., how close to stand, whether to bow or not, etc.), people might reject it.

Interestingly, our interviews revealed that many users initially had limited expectations for a robot's social behaviour–they did not expect a machine to follow human conventions. However, once they interacted with the GR, they realized they did appreciate human-like non-verbal behaviour. For example, a university employee mentioned that seeing the robot's "gaze" or at least some indication of attention was very important: *"You are used to talking to a person face to face; even when you talk to a machine, you are still not sure in the back of your head whether it heard you [if it does not show signs of listening]"* [P20]. This suggests that users need feedback from the robot (like looking at the speaker or a text on screen such as *"I'm listening …"*) to feel confident that the interaction is working. Because of these subtle uncertainties, several respondents proposed that users be given short training or orientation on how the robot behaves. They felt that, in addition to a technical manual, there should be a simple guide to the robot's behavioural patterns–essentially "What to expect when interacting with me." As one participant put it, *"The robot could say: I'll tell you about myself–how I behave, move, why I do something, etc. What should you consider when communicating with me? What I can do well, and where I still need practice*" [P23]. Another said, *"I would even expect prior training or instructions*" [P20] before using a robot as part of your job. This highlights that building user self-efficacy might require preparatory orientation, not just good design of the robot alone.

A specific question we posed was how participants felt about the possibility of a robot physically touching them (or vice versa). The consensus was clear: a robot should not initiate touch with a person under normal circumstances. *"I do not dare shake the robot's hand, because I know that there is no human brain but a machine,"* one user remarked [P20], reflecting a discomfort with anthropomorphic gestures like handshakes from a robot. However, participants were more open to scenarios where the human initiates or consents to touch. For instance, a robot could offer a handle or arm for a person to hold onto if they need balance support. *"It is not that it holds on to you, but the robot could have a place to lean on, if you wish. It offers the possibility to lean on, rather than holding on [to you],"* explained [P26]. In a caregiving context, an interviewee reacted positively to the idea of a robot offering support: *"…if a person has difficulty walking, a robot could offer them help so that the person can lean on the robot's arm*" [P24]. Thus, any physical interaction must be on the user's terms–the robot can offer but not impose contact. This insight is important for future GR designs (e.g., whether to include physical guiding or haptic feedback).

Participants from the distributor and manager groups pointed out a crucial organizational barrier: lack of support from top management and unclear role definition for the robot within the organization. One distributor noted that clients often do not have a plan for the robot after purchase: *"A common question is how to use the robot effectively in specific situation*s" [P8]. Similarly, a manager admitted, *"We could not find enough activities for the robot or explain it to our employees*" [P9]. Another manager echoed, *"We need to better* *explain the role of the robot in our department to our employees"* [P19]. Without strong leadership support and a clear integration plan, staff may ignore the robot or use it inconsistently, undermining its value. This points to the need for change management when introducing GRs–staff should be briefed on why the robot is there, what it should be used for, and how it benefits their work, to avoid confusion or resistance.

RQ5 (Application Areas and Organizational Adjustments, similar to what is depicted in Figure 6): Our findings suggest that guide robots are well-suited for certain kinds of tasks in organizations, but not all. Participants generally agreed that GRs excel at routine, repetitive tasks that do not demand emotional intelligence or complex decision-making. These include guiding visitors through a facility, providing standard information, assisting with simple logistics, such as delivering small items or documents, and managing inventory queries. For instance, a distributor mentioned that some GRs are already used to *"serving food/snacks in restaurants or events"*, implying tasks that involve moving items around predictably [P8]. A librarian participant hoped, *"If TEMI could guide the reader to the exact spot–say, 'Look here, there's your book' – that would be great"* [P12]. In a hospital scenario, one idea was: *"While the human is waiting, the robot might say: 'Take out these documents that need to be submitted'"* [P3], meaning the robot could instruct patients on preparatory steps in a process. These examples illustrate how robots might take on assistant roles to free up staff time and streamline services.

Conversely, participants noted that GRs are unsuitable for tasks requiring empathy, complex judgment, or high adaptability. Anything that demands human understanding, emotional support, or intricate problem-solving is not (yet) in the robot's wheelhouse. This underscores the importance of clearly defining the roles of GRs within organizations: they should augment humans by handling straightforward tasks, while humans continue to handle the nuanced ones. One participant emphasized that making this role clarity explicit to everyone is key to successful adoption.

From an organizational perspective, the introduction of GRs raised concerns among staff about workloads and job security. Several staff members initially feared the robot might increase their work or even replace them. One participant shared an incident: *"The receptionists did not want to show their faces during calls. The employee should understand that TEMI helps them* [*rather than replaces them]"* [P9]. This indicates that some staff avoided using a new video-call feature through the robot, possibly out of discomfort or fear of being monitored. Addressing these fears requires communication that the robot is a tool to assist, not a threat to jobs, and possibly redesigning workflows so that employees clearly see a reduction in their burden.

Privacy and security improvements were also deemed essential to build trust in GR deployment. As mentioned in RQ4, users worry about data and surveillance. Both end-users and managers recommended transparency in what data the robot collects and why. As one participant succinctly put it, *"Transparency about data collection is necessary to alleviate fears"* [P9]. This might involve giving users some control (like a privacy mode) or providing clear signage or verbal assurance about any cameras or recordings.

Participants had various opinions on technical settings like the robot's speed (as discussed), but generally they agreed that the appropriate behaviour might vary by use case. For example, in a hospital, the urgency might dictate quicker movement, whereas in a museum a slower, leisurely pace is preferable. One interviewee described internal debates: *"There are different opinions in the hospital. Some thought it moved too slowly when needing to reach another ward quickly; but if it is just patrolling, then it can move at a leisurely pace"* [P26]. This again highlights the need for context-aware adaptability in GRs, either through configuration or intelligent sensing.

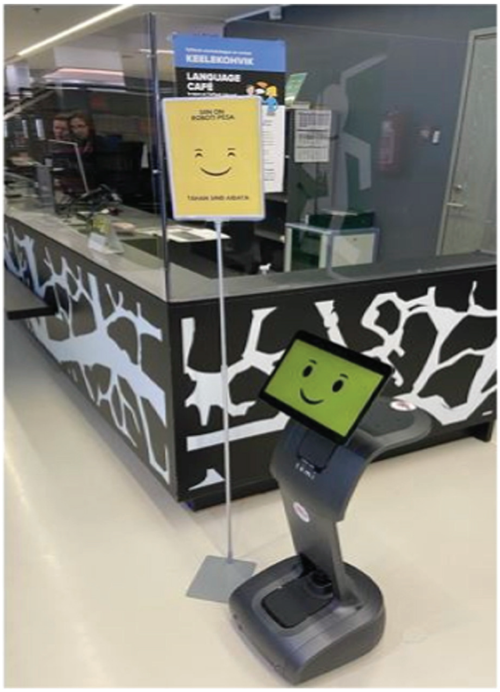

FIGURE 6
TEMI V3 robot working in TalTech library, guiding a user to a section–an example of GR deployment in an organizational setting.

As a new suggestion beyond our original questions, participants imagined future enhancements where GRs could take on more proactive roles. One intriguing idea was equipping the robot with the ability to detect human behaviour anomalies and offer help unprompted. For instance, in large buildings like airports or hospitals, a GR could notice if someone looks lost (e.g., standing in one spot and looking around for a few minutes) and then approach to ask if assistance is needed. One interviewee described it: *"A person does not understand where to go. They might stare at the directory board for 3 min. The robot could notice that and go ask if it can help"* [P20]. This kind of initiative could greatly increase the robot's value as a guide. Participants noted that robots could also perform helpful tasks like reminding patients about medications or schedules (a distributor said robots are effective at *"providing reminders to patients to take their medications or guiding people in a large hospital"* [P8]). These forward-looking ideas suggest that once basic issues are solved, users are excited for GRs to have more autonomy in assisting people.

In summary, the qualitative study's findings emphasize that while GRs are currently best at routine guidance and information tasks, their acceptance in organizations hinges on improving technical reliability and behaviour (especially nonverbal interactions), addressing user fears (through better design and training), and making organizational adjustments (clear roles, infrastructure, support). Users and stakeholders have a clear vision of both what the robots should ideally do and what needs to be in place around the robots for them to succeed.

4.2 Findings from the survey study

We now turn to the results of the preliminary self-efficacy survey, which assessed GR users' confidence levels and how these were affected by personal factors and usage context. As noted earlier, these findings should be interpreted as exploratory since the GRUSES scale is newly developed and this stage was intended primarily to inform and complement the qualitative insights.

Before addressing RQ1 and RQ2 directly, we provide an overview of the scale's properties. Supplementary Table 2 (see Supplementary Appendix 2) lists the GRUSES item means, which ranged from approximately 4.7–5.8, the overall mean was M = 5.40. Participants responded on a 7-point scale (1 = strongly disagree, 7 = strongly agree). The overall mean indicates that, on average, participants tended toward agreeing with positive statements about their ability to use the GR. In fact, we observed a generally positive response bias–item means ranged from about 4.7 to 5.8 on the 7-point scale, suggesting most users felt reasonably confident and comfortable using the robot. This could reflect curiosity and enthusiasm in the controlled trials, but it also raises the possibility that some participants gave optimistic ratings. The high mean scores indicate a possible positive response bias and ceiling effect. In the available pilot output, several core items had high means and negative skewness, for example, complexity/ease of communication (M = 5.89, skewness = −1.0), clarity (M = 5.91, skewness = −0.8), security (M = 5.69, skewness = −0.7), suitability (M = 5.76, skewness = −0.7), and comfort (M = 5.50, skewness = −1.0). These values suggest that the scale may be less sensitive to variation among users who already feel moderately or highly confident.

We assessed the internal reliability of the GRUSES scale with Cronbach's alpha that was approximately 0.9. The exploratory factor analysis supported using the scale as a single composite score in this exploratory study. The scale showed high internal consistency, meaning the items were strongly interrelated and likely measuring a single underlying construct (user self-efficacy in using a GR). The exact reliability analysis is summarized in Supplementary Table 2 (Supplementary Appendix 3). An alpha of 0.90 exceeds the common threshold (0.8) for research instruments, suggesting that GRUSES provides reliable scores for our sample. We also took steps to establish content validity (by involving HRI and psychometrics experts during development) and face validity (through pilot feedback, it appeared to measure what it intended to).

To examine the scale's structure (construct validity), we performed an exploratory factor analysis. We initially hypothesized two subscales (operational vs. affective efficacy), but the factor analysis results indicated that the scale was essentially unidimensional–all items loaded on one dominant factor. In other words, participants who felt confident in one aspect (like operational use) also tended to feel confident in the other aspects (like comfort and safety), so it made sense to treat the GRUSES score as one overall self-efficacy measure. (See Supplementary Table 2 in Supplementary Appendix 4 for factor analysis details.). Consequently, for this study we used the scale as a single composite measure of GR self-efficacy.

At this stage, the article reports content validity based on expert item generation, face validity based on pilot feedback, internal consistency based on Cronbach's alpha, and preliminary factor-structure evidence. However, convergent and discriminant validity were not tested because no established comparator instrument, such as RUSH-3 or SE-HRI, was administered to the same participants. Accordingly, the quantitative results are treated as preliminary and hypothesis-generating rather than as evidence from a fully validated scale.

Based on the survey results, we can answer RQ1 and RQ2 as follows:

- RQ1 (Self-efficacy differences by gender, age, experience): Overall, participants rated their ability to use the guide robot quite positively (mean around 5.4 on the 7-point scale), indicating a generally high self-efficacy. We found that previous experience with robots was a significant differentiator in self-efficacy scores. As expected, participants with prior experience using robots reported higher self-efficacy (average M ≈ 5.69) than those without prior experience (M ≈ 5.09). This difference was statistically significant (independent samples t-test, $t(219) = 3.47$, $p < 0.01$). In contrast, we did not find significant differences in self-efficacy between different age groups or between men and women in our sample–any small differences in means were not statistically meaningful. It appears that regardless of age or gender, people's confidence in using the GR was more uniformly high, but prior hands-on experience did give some participants an edge in confidence. These results underline that familiarity with technology (especially robots) can boost users' self-efficacy, whereas demographic factors like age or gender alone did not show an effect in this context.
- RQ2 (Effect of controlled vs. uncontrolled context on self-efficacy): We observed a clear context effect. Participants who used the robot in the controlled, guided environment reported significantly higher self-efficacy (mean M ≈ 5.68) compared to those who used it in an uncontrolled, real-life scenario (mean M ≈ 5.05). This difference was statistically significant ($t(219) = 4.91$, $p < 0.01$). In practical terms, interacting with the GR under ideal, supportive conditions led to more confidence, while the challenges of the real-world setting made some participants feel less efficacious. This pattern held true not just for the overall score but was also reflected on individual items and any attempted subscales: the situational context had a broad impact on how users felt about their capabilities. The drop in self-efficacy from controlled to uncontrolled scenarios suggests that even if users initially feel confident (perhaps due to novelty or supportive introduction), that confidence can falter when they face the complexities of a real environment without guidance. We interpret this as evidence that contextual factors (like unpredictable interference, absence of immediate help, greater stakes of failure) play a significant role in user

confidence. Differences in GRUSES scores may reflect not only the level of researcher support and interaction autonomy, but also contextual differences between venues, user groups, and recruitment situations. For this reason, the results are described as an observed association between interaction context and self-efficacy, not as causal evidence that the setting alone produced the difference.

In summary, the survey's results reveal that prior exposure to robots increases user self-efficacy, and that users' confidence can be considerably higher in test/demo conditions than in authentic usage conditions. These findings provided important context for our interviews: they signalled, for example, that organizations should pay attention to training novice users (since experience matters) and that positive attitudes seen in trials may not directly translate to unassisted usage. The survey findings were used to shape the interview questions–for instance, we probed interviewees about why they thought people might feel less confident in real settings and what could be done to bridge that gap. However, it is important to note that the survey results are preliminary. The GRUSES scale is still in an early validation phase, and the positive bias observed suggests that future work (discussed below) should refine the instrument to capture a wider range of user feelings, including potential negative experiences, to avoid ceiling effects.

4.3 Integration of survey and interview findings

The survey and interview findings are integrated here not only by alignment, but also by extension and reinterpretation. At the user level, the survey indicated that prior robot experience was associated with higher self-efficacy. The interviews extend this finding by showing that "experience" is not only repeated exposure to a robot, but also a form of interaction literacy: users need to know what the robot can do, how it signals attention, how close it will come, how it moves, and what to do when interaction does not proceed as expected. Thus, the qualitative findings reinterpret the quantitative experience effect as a training and sense-making issue rather than merely as a demographic or familiarity effect.

At the robot and interaction level, the survey showed generally positive GRUSES scores and possible ceiling effects. The interviews qualify this result by revealing that positive self-efficacy ratings can coexist with fragile confidence. Participants often evaluated the robot favourably but still described concrete sources of uncertainty, including navigation reliability, abrupt movement, unclear gaze direction, language limitations, privacy concerns, and uncertainty about error recovery. The qualitative data therefore suggest that the survey captured general confidence after interaction, whereas the interviews exposed situational conditions under which that confidence may weaken.

At the organizational level, the survey showed lower self-efficacy in uncontrolled real-life settings than in controlled guided settings. The interviews reinterpret this difference as more than a simple contrast between two technical environments. Users' confidence declined when immediate support was absent, when the robot's role in the workflow was unclear, when staff were unsure how to intervene, or when users felt publicly observed while using the robot. Together these two strands show that guide-robot acceptance depends on the joint configuration of user readiness, robot capability, and organizational readiness. The survey identified where confidence differed, while the qualitative findings explain why the differences may occur and how organizations can reduce them through training, role definition, legible robot behaviour, privacy transparency, and support routines.

5 Discussion

The worsening shortage of skilled workers in key service sectors (retail, healthcare, education, etc.), especially in aging societies, has fuelled interest in adopting robotic technologies as a partial solution. Over the past decades, technologists have been optimistic about integrating robots into service organizations, yet in practice, such integration has rarely moved beyond experimental or pilot stages. Our study underscores that successful adoption of robots in socially structured environments entails much more than procuring advanced hardware and deploying it on site. As our theoretical review highlighted, adopting robots is a complex social process that must draw on interdisciplinary research–combining insights from social sciences (user attitudes, organizational behaviour, etc.) with technological development (robot capabilities, AI behaviours) to ensure robots can truly function in human-centric settings.

In this research, we focused on GRs as an example of SSRs and examined both technological features and human factors influencing their acceptance in organizations. A central human factor we investigated was user self-efficacy, drawn from Bandura's theory, which we argue is critical in HRI within workplaces. Our preliminary findings indeed show that certain demographic and experiential factors shape user self-efficacy. Specifically, prior exposure to technology–in this case, having used robots before–was associated with higher self-efficacy among GR users. This aligns with prior research on technology adoption which suggests that more experienced or tech-savvy users are quicker to embrace new systems (Nomura and Kanda, 2021). It indicates that when introducing GRs, organizations should consider the characteristics of their user groups (age, tech experience). For example, younger staff or those who have seen or used robots before might become early adopters or "robot champions" in the workplace, whereas extra support might be needed for those with no prior exposure. Interestingly, our data did not show a significant gender difference in self-efficacy, which is a positive sign–at least in this sample, women and men were equally confident in using the technology, contrary to some stereotypes regarding technology use. This finding agrees with some recent studies that find gender gaps in technology perception are narrowing (Moseley and Mead, 2023; Draxler et al., 2023) though it contrasts with others that still find differences (Jones et al., 2025). It may be context-dependent and merits further study.

Our survey also revealed a situational effect: self-efficacy drops in real-life usage conditions compared to controlled trial conditions. In controlled settings (which often resemble demos or training sessions), participants felt quite confident, but in the uncontrolled, "live" environment, their self-efficacy was significantly lower. This result serves as a cautionary tale against over-interpreting positive user feedback from lab tests or short pilot programs. It suggests that many optimistic conclusions from previous laboratory-based HRI studies–which often report high user interest and acceptance–may not fully hold up in everyday practice. Our finding echoes observations by Hung et al. (2019), who noted that users often exhibit higher confidence and comfort in controlled experiments due to the predictable environment and the availability of immediate support. When those safety nets are removed, users may encounter unexpected issues or simply feel a greater sense of responsibility (and thus anxiety) in making the robot work properly. In our case, realizing this discrepancy was one of the motivations for conducting a qualitative study. We saw that *"trying GRs just for fun"* versus *"using them as part of routine workflows"* led to different user experiences, so we set out to understand *why* and *how to mitigate* that gap.

The decline in self-efficacy from controlled to real-world use can be interpreted through several psychological mechanisms. In the controlled condition, the presence of a researcher reduces uncertainty, provides immediate corrective feedback, and creates a low-stakes mastery experience. In the uncontrolled condition, users must interpret the robot's prompts, recover from possible errors, and complete the task under public visibility without immediate assistance. This may increase cognitive load, reduce perceived control, and heighten anxiety about making a mistake. The available qualitative evidence from related TEMI deployments also suggests that unexpected queries, technical glitches, bystander observation, and lack of immediate support can make users attribute interaction problems to their own inability rather than to the robot or context (Leoste et al., 2024). Thus, the controlled-to-real-world decline should be understood not only as a usability issue but also as a self-efficacy mechanism shaped by support, predictability, and error-recovery opportunities.

The importance of gaze, proxemics, facial expression, and predictable movement can be interpreted through social presence and human-likeness in interaction design. When the robot turns its screen toward the user, keeps an appropriate distance, signals its intention before moving, and displays readable facial expressions, users can more easily treat it as an attentive interaction partner. These cues do not need to make the robot fully human-like; rather, they make the robot's state and intention legible. This legibility supports self-efficacy because users can predict what the robot is doing and how they should respond. Conversely, abrupt movement, unclear gaze direction, or poorly timed feedback can reduce perceived control and create uncertainty. The findings therefore suggest that nonverbal behaviour contributes to guide-robot acceptance through perceived social presence, predictability, and interactional clarity (Saunderson and Nejat, 2019; Leoste et al., 2024).

The findings from the interviews provide richer insight into the barriers and enablers of GR acceptance. One of the significant contributions of this study is highlighting how improving certain robot behavioural features can positively influence user self-efficacy and trust, thereby easing integration. Participants pinpointed gestures, facial expressions, emotional tone, speech patterns, movement styles, and other nonverbal cues as important factors that affect how comfortable they felt using the robot. Our results show that when GRs behave in ways that align with human social expectations (e.g., maintaining a polite distance, making "eye contact," moving predictably), users gain confidence and are more willing to engage. This finding extends prior work that has called for human-aware robot behaviours by demonstrating the direct link to self-efficacy: not only do such behaviours make interactions more pleasant, but they also actually empower users by making them feel more in control and capable. Conversely, when the robot's behaviour violates social norms or behaves erratically, users' confidence drops and they may even abandon the interaction (as seen in some uncontrolled trial anecdotes). Thus, from a design perspective, socially intelligent behaviour in robots is not just about user satisfaction but also about user efficacy.

Our respondents also emphasized the importance of user training and support mechanisms as complementary to technical improvements. Many interviewees argued that giving users a bit of orientation–whether via formal training sessions or built-in robot tutorials–can build the necessary self-efficacy for sustained robot use. This aligns with Bandura's idea that mastery experiences (successful practice) build efficacy, and vicarious experience or verbal persuasion (being guided or reassured) can also help. In practice, organizations should treat the introduction of GRs similar to introducing a new software system: provide documentation, quick-start guides, and responsive support, especially in the early phase. We found that users appreciated knowing help was available (in the controlled trials) and that boosted their confidence; by extension, if organizations ensure ongoing technical support or a "robot helpdesk," users might be more inclined to persevere through initial difficulties.

These insights underscore a broader point: there is a complex interplay between human and technological factors in determining HRI outcomes. It is not enough to fix either the human side (train the users) or the technology side (improve the robot) in isolation–both must advance together for successful implementation. Our study suggests such interplay: we saw that demographic/human factors (experience, attitudes) influence how people approach the robot; the robot's design (behavioural cues, interface) influences how people feel and react; and organizational context (management support, clarity of the robot's role) influences whether the conditions for fruitful interaction are present. All these factors loop back to affect user self-efficacy and acceptance.

Comparing our findings to existing literature: earlier HRI studies have extensively discussed trust, perceived usefulness, and ease of use (e.g., in terms of the Technology Acceptance Model), but self-efficacy has been less of a focus in robotic contexts. Our work contributes by explicitly focusing on self-efficacy and showing how it is shaped by and also shapes these other factors. For instance, trust in technology (a commonly studied construct) is likely bidirectional with self-efficacy–as users feel more capable, they trust themselves and the robot more, and as the robot proves trustworthy, it reinforces their self-confidence. We also resonate with studies such as (Savela et al., 2022) which noted that familiarity breeds acceptance–our data on prior experience confirms that. We add nuance by showing that even without prior experience, certain design choices can make first-time users feel capable (some of our controlled environment users had no experience but still rated high efficacy, presumably due to the supportive design of the interaction). In organizational HRI, self-efficacy therefore serves as a distinct analytical bridge between robot-level affordances, user-level confidence, and organization-level readiness, explaining not whether a robot is judged useful or trustworthy, but whether users feel capable of engaging with it competently within real work routines.

It is worth noting that organizational factors emerged in our study as fundamental but are often underrepresented in HRI research. Many studies treat the environment as a static background, whereas our interviews with managers and distributors revealed issues like lack of clear strategy for robot usage, staff resistance due to misunderstandings, and insufficient maintenance support. These are not robot "problems" *per se*, but they can make or break a deployment. Our results thus align with frameworks that call for socio-technical integration efforts, for example, ensuring that the introduction of a robot is supported by organizational change management. Participants repeatedly mentioned that if management does not actively endorse the robot and define its role, employees either ignore it or use it inconsistently, which in turn means the robot does not deliver value. This highlights a practical recommendation: organizations need to treat a GR like introducing a new team member–with announcements, role definitions, and processes to incorporate it–rather than like a gadget that is just put in the corner to see what happens.

The organizational barriers identified in the interviews can be interpreted through socio-technical systems theory. A guide robot is not adopted only as a technical artefact; it becomes part of an interdependent system of people, tasks, infrastructure, routines, and managerial expectations. Technical reliability and navigation are necessary, but they do not by themselves create organizational value. Value emerges when the robot's role is defined, staff know when and how to involve it, users understand what the robot can and cannot do, and the physical and digital environment supports its operation. From a change-management perspective, guide-robot deployment therefore requires communication, role definition, staff preparation, and feedback loops rather than one-time installation. This interpretation explains why unclear management support and weak role definition appeared as central barriers in the qualitative findings (Zeller and Dwyer, 2022; Bostrom and Heinen, 1977; Kotter, 1996).

5.1 Practical implications

Based on the integrated findings, the following recommendations should be prioritized. First, organizations should define the robot's role before deployment, including which tasks the robot performs, when staff should intervene, and how users are informed about the robot's purpose. Without role clarity, even technically capable robots may remain underused. Second, basic technical reliability, navigation accuracy, language support, and privacy transparency must be ensured because failures in these areas directly undermine user confidence. Third, users and staff need short orientation and accessible support materials, especially for first-time users and public-facing employees who may need to assist others. Fourth, robot behaviour should be made legible through appropriate gaze, proxemics, speed, pre-movement signals, and expressive feedback. Fifth, organizations should adapt the physical and digital environment, including routes, signage, charging, and integration with relevant information systems. This ordering should not be read as an empirical ranking of effect sizes, because the study was exploratory and did not statistically differentiate the relative importance of these recommendations. It reflects implementation logic derived from the integrated findings: role clarity and reliability are prerequisites for meaningful use, training and legible robot behaviour help users build confidence during interaction, and infrastructure adaptation and feedback loops support sustained organizational use over time.

5.2 Limitations

Given the scope and design of our study, there are several limitations to acknowledge. First, the sample size in the qualitative stage (N = 26), while providing depth, is still relatively small and drawn from specific sectors (education, healthcare, etc.) in one country. This means the themes we identified, though salient, may not cover all possible issues or may not generalize to other cultural or organizational contexts. There is a potential self-selection bias as well: the individuals who agreed to participate might be those more interested in or positive about robotics, which could skew the findings towards highlighting improvement possibilities rather than outright rejection. We attempted to include some sceptical voices (indeed, some participants voiced strong concerns), but a broader outreach might have found individuals unwilling to even participate because of disinterest or negativity toward robots.

Second, while our mixed-method approach is a strength, the two stages were unbalanced in weight–the survey was preliminary and the scale still undergoing validation. The GRUSES scale we developed is in early stages and was tailored to our scenario; thus, the quantitative results should be interpreted with caution. The positive bias in responses suggests that perhaps some items were phrased in a way that elicited agreeability, or participants in controlled trials felt compelled to give high ratings (social desirability). Future research should refine this instrument: we plan to assess its convergent validity (does it correlate as expected with related constructs like general self-confidence or tech anxiety?) and discriminant validity (does it avoid overlapping too much with, say, general attitude toward robots?). We also realized that our scale might need items specifically addressing obstacles or frustrations, to capture negative experiences; currently it might be too focused on positive aspects, which could explain the skew. Our findings should be interpreted as indicating generally positive self-efficacy tendencies rather than finely differentiated levels of confidence. Future GRUSES versions should include items that capture hesitation, uncertainty, error recovery, frustration, and discomfort, and may also include carefully designed negatively worded or difficulty-sensitive items to reduce acquiescence bias.

Third, our experimental design for RQ2 – comparing controlled vs. uncontrolled conditions–was not a pure randomized experiment but rather quasi-experimental, since participants were not randomly assigned. There could have been differences between the groups aside from the condition (for example, those at the tech fair might have been more tech-savvy than those at the library). We mitigated this by mixing venues for both conditions as much as possible and by having a fairly large N, but uncontrolled factors could have influenced the outcomes. For instance, the uncontrolled trials happened later in the timeline; by then, maybe the novelty had worn off a bit or we (researchers) were less actively enthusiastic in inviting participants, etc. Longitudinal effects were not measured; ideally, one would want to measure the same individuals' self-efficacy first in a demo and later after actual usage, to really see the drop within-subject. Because of various limitations, the results are offered as evidence of an observed association between the interaction context and self-efficacy, and not that of causal evidence that the setting alone produced the difference.

Finally, the cultural context (Estonia) is relevant–Estonia is quite tech-forward (e.g., e-government, delivery robots on sidewalks are not unheard of), so baseline receptiveness might be higher than in places where robots are rarely seen. This could have influenced the generally positive tone of responses. Conversely, some findings like not fearing job loss too much might not hold in other labour markets. We acknowledge that our findings, while internally valid, remain limited and need to be tested with older and less technology-oriented populations, in other national contexts, and across multiple robotic platforms.

5.3 Future research directions

This work opens several avenues for further studies. One immediate next step is to continue validating the GRUSES scale. We plan to conduct larger surveys with more diverse populations, including settings where the robot is used over longer periods. Testing the scale in multiple countries would also help ensure it is capturing the same constructs across cultures (for example, perceptions of safety and comfort might differ culturally). We are also interested in testing a short-form of the scale for practical use–for organizations to quickly gauge user self-efficacy with minimal burden.

Another future direction is to conduct longitudinal studies. Many participants only had brief exposures to the GR. It would be valuable to see how self-efficacy and acceptance evolve as people work with a robot regularly over weeks or months. Does self-efficacy naturally increase as familiarity grows (likely yes), and does that plateau or even dip if, say, a malfunction happens that breaks trust? Longitudinal data could also show how training interventions impact self-efficacy retention over time.

Additionally, future studies should differentiate more clearly between real-world and laboratory settings in their analysis and discussion of results. Our work showed one way to simulate "real" vs. "lab" usage; building on this, researchers could design experiments where the only difference is the presence of help or the framing of the task (optional vs. mandatory) to isolate which aspect causes the confidence drop.

Another interesting line of research would be exploring adaptive robot behaviour driven by AI that can sense user discomfort or uncertainty. Some participants basically suggested this–e.g., the robot noticing a confused person and offering help proactively. If a robot could detect that a user is struggling (perhaps by inactivity or facial expression analysis) and then adjust its behaviour (slowing down, offering more guidance, switching to an "assist mode"), would that improve the user's self-efficacy in the moment and subsequent interactions? Such adaptive systems could personalize support, which ties in with Bandura's idea of guided mastery–the robot itself could become the guide in teaching the user, not just physically guiding them in space.

From an organizational perspective, future work could also examine organisational change-management strategies for robot integration. For example, study two similar organizations where one introduced a GR with a comprehensive staff engagement program and the other just deployed the GR without much support. Compare outcomes in acceptance, usage rates, and employee attitudes. This would provide evidence on the best practices for organizational adoption of robots.

Ethical considerations also merit more research. Privacy and autonomy concerns came up in our study; exploring how different transparency measures (like a "privacy mode" indicator on the robot, or providing users control over data) affect acceptance could guide ethical design. Additionally, as robots get more capabilities (e.g., anomaly detection as suggested), ensuring they respect human dignity and agency will be crucial for acceptance. For instance, a robot approaching someone to help could be seen as great by one person but as intrusive by another; research on consent and social norms for robot-initiated interaction would be valuable.

6 Conclusion

In conclusion, our study highlights that integrating guide robots into organizational workflows is not just a technical deployment, but a socio-technical transition that involves user confidence, robot design, and organizational readiness. By treating user self-efficacy as a focal lens, we were able to uncover how these dimensions interact. We hope that our findings encourage both researchers and practitioners to devote as much attention to the "human side" of HRI–training, support, social behaviour–as they do to improving the robots' technical capabilities. With a balanced approach, guide robots can indeed become effective partners in service organizations, augmenting human labour and enhancing experiences for users and customers.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by Academic Ethics Committee of Tallinn University of Technology. The studies were conducted in accordance with the local legislation and institutional requirements. The ethics committee/institutional review board waived the requirement of written informed consent for participation from the participants or the participants' legal guardians/next of kin because the study posed minimal risk, only involved adult participants, did not collect sensitive or personally identifiable data for analysis, and complied with local legislation and institutional requirements. Participants were informed about the study procedures, confidentiality, and voluntary nature of participation, and verbal informed consent was obtained before data collection. Written consent was obtained from participants who gave their data in writing.

Author contributions

KM: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Project administration, Resources, Validation, Writing – original draft, Writing – review and editing. JL: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Supervision, Validation, Visualization, Writing – review and editing. MH: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Supervision, Validation, Writing – review and editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was used in the creation of this manuscript. The authors are native Estonian speakers. Generative AI was used for improving English language. in the manuscript.

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Supplementary material

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SUPPLEMENTARY TABLE 1
Thinking about your experience today, how do you rate your interaction/communication with the robot? Think about the tasks you solved in cooperation with the robot today. How would you assess the completion of these tasks (such as moving from one room to another, etc.) together with the robot? While you were working with the robot, other people were also present in the room. What was their attitude towards the interaction between you and the robot and acting together?.

SUPPLEMENTARY TABLE 2
Descriptive statistics of the GRUSES scale items.

SUPPLEMENTARY TABLE 3
Reliability of the GRUSES scale.

SUPPLEMENTARY TABLE 4
Factor analysis of the GRUSES scale items.

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Appendix 2

Publication II

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Review

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Nonverbal Behavior of Service Robots in Social Interactions – A Survey on Recent Studies

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Review

Nonverbal Behavior of Service Robots in Social Interactions–A Survey on Recent Studies

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Featured Application: Robotics is a promising tool with the promise of boosting efficiency and reducing human effort. In the collaboration between individuals and social service robots nonverbal communication cues in human-robot interaction (HRI) becomes important. Our study focused on these cues, aiming to improve HRI dynamics, particularly in healthcare, education, and elderly care. Enhanced nonverbal communication facilitates the seamless integration of robots into daily human lives. Our research findings aim at understanding advancements in HRI, envisioning a future where efficient collaboration is enriched by nuanced nonverbal cues, crucial for widespread robot acceptance in society.

Abstract: This study presents a literature review focused on nonverbal communication in human-robot interaction (HRI) that involves service robots with social capabilities. We aim to list the types of robots used and nonverbal communication cues examined in the reviewed studies; and the main research objectives, participant characteristics, data collection methods, and primary findings of these studies. To achieve this, we conducted a literature review of 39 relevant open access academic papers published from 2006 to 2023 that examined the utilization of nonverbal cues by both humans and robots during HRI. The results suggest that enhancing the quality of communication between humans and service robots must be improved, while there are several aspects that require more thorough exploring, needed to strengthen robot self-efficacy, trust and trustworthiness in HRI or overcome cultural differences. The results emphasize the importance of nonverbal communication in shaping the dynamics of interactions between humans and service robots.

Keywords: service robot; robot assistant; nonverbal behavior; human-robot interaction; social interaction; embodied communication; social robot; collaborative robots

1. Introduction

A growing number of service robots are emerging from factories and research laboratories into people's daily lives. In terms of financial numbers, the whole service robotics market is forecasted to grow from 41.5 billion USD in 2023 to 84.8 billion USD in 2028 [1]. A service robot, according to one of its earliest definitions, is "*a freely programmable kinematic device that performs services semi-or fully automatically*," whereas services here are understood as "*useful work for humans and equipment*" [2], excluding industrial automation applications (see also [3,4]). More recently, service robots are increasingly expected to make use of AI and natural communication [5] to be able to operate in an uncontrolled environment [6,7], enabling them to act as socially-capable assistants [8]. Such social service robots are becoming increasingly important in various fields of human life, enhancing efficiency in production or alleviating the lack of workforce in other areas such as education or healthcare [1,9,10]. In everyday life scenarios, people can increasingly encounter these robots in public spaces without warning. To preclude minor conflicts, robots navigating shared physical spaces with humans will likely need to conform to the same general interaction norms applicable to people. As the assimilation of robots into diverse aspects of human existence continues to expand, a nuanced comprehension and effective utilization of non-verbal cues emerge as imperative for achieving harmonious and efficient human-robot interactions [11]. For instance, when a person encounters a delivery robot on a narrow sidewalk, mutual understanding of intentions is crucial for a safe and efficient passage, allowing both parties to proceed along their respective paths seamlessly. Consequently, service robots operating amidst ordinary individuals must be ready for social interaction [12]. These robots should have the capacity to interact with people, move alongside them, while with some of them, their control can be taken over remotely by a human operator or they can be used as telepresence robots for direct interaction between physically present and remote participants. In the context of this paper, we focus on service robots that have significant social capabilities (*social service robots*) being able to participate as independent social entities in communication situations. The subcategories of such social service robots that fit this description are *social robots* and *robot-assistants*. According to [13], a social robot is an intelligent machine characterized by its ability to engage in interactive and conversational exchanges, embodying features such as automated personal assistance, ambient assistive living technologies, and computational intelligence in the realms of games, storytelling, health care, and education services, reflecting a shift from traditional notions of purpose-built machines. Whereas a robot-assistant, as stated by [14], is an autonomous physical device capable of providing services independently, offering benefits such as reduced service time, accessible information, personalized service, and consistent, albeit limited, service quality.

Modern social service robots are state-of-the-art machines that can be quite expensive. For example, the 5G capable TEMI robot assistant costs $7500, and to use all of its features, an additional subscription is needed with the yearly price of $1500 [15]. Another robot assistant by LG, CLOi, costs $39,999 [16]. In order to justify the implementation costs and successfully capitalize these robots, their human users need to be skilled and motivated to accept them [9]. The efficient use of social service robots seems to depend on their users' self-efficacy and is strongly influenced by the robot's natural communication skills, especially its nonverbal communication abilities [5,9,17]. The discernment of human emotions stands as a pivotal aspect of HRI facilitated by non-verbal cues. The tacit language of facial expressions, gestures, and body language emerges as a conduit for deciphering and responding to human affective states. This interpretative acumen engenders a more empathetic and adaptive robotic interaction, transcending the confines of explicit verbal communication.

In the establishment of trust and rapport, non-verbal cues assume a critical role. In collaborative work settings where humans and robots converge, the ability of robots to convey attentiveness through judicious employment of eye contact, nodding, and other non-verbal manifestations contributes substantively to the perception of reliability and mutual cooperation [12,18]. This, in turn enhances the efficacy of human-robot collaborative endeavors. Moreover, the integration of non-verbal cues substantially contributes to the enhancement of the overall user experience, rendering interactions more organic and intuitive [19]. In domestic environments, for instance, a robot adept at discerning and responding to non-verbal prompts, such as gestures or pointing, seamlessly integrates into the fabric of daily life. This adaptive responsiveness fosters a more fluid and humanized exchange.

Due to their relatively high acquisition and implementation costs [20], it has great economic importance to understand the influence of the social service robots' nonverbal skills on their efficient implementation. For this end we conducted the literature review, where we explored the general statistics of available papers (i.e., the number of available papers, their publishing years, the main contributing countries and authors), and also studied the more specific aspects of the literature, such as the robots used in the experiments, the main research aims and the nonverbal cues examined, the methods used for obtaining data, and the main results of the studies.

Given the aforementioned context, the question of providing social service robots with adequate nonverbal communication abilities becomes increasingly important as it holds the keys to efficient use of this promising although relatively expensive emerging technology. Our aim is to conduct a literature review to examine the state of the art of the research conducted on the real-life use of nonverbal behavior by social service robots in HRI. We will focus on the use of nonverbal characteristics such as distance, personal space, touch, gaze, and others as expressed or observed and interpreted by physical (not simulated) social service robots in their communication with physically

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present humans in a social environment. We have formed the following **research questions** to guide our study:

1. What is the state of the art of literature about nonverbal interaction in HRI with social service robots? We are interested in the following general metrics:
   a) the number of available articles;
   b) the publishing years of the papers;
   c) the main contributing countries; and
   d) the main contributing authors.
2. In addition our interests lay in the following specific aspects of the studies:
   a) What robots were mainly used in the studies?
   b) What were the main research aims?
   c) What types of nonverbal communication were mostly examined?
   d) What methods were used for research?
   e) What are the main results of the studies?

2. Materials and Methods

The goal of the study was to understand which nonverbal behavior cues (e.g., distance, personal space, touch and gaze) were considered relevant in the literature about HRI between people and social service robots (i.e., robot assistants or social robots) in higher education. For these purposes, we conducted a literature review of open access papers, basing our search on three well-known, academically respectable and most relevant search engines [21]: Web of Science [22], Scopus [23] and EBSCO Discovery Service [24]. We formed our search formula as follows, using the terms "robot assistant" and "social robot" in order to narrow down the search results to match better our focus on service robots with social abilities:

`(HRI) AND ((robot assistant) OR (social robot)) AND ((non-verbal) OR (nonverbal))`

We used the terms "robot assistant" and "social robot" because these are service robots with dedicated social capabilities, and also because the search phrase "(`HRI) AND (SERVICE ROBOT) AND ((NONVERBAL) OR (NON-VERBAL))`" gave significantly less matches (e.g., only two papers with full text available in EBSCO Discovery).

Next, we refined our search parameters by restricting the retrieval of articles to those classified as "Full text available" within EBSCO Discovery and those falling under the category of "Open access papers" in both Scopus and Web of Science. This selection process, as illustrated in Figure 1, was executed on the 28 October 2023, and it yielded 150 articles across these platforms: EBSCO Discovery yielded 36 papers, Scopus contributed 57, and Web of Science presented 57 papers. Subsequently, to ensure the quality of our dataset, we identified and eliminated any duplicate entries. This curation process left us with 88 distinctive research papers. Next, we examined the selected papers, excluding any that did not align with the criteria of substantial academic content, such as posters, one-pagers or documents that were not peer reviewed. After this thorough examination, we were left with a refined set of 81 academic papers.

Our primary objective was to chart research on real HRI with service robots. We excluded purely theoretical studies due to their inability to incorporate modern technological advancements, emphasizing the importance of examining the human element in real-world HRI experiments while considering the surrounding context [25]. In addition, we excluded studies where robots were presented through mediating tools, such as computer screens, virtual, or augmented reality. After this exclusion, 39 papers remained to be studied (Figure 1 and Appendix A).

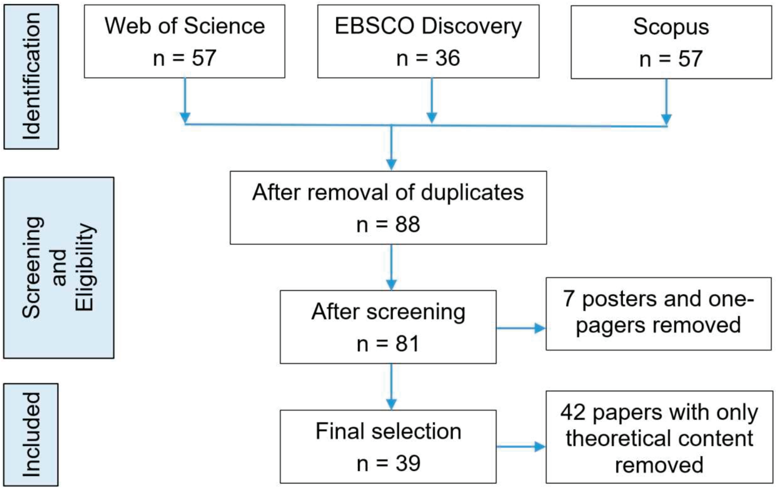

Figure 1. Literature selection process flowchart.

In the analytical phase, the chosen papers underwent a meticulous process of open coding, conducted by two researchers. Their objective was to discern and delineate clusters of meaning that encapsulated the nuances of nonverbal interaction cues within Human-Robot Interaction (HRI). This intricate coding procedure involved thorough scrutiny and interpretation of the content. Any disparities in coding were addressed through thoughtful discussions, ensuring a harmonized and comprehensive extraction of themes.

3. Results

Our final selection of papers concerning nonverbal communication in HRI involving service robots with social capabilities, referred to as social robots or robot assistants, was based on a search conducted on October 28, 2023, resulting in the inclusion of 39 works. This collection of papers can be characterized using the following key metrics:

Firstly, these papers emanate from 20 distinct countries. Among these, the most prominent contributors were the United States and Japan, each with 8 papers, followed by the United Kingdom and Italy, both contributing 7 papers. Additionally, the Netherlands and France each had 5 papers, while Germany, Sweden, and Belgium all contributed 3 papers. Next, there were in total 167 individual authors associated with these papers, with only 16 of them having authorship in more than one paper. Notably, Francesco Rea emerged as the most prolific author with 5 papers, followed closely by Alessandra Sciutti, who authored 4 papers. Finally, the publication dates of these articles span from 2006 to 2023 (Figure 2). An analysis of this data suggests that the popularity of the subject matter concerning the nonverbal communication skills of service robots experienced a decline during the years 2015-2018. However, it is worth noting that the unique circumstances of the recent COVID-19 pandemic appear to have rekindled interest in this topic. Beginning in 2018, the number of papers addressing this subject has displayed a consistent upward trend. The relatively lower number of papers available for the year 2023 can be attributed to the fact that our search was conducted in October 2023, and many papers for that year were still in the process of being published.

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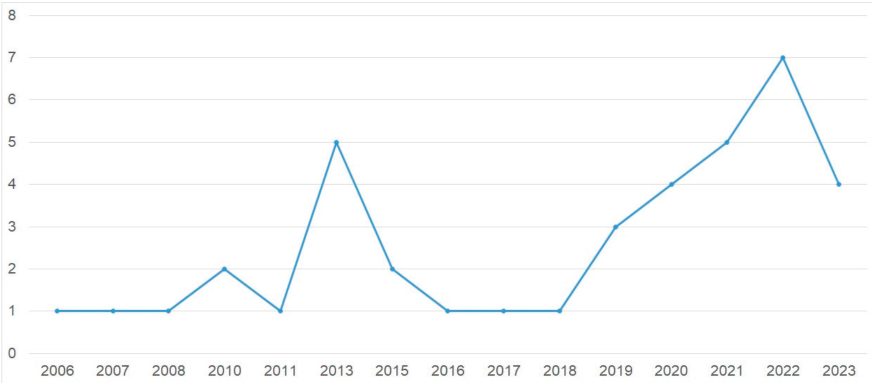

Figure 2. Number of papers by years.

Next, we will examine the results for the following specific aspects of the selected studies: the robots used; the main research aims; the types of nonverbal communication mostly examined; methods used; and the main results.

3.1. Robots Used in the Examined Studies

In the empirical parts of the examined papers, various robot platforms were used to investigate the dynamics of communication and engagement between humans and robots. Next, we will provide an overview of the most prevalent robot designs and types employed for experiments in these studies.

Humanoid robots are a dominant category, representing 27 instances across the examined studies. Among humanoid robots, the NAO robot stands out as the most popular choice, with mentions in 10 articles. The NAO robot's humanoid appearance, coupled with its programmable capabilities, seems to make it a versatile platform for investigating nonverbal communication in HRI. iCub, another humanoid robot, is featured in 6 studies, and Pepper, together with Robovie II, (both with 2 mentions) also contribute to the diversity of humanoid robots in the studies.

Bust and face robots provide a unique dimension to HRI research, with 4 instances identified in the examined papers. Furhat [26] and SociBot [27,28] are notable representatives of this category. These robots, designed to focus on facial expressions and interactions, offer insights into nonverbal cues and facial communication between humans and robots.

AIBO, *the robot dog* [29], and Pleo, *the robot dinosaur* [30], are featured in 2 studies, emphasizing the interest in exploring how animals' behavior and interactions with humans can inform robot design and nonverbal communication, but also the potential for unconventional robot designs to engage with humans.

The Roomba iRobot Create 2, *a robot vacuum*, appears in 1 study [31]. Although not a typical HRI robot, its inclusion suggests the exploration of nonverbal cues and interactions with non-humanoid robots in domestic settings.

Five studies [32–36] highlight *robots with product-oriented appearances* designed to maximize dedicated functions (see [37]). These robots represent a different approach to nonverbal communication and human-robot engagement, emphasizing specific functions and purposes.

The selection of robots in academic studies on nonverbal communication in HRI reflects a broad variety of robot types and designs. Humanoid robots, such as NAO and iCub, dominate the field, highlighting their adaptability for studying nonverbal communication. In addition, bust and face robots, a robot dog, a robot vacuum, and even a robot dinosaur provide unique approaches on nonverbal interactions between humans and robots. The inclusion of product-oriented robot appearances further diversifies the robot platforms used in these studies, highlighting the importance of nonverbal communication in various contexts (e.g., in production or warehouses).

3.2. Main Research Aims

The predominant research aim among the selected academic papers is to assess various facets of HRI. This overarching objective encompasses studies that scrutinize the technical proficiency of robots, gauge trust levels, probe connections between familiarity and engagement, and explore the consequences of robots on human behavior and emotions. We have categorized this wide-ranging array of research objectives into five discernible categories.

Understanding Human-Robot Communication and Interaction. Researchers have embarked on comprehensive investigations to unravel the intricacies of human-robot interaction from diverse vantage points. For instance, one study delved into the acceptance and utilization of robots, with a particular emphasis on their roles in interactions with children diagnosed with autism [38]. Another scholarly work sought to establish correlations between human verbal behavior and robot behavior predicated on the personality traits of the interacting humans, distinguishing them as introverted or extraverted [39]. Trust and the impact of nonverbal communication were paramount in a different study [40], while another explored the influence of robot nonverbal cues on individuals' perceptions of the robot's social agency [27]. Cross-cultural interactions and the efficacy of robot greetings and gestures were examined in a particular context [41,42]. Researchers aspired to devise empathetic and multi-modal interactions grounded in the emotional-cognitive profiles of users [43].

Emotional Interaction. The study of the emotional dimensions of human-robot interaction has constituted a point of high interest for some researchers. One study probed the impact of a humanoid robot on human emotional responses, particularly within cognitively demanding tasks [25]. Another investigation delved into the realm of personality in human-robot interaction, utilizing AIBO, a social robotic pet developed by Sony [29]. Furthermore, researchers delved into emotional expression and mood recognition in robot-human interactions, seeking to comprehend their effects on participants [44,45].

Robot Learning and Teaching. The nexus of human-robot interaction extends into the domain of learning and teaching. Researchers evaluated the performance of machine learners when instructed by human teachers [46]. Simultaneously, they probed the manner in which humans construed and integrated robot actions within their own plans [47]. A distinct study grappled with the challenge of evaluating engagement in human-robot interaction by amalgamating verbal and nonverbal behaviors [48].

Cognitive and Behavioral Aspects. Cognitive facets of interaction have assumed a central role for specific researchers. They endeavored to devise cognitive architectures for robots, facilitating close collaboration with humans in cooperative tasks [49]. The examination of the role of interaction dynamics and gestures within human-robot interaction was a pivotal focus within a study, particularly in joint tasks [50]. In addition, the perception of a robot's speech and its influence on language acquisition during interactions were subjects of investigation [51]. The inner workings of engagement and the formulation of a model delineating its components underwent scrutiny as well [30]. Other studies scrutinized the effectiveness of gaze-control techniques and control interfaces in shaping robot behavior [52] and monitored visual attention and head pose within human-robot interaction [53]. Implementing gaze behavior in functional robots to assist humans in deciphering their intent assumed primacy for another cohort of researchers [31].

Robot Behavior and Communication. The formulation of methods for inducing and detecting user affect within human-robot interactions has emerged as a noteworthy area of exploration [54]. Additionally, the impact of non-verbal communication on the efficacy and teamwork of human-robot partnerships has been a pivotal focus [36].

These diverse thematic clusters encompass a comprehensive array of research aims, reflecting the depth and breadth of scholarship within the field of human-robot interaction. From deciphering the psychological underpinnings of these interactions to enhancing robot behavior and communication, the research continues to advance our comprehension of this evolving domain.

3.3. Types of Nonverbal Communication Examined

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The focus of our study encompasses the nonverbal communication cues investigated in the selected papers. These cues play a pivotal role in understanding and enhancing the quality of interactions between humans and robots. We categorized the nonverbal communication cues found in the selected papers as follows:

Gesture and Facial Expression. A substantial body of research has explored the use of gestures and facial expressions in HRI. Non-verbal gestures, including hand movements, head poses, and bodily movements, have been a common focus in HRI research. These gestures serve as crucial elements in conveying information, emotions, and intentions in human-robot interactions [31,49,50,53]. Researchers have also delved into conveying emotions such as sadness, boredom, and happiness through gestures and expressions. This includes the study of expressive motions and the mimicry of human gestures by robots. Additionally, facial expressions like happiness, sadness, surprise, anger, and laughter have been scrutinized as essential nonverbal communication elements in [29,38,55,56] and others.

Affective States and Emotions. Researchers have explored affective states and emotions in HRI, examining how robots can detect and respond to emotional cues from humans. This includes the investigation of emotional expressions, such as arousal-valence and action units [25,55,57,58].

Eye Gaze. The direction of eye gaze, as well as the dynamics of gaze via head movement, has been a focal point of several studies. Eye gaze serves as a crucial means of nonverbal communication, influencing the understanding and interpretation of social interactions in HRI [25,28,42,47, and others].

Voice and Speech Cues. Aspects related to speech, including speech volume, speed, pitch, style, vocabulary, topic selection, feedback, syntax, and backchannel, have been examined. These factors contribute significantly to nonverbal communication, impacting the quality of human-robot conversations by influencing mutual engagement and attentiveness [26,48,59].

Human-Robot Proximity and Movement. Studies have explored physical and psychological distances between humans and robots in various contexts, such as movement within a room. The extent and speed of movements, as well as distances during interactions, have been scrutinized to understand how these factors affect communication and engagement [42,60].

Cultural Aspects and Greetings. Cultural differences in nonverbal communication, particularly in greetings and gestures, have been a point of interest. Understanding how cultural norms influence nonverbal behavior in human-robot interactions has been a key theme [41,42].

These categories of the wide range of nonverbal communication cues play a significant role in shaping the effectiveness of service robots during human-robot interactions, enhancing engagement, trust, and the overall user experience.

3.4. Sample and Methods Used

3.4.1. Sample Size and Characteristics

All reviewed papers reported the size of their human samples. The average sample size across these studies is 27, with the largest sample consisting of 120 participants and the smallest encompassing 5 individuals. Notably, a subset of 5 papers specifically focused on children as their sample. Among these papers, the sample sizes varied, with the largest involving 67 child participants and the smallest comprising 7. In a distinct context, university students were the focal group in 16 of the examined papers. Within this category, the average sample size stood at 34 participants, with the largest encompassing 120 individuals and the smallest comprising 12.

Regarding the gender distribution within the examined papers, a notable equilibrium was observed. On average, the samples consisted of 46% female participants and 54% male participants. This balanced gender representation within the studies highlights the diversity and inclusivity of human participants in human-robot interaction research.

Age data was provided in 27 of the reviewed papers. The average age of participants across these studies was approximately 27 years. The range of ages within the samples varied, with the eldest participant reported as 84 years old and the youngest participant as young as 3. This

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comprehensive age range underscores the inclusivity of participants across different age groups in the realm of human-robot interaction research.

3.4.2. Data Collection

The reviewed studies employed a wide array of data collection and analysis techniques. Based on the sources of the data, we categorized them into three primary groups: (a) data generated by participants, such as interviews and questionnaires; (b) data measured during the experiments, including distances and ranges of hand gestures; and (c) alternative approaches for data collection. These categorized methods played a pivotal role in achieving a comprehensive understanding of human-robot interactions, encompassing both objective and subjective data, as well as diverse and innovative approaches.

To begin with, the direct collection of data from participants heavily relied on questionnaires. For instance, [32,39,56,61] utilized Likert scale questionnaires to assess various aspects of human-robot interaction. [45] and [51] employed pre-test and post-test questionnaires. In [43] the participants were requested to complete the Chat-bot Usability Questionnaire. In [28] the length of human speech was measured through questionnaires, while in [58] data was gathered using TIPI and RoSAS questionnaires. In [54] non-verbal emotional behaviors were measured through EEG signals. In addition, structured interviews were conducted by [46], and participant feedback was solicited by [40].

Moving on, the studies also collected objective data through various methods. Video analysis was a prevalent technique in the studies of [38] and [62], where it was employed to scrutinize social interactions and initial reactions of children with autism. In [61] it was used to assess the adequacy and intensity of human responses, while [55] applied it for automatic personality prediction. In [25] the impact of humanoid robots on human emotional responses was explored through video analysis. In [30] this method was also employed to test a model specifying the components of engagement. In [58] video analysis was utilized to investigate the extent to which a humanoid robot can influence someone's comfort. In [53] visual attention was monitored using this technique, and in [44] video analysis was used to recognize valence and arousal. In addition, the authors also used techniques such as collecting Inertial Measurement Unit sensor data about micro-movements [61] or measuring physiological signals and audio-visual behavior to collect physiological data [55] or motion sensors for gathering synchronized information streams [53].

Finally, the researchers of the selected studies also employed some unique or diverse data collection methods. For example, [54] used non-verbal emotional behaviors designed to elicit user affect, which was measured through EEG signals; in [34] a device called the "Interruptedness Metre" was used to collect ranked data from participants. Additional data collection methods included reflection and observation. For instance, in [38], the collection of qualitative data involved reflecting on parents' and children's views. In [40] free-form observation notes were used to capture body language and speech, while in [32] the graffiti wall method was employed to understand feelings and perceptions.

3.5. Main Empirical Results

To articulate the empirical study directions presented in the analyzed papers, we synthesized the principal findings extracted from these documents. Considering the frequency of occurrences in the studied works, we categorized the findings into seven distinct general themes as follows.

Nonverbal Communication and Robot Self-Efficacy. Nonverbal communication, encompassing facial expressions, gaze, and gestures, is a recurring theme across several academic papers. In [27] the powerful impact of facial expressions on the perceived anthropomorphism of a robot was emphasized. In addition, in [34] it was discussed how nonverbal cues such as speed of motion and proximity contribute to conveying interruption urgency and affect the perception of disruption by people. Nonverbal cues play a pivotal role in shaping the robot's self-efficacy, influencing how participants perceive it.

Robot Personality and Engagement. The exploration of robot personality as a key factor in engaging participants during interactions is a common thread in various papers. In [39] the importance of a robot's personality in influencing participants' perceptions and preferences was underscored. Combining gestures and speech, as suggested in [39], enhances the robot's engagement and naturalness, making it more appealing and effective. In [60] the potential for improving human-robot interaction by modulating robot behavior to express different moods was also indicated.

Trust and Trustworthiness. The topic of trust is addressed in several papers. In [40] the correlation between self-assessed trust and trust measured during a game was highlighted, emphasizing the positive impact of nonverbal communication on trust levels. Trust is a critical component in human-robot interactions, and nonverbal cues contribute to building and maintaining trust with robots. In [49] it was demonstrated how nonverbal cues, such as gaze, significantly improve cooperation between the robot and the human participant, underlining the role of trust in collaboration.

Sociability and Familiarity. Participants' perceptions of a robot's sociability and familiarity are examined in [61], where more sociable robots lead to a greater sense of familiarity. This highlights the significance of nonverbal cues in creating a sense of comfort during interactions. In [42] it was also discussed how different robot appearances affect nonverbal behaviors, such as the distance and delay of response, further illustrating the role of sociability in human-robot interaction.

Transparency and Active Learning. Transparency in robot behavior is a central theme in [46]. It is noted that active learning may not always be the best approach, as some participants prefer more control over the interaction. Transparency is vital for ensuring that the robot's behavior aligns with participants' expectations. In [43] the importance of balancing transparency and legibility of the robot's goals were highlighted, emphasizing that a clear understanding of the robot's intentions contributes to successful interactions.

Joint Tasks and Adaptation. Papers such as [47] and [25] delve into how participants respond to joint tasks with robots. Participants adapt their gaze patterns and engage in joint actions, but there can be challenges, such as finding robot movements less humanlike. This topic underscores the need for robots to adapt effectively in collaborative settings. In [49] and [55] it was emphasized the role of adaptability in human-robot interactions and how different expression levels and behaviors influence participants' emotional states and the analysis of the robot's role.

Cultural Differences and Shared Perception. The influence of different robot appearances and cultural differences is explored in various papers. For instance, in [63] it is discussed how shared perception in interactions improves cooperation and performance. Cultural nuances, such as bowing and handshakes, play a role in shaping the interaction's dynamics. In [41] and [58] insights are provided into how cultural differences affect the robot's learning progress and the robot's behavior in response to different cultural contexts.

These outlined themes underscore the role of nonverbal cues in shaping robot self-efficacy, trust, engagement, transparency, adaptation, and the impact of cultural differences in human-robot interactions.

3.6. Theoretical Approaches Proposed

In order to put the results into proper context, we need also to review the theoretical approaches proposed in literature, starting from the acceptance of service robots by their users. An important aspect of technology acceptance is self efficacy that refers to the person’s confidence and motivation in using the technology [9]. According to [64], general self-efficacy is “*defined as people’s beliefs about their capabilities to produce designated levels of performance that exercise influence over events that affect their lives.*” People's self-efficacy in using technology, often referred to as computer self-efficacy, is associated with their attitudes toward technology, perceived usefulness, ease of use, and reduced anxiety [65]. The same principles apply to service robots, as robotics and self-efficacy are closely linked, impacting initiation, retention, and overcoming challenges. Robot self-efficacy is linked to general self-efficacy, tech interest, and willingness to use. Although self-efficacy cannot be used as a direct indicator for technology acceptance, due to reliance on others and technical issues, it is still usable for predicting the individual willingness to use the technology [65].

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In the case of service robots as social entities, self-efficacy depends on the robot's positive social influence on people [66], i.e., its ability to change people's "*motives and emotions, cognitions and beliefs, values and behavior that occur in an individual*" [67]. In other words, self-efficacy depends on the robot's ability to be perceived as a social entity that has a potential for establishing and maintaining a social relationship [68]. As suggested by [66,69,70], a robot's social influence and its user's self-efficacy hinges on the effective utilization of nonverbal cues, a crucial element in human communication, i.e., the robot's ability to have 2-way natural communication with humans [5]. In essence, the robot's capacity to emulate natural human interaction plays a pivotal role in determining self-efficacy, highlighting the interconnectedness of both direct verbal and indirect nonverbal communication [71]. The importance of the robot's natural communication skills is stressed by [17] by proposing that robots with only verbal interaction skills are more likely ignored when asking help, compared to the robots that also use nonverbal cues in HRI. This suggests that effective collaboration between a human and a robot would be at least partly based on using both verbal and nonverbal cues in their interaction.

In verbal interaction, mostly language-based information is shared while nonverbal interaction carries various cues that help people to share interaction roles and to put relayed information into proper context [72]. In addition, nonverbal cues help interaction parties predict the next appropriate action. For example, the end of someone's speech can be understood even before the speaker tells it [73]. Nonverbal cues involve physical appearance, gestures and posture, face and eye behavior, vocal behavior, space and environment [72]. However, as robotic bodies still do not have full capacities to relay immaculately human nonverbal cues, these cues could become inadequately presented or go missing in HRI. Inadequate nonverbal cues could determine robot use self-efficacy and acceptance in scenarios where people are interacting in social environments with robots or other persons mediated via robots, such as in higher education teaching and learning, in elderly care or in health care in general [9,10].

However, there is limited information regarding the real-world utilization of nonverbal behaviors in service robots. To address this gap, we delve into three case studies [17,65,69] related to robot self-efficacy and the significance of nonverbal communication skills in service robots. These case studies served as a foundation for shaping our research inquiries.

The authors of [65] investigate the relationship between self-efficacy and the use of robots. The paper highlights the importance of self-efficacy in the context of technology adoption, specifically robots. The authors suggest that robot self-efficacy in healthcare is correlated with general self-efficacy, interest in technology, and willingness to use robots. Their study emphasizes the role of successful experiences in enhancing self-efficacy, such as interacting with a social robot on household-related tasks. This kind of interaction can lead to more positive evaluations of the robot. The authors describe their experimental design, including measures for participant data, the Robot Self-Efficacy Scale, likability, and willingness to use the robot, in their case – the Pepper robot. The results indicate that brief interactions with the robot and its likeability play a significant role in changes in people's robot self-efficacy. The study demonstrates the importance of self-efficacy in HRI.

The authors of [69] presented a study about the impact of a social robot's expressions, both verbal and non-verbal, on self-efficacy during cognitive tasks. The robot, Kebbi, showcased four different expressions: default voice and motion, default voice and designed motion, designed voice and default motion, and designed voice and designed motion. Seventeen university students with technical backgrounds engaged in the Wisconsin Card-Sorting Task, a test involving rule changes leading to mistakes. The study monitored participants' heart rates and brainwave data to gauge arousal and stress levels and recorded the experiment for comprehensive analysis. The study revealed that robot expressions influenced participants' perceptions and stress levels. Designed motion, combined with voice feedback, made the robot more likable and reduced frustration and stress. Individual personality traits also played a significant role in participant responses. The research underscores the importance of considering both verbal and non-verbal robot actions in educational support robots. It highlights the role of personal traits and individual differences in human-robot interactions, especially when enhancing self-efficacy in educational contexts.

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The authors of [17] explored the impact of conversational interactions, both nonverbal and verbal, between robots and humans on relationship building. Their aim was to determine if such interactions could create a partnership between humans and service robots, potentially increasing helpful behavior from humans towards the robots. The authors suggest that as humans can form emotional connections with non-living entities, direct, personal, and spontaneous interactions are important in building relationships. In addition, for successful interaction, humans must perceive the robot as a genuine social actor. In their study, twenty-five students interacted with both an interactive and a non-interactive robot. Their results showed that the interactive robot was perceived more positively, resulting in higher social presence and a stronger human-robot relationship. The authors suggest that conversational interactions can enhance social presence and relationships in human-robot interactions, but understanding and predicting helping behavior remains a complex challenge. The authors propose that to foster effective cooperation, robots need to establish partnerships with humans, akin to how humans naturally collaborate using both verbal and non-verbal communication.

4. Discussion and Conclusions

In this study, we explored nonverbal communication in human-robot interaction (HRI), particularly focusing on service robots with social capabilities, often also referred to as social robots or robot assistants. The comprehension of how individuals perceive robots stands as a pivotal concern in gaining deeper insights into the realm of HRI [74]. As social robots become more prevalent within social landscapes, then they need to be perceived positively in order to become seamlessly integrated into our daily lives. The study of social perceptions regarding robots is an emerging field of research, one that is poised to gain increasing prominence in the years to come [75]. Our investigation has provided some insights into the state of research in this domain and unveiled findings that shed light on various aspects of this dynamic field.

Robots Used in the Examined Studies. The studies used a relatively diverse selection of robots in their experiments on nonverbal communication in HRI, reflecting the dynamics of the rapidly evolving landscape of HRI. Humanoid robots, particularly the NAO and iCub, have emerged as dominant platforms for studying nonverbal communication. Their humanoid appearance and programmable capabilities make them versatile choices for investigating the intricacies of HRI. The inclusion of bust and face robots, a robot dog (AIBO), a robot dinosaur (Pleo), and even non-humanoid robots (e.g., Roomba iRobot Create 2) provides further perspectives on nonverbal interactions between humans and robots. These diverse robot platforms enrich our understanding of nonverbal communication in various contexts, from social robots that mimic human features to product-oriented robots designed for specific functions. As evidenced by [21] and [76], engaging with robots can create a robust social context capable of influencing psychological needs, even in the absence of humanoid features.

Main Research Aims. Our analysis has revealed a wide range of research objectives within the selected academic papers. Understanding HRI remains a predominant focus, encompassing investigations into acceptance and utilization of robots, correlations between human verbal behavior and robot behavior, and the influence of nonverbal cues on individuals' perceptions of the robot's social agency. Emotional interaction has also been a central theme, with studies probing the impact of humanoid robots on human emotional responses and exploring personality in HRI. Learning and teaching in the context of HRI have also been addressed, examining the performance of machine learners when instructed by human teachers and the manner in which humans integrate robot actions into their plans. Cognitive and behavioral aspects have assumed a critical role in specific research, from devising cognitive architectures for robots to studying the role of gestures in joint tasks. The impact of robot behavior and communication on user affect and teamwork has been another notable focus. These diverse thematic clusters reflect the depth and breadth of scholarship within the field of HRI, encompassing a wide array of research aims that continue to advance our comprehension of this evolving domain.

Types of Nonverbal Communication Examined. The types of nonverbal communication cues examined in the selected papers are integral to understanding and enhancing the quality of interactions between humans and robots. We refrained from differentiating between studies that concentrated on robots interpreting nonverbal cues from people and those that centered on people interpreting the nonverbal cues of robots. This lack of distinction arises from the fact that these particular directions of communication are still in their rudimentary stage. Ideally, both communication parties should possess the capability to reciprocally indicate and comprehend intentions, even in scenarios where the robot lacks humanoid features, as demonstrated by [76]. Gesture and facial expression have been significant areas of exploration, with research focusing on hand movements, head poses, bodily movements, and facial expressions. These cues play a vital role in conveying information, emotions, and intentions in human-robot interactions. Affective states and emotions have also been extensively examined, with a focus on emotional expressions and mood recognition in robot-human interactions. Eye gaze, an essential means of nonverbal communication, has been scrutinized in terms of its impact on social interactions. Voice and speech cues have been explored, encompassing various aspects of speech, such as volume, speed, pitch, and style. Human-robot proximity and movement have been investigated to understand how physical and psychological distances influence communication and engagement. Cultural aspects and greetings have provided insights into the influence of cultural norms on nonverbal behavior in human-robot interactions. These categories of nonverbal communication cues play a pivotal role in shaping the effectiveness of service robots during human-robot interactions, enhancing engagement, trust, and the overall user experience.

Sample and Methods Used. The diversity in sample sizes and characteristics across the reviewed papers reflects the inclusivity and breadth of human participants in human-robot interaction research. Notably, a balanced gender distribution within the studies highlights the importance of diverse gender representation in these interactions. The wide range of participant ages underscores the inclusivity of different age groups in human-robot interaction research. The varied data collection methods employed in the selected studies encompassed a mix of quantitative and qualitative approaches, providing a comprehensive understanding of human-robot interactions.

Main Empirical Results. The main findings extracted from the analyzed papers can be categorized into several themes. Nonverbal communication has been identified as a key factor influencing robot self-efficacy, influencing how participants perceive and interact with robots. Robot personality and engagement are central themes, underscoring the significance of a robot's personality in shaping participants' perceptions and preferences. Trust and trustworthiness have been addressed, highlighting the positive impact of nonverbal communication on trust levels. Sociability and familiarity have also been explored, demonstrating the role of nonverbal cues in creating comfort during interactions. Transparency in robot behavior is emphasized, as it is vital for ensuring that the robot's behavior aligns with participants' expectations. Joint tasks and adaptation have been scrutinized, revealing the need for robots to adapt effectively in collaborative settings. Cultural differences and shared perception have provided insights into how different robot appearances and cultural norms influence the interaction's dynamics.

In the HRI, our examination of various studies leads us to a general observation: the predominant focus is on leveraging nonverbal communication to enhance the perceived seriousness of robots in their interactions with humans and make them more trustworthy. This approach aims to increase people's robot efficacy in various settings, be it at home, in the office, or other contexts. Moreover, our research suggests a potential avenue for granting robots distinct personalities, allowing people to view them as genuine social entities that are able to make decisions about which they need to assist first [77]. This opens the door to meaningful interaction, relationships, and even negotiations with these robotic companions, with opportunities for assistance and support.

One intriguing aspect that could propel robots toward developing unique personalities while adhering to social norms is rather contentious. Often, robots offering services aren't owned by the individuals they assist. This can be attributed to factors such as their relatively high cost, making it inappropriate for individuals to engage with these robots beyond the scope of their designated

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services. Additionally, any interference with a robot's prescribed activities could lead to financial or health-related repercussions. Consequently, it becomes evident that maintaining an appropriate social distance [78] emerges as a fundamental social norm in HRI.

However, as we contemplate enabling robots to acquire distinct and evolving personalities, it raises several challenging questions. Philosophers find themselves grappling with issues like the concept of robot slavery or their potential for free will in the coming decades. On a more immediate note, regular individuals must ponder the issue of privacy. Personality-enabled robots naturally require data about the people they interact with to fine-tune their behavior (as discussed in [79]). Ideally, this data should remain localized, avoiding any cloud-based uploads, much like how we, as humans, collect and utilize data to inform our own actions.

The increasing number of articles, as indicated in Figure 2, suggests a growing interest in this field, likely influenced by the COVID-19 pandemic and rapid technological advancements. In recent years, there has been substantial development in both hardware and AI solutions for shaping robot personalities. It's crucial to explore not only how to make robots more acceptable to humans during initial encounters but also to delve into the psychology of developing personalities for robots that evolve in harmony with the context and the individuals they interact with in their work. This journey must ensure that the development of robot personalities does not lead to mental health-like impairments or issues.

The studies we have reviewed predominantly focus on the tangible hardware aspects of robot design. Nonverbal cues and behavior patterns are vital elements of robot personalities, which are essentially software-driven. While imparting nonverbal characteristics contributes to building trust with humans, creating an effective robot personality involves a collaborative process with people, their surroundings, and the specific context. This entails software memory and algorithms that consider other individuals, robots, and the environment in which the robot operates. For example, a household robot remembers those it encounters regularly and can differentiate them from newcomers, but this gives rise to questions regarding GDPR compliance.

Theoretical Approaches Proposed. Our results also underscore the significance of theoretical approaches in contextualizing the findings. Key concepts include technology acceptance and self-efficacy, emphasizing the essential role of self-efficacy in using service robots [9,65]. Self-efficacy, a critical aspect of technology acceptance, is linked to users' confidence, motivation, and their perception of a robot's social influence [64,66]. We draw attention to the interconnectedness of self-efficacy, robot social influence, and the effective utilization of nonverbal cues, pointing out their impact on users' willingness to engage with service robots [5,17,66]. Nonverbal communication, essential in human interaction, becomes a pivotal component for effective human-robot interaction, particularly in scenarios such as education, elderly care, and healthcare [9,72]. We highlighted three case studies on robot self-efficacy and the role of nonverbal communication in service robots [17,65,69]. These studies emphasize the influence of self-efficacy on technology adoption and the impact of robot expressions, both verbal and nonverbal, on user perceptions and stress levels. They highlight the significance of considering nonverbal cues in educational support robots and the importance of creating genuine, interactive relationships between humans and robots. Overall, we imply that self-efficacy, nonverbal communication, and the interplay between human perception and robot interaction play critical roles, shedding light on the complexities and importance of these dynamics in human-robot relationships.

In conclusion, our aim was to contribute to the growing body of knowledge in the field of HRI, with a specific focus on non-verbal communication in service robots endowed with social capabilities. The results underscore the potential of enhancing the quality of communication between humans and service robots. Nevertheless, there are aspects that have not been thoroughly explored thus far. To date, assessments have predominantly measured technology acceptance by humans or their perceived efficacy in using the robot within a simulated environment, specifically tailored for a particular scenario. In forthcoming studies, we emphasize the importance of conducting experiments in real public spaces, given that service robots find significant applications in such environments. Additionally, scenarios involving collaborative actions between humans and robots were limited, despite articles emphasizing the creation of an effective robot personality through a collaborative process with humans. The interaction between humans and robots in public spaces encompasses yet another crucial aspect that the analyzed studies failed to reflect. Little attention has been given to understanding how individuals feel in communication or collaborative situations with robots, particularly in public spaces where others are present. As a final point, despite studies highlighting the impact of self-efficacy on technology adoption, there has been no measurement of whether individuals' self-efficacy was higher when they achieved their goals in collaboration with the robot.

As technology continues to advance, further research in this field is paramount to ensuring that robots can effectively communicate with humans in diverse contexts, ultimately enhancing the overall HRI experience. This article provides a comprehensive overview of the current state of research and lays the foundation for future investigations in this dynamic field.

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Appendix A The Results of the Literature Selection Process

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Appendix 3

Publication III

Marmor, K., Leoste, J., Heidmets, M., Kangur, K., Rebane, M., Pöial, J., & Kasuk, T. (2024). Keeping social distance in a classroom while interacting via a telepresence robot: A pilot study. *Frontiers in Neurorobotics*, 18, 1339000. https://doi.org/10.3389/fnbot.2024.1339000

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Keeping social distance in a classroom while interacting via a telepresence robot: a pilot study

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Introduction: The use of various telecommunication tools has grown significantly. However, many of these tools (e.g., computer-based teleconferencing) are problematic in relaying non-verbal human communication. Telepresence robots (TPRs) are seen as telecommunication tools that can support non-verbal communication.

Methods: In this paper, we examine the usability of TPRs, and communication distance related behavioral realism in communication situations between physically present persons and a TPR-mediated person. Twenty-four participants, who played out 36 communication situations with TPRs, were observed and interviewed.

Results: The results indicate that TPR-mediated people, especially women, choose shorter than normal communication distances. The type of the robot did not influence the choice of communication distance. The participants perceived the use of TPRs positively as a feasible telecommunication method.

Discussion: When introducing TPRs, situations with greater intrapersonal distances require more practice compared to scenarios where a physically present person communicates with a telepresent individual in the audience. In the latter situation, the robot-mediated person could be perceived as "behaviorally realistic" much faster than in vice versa communication situations.

KEYWORDS

social presence, telepresence robots, remote communication, proximity, human-robot interaction, social norms, behavioral realism

1 Introduction

The COVID-19 era pushed various sectors (including business and education) to make wide-scale use of digital technologies that allow people to communicate over distance. These digital technologies provide people with means for communicating, usually allowing them to relay their ideas, visual and voice, while being able to perceive their communication partners' ideas, visual and voice. Compared to face-to-face communication, human presence (i.e., the extent of perceiving the communication parties as real human beings) in digitally relayed conversations is limited. For example, there is no perceivable human body, the role of body language is limited or even absent; people can only be seen partially or they are represented on computer screens only by their names; and their relayed voices could have distortions. These limitations have encouraged academic discussion about maintaining the richness of human communication, inherent to real-world communication, in situations where communication is upheld by digital technologies (Gunawardena, 1995; Lowenthal and Dunlap, 2018; Carillo and Flores, 2020).

In face-to-face communication, information is moving via two different channels: verbal communication and non-verbal communication. When communication is mediated via digital technologies (e.g., teleconferencing systems), the non-verbal side of communication mostly suffers, losing the participants' mimicry, their mutual location, etc.

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FIGURE 1
TPR as an agent, mediating the TP's presence between the real-world and mimicked environments.

Some digital technologies are better prepared for mediating non-verbal communication. Telepresence robotics is a promising emerging technology that provides people with robotic bodies with limited support to non-verbal communication. In this paper, we are examining an important aspect of non-verbal communication—the intrapersonal distance used when telepresent persons (TPs) communicate with physically present persons (PPs), using a telepresence robot (TPR) as a mediating tool. We lean on the concept of behavioral realism (Freeman et al., 2000), wherein it is proposed that the perceived level of authenticity in a communication scenario, encompassing both verbal and non-verbal elements, plays a role in enhancing the productivity of interaction and the subjective pleasantness experienced by the communicative participants. In our theoretical reasoning, we also make use of papers from earlier periods, as the current research on TPRs is scant (Leoste et al., 2022). In addition, we compare our results with the ones of our previous study (Leoste et al., 2023), introduced in Section 1.3.

1.1 TPR-mediated telepresence

In 1980, Marvin Minsky, a co-founder of the Artificial Intelligence Laboratory at the MIT and a pioneer in this field, introduced the term "telepresence" to refer to teleoperation systems used for manipulating remote physical objects (Rae et al., 2015). The meaning of the term "telepresence" leans on the concept of "presence" (or its various aspects, such as physical presence or social presence—see Biocca et al., 2003) that characterize the feeling of being present somewhere, felt by a person whose biological body is somewhere else (Freeman et al., 2000). Thus, **telepresence** refers to the sensation, felt by a TP, of being present in a location distant from one's physical location when using a TPR. In other words, telepresence via a TPR allows a real person to experience a real-life environment remotely (El-Gayar et al., 2008), using the mediated sensory input that is provided by a TPR. From the TP's point of view, the TPR is used to mediate a real-life environment in order to create an interactive environment in a remote location (Figure 1). This interactive environment mimics closely the mediated real-world environment, where the TPR is located. In this simulated environment, information and communication technologies (ICTs) provide the TP with realistic sensory input that allows the TP to project their self-image around the TPR (see also Nakanishi et al., 2017) and accept the mimicked environment as real. And, *vice versa*, the TPR as a mediating agent allows the on-site persons to perceive the TP as being present (Figure 1).

The feeling of the TP's presence, as felt by both the PP and TP, depends on several factors, one of them being the TPR's abilities. In case of a typical modern TPR, it is usually a movable, remote-controlled device, equipped with cameras, speakers, microphones, screens, sensor-assisted motion control, and other interactive features designed for remote communication and collaboration. Such a TPR generally supports two-way audio and video communication with persons in remote locations (telepresent persons). Advanced TPRs have features such as laser pointers, auto-navigation, mapping features, and real-time full-resolution zoom that provides UHD 4K resolution of objects like whiteboards (Davey, 2021). However, the ability to manipulate objects in remote environments and receive tactile feedback is still limited.

Controlling a TPR and providing the TP with a mimicked environment require wireless internet connection and a computer or a smart device (Takeuchi et al., 2020; Kaelin et al., 2021), where the mimicked environment is created with the help of the computer's screen and speakers. At the same time, the camera and microphone of the TP's computer are used to project the TP's face and audio onto the TPR's screen and speakers, allowing the on-site persons to communicate with the TP face-to-face, supporting the TP's presence in the real-world environment (Perez, 2020).

Assessing the level of presence subjectively, as felt by the TP, is somewhat difficult as: (a) the feeling is constructed in the awareness of a person as a dynamic sum of sensory information and relevant memories (Freeman et al., 1999); (b) the vocabulary for expressing the degrees of presence is limited (Freeman et al., 2000); and (c) in the situation where presence is measured, the test subject is most likely aware of the true location of their biological body. In order to bypass these limitations, **behavioral realism** can be used as another way of assessing the level of the TP's presence. The behavioral realism approach was originally used to characterize the behavior of simulated beings in simulated environment as perceived by a human that is present in this simulated environment (Guadagno et al., 2007). As TPRs mediate the real-world environments to TPs as mimicked (digitally mediated, limited environments), behavioral realism can also be used to study the behavior of test subjects in these mimicked environments, and compare it with their behavior in real-world environments. Research (Garau, 2003; Bailenson et al., 2005) suggests that lower levels of behavioral realism indicate communication parties' lower perception of social presence, while higher levels of behavioral realism are associated with lesser association of being in a virtual environment.

1.2 Interpersonal communication distance

An important component of non-verbal communication is the spatial arrangement between communication partners—how far apart they are and what distance they choose. Over half a century ago, American anthropologist Edward Hall proposed a classification of communication distances (Hall, 1966). According to Hall, people use four different distances in everyday communication, which he called intimate, personal, social, and public distances. Many subsequent studies have confirmed Hall's approach while also pointing out significant cultural differences in people's spatial behavior.

According to Hall, the choice of distance depends on the relationship between communication partners (the closer the relationship, the smaller the distance), as well as the person's emotional state and what they are currently doing (Hall, 1966). It is important to note that the "selection" of distance is not a conscious activity—we do not think or calculate how close or far we should be from other people. It simply happens spontaneously, reflecting the norm that has been established in a society and internalized by people—an appropriate distance and arrangement are subjectively pleasant. Likewise, a violation of distance norms can be unpleasant, for example forced communication at a very close range. The distances described by Hall are as follows:

1. **Intimate distance** is <50 cm and is used for communication between very closely related individuals, such as a parent and child or spouses. It involves visual, haptic, and olfactory cues.
2. **Personal distance** is ∼50–120 cm away and it is used while there is small talk between friends or well-known partners. In this distance, the visual cues are still observed, but haptic and olfactory cues are less significant.
3. **Social distance** is around 120–350 cm away and is used for more formal communication situations, such as talking with strangers or placing customer seats at offices. Personal details are hidden, and communication becomes optional.
4. **Public distance** is more than 350 cm away and is used in public situations such as speeches, lectures or when communicating with superiors. Visual cues are less intimate, and communication relies more on speech volume and gestures.

While Hall's (1966) proximity zones have been supported by subsequent studies, it is important to acknowledge that the size of these zones can be influenced by a range of factors, including cultural background, gender, and other individual characteristics (Lewis, 1998). For instance, Kilbury et al. (1996) discovered that less space was given to disabled individuals than to non-disabled individuals, and that men tended to use longer distances than women did during conversations. Such factors may lead communication parties to prefer different proximity zones, resulting in a situation where the actual communication distance is perceived as inappropriate by one of the parties. Inaccurate proximity distance selection may lead to less desirable communication outcomes due to expectancy violation, where one of the communication parties perceives unexpected social norm violations (Burgoon and Hale, 2009). In addition, in certain situations, such as in education, closer distances can enhance instructional efficiency (Miller, 1978)—or refer to communication party's inability to view robotic bodies as social entities (Walters et al., 2005).

The choice of communication distance in situations, where one of the parties is present via a TPR, is little researched. People's spatial preferences when interacting with a (telepresence) robot can be affected by their gender, pre-existing attitudes toward robots, their experience with robots, their cultural background, robots' appearance, and the interaction's context. For example, Takayama and Pantofaru (2009) found that users' gender may influence perceptions of proximity in human-robot interaction, and Mumm and Mutlu (2011) found that participants who disliked the robot would maintain a greater distance from it, with male participants distancing themselves further than female participants would Joosse (2017) also found significant gender differences in people's spatial behavior. Nonetheless, as suggested by Leichtmann et al. (2021), the current research results in this area are not conclusive.

1.3 Research questions

This paper presents the second study of a research cycle focused on behavioral aspects of communication situations between TPs and PPs.

- Study 1: In the first paper by Leoste et al. (2023), we measured the distance chosen by PPs when interacting with TPs. In that study, we focused on an aspect of spatial behavior—interpersonal distance—by examining four social zones: intimate, personal, social, and public. Employing the Double 3 TPRs in simulated situations, we compared interactions with TPRs to in-person interactions. Our findings indicated that, irrespective of status or prior relationships, participants maintained a communication distance similar to normal human-to-human interactions, with participant gender and their experience in computer gaming influencing preferences. This research implied that, in general, TPR-mediated communication adheres to established social norms and may not necessitate additional physical space in educational settings, presenting implications for the integration of TPRs in education.
- Study 2: In this paper, we analyze in greater depth the spatial behavior of TPs when interacting with PPs.

Specifically, we are interested in explaining: (a) to what extent the communication distance selected by a TP, when communicating with a PP, differs from the distance selected by a PP when communicating with a TP; (b) how much the distance chosen by a TP is "behaviorally realistic," i.e., how it corresponds to the norms of spatial behavior established between physical individuals; and (c) the assessments of individuals communicating in a "TP and PP" situation, regarding the technical suitability and subjective pleasantness of such a communication method. In order to meet these research aims, we have formed the following research questions:

1. What is the communication distance chosen by a TP when communicating with a PP, and does it differ from the communication distance chosen by a PP when communicating with a TP?
2. Does the communication distance chosen by a TP depend on the TP's gender or the type of TPR used?
3. To what extent does the communication distance chosen by a TP differ from the "behaviorally realistic" distance that people maintain when communicating without a robot?
4. How do TPs and PPs evaluate the technical suitability and subjective comfort of communication TPR-mediated communication?
5. Do the assessments of TPs and PPs regarding the technical suitability and subjective comfort of the communication process depend on the type of robot used?

2 Method

2.1 Telepresence robots

We used three different TPRs in the study: (a) Double 3 by Double Robotics (https://www.doublerobotics.com/tech-specs.html); (b) Ohmni Gen 12 by OhmniLabs (https://ohmnilabs.com/products/ohmni-telepresence-robot/); and (c) TEMI 2 by TEMI (https://www.robotemi.com/product/temi/). All of these robots feature a strongly simplified humanoid shape, having upright posture and a separate head unit attached to the body that is able to move around using a wheeled base at its lower end. TEMI 2 is the shortest with the height of 100 cm. The height of Double 3 is adjustable from 119 to 152 cm, and Ohmni has a fixed height of 146 cm. The head unit contains a tablet-like display for relaying telepresent person's face, a microphone array, speakers and various cameras. While the robots have some limited autonomous movement abilities, normally their moves are controlled by a TP via a browser-based interface. None of these robots has movable arms or other manipulators for opening doors, holding objects or for other similar activities.

2.2 Sample

The sample for the study ($N = 24$) consisted of teaching staff and administrative employees from different Estonian and foreign universities. The people in the sample had varying experiences with telepresence robots: some had not encountered them at all, some had encountered them briefly, and some had briefly used them in their work. The sample included both men ($N = 9$) and women ($N = 15$), as well as people from different nationalities. Half of the sample ($N = 12$, of these three male and nine female) took the role of TP; the other half ($N = 12$) were PPs. The roles did not change during the experiments. Next, the sample was divided into four groups of six members each (three TPs and three PPs). The groups were formed to be as heterogeneous as possible: equal representation of different genders, different nationalities, different institutions, and different levels of experience. Each participant was given a unique code to use in data collection. In experiments, each TP used TPRs three times (each time a different TPR, 36 iterations in total). In average, participants of both genders used TPRs equally to communicate with PPs of both gender equally. After excluding the iterations with invalid measurements, 33 valid iterations remained.

2.3 Ethics

Written consent was obtained from all participants before the experiment. The participants signed a consent form, stating that personalized data would not be collected. The form also stated that all photos would be blurred for research purposes, and videos would be deleted after analyzing observation data. Studies involving human subjects: Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements.

2.4 Experiment

In our previous study (Leoste et al., 2023) we had identified three general communication scenarios that happen when in-person and telepresent persons interact: (a) ordinary verbal discussion between two parties; (b) the in-person party demonstrates an object (a page with text and figures) to the telepresent party; and (c) the telepresent party demonstrates an object (a page with text and figures) to the in-person party. These observations were used to create scenarios for communication situations in this study. The scenarios made use of a common topic—choosing a restaurant, as it allows all participants to contribute on relatively equal bases.

The experimental situation in this study is a 3-part short-term communication situation between a person and a person mediated via a TPR. During the situation, the TPR-mediated person must first approach the PP, chat with them, next share information on the robot's screen, and then read information from a piece of paper in the hands of the PP. All these parts followed the general scenario of choosing a restaurant, while the information shared was a menu of a restaurant.

2.4.1 Room setup and process

Three types of rooms (five rooms in total) were used to conduct the experiment: (a) a typical university study room as the communication room where the communication situation was played out; (b) three smaller rooms were used as the control rooms where TPs controlled TPRs; and (c) a typical university study room were workshops were held for waiting participants (the workshops were not related to robotics or telepresence). The robots and the computers that were used to control them were connected to a separate Wi-Fi internet router that operated on a 5 GHz frequency with a speed of at least 10 Mbit/s.

The following persons were present in the communication room at the beginning of the communication situation: (a) three PPs; (b) three TPR mediated TPs (i.e., physically there were three TPRs in the room); (c) three observers, who each observed a different TPR and noted down their observations; (d) two technical persons who monitored the discussion situation sessions with a video camera and with a depth camera; and (e) a supervisor who introduced the experiment to participants and monitored the conduction of the experiment. The communication room layout is depicted on Figure 2.

The following persons were present in each of the control rooms: (a) one TP (in-person); and (b) one observer-assistant, who instructed the TP for 3 min before the experiment, monitored the experiment and provided the TP with technical support when needed (Figure 3).

Instruction and training of the observers took place 2 weeks before the experiment and directly before the experiment on the spot. The observers were not allowed to interfere and they had to adhere to ethical principles (described in Section 2.3) during the observation.

Each group (from total four) of six participants (three PPs and three TPs) repeated the same experiment nine times, which

FIGURE 2
The layout of the communication room. The TP is interacting with a PP via a TPR **(center right)**. The other two PPs are waiting for their turn **(left)**. A technical person is standing near the camera. The supervisor is sitting **(back right)**.

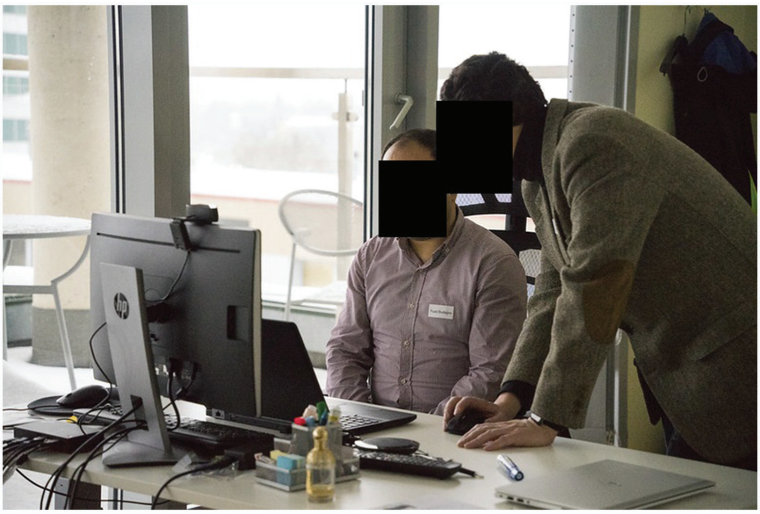

FIGURE 3
The layout of the control room. The TP is sitting behind the computer that is used to control the TPR. An observer-assistant (standing) is guiding the TP.

means that each PP had a discussion with three different TPR-mediated TPs and each TP could be in charge of three different TPRs. For this end, the TPs in the robot control rooms switched places with each other after each communication situation was played out. Playing out each communication situation took about 3 min and the whole session for each group took about an hour. After all nine discussion situations had been played out, all participants in the sessions filled in a questionnaire on paper. After completing the questionnaire, the group was replaced with a new one.

2.4.2 Description of communication situation

The PPs were sitting down. The first PP stood up, went to a certain location in the room and stayed there, holding a printed menu with font size 12 pt. The first TP approached,

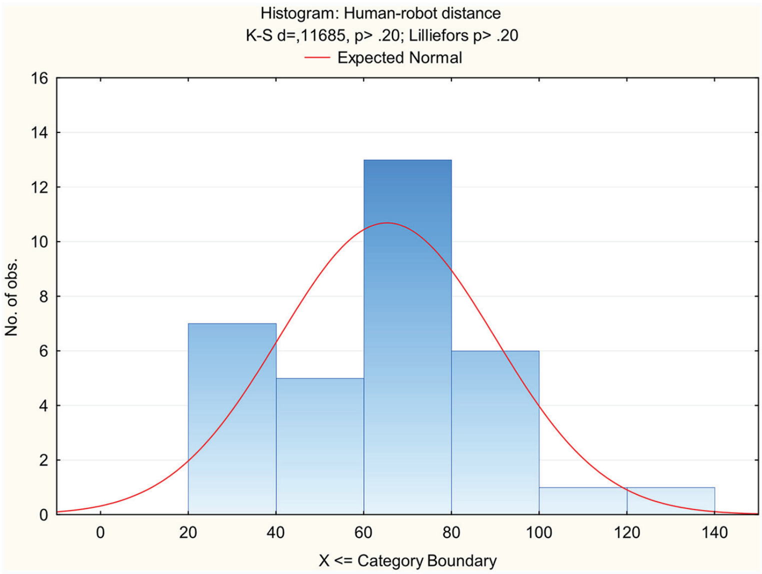

FIGURE 4
Normality testing results for distance between a TPR and a physically present person, as chosen by telepresent persons.

using the Double 3 robot, and stood at a comfortable distance from the PP with the menu. A conversation started with greetings, followed by a discussion about which restaurant to go to. The TP said that they knew a good restaurant and shared a photo of one of the dishes being offered. The PP looked at it. Then, the PP showed the menu to the TP and asked if it was the same menu. The TP had to read the menu aloud then. The communication situation ended, and the TP moved the TPR back. The scenario took about 3 min. Then, the next TP started to move the Ohmni robot, and the situation was repeated. The same was repeated with the TEMI 2 robot. To avoid repetitions, each robot operator had a menu of a different restaurant, and the people in the room had to choose the corresponding menu out of six menus.

After the first PP had played out the discussion situation with all three TPRs, the PP sat down, allowing the second PP to repeat the procedure. For the second round, all TPs switched the robots they were controlling. The third round with the third PP was conducted similarly, with all TPs switching their robots again. The impact of the familiarity of discussion participants on distance, arising from potential repetition, was mitigated by ensuring that there were no discussion situations with identical combinations of participants. We could not achieve full randomization of the discussion situations because our goal was to include groups with as much diversity in terms of gender and ethnicity as possible.

2.5 Data collection and analysis

The data about distance between the in-person and telepresent participants were collected using an Intel RealSense D415i depth-camera, which allows measuring distance between PPs and TPRs, and a regular video camera for control. A depth-camera records a distance from a camera for each pixel in a video. A single depth-camera frame from a greetings phase at the beginning of the conversation was chosen from a video stream for each experiment. The frame was chosen at a time step where both of the parties (the PP and TP) had chosen their positions and started a conversation. The frames were saved and (using markers) analyzed for distance between the communication parties. The markers were placed at the point closest to the PP on the TPR's upper body, and at the point closest to the TPR at the PP's face. The distance between those two points was calculated and recorded into a spreadsheet.

The observers had to note down information regarding problems, failures, abnormalities, etc. that could have had an impact on results. The observations were marked on a separate A4 sheet for each observation, with space for notes allocated for each unit of meaning. The observation protocols were digitized after the experiment and joined with the data extracted from the camera recordings.

The participants were asked to fill in a survey on paper right after the experiment. The surveys were digitized later and analyzed with the Excel spreadsheet software and the SPSS statistics software.

The normality of the data was confirmed (see Figure 4), taking into account that normality testing with relatively small sample sizes ($<$50) can have certain complications: deviations from normality typically do not significantly impede hypothesis testing; normality tests exhibit limited power to reject the null hypothesis for small samples, resulting in their frequent acceptance for such cases (Ghasemi and Zahediasl, 2012; Knief and Forstmeier, 2021).

3 Results

3.1 Communication distance chosen by TP

Our first research question was "*What is the communication distance chosen by a TP when communicating with a PP, and does it differ from the communication distance chosen by a PP when communicating with a TP?*"

To answer this research question we compared the average communication distance ($M = 104$ cm; SD $= 33.1$ cm) that was chosen by PPs ($N = 63$) as measured in Study 1 (Leoste et al., 2023) with the average communication distance ($M = 67$ cm; SD $= 23.8$ cm) chosen by TPs ($N = 33$) as measured in Study 2 (this study), as demonstrated on Figures 4, 5 and 6. According to the t-test, the distances were statistically different: $t_{(32)} = 6.25, p < 0.01$.

3.2 Influence of TP's gender or the type of TPR used

Our second research question was "*Does the communication distance chosen by a TP depend on the TP's gender, or the type of TPR used?*"

To answer this research question, we first compared the communication distances chosen by male TPs ($M = 87$ cm) to those of chosen by female TPs ($M = 62$ cm). The t-test indicates that these distances are statistically different: $t_{(32)} = -2.67, p < 0.01$. Male TPs chose a significantly larger communication distance (Figures 7, 8).

3.3 Behavioral realism of chosen communication distances

Our third research question was "*To what extent does the communication distance chosen by a TP differ from the 'behaviorally realistic' distance that people maintain when communicating without a robot?*"

In order to determine the behaviorally realistic communication distance we departed from Hall's (1966) classification of communication distances. In our Study 1, about 80% of participants kept the communication distance of 60–160 cm, which, according to Hall, covers the far phase of personal distance and the close phase of social distance, and therefore may be considered as "behaviorally realistic." The communication distances chosen by TPs in this study were significantly shorter ($M = 67$ cm), representing Hall's personal distance. As in Hall's theory, the personal communication distance is kept mainly with good acquaintances, and as the TPs in this study were not close acquaintances at all with the participating PPs, then this choice of communication distance cannot be considered as behaviorally realistic.

3.4 Technical suitability and subjective comfort of using TPR

Our fourth research question was "*How do TPs and PPs evaluate the technical suitability and subjective comfort of the TPR-mediated communication?*"

To understand the technical suitability and subjective comfort of the TPR-mediated communication we used the questionnaire that was piloted in Study 1 (Leoste et al., 2023). The questionnaire was filled in by the participating PPs and TPs immediately after the end of the experimental communication. In order to evaluate the technical suitability of the TPR-mediated communication the following statements were presented:

- *How successful do you think the communication was (were you able to convey your message to the people in the room)?* (Scale: 1-very poorly; 2-poorly; 3-not sure; 4-well; 5-very well).
- *How well could you hear your communication partners?* (Scale: 1-very poorly; 2-poorly; 3-not sure; 4-well; 5-very well).
- *How well did the robot obey your commands?* (Scale: 1-very poorly; 2-poorly; 3-not sure; 4-well; 5-very well).
- *How comfortable was it for you to read the text printed on paper shown by your communication partner?* (Scale: 1-very uncomfortable; 2-uncomfortable; 3-not sure; 4-comfortable; 5-very comfortable).

After being added up, the internal reliability of these statements was sufficient ($\alpha = 0.75$) in order to use them as a scale for "technical suitability." The scale's psychometric indicators were: $M = 3.89$; Min $= 1.75$; Max $= 5.0$; SD $= 0.78$.

To assess the subjective comfort of the TPR-mediated communication, the following two statements (or their one-statement alternative) were used:

- *How pleasant is this communication situation for you?* (1-very unpleasant; 2-unpleasant; 3-not sure; 4-pleasant; 5-very pleasant).
- *How comfortable did you find using a telepresence robot for communication, while you were in the robot and other people were physically present in the room?* (1-very uncomfortable; 2-uncomfortable; 3-not sure; 4-comfortable; 5-very comfortable).

or

- *How comfortable did you find using a telepresence robot for communication, while you were physically present in the room and the other person was in the robot?* (1-very uncomfortable; 2-uncomfortable; 3-not sure; 4-comfortable; 5-very comfortable).

After being added up, the internal reliability of these statements was sufficient ($\alpha = 0.77$) in order to sum them up and use them

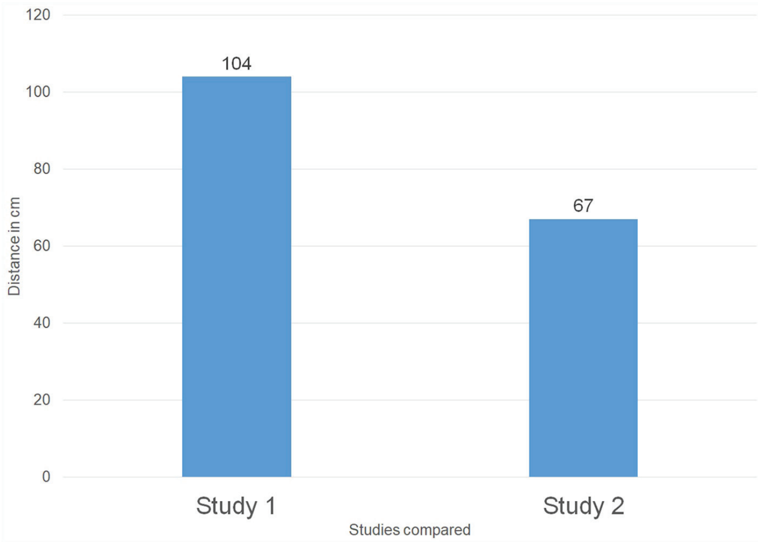

FIGURE 5
The average communication distance (in cm) chosen by physically present persons in Study 1 **(left)** compared to the one chosen by telepresent persons in Study 2 **(right)**.

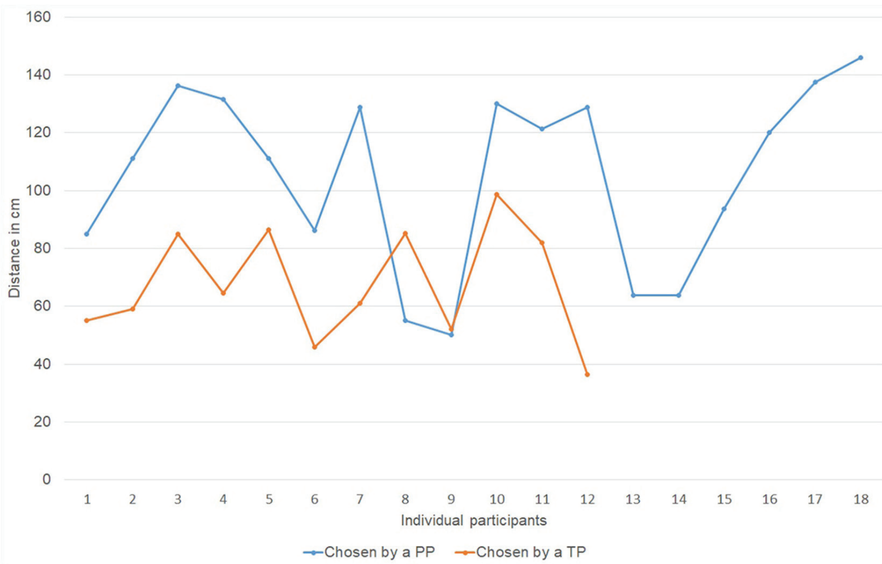

FIGURE 6
The communication distance (in cm) chosen by physically present persons in Study 1 (blue) compared to the one chosen by telepresent persons in Study 2 (orange). Each dot represents the average distance selected by an individual participant throughout valid iterations.

as an indicator for "subjective comfort." The scale's psychometric indicators were: $M = 3.73$; Min $= 2.50$; Max $= 5.0$; SD $= 0.71$.

As the mean value of both 5-point scales was almost 4, it allows to deduct that the majority of respondents considered the TPR-mediated communication as technically suitable and subjectively comfortable. From 33 respondents, six persons assessed communication comfort as low (mean value under

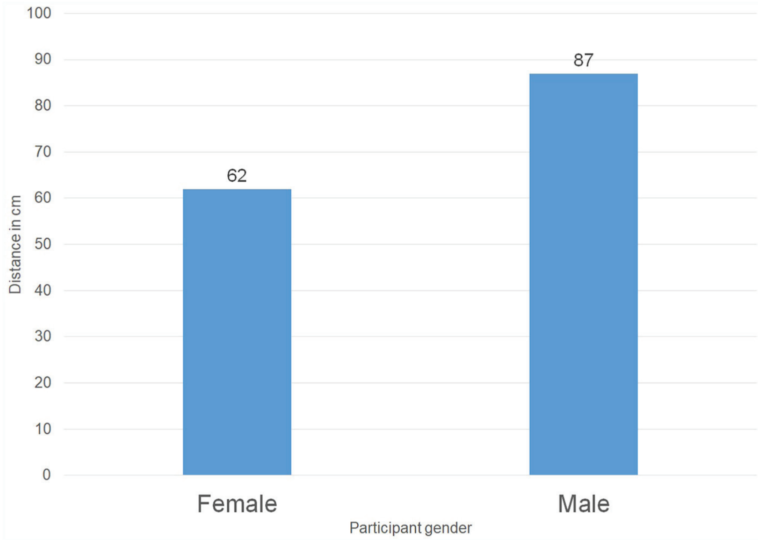

FIGURE 7
The average communication distance (in cm) chosen by female telepresent persons vs. male telepresent persons.

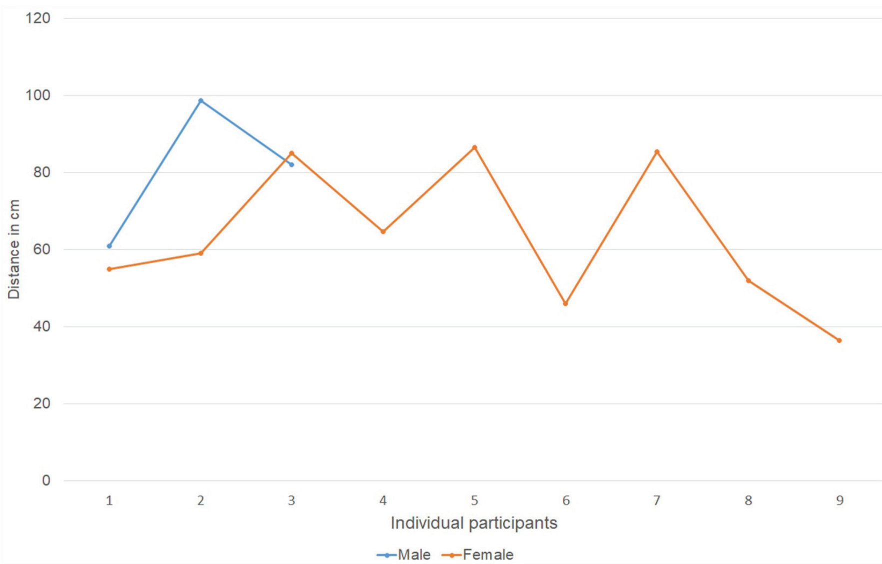

FIGURE 8
The communication distance (in cm) chosen by female telepresent persons vs. male telepresent persons. Each dot represents the average distance selected by an individual participant throughout valid iterations.

2.5), and three persons assessed the whole procedure as technically unsuitable.

These two assessments were not influenced by the responder's gender or their role as a TP or PP. Although the mutual correlation between these two scales was statistically significant ($r = 0.28$, $p < 0.05$), suggesting that the ability to cope with the TPRs' technical side could also affect the general pleasantness of the TPR-mediated communication.

3.5 Influence of the robot's type on technical suitability and subjective comfort

Our fifth research question was "*Do the assessments of TPs and PPs regarding the technical suitability and subjective comfort of the communication process depend on the type of robot used?*"

The differences between the three used types of TPRs were evaluated with a one-way ANOVA. As for subjective comfort, there were no differences between the robots. However, based on technical suitability, the TPRs did differ significantly. A one-way ANOVA revealed a statistically significant difference between the three types of TPRs. The Double robot got the highest score (M = 4.24; SD = 0.64), followed by Ohmni (M = 3.88; SD = 0.95), and TEMI 2 (M = 3.54; SD = 0.58); $F_{(2.68)} = 5.34$, $p = 0.007$.

4 Discussion and conclusions

The two studies we examined indicate that the choice of distance differs for people who communicate as a telepresent (TP) person compared to a situation where they participated as a physically present (PP) person. In the former case, a "behaviorally realistic" distance is preferred, while in the latter, a significantly closer/smaller distance is chosen. PPs choose more "normal" distance (according to the Hall categories), when facing TPRs (Leoste et al., 2023), while the people who interact via TPRs, tend to get unreasonably close/intimate. Which in turn means that a TP person can put the other communication partner in an uncomfortable situation.

At least some of the reasons for such "abnormal" distance choice may be technical in nature. When communicating as a TP, people lack distance experience, and excessive proximity could be due to a natural desire to see the conversation partner's face on the screen as large and detailed as in ordinary face-to-face communication, to see the partner's facial expressions, make eye contact, etc. The different field of view offered through a TPR may also have an effect, which in turn depends on the type of robot used.

The resulting message could be that when introducing TPRs, for example in education, the situations with greater intrapersonal distances (e.g., a person is present in the lecture hall via telepresence) require significantly more practice/training compared to situations where a PP communicates with a TP person in the audience. There is reason to believe that in the latter situation the robot (and the person behind it) is perceived as "behaviorally realistic" much faster than in vice versa communication situations.

In our sample, the choice of distance did not depend on robot type. However, it does depend on person's gender, and the results are somehow contradictory: women move closer when they "are in the robot," while men do so when communicating "with the robot". When acting as TPs (in TPRs), women move significantly closer to their communication partner (M = 62 cm) than men (M = 87 cm). However, as it was revealed in Study 1, when communicating as PPs, the opposite is true: men choose shorter distances (M = 87 cm) than women (M = 115 cm). There may be several reasons for this result, besides being connected to this specific and small sample. For example, female participants could dislike TPRs' robotic bodies more than men (Mumm and Mutlu, 2011); male participants could provide more personal space for persons that are perceived as disabled (see Kilbury et al., 1996); but the different choice of distance can be also connected to differently perceived social presence of the other communication party (Garau, 2003; Bailenson et al., 2005). Finally, the different choice of distance could be caused by the technical characteristics of TPRs, leading to distortions when mediating the real-world environment to TPs—the different focal length of TPRs' cameras combined with its small height could make it difficult for TPs to estimate distances correctly.

As for the technical suitability and subjective comfort, the TPRs in our study received mostly positive feedback from the participants. This positivity could be a result of the so-called novelty effect—as most of the participants were not routine users of TPRs, they might have perceived robots as novel and exciting. At the same time, the three types of TPRs used in the study were evaluated quite differently. Different factors may have a play here, from the usability of computer interface when controlling a TPR, to the TPR's height, the clarity of its display or resolution of its camera feed. These factors should be investigated in a dedicated separate study.

Our study is a piloting one and has several limitations. First, the sample in future studies should be larger and include wider diversity in order to represent groups with different social and cultural backgrounds more evenly. Second, the scale we used in this and in our previous study (Study 2 and Study 1) is still in a stage of piloting. For future studies, the scale should be more tested and maybe supplemented with question blocks about the TPR's features. Subsequently, scripted communication scenarios were employed, and the data collection mechanisms were readily identifiable. The studies ought to be replicated in authentic environments, employing less obtrusive methods for data collection. Lastly, forthcoming research endeavors should comprehensively investigate non-verbal language cues. In human communication, the significance of gaze and leaning is evident right from the initial contact moment, a fact validated also in human-robot interaction by Kanda et al. (2008) and Jirak et al. (2022). In these situations, of course, the researchers need to acknowledge the technical limitations of TPRs, such as relatively rudimental body or limited eye-sight, as highlighted by Talisainen et al. (2023).

In future research the communication distances under specific situations and environments (classrooms, hospitals, nursery homes, etc.) should be studied as well as combined with other aspects of non-verbal behavior—orientation, gestures etc. For example, do people keep shorter distances with TPs who are their close acquaintances, or would they keep larger distances with people of higher social status? Furthermore, we plan to enhance the depth of our research by broadening the study's focus to include individuals beyond direct communication scenarios. A more intricate analysis of the non-verbal parameters of communication through TPRs is imperative, encompassing the examination of non-verbal patterns exhibited by individuals in the immediate vicinity of the communication setting. Next, the impact of gender or different cultural background should be examined. Future studies should offer understanding or hints for questions, such as—how do we react when someone watches a play in the theater via a TPR? Or—how would people react if we would walk in a park with a TPR-mediated companion? These and other future studies should aim at supporting the development of TPRs toward "behavioral realism", but also suggest how to teach people to use TPRs more efficiently.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://drive.google.com/drive/folders/1erMkR9k8YabNxb4k9Qewea_3hF6yGteY?usp=sharing.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements.

Author contributions

KM: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing—original draft, Writing—review & editing. JL: Conceptualization, Data curation, Investigation, Methodology, Project administration, Supervision, Visualization, Writing—original draft, Writing—review & editing. MH: Conceptualization, Formal analysis, Methodology, Validation, Writing—review & editing. KK: Investigation, Validation, Writing—original draft. MR: Investigation, Software, Writing—original draft. JP: Investigation, Methodology, Writing—original draft. TK: Investigation, Writing—original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Appendix 4

Publication IV

Leoste, J., Marmor, K., Hollstein, T., Hinkelmann, H., & Leoste, L. B. (2024). Enhancing university visitor satisfaction: A human–robot interaction study on the design and perception of a guiding robot assistant. In R. Balogh, D. Obdržálek, & M. Fislake (Eds.), *Robotics in Education. RiE 2024*, 1084, 223–234. Springer, Cham. https://doi.org/10.1007/978-3-031-67059-6_20

Enhancing University Visitor Satisfaction: A Human-Robot Interaction Study on the Design and Perception of a Guiding Robot Assistant

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Abstract. The buildings within higher education institutions are expansive, posing challenges for individuals attempting to navigate to specific rooms. Due to the permanent stationing of receptionists, physical guidance is not feasible, resulting in lengthy explanations and people still experiencing difficulty finding their way. To enhance the satisfaction of university visitors, we developed a human-robot interaction application to imbue the semi-autonomous robot assistant TEMI with complex behaviors for greeting and house guiding. Through this application, the robot effectively directed visitors to their chosen locations on the floor, facilitated video calls with the secretary for inquiries upon arrival, displayed additional destination information on its screen, and prompted visitors to respond to a feedback questionnaire presented on the robot's display. Significantly, both verbal and non-verbal behaviors were incorporated to ensure that visitors perceived the robot as a welcoming service provider. To assess the efficacy of the complex behavior application, an experiment was conducted in a controlled environment, involving 28 voluntary students and university teachers. Participants followed prescribed activities under the guidance of a researcher and subsequently completed a feedback questionnaire. The results overwhelmingly indicate positive perceptions of interaction and collaboration with the robot assistant among visitors. Plans involve conducting a study in a real-world environment, where visitors interact with the robot without technical assistance from researchers.

Keywords: Robot Assistant, Social Robot, Service Robot, Human-Robot Interaction, HRI, Nonverbal Behavior, Verbal Behavior.

1 Introduction

Robots have been in existence for quite some time. The aging population underscores the need to enhance and prolong individuals' work capabilities by substituting them in routine, demanding, or dangerous tasks with robots [1]. Until recently, robots were only feasible in industrial settings (see [2]). Breakthroughs in various technologies, such as sensors, AI, and battery technologies, have allowed robots to start propagating into the everyday environment of individuals. Operating in environments natural for humans but relatively uncontrolled for robots [3,4] requires the application of recently matured technologies. These include sensor fusion, planning and decision-making, movement dynamics prediction, on-the-fly rerouting, natural communication, and social abilities [5,6]. The necessary hardware with appropriate capabilities has only become commercially feasible in the last decade. Notably, advancements in Li-Ion battery energy storage, exceeding 1.5 times the capacity of a decade ago, and rapid progress in AI capabilities have played crucial roles [7,8]. AI's swift evolution has surpassed human abilities in various areas since 2012, such as handwriting recognition, speech recognition, image recognition, reading comprehension, and language understanding [8]. These capabilities are vital for socially capable service robots to function independently, and this has become achievable only within the last decade. This significant progress in algorithms and hardware, exemplified by Boston Dynamics' 2016 introduction of the Atlas robot's human-like movement patterns [9], has led to the emergence of autonomous, collaborative, intelligent, adaptable, and socially capable *service robots* [10].

A service robot is a kinematic device that can be freely programmed, performs semi- or fully automatic services, i.e., useful work for humans or equipment, and is not an industrial automation application [11]. While industrial robots typically operate in isolation from humans, except for cobots [12], service robots are designed to work in close proximity to people, thus increasingly expected to possess a social dimension [6]. For this, service robots need to be able to process *natural language* to effectively understand, interpret, and respond to human language [6]. Natural language is the intricate system of human communication, encompassing spoken or written words, grammar, and syntax. Verbal communication, involving phonetics, syntax, and semantics, provides explicit content. Nonverbal communication, using facial expressions, gestures, and intonation, enhances the emotional tone and context. The synergy between verbal and nonverbal communication is fundamental, enabling effective and nuanced interactions within linguistic communities [13].

Besides the ability to process natural language, socially adept service robots need to possess several other skills, such as the ability to recognize a person, contact a remote person, or navigate in a room. Many of these skills involve a specific use of robot sensors and actuators and are programmed with high precision at a fundamental level. However, when it comes to coordinating different skills to perform *complex behaviors*, a transition to a higher level of abstraction becomes necessary. Similar to the structure of simple computer algorithms, these complex behaviors can be systematically organized in a modular and flexible manner that follows a hierarchical structure, outlining layers of potential behavior for the robot [14]. Fundamentally, the effectiveness of service robotics lies not only in its individual skills but also in the seamless integration and coordination of these skills. This integration enhances the machine's capabilities, enabling it to operate in complex and unpredictable environments.

In education, robots have traditionally served as programmable tools with simple actuators for STEAM education [15], following the footsteps of Seymour Papert [16]. Recently, due to the demands of the COVID-19 era and the new possibilities arising from the maturation of the technologies discussed above, there has been a growing interest in utilizing specific socially capable service robots as *robot assistants* to enhance teaching and learning processes, with some reported success in the literature (see [17]). Nonetheless, the implementation of robots in tasks involving human-robot interaction (HRI) may encounter challenges due to people's discomfort in HRI, their lack of trust in robots, or a preference for human interaction partners.

Research on the reactions of students and teachers when interacting with robot assistants in educational settings is limited (see [18]). To address this gap and enhance our understanding of the use of autonomous and socially capable service robots in higher education settings, we conducted a study exploring various aspects of specific HRI situation – helping a service attendant working at the university reception desk to guide a university visitor to their desired destination using the TEMI robot assistant (Figure 1; see [19]). We pre-designed a complex behavior for the TEMI robot to employ natural language when greeting and guiding students and teachers (see Figure 2), aiding them in navigating university rooms or contacting the university's administrative staff. In addition, we formulated a questionnaire to map the different aspects of the experience of participants (N=28) and gather valuable feedback. The research question that guided our research was "*How do students and teachers perceive interaction with a robot assistant that functions as a house guide in university settings?*"

2 Methods and Materials

2.1 The TEMI v3 Robot

We used the TEMI robot assistant version v3 in this study [19]. The TEMI robot is a sophisticated, autonomously functioning AI assistant robot that offers various features, such as command recognition, preset location storage, and adept navigation. The robot can be employed to connect with acquaintances, family members, and online services. A crucial element for TEMI is the TEMI Center Pro service, necessary for unlocking the robot's full functionality. This includes room mapping, mobile application integration, Alexa/Hey functions, video calls, and more. The TEMI Center Pro is also valuable for implementing multi-party calls, scheduling, face recognition, and various applications, thereby enhancing the overall user experience. The TEMI robot has the capability to function as a telepresence robot, allowing remote participation through the robot. It can also serve as a personal AI assistant, autonomously interacting with people and performing simple tasks.

Fig. 1. The TEMI v3 robot [19].

2.2 The Functionality of the Guiding Application

Socially capable service robots, such as the TEMI robot assistant, are operable through apps with algorithms that describe complex behaviors that can consider social norms to make HRI more natural. Adhering to social norms is vital for service robots, ensuring that appropriate verbal and non-verbal behaviors are tailored to the interaction context and persons being served [14]. Depending of the robot’s abilities, non-verbal behavior could encompass facial expressions, movement, maintaining distance, screen-displayed expressions, voice intonation, intervals before initiating the next interaction, etc. (see [18]).

The guiding application for the TEMI robot was programmed using Android Studio 11.0 Kotlin application, seamlessly integrating the built-in features of the TEMI Center Pro (https://center.robotemi.com/). The resulting application enabled the robot to guide itself to a location selected from the robot's screen, initiate a telepresence call through the robot's screen with a remote secretary, open a webpage on the robot's screen with additional information about the institution, or conduct a feedback questionnaire on the use of the robot. Users could also choose their preferred language of communication directly from the robot's screen. In the programming of the application, careful consideration was given to recommendations derived from academic literature regarding the verbal and non-verbal elements of human-robot interaction to enhance trust and positive attitudes. Verbal elements included communication in the user's native language, a neutral yet moderately strong, expressive, and clear robot voice, and proactive sentences guiding the interacting individual, such as greetings, menu selection, call termination, questionnaire completion, and providing information. Non-verbal aspects comprised maintaining social distance, maintaining eye contact, adjusting the screen tilt, displaying a cheerful humanoid facial expression, introducing pauses between events to mimic human awareness, and adapting movement speed to suit human preferences. A part of the application, namely the greeting algorithm, is presented on the Figure 2.

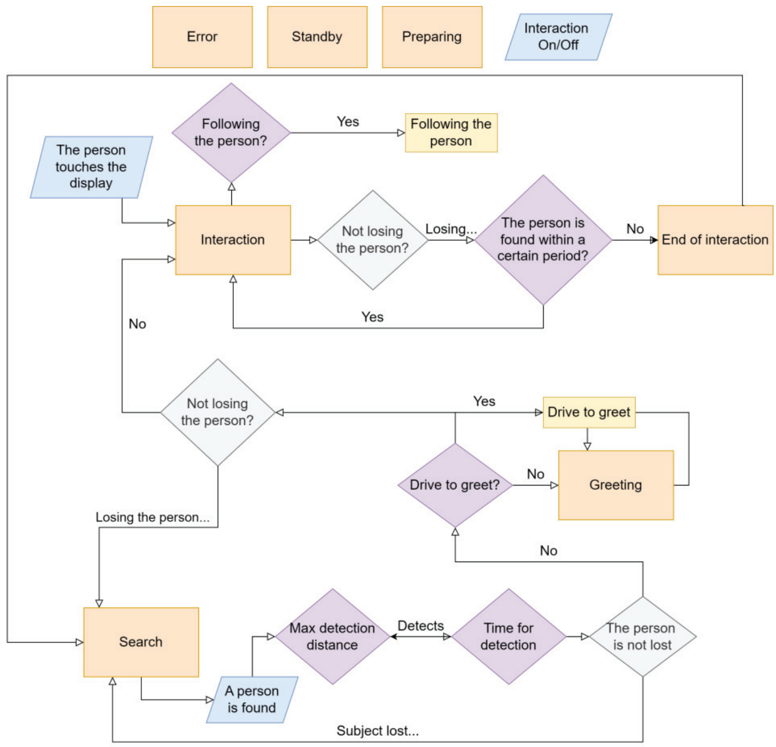

Fig. 2. The algorithm for the greeting interaction.

2.3 Sample, Procedure, and Data Collection and Analysis

Participants for the experiment (11 females, 17 males; N=28) were recruited from the lecturers and students present at the Taltech IT College a few hours before the experiment. Participation was voluntary and did not influence the grades of participating students in any way. Participants were asked for written informed consent, acknowledging that data would be collected anonymously and not personalized. In addition, the participant was informed about the approximate duration of the experiment, around 10 minutes. However, the participant was not provided with details regarding the verbal and non-verbal behavior of the robot during the course of the experiment.

The experiment was conducted on the main corridor of the administrative floor of Taltech IT College (see the floor map in Figure 3). The corridor was mapped by the TEMI robot before the start of the experiment.

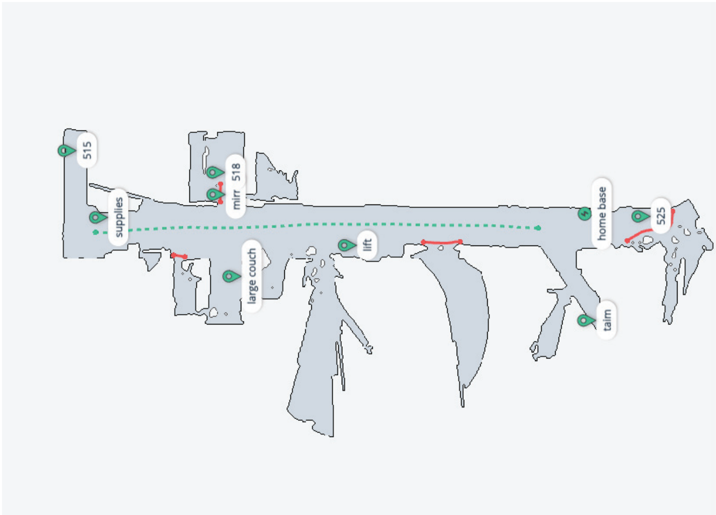

Fig. 3. The administrative floor of Taltech IT College, as mapped by the TEMI robot.

Before the commencement of the experiment, a researcher instructed the participant on the sequence of actions they were required to perform. These included approaching the robot, selecting the secretary's location from the house guide’s menu, being guided to the destination, making a call to the secretary through the robot, viewing the institution's webpage on the robot's screen, being directed to a relaxation area, and completing a questionnaire. Once the participant was ready, they approached the robot positioned along the corridor wall, and the experiment began. After its conclusion, the researcher guided the robot back to its initial position, and the participant filled out a questionnaire on paper.

The interaction scenario with the robot unfolded as follows: the robot displayed a curious expression on its screen when a person entered its field of view at an angle of 90 degrees or closer for at least 2 seconds (see also the greeting interaction in Figure 2). It greeted the person with an animated face and activated the menu. The person was informed about the language change option and menu choices. After the person made a menu selection, the robot provided information about the subsequent actions. For example, instructing the person to choose a destination from the menu, follow the robot, reach the destination, initiate a call, wait for 30 seconds, end the call, fill out the questionnaire, express gratitude, and wish a good day. If the person was out of the focus area for more than 10 seconds and not in motion, the robot bid farewell and returned to the waiting mode.

Evaluating how human individuals perceive robots is one of the key aspects of understanding HRI [20]. As the social capabilities of service robots are continuously developed to enable them to function in diverse roles and environments, it is crucial to measure how people perceive robots, considering the resulting dynamics of social interaction between humans and robots [21]. In order to measure these aspects in our study, we designed a questionnaire that is based on The Human-Robot Interaction Evaluation Scale (HRIES) by [20] and The Social Perception of Robots Scale (SPRS) by [22]. The HRIES introduces a composite questionnaire to assess how people perceive robots and their human-like qualities, employing a 7-point Likert scale, where participants are asked to evaluate the degree of association of words with four proposed dimensions: Sociability (Warm, Likable, Trustworthy, Friendly), Animacy (Alive, Natural, Real, Human-like), Agency (Self-reliant, Rational, Intentional, Intelligent), and Disturbance (creepy, scary, uncanny, weird). The SPRS encompasses sociability, competence, morality and anthropomorphism, and can be applied to various robots in diverse settings. In addition, we considered the suggestion by [23] emphasizing the need for a measurement mechanism capable of assessing people's perceptions of trust in technology in specific contexts – drawing attention to the factors (such as risk perception, competence, benevolence and reciprocity) that may predict trust in human-robot interaction in an industrial context.

In our questionnaire, there were 5 general themes, involving 17 questions with Likert scale answers (Table 1). The questionnaire, along with the written consent form, was accessible through both the guiding application on the robot and as a double-sided leaflet. Following their interaction with the robot, participants were prompted to confirm their consent and complete the questionnaire using their preferred medium – either on the robot's display or on paper. Participants were directed to the designated recreation area, as indicated by the "large couch" in Figure 3, where they had ample time for the activity. The paper-based questionnaires were collected and digitized by a researcher, who also incorporated results from forms filled out on the robot's display. Subsequently, the gathered data was analyzed by researchers utilizing Microsoft Excel. Likert values were condensed by grouping responses with similar meanings; for instance, responses such as "I like" and "I really like" were categorized under a "Positive" attitude, while responses like "I don't like" and "I really don't like" were classified as "Negative" attitude, as depicted in Figures 5 and 6. To uphold participant confidentiality, filled-in questionnaires were appropriately disposed of to eliminate potentially identifiable data.

Table 1. Questions of the feedback questionnaire.

Theme	№	Question
Interaction	1	*Complexity*. Communicating with the robot seem to you...
	2	*Clarity*. Was it understood from the conversations/messages mediated by the robot...?
	3	*Position*. Was the robot position during the interaction for you ...
	4	*Security*. Do you consider interacting with the robot...
	5	*Reliability*. Do you consider the robot as a reliable communication partner for you...
	6	*Pleasantness*. Do you consider the robot as a pleasant communication partner for you...

	7	*Self-confidence*. How confident or uncertain did you feel during your interaction with a robot?
Collaboration	8	*Effectiveness*. Do you consider that collaborating with the robot helped to complete the tasks better or worse?
	9	*Comfort*. How convenient was it for you to solve today's tasks in cooperation with the robot?
	10	*Speed*. Do you consider working with the robot make solving tasks faster or slower for you?
	11	*Suitability*. Was the cooperation with a robot just for solving such tasks (like today's)...
	12	*Naturalness*. How natural was solving tasks with a robot for you?
Reaction of by-standers	13	*Attention*. To what extent was attention paid to your and the robot's activities?
	14	*Intervention*. To what extent did bystanders interfere in your and the robot's activities?
	15	*Acting in front of others*. Was working with a robot under the eyes of other people for you...
Previous experience	16	Your earlier experience with these robots...
Anthropomorphism	17	Did you perceive today's robot more as a machine or as a person?

3 Results

Our research question was, "*How do students and teachers perceive their interaction with a robot assistant functioning as a house guide in university settings?*" To address this query, we developed a house guide application, equipping the robot assistant TEMI V3 with intricate behaviors for the study. We employed the questionnaire outlined in Table 1 to gather feedback data from participants.

Among our participants, the majority (64%) lacked prior experience with using robot assistants. Meanwhile, 25% of participants possessed some familiarity, and 11% had previously engaged with such technology, as illustrated in Figure 4.

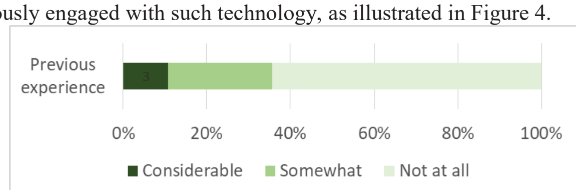

Fig. 4. Participants' previous experience with robot assistants.

Our questionnaire (see Table 1) encompassed three major themes: interaction with the robot, collaboration with the robot, and bystanders' reactions, each comprising several Likert items. As depicted in Figures 5 and 6, participants reported a general ease of interaction (88%) and collaboration (82%) with the robot assistant. However, more than half (52%) indicated experiencing disturbance from bystanders when utilizing the robot assistant.

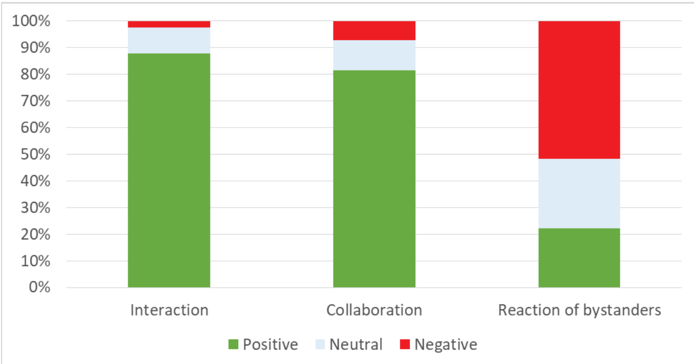

Fig. 5. Attitudes of participants toward key aspects of using robot assistants.

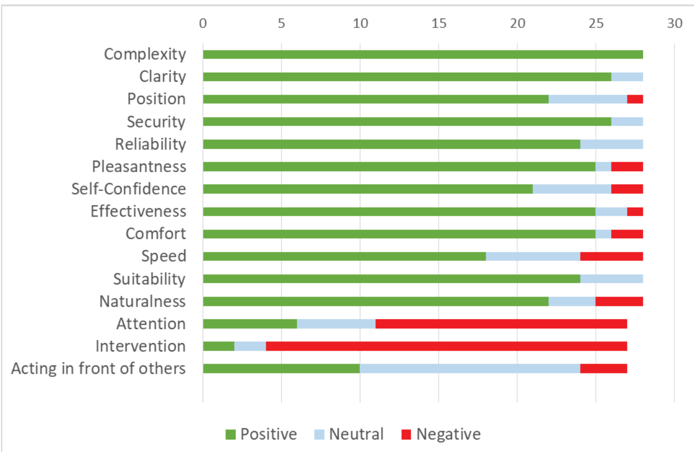

Fig. 6. Detailed attitudes of participants toward using robot assistants.

Less than half of the participants (43%) were confident that they were interacting with a machine, while 36% felt as though they were interacting and collaborating with a human being. Additionally, 21% of participants had mixed feelings about this issue, as illustrated in Figure 7.

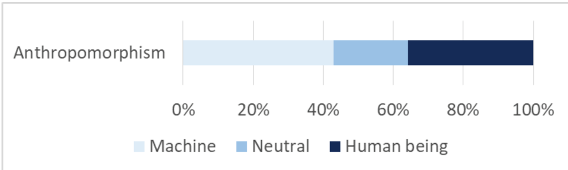

Fig. 7. Perceptions of participants regarding the anthropomorphism of the robot assistant.

4 Discussion

In this study, we developed a sophisticated behavior for the TEMI v3 robot assistant, focusing on greeting and guiding within university settings. The resulting application provided the robot with the ability to direct visitors, initiate telepresence calls, display webpages, and administer feedback questionnaires. We considered both verbal and non-verbal behavior elements, including utilizing the user's native language, ensuring a clear robot voice, and incorporating non-verbal cues such as maintaining social distance and presenting a cheerful facial expression. To gauge the perceptions of students and teachers regarding their interactions and collaborations with the assistive robot, along with their observations of bystanders' attitudes, we devised and implemented a comprehensive Likert scale questionnaire. This questionnaire aimed to capture detailed insights into participants' experiences with the robot assistant, outlining both the positive aspects of interaction and collaboration and the challenges associated with bystanders' reactions.

Our findings indicate the technical feasibility of employing socially adept robot assistants in educational settings, as individuals find interaction and collaboration with robots to be easy, even when they had no previous experience with robot assistants. This perception is likely influenced by the integration of natural language and non-verbal communication to enhance emotionally the robot's acceptability, resulting in participants forming emotional attachments to the robot. Similar observations were made by [24] in their study of 60 students interacting with service robots in a hotel context. The findings suggest that robot assistants can be used successfully in simpler tasks like guiding.

However, it is noteworthy that half of the participants experienced heightened attention from bystanders during collaboration with the robot, possibly due to a lack of confidence in interacting with the robot. This increased unwanted attention may diminish over time as the novelty wears off (see [25]) or, conversely, become a nuisance that dissuades some individuals from using the robot assistant. Nevertheless, addressing societal perceptions of robot presence in public spaces, particularly in educational settings, seems to be important.

The impact of anthropomorphism on people's perception of robots is a widely discussed topic. The consensus generally leans toward anthropomorphism enhancing bonds in HRI, although in specific cases, it can evoke feelings of eeriness [26]. Given the relatively few physical human features of the TEMI v3 robot (Figure 1), our results suggest that perceived anthropomorphism may result from engaging with the robot through natural language and incorporating nonverbal behavioral cues inherently human in nature (e.g., maintaining proper social distance or simulating eye contact). In our case, telepresence function could have influenced the participants' perceptions. These findings imply that future research should explore how interaction with real people through robots influences perceptions of robots as human or machine.

Finally, we noted that the majority of participants lacked prior experience with robot assistants. This suggests that the approaches outlined in this study could prove beneficial in introducing robot assistants to a wider population.

This study contributes to the understanding of HRI within educational contexts. While positive attitudes among participants indicate considerable potential, it is imperative to address bystander reactions and enhance the anthropomorphism grounded in natural language and complex behaviors. The incorporation of nonverbal behavioral cues becomes crucial for refining the interaction dynamics. The findings of this study, therefore, provide actionable insights for refining the design and implementation of service robots in educational settings, emphasizing the need to account for both technical aspects and the broader socio-environmental landscape.

The study's potential generalizability is limited by the controlled environment and a small sample size. To enrich future research, studies should examine more activities beyond guiding tasks and diversify the participant pool, while focusing on long-term impacts and uncontrolled environments. The Creativity Matters research group (see also https://cm.taltech.ee/publications), which conducted the present study, is presently preparing a more extensive investigation. This forthcoming study focuses on the utilization of robot assistants in hospital environments, with the main aim of addressing the scarcity of medical personnel and enhancing elderly care. The primary focus is on understanding the feasibility of deploying robot assistants in such critical settings.

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Appendix 5

Publication V

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User Perceptions of Social Service Robot Guidance in an Academic Library

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Abstract. Academic libraries face persistent wayfinding demands and limited capacity for routine guidance tasks. This exploratory mixed-method field study examined user perceptions of social service robot (SSR) guidance in an academic library and the role of robot size in user choice. Two SSR models, temi (TEMI V3) and temi GO, were deployed for five days in the Tallinn University of Technology Academic Library to guide visitors to requested book locations. Visitors could freely choose one robot, and no participant used both robots. In total, 47 visitors interacted with the robots, 13 provided written consent for observation-based analysis, and 8 completed in situ interviews. Descriptive results showed nearly balanced robot selection (V3: 7, GO: 6), with modest differences by gender and age group that should be interpreted cautiously due to the small sample. Thematic analysis indicated that users primarily valued usefulness and interaction clarity, while robot size influenced preferences mainly through screen height, visibility, and perceived mobility robustness. Across interviews, acceptance was high, but it depended on precise stopping and clear handover at the final shelf location, as well as readable text and a minimal interaction flow. The findings suggest that for library guidance tasks, design priorities should focus on navigation precision and transparent task completion cues, while embodiment differences such as size play a secondary role.

Keywords: Social Service Robots, Academic Libraries, Human-robot Interaction, User Acceptance, Robot Guide

1 Introduction

Academic libraries increasingly face a tension between rising expectations for fast, self-directed access to physical resources and limited capacity for routine guidance tasks. Visitors may need help locating specific books, navigating classification systems, or understanding the spatial layout of the library. Wayfinding problems in libraries have been repeatedly documented in library and information studies research [1,2]. These small guidance needs can accumulate into a meaningful service burden, especially in large academic libraries where visitors may have short time windows and limited familiarity with local shelf logic [1].

Academic libraries therefore need scalable support for routine guidance tasks, especially book-location help, while staff time remains limited and service expectations remain high [1,2]. Social service robots (SSRs) have been proposed as one practical response to this challenge. These robots interact directly with users in public or semi-public spaces and support everyday service tasks through embodied interaction, navigation, and simple dialogue [3]. In library contexts, automation and AI-driven services have been positioned as tools to enhance user experience and service accessibility while allowing staff to focus on higher-level support [4,5]. Field-oriented library discussions and guidance emphasize that successful adoption depends on aligning the robot's role with the service context and user needs, rather than treating the robot as a generic novelty [4,5]. In guidance tasks, however, successful adoption depends not only on whether the robot can technically complete the route, but also on whether the interaction is understandable from the user's perspective. Users need to interpret the robot's behavior, follow its guidance, and recognize when the guided phase ends and independent action begins.

User interaction with SSRs is influenced not only by task performance but also by appearance-related characteristics, including size, form, and perceived social presence. Research on service robots shows that anthropomorphic cues and embodied design choices can shape users' first impressions and willingness to engage [6,7]. At the same time, evidence from real-world library deployments where users interact voluntarily under everyday conditions is still developing, and recent field studies suggest that pragmatic qualities such as usefulness, control, and clarity may influence intention to use more strongly than attractiveness alone [8]. This study addresses that gap through an exploratory field experiment conducted in an academic library, where visitors could freely choose between two SSRs of different sizes performing the same guidance task. By combining observational data and in situ interviews, the study examines visitor choice and user experience, with particular attention to how embodiment and interaction clarity shape acceptance in a real service context.

2 Theoretical Background

2.1 SSRs and Guidance Tasks

SSRs are commonly defined as robots designed to support humans through social or informational interaction rather than physical labor [3]. In public and institutional environments, such robots often act as intermediaries between users and complex systems, such as buildings, services, or information infrastructures. In libraries, guidance tasks represent a particularly suitable application domain, as they are repetitive, location-based, and often required by first-time or infrequent visitors.

Previous research suggests that robots are more readily accepted when their role is narrow and clearly communicated, for example as guides or assistants rather than as general-purpose companions [9]. In such cases, users tend to evaluate robots pragmatically, focusing on whether the robot helps them achieve their goal efficiently rather than on broader attitudes toward automation. In guidance settings, this also means that acceptance depends on whether the robot supports a clear service process from request to task completion.

2.2 User Acceptance, Self-Efficacy, and Trust

User acceptance of service robots is typically explained through constructs such as perceived usefulness, ease of use, trust, and emotional comfort [10]. In short-term interactions, such as one-time guidance tasks, acceptance is highly sensitive to immediate interaction quality. If a robot performs its task clearly and reliably, users are likely to accept it regardless of prior experience or general attitudes toward robots.

Self-efficacy plays an important role in this process. Users who feel capable of understanding the interaction and predicting the robot's behavior are more likely to perceive the robot as useful and trustworthy [11]. Conversely, unclear interfaces, redundant steps, or ambiguous feedback can increase cognitive load and reduce perceived usefulness, even when the robot ultimately reaches the correct location.

Trust in service robots is closely linked to predictability and transparency, especially in navigation tasks. Users need to understand when a task has been completed and what is expected of them next. In guidance scenarios, the transition from robot-led navigation to independent shelf-level search is a critical moment where trust can be strengthened or undermined. In this sense, guidance interaction can also be viewed as a coordination process. The user must understand what the robot is doing, when to follow, when the route is complete, and what to do next. If this coordination remains clear, usefulness, trust, and self-efficacy reinforce one another [10,11]. If it breaks down, even a technically successful route may be experienced as incomplete or less reliable.

2.3 Robot Appearance and Size

Robot appearance influences interaction primarily through first impressions and approachability. Anthropomorphic cues, such as faces or expressive displays, can increase perceived friendliness and encourage engagement, even in non-humanoid robots [6]. However, excessive anthropomorphism may lead to unmet expectations if the robot's functional capabilities do not align with its appearance. Robot size is a less frequently studied but relevant dimension of appearance. Smaller robots are often described as less intimidating and easier to approach, while larger robots may convey robustness, visibility, or technical competence [7]. In constrained environments such as libraries, size also affects mobility, noticeability, and how much physical space the robot occupies. Importantly, size may be interpreted differently depending on the task: for guidance tasks, users may value visibility and screen height, while perceiving bulkiness as unnecessary. Accordingly, embodiment in guidance tasks is not only a matter of visual impression, but also of practical affordances that shape how easily the robot can be noticed, followed, and used in a shared environment.

Despite these insights, few studies have examined how users choose between robots of different sizes when both are available in the same real-world setting and perform the same function. This study contributes to filling this gap by examining user choice and experience in an operational academic library, while also considering how embodiment interacts with interaction clarity at the point of task completion.

3 Research Questions

Based on the study objectives and the exploratory nature of the deployment, the following research questions were formulated to guide this study:

- **RQ1:** How do visitors engage with the two TEMI models (V3 and GO) in book-guidance tasks, and are there observable descriptive differences in robot choice by gender or age group?
- **RQ2:** What reasons do users report for their robot choice, and how do embodiment-related features such as size influence first impressions and practical interaction conditions?
- **RQ3:** How do users perceive the robots' usefulness, comfort, and interaction clarity during guidance tasks, particularly at the final handover to shelf-level search?

4 Method and Materials

4.1 Robots

Two SSRs from the same manufacturer were used, temi (TEMI V3) and temi GO [12,13]. According to the manufacturer specifications, TEMI V3 is 100 cm tall and weighs 12 kg, and it is equipped with a 13.3-inch touchscreen display, front-facing camera, microphone array, and speakers, enabling speech-based interaction, audio–visual communication, and telepresence functionality in addition to autonomous navigation [12]. The robot supports Wi-Fi connectivity, remote communication, and application-based interaction, which allows it to function both as a mobile guide and as a telepresence interface. The temi GO platform represents a larger and heavier embodiment, with a 50 cm diameter base, a 125 cm platform height, and a 25 kg net weight. It is designed as a more robust autonomous mobile platform, integrating sensors for indoor navigation, obstacle avoidance, and stable movement in shared public spaces, while supporting the same core interaction capabilities as the TEMI V3 when configured with the same application software [13]. In this study, both robots were configured to run the identical guiding application and interaction flow, including touchscreen input, audio output, and autonomous movement, meaning that the primary embodiment-level differences relevant for analysis were physical size, footprint, and weight, rather than interaction logic or task functionality [12,13].

Fig. 1. Temi V3 (left) and Temi GO (right) robots.

4.2 Setting and Procedure

The experiment was conducted in the Tallinn University of Technology Academic Library in June 2025. Data collection took place over five consecutive days, with two-hour observation sessions each day. The study period overlapped with the end of the semester and the start of the summer break, which likely reduced overall library footfall. In total, 47 visitors interacted with the robots during the study window. The study focused only on visitors who were looking for a specific book and were therefore able to complete the full guidance task. Visitors who did not have a concrete book-search goal (for example, visitors using the library space without searching for a book) were not included in observation-based consent collection. Two SSRs (TEMI V3 and TEMI GO) were positioned in the same visible area of the library so that visitors could approach either robot under comparable conditions. Both robots ran the same guiding application and offered the same interaction flow. Visitors could freely choose which robot to use, and no visitor used both robots during the observed interaction. After selecting a robot, the visitor entered the book title or call number. The robot then initiated guidance by asking the visitor to follow and navigated to the expected shelf location of the book. The guidance session ended when the robot stopped at the target location and displayed the shelf position information on the screen.

4.3 Participants

During the study period, 47 visitors interacted with the robots. Of these, 13 visitors provided written consent for the use of their observational data, and 8 of these participants also agreed to participate in a short semi-structured interview immediately after the guidance task. The observed sample consisted of 6 women and 7 men. Based on the study's age grouping, 6 participants were classified as young (18–30) and 7 as mid-age (31–60). No participants in the observed sample belonged to the elderly group (61+). While the overall number of robot interactions was higher (n = 47), the smaller observed sample (n = 13) reflects the study's inclusion focus on visitors who: (a) were searching for a specific book; (b) completed the robot-guided guidance task; and (c) provided written consent. Three of the eight interviewees were library staff members who used the robot similarly to other visitors (to locate a specific book). At the time of the interaction, the researchers were not aware of these participants' staff status. In the qualitative analysis, these participants are treated as users with a dual perspective, because their statements sometimes reflect both user and staff viewpoints (for example, usability for readers versus feasibility in daily library service).

4.4 Data Collection and Analysis

Two types of data were collected: observational data and interview data. Observational data captured the visitor's robot choice (TEMI V3 or TEMI GO), gender, and age group (young, mid-age, elderly). Only visitors who could choose between the two robots and who interacted with a single robot for the guidance task were included in the observed sample. The experiment was conducted by three researchers in the library setting, while a fourth researcher developed the guiding software used during the study. As one of the researchers was a PhD student, the study design and implementation were supervised and directed by their supervisor.

Qualitative data were collected through semi-structured interviews conducted in situ, immediately after the robot completed the guidance task, to reduce recall bias and to keep responses grounded in the just-experienced interaction. Interviews lasted approximately 5-7 minutes and followed a fixed set of questions addressing attraction to the robot, appearance impressions, comfort, perceived usefulness, prior robot experience, improvement suggestions, and willingness to use the robot again: (1) *What attracted you to this robot?* (2) *Describe this robot's appearance. Did it influence your interaction?* (3) *Did its appearance match your expectations?* (4) *How comfortable were you interacting with it?* (5) *How useful was it in helping you find your destination?* (6) *Have you used other robots before? How does this compare?* (7) *What improvements would you suggest?* (8) *Would you use the robot again? Why or why not?*

Interviews were conducted in Estonian. Most interviews were audio-recorded; in one case, the participant preferred not to be recorded and provided written responses instead.

Quantitative observational data were analyzed using descriptive statistics in Microsoft Excel. Due to the small sample size and the exploratory design, analyses focused on frequency distributions and simple comparisons by robot model, gender, and age group, without inferential testing. Results are reported as counts and proportions to support transparent interpretation. Interview data were analyzed using a light thematic analysis approach informed by Braun and Clarke's framework [14]. Coding focused on semantic-level meanings directly expressed in participants' responses, particularly regarding reasons for robot choice, perceived usefulness for the guidance task, interaction comfort and approachability, and improvement suggestions. Coding and theme refinement were conducted iteratively within the research team to ensure that the themes remained closely tied to the data and to reduce over-interpretation. For reporting, illustrative excerpts were translated from Estonian into English with an emphasis on preserving meaning rather than literal word-for-word translation. Participants are anonymized and quoted using codes P1-P8.

5 Results

5.1 Quantitative Results: Robot Choice

During the study period, 47 visitors interacted with the robots. Thirteen visitors chose one of the robots for a book search and provided written consent for the use of their observational data. These 13 participants constitute the quantitative sample for robot preference analysis.

Across the 13 observed participants, TEMI V3 was chosen slightly more often than TEMI GO (V3: 7, GO: 6). When broken down by gender, women selected TEMI GO more frequently (GO: 4, V3: 2), while men selected TEMI V3 more frequently (V3: 5, GO: 2). When broken down by age group, the pattern differed, young participants tended to choose V3 (V3: 4, GO: 2), whereas mid-age participants tended to choose GO (GO: 4, V3: 3). Because the sample is small, these descriptive differences should be interpreted as tendencies rather than robust group effects.

Table 1. Distribution of observed participants by robot model, gender, and age group.

Group	N	TEMI GO (n)	TEMI V3 (n)
Total observed	13	6	7
Women	6	4	2
Men	7	2	5
Young (18–30)	6	2	4
Mid-age (31–60)	7	4	3

A combined gender-and-age breakdown is possible, but given the small cell sizes (n = 3–4 per subgroup), it is most appropriate to report it only as descriptive context rather than as a main result. Still, for completeness: female mid-age participants (n = 3) selected GO in all observed cases, while male mid-age participants (n = 4) selected V3 in most cases (V3: 3, GO: 1). Young women and young men showed the same pattern (in both groups, V3: 2, GO: 1). These results imply that the overall gender and age patterns may partially reflect subgroup composition rather than independent effects.

5.2 Reasons for Choosing One Robot Over the Other (RQ2)

Interview data (n = 8) provide context for why participants may be attracted to one model, or why model differences may not matter at all. A dominant theme was that many users approached the robots primarily because of practical value and curiosity, rather than because of a planned preference for a specific model. Several participants described the interaction as attractive because it offers a concrete benefit in a large and complex space, namely guidance to a precise location: "*It guided me to the exact place*" (P1). At the same time, users repeatedly noted the novelty and playfulness of the robots, including interest in "what this is" and what the system can do (P1, P5, P8). One participant framed the attraction specifically as interest in the behavior of AI itself, rather than in the robot as a device: "*I was attracted by the behavior of artificial intelligence*" (P7).

Size-related reasons were present but not consistent. Some participants described the larger GO model as more comfortable because it reduced physical strain and improved screen visibility: "*I liked that I didn't have to bend down, and that it was at a comfortable height*" (P3). A second size-related rationale was mobility performance: one user noted that the larger robot worked better on carpet, which made them interpret the larger model as practically "better" in that environment: "*The bigger one worked better on the carpet, so I see it is better*" (P1). However, other participants made the opposite evaluation, describing the larger robot as too bulky for a guidance-only task: "*The larger one is a bit clumsy… since the purpose isn't to carry things, it could be more streamlined*" (P6). Importantly, several participants explicitly downplayed appearance or size as a decision factor, emphasizing a functional view: "*A robot is a robot and a machine is a machine. I don't really think about its appearance when I'm asking it to perform a task*" (P5).

5.3 Appearance, Expectations, and First Impressions (RQ2, RQ3)

Across interviews, users described both robot models in similar terms because interaction content was largely identical (screen interface and guidance flow). The most salient appearance-related element was not size, but the smiling display and greeting behavior, which made the robots feel friendly and approachable. Participants repeatedly described the "face" as an invitation to interact: "*The smiling face was really cool… it felt friendly*" (P1), and "*When the smiling face appears… it invites people to come closer and try*" (P4). This effect was also visible in the written interview: "*I like the robot's smiling display*" (P7).

At the same time, some participants reported a mismatch between appearance expectations and the actual robot form. The most common unmet expectation was a more humanoid body shape: "*I thought the robot would look more human-like*" (P3), and similarly, "*I would expect more human-like shaped*" (P7). Several participants stated they had no expectations at all, suggesting that in a public library context, many users evaluate the robot pragmatically without a pre-formed mental model: "*I didn't really have any expectations*" (P5), and "*It was just brought in and I thought, oh, how fun*" (P8). This combination suggests that appearance matters mostly at the stage of attracting attention and reducing hesitation, while detailed form expectations may be weak in many users.

5.4 Perceived Comfort, Approachability, and Interaction Friction (RQ3)

Most participants described interaction as comfortable, with several using strong positive wording such as "*very comfortable*" (P7) or "*pleasant*" (P8). Comfort was supported by two factors: (a) an interaction style that felt socially acceptable in a public space (smiling face, greeting), and (b) a task flow that became simple once demonstrated. This was expressed clearly by one participant: "*Once someone shows you how it works, there's nothing difficult about it*" (P8). However, comfort was sensitive to interaction friction. One recurring issue was attention and speech recognition, described as difficulty getting the robot to "listen": "*At some times it was difficult to get it to listen… to realize that I was talking to it*" (P2). A second friction point was perceived complexity or non-intuitive interface logic: "*At times it felt a bit complicated*" (P3), and "*The UI could be more user-friendly and logical… fewer options*" (P3). A third friction point concerned screen readability and language quality, where participants asked for larger font size and more correct phrasing: "*The texts could be more linguistically correct… and the text could be larger*" (P4), and "*Larger font size*" (P7). These comments suggest that comfort was not primarily an emotional reaction to robots but rather a response to interaction clarity, readability, and responsiveness.

5.5 Perceived Usefulness for Book Guidance (RQ3)

Perceived usefulness was consistently high across interviews, especially when participants positioned themselves as first-time visitors or as users unfamiliar with the collection. Users described the guidance as reducing cognitive load and accelerating search: "*I didn't even have to think… it guided me completely*" (P2), and "*I know nothing about this library and it led me very quickly to the exact right shelf*" (P1). Several participants explicitly noted that usefulness depends on the library context, where maps and shelf systems can be overwhelming for new users: "*Especially if you're in the library for the first time, it can be overwhelming… the robot definitely knows how to guide better*" (P2). At the same time, usefulness was constrained by a critical operational factor: precision at the final location and clarity about what to do next. Two staff-perspective participants described situations where the robot overshot the correct section, or stopped at the end of a category rather than the relevant sub-area. One participant explained the risk clearly: "*The first time it passed the correct section a bit… the screen showed the code, but the robot went past it. It depends whether the reader notices this or not*" (P5). The same participant described that when the robot stops at the wrong end of a category, users may end up in a nearby but incorrect shelf segment, which reduces trust in the guidance even if the robot is "close." In response, participants suggested that usefulness could be strengthened if the robot provided explicit arrival instructions, for example directing attention to shelf labels and indicating left or right: "*We've arrived. Look left/right… match the screen location with the shelf label*" (P5). This indicates that usefulness is not only about navigation but also about handover quality, meaning the transition from robot guidance to independent shelf-level search.

5.6 Improvement Suggestions and Design Implications from Users (RQ3)

Improvement requests were consistent across interviews and clustered into four practical areas. First, participants emphasized location accuracy and robustness, particularly the ability to stop at the correct shelf marker and not be confused by obstacles near shelf labels: "*It should become more accurate with the exact location*" (P6), and "*It wouldn't get confused if something is in front of or behind the call number*" (P8). Second, participants requested simpler and more logical interface flow, including removal of redundant steps such as selecting the same function twice: "*I shouldn't have to choose 'Guide' twice*" (P5). Third, participants repeatedly requested better readability and language quality, especially larger fonts and more correct phrasing: "*Text size should be increased*" (P4), and "*Larger font size*" (P7). Fourth, several participants suggested stronger real-time feedback during navigation, for example showing movement on a map or reducing duplicated map display: "*Maybe it could show on a map where it's moving*" (P1), and "*The duplicated map display was not good*" (P7). A smaller but interesting recommendation focused on attention attraction when idle, for example through animated "eyes" that signal readiness to interact: "*The eyes that change and show emotions… grab attention… it should invite interaction*" (P6).

5.7 Willingness to Use Again and Social Boundaries (RQ3)

All interviewees expressed willingness to use the robot again, mainly because it simplifies search and reduces dependence on staff: "*I would definitely use it again, it simplifies the search process and decreases the need to approach a staff member*" (P7), and "*Definitely, I would… from a reader's perspective, it's really great*" (P8). Staff-perspective participants emphasized the value particularly for students and busy periods: "*For students… they want something quick… the robot should guide them to the right place quickly*" (P6). At the same time, users did not frame the robot as a replacement for humans; instead, several comments positioned it as supportive infrastructure. One participant reported a negative reaction from an older visitor who interpreted robots as threatening jobs, but this was described as exceptional rather than typical: "*One reader once told us… they're taking your jobs… she seemed quite upset… I haven't heard that since*" (P8). Overall, reuse intention was strong, but it appears to depend on the robot's reliability in the final "handover" to the shelf-level search.

6 Discussion

This study explored user interaction with two differently sized SSRs in an academic library guidance task. Overall, the findings suggest that robot size is not a dominant driver of user choice, but it can shape practical interaction conditions such as screen height, visibility in a busy space, and perceived mobility robustness. In the observed sample (N = 13), both robots were selected at similar rates, and the small differences by gender and age should be treated as descriptive patterns rather than group effects. More importantly, the findings suggest that acceptance in this context depended less on embodiment alone and more on whether the robot supported a clear and coordinated service encounter. In other words, users appeared to evaluate the robot mainly by whether it could be understood, followed, and relied on in the moment while helping them accomplish a concrete goal efficiently [3,10,15].

Seen from this perspective, robot-guided wayfinding can be understood as a coordination process between user and system rather than only as a navigation task. The user must interpret the robot's invitation to interact, understand how to initiate the task, follow the movement through the library, and recognize when robot-led guidance ends and independent action begins. When this coordination remains smooth, the interaction is experienced as useful, comfortable, and trustworthy. When it is disrupted, users may still reach the approximate destination, but the service experience becomes less coherent. In the present study, such interaction breakdowns were visible not only in stopping imprecision at the final location but also in smaller moments of misalignment, such as difficulty getting the robot to "listen," redundant interface steps, and limited readability. These findings suggest that perceived usefulness in library guidance tasks is not simply a result of technical movement from point A to point B, but of expectation alignment throughout the interaction, including clear signals about what the robot is doing and what the user should do next [10,11]. This framing also helps sharpen the role of *the handover moment*, which emerges here as the central conceptual contribution of the study rather than only as a design issue. In this context, handover refers to the transition from robot-led navigation to user-led shelf-level search. The robot may successfully guide the user to the relevant area, but the task is not yet complete unless the user can correctly interpret the final location and continue independently. The findings show that this transition is precisely where trust, usefulness, and self-efficacy are jointly tested. If the robot overshoots the correct section, stops at the wrong end of a category, or fails to provide an explicit completion cue, the user must compensate by interpreting an ambiguous situation. In such cases, the route may be technically close to correct, yet the service experience remains incomplete. This suggests that in SSR guidance tasks, successful task completion should be conceptualized not only as arrival at a destination category but as a successful transfer of orienting responsibility from robot to user. Handover quality therefore becomes central to whether the robot is experienced as genuinely helpful and reliable [10,11].

Interview results also clarify that users' stated reasons for choosing one robot over the other were not consistently about size. Some users associated the larger robot with better ergonomics and smoother movement in the library environment, while others described it as unnecessarily bulky for a guidance-only role. At the same time, multiple participants explicitly downplayed embodiment as a decision factor and framed the robot as a tool: if it guides correctly, it is acceptable. However, embodiment in this study should not be reduced only to ergonomic or functional aspects. The findings also suggest that embodiment shaped first impressions, social legibility, and expectations about what kind of agent the user was encountering. The smiling display and greeting behavior made the robots feel approachable, while some participants expected a more humanoid form and others interpreted size as signalling robustness or clumsiness. Thus, embodiment mattered not only because it affected physical usability, but also because it framed the robot's social meaning at the start of the interaction. In this sense, embodiment operated as both practical affordance and expectation cue: it shaped how the robot was noticed, how readily users approached it, and what level of capability or fluency they anticipated from it [6,7]. At the same time, the study suggests that embodiment alone did not determine acceptance. Rather, users appeared willing to overlook embodiment-related preferences when the robot's behavior matched the service context and the interaction remained clear. This is important because it indicates that in public library guidance, users do not necessarily seek a highly anthropomorphic or emotionally expressive robot. Instead, they appear to value a coherent fit between form, behavior, and task. A modestly social robot that clearly signals friendliness and readiness to help may therefore be sufficient, provided that its guidance performance and interface logic support the task effectively [6,7,16-18].

A strong theme across interviews was high perceived usefulness, particularly for first-time visitors or users unfamiliar with the collection. Users reported reduced cognitive load and faster access to the target shelf, which is consistent with the idea that service robots can offload routine frontline support and improve service accessibility [3,4]. However, the present findings suggest that usefulness should be understood as conditional and interactional, not simply instrumental. Users did not evaluate usefulness only by whether the robot moved them closer to the shelf, but by whether the entire guidance sequence felt understandable and complete. This is why seemingly small issues, such as duplicated interface choices, hard-to-read text, or unclear completion cues, became so important in participant accounts. These were not merely usability annoyances. They were points where the interaction risked breaking down and where the user had to work harder to restore coherence.

Participants also highlighted that approachability and comfort were supported by simple social cues such as a smiling display and greeting behavior. This aligns with research showing that modest anthropomorphic cues can increase willingness to engage and shape first impressions of warmth and social presence, even when the robot is not humanoid [6,7]. At the same time, discomfort in this study came mainly from interaction friction, including small font, redundant steps, and occasional speech or attention issues, rather than from emotional fear of robots. This suggests that, in this context, the social dimension of HRI was expressed less through stronger anthropomorphic expectations and more through readable, predictable, and low-friction interaction. For library guidance tasks, increasing acceptance is therefore likely to depend more on interaction clarity, responsiveness, and task completion cues than on stronger anthropomorphic design. This point is consistent with recent reviews highlighting that nonverbal and appearance-related features matter, but they need to be aligned with usability and context expectations [16-18].

A secondary insight concerns the ethical positioning of SSRs in public institutional spaces. Although ethics was not a primary focus of this study, the findings indicate that even a relatively simple guidance robot is interpreted within broader social meanings of work, service, and automation. Most users described the robot as support rather than replacement, which suggests that they understood it as part of the library's service infrastructure rather than as a substitute for human assistance. At the same time, one reported negative reaction from an older visitor shows that some people may interpret robot deployment through the lens of labour replacement or loss of human contact. This implies that public deployment should include light expectation management and role clarity, for example by framing the robot as a tool for routine navigation while keeping staff support clearly available [4,9]. There is also a smaller but relevant ethical aspect in the handover moment itself: if the robot presents its guidance as authoritative but leaves the final interpretation ambiguous, some of the burden of error is silently shifted to the user. From this perspective, transparent completion cues and clear shelf-level instructions are not only design improvements but also part of a responsible deployment logic in public service settings.

Overall, the contribution of this study is therefore not limited to the observation that robot size played a secondary role in user choice. More importantly, the findings suggest that acceptance of SSR guidance in an academic library is shaped by how well the robot supports coordination across the full service sequence, from first approach to final shelf-level handover. The study thus highlights handover as a conceptually important point of transition in public service HRI: the moment where navigation, expectation alignment, trust, self-efficacy, and perceived usefulness converge. In practical terms, this means that library guidance robots should prioritize reliable stopping accuracy, explicit arrival cues, readable text, and minimal interaction flow. In conceptual terms, it suggests that future HRI work on public guidance robots may benefit from examining not only route success or general acceptance, but also how responsibility for task completion is transferred between robot and user in real settings [10,11].

6.1 Limitations and Future Research

This study is exploratory and has clear limitations. First, the quantitative sample is small (N = 13) and based on consented observations, which limits statistical conclusions and may introduce self-selection bias. Second, interviews were conducted with only eight participants, and three were library staff, who may evaluate usefulness differently from typical visitors, even though they used the robots in a visitor-like manner. Third, the study focused on a specific period (end of semester) with relatively low footfall, which may affect interaction dynamics and the diversity of user profiles. Fourth, interviews were conducted in Estonian and translated for reporting, which can reduce linguistic nuance despite careful meaning-preserving translation [14].

Future research should test the same guidance task with larger samples across different library periods (for example, start of semester and exam periods) and should include explicit matching between observed users and interview responses to strengthen mixed-method interpretation. It would also be valuable to measure guidance success more concretely (for example, whether the user actually found the book without extra staff help) and to compare design variants for the “handover moment,” such as explicit arrival prompts, directional cues, or simplified confirmation screens. Finally, future studies could separate embodiment effects (size, shape, visibility) from performance effects (navigation accuracy, speech recognition, UI) using controlled A/B configurations while still operating in naturalistic field conditions.

6.2 Conclusions

In an academic library guidance task, users evaluated SSRs primarily by usefulness and interaction clarity, while robot size played a secondary role. Size influenced visibility and ergonomic comfort for some users, but it did not appear to be a decisive factor in acceptance. The strongest practical implication is that library guidance robots should prioritize reliable stopping accuracy, clear completion cues, readable text, and a minimal interaction flow. Modest social cues (friendly face, greeting) can support approachability, but improving the final handover and reducing interaction friction is likely to yield the largest gains in user experience and perceived trust.

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Appendix 6

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Enhancing Human-Robot Interaction Through Nonverbal Communication and User Self-Efficacy

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Abstract. Social service robots are increasingly being deployed in public spaces such as libraries, hospitals, and offices to assist and engage people. A critical yet underexplored factor in their success is nonverbal communication (the robot's use of gaze, gestures, interpersonal distance and other cues) which profoundly shapes human–robot interaction. Equally important is user self-efficacy, or the confidence users have in their ability to interact with these robots effectively. This paper investigates how integrating nonverbal behaviors in a social service robot (TEMI) can enhance human interaction in real-world public spaces. We present findings from 15 qualitative interviews with end users, collaborators (on-site staff), and robot sellers, structured to explore users' experiences, self-efficacy levels in controlled vs. real settings, and perceptions of the robot's nonverbal cues. The results identify key categories of nonverbal behavior that influence user trust and comfort: Gaze & Eye Contact, Proxemics, Gestures & Movement, Posture/Height, Movement Speed, Expressiveness, and Cultural Sensitivity, as well as a notable drop in user self-efficacy when moving from training to real-life use. We discuss design and deployment recommendations to address these findings, emphasizing that successful social robot integration requires not only technical proficiency but also careful attention to nonverbal "*social skills*" and user support.

Keywords: Human–Robot Interaction; Social Robots; Nonverbal Communication; Self-Efficacy; Public Spaces; User Experience.

1 Introduction

Social service robots, designed to interact with people and provide useful services, have shown promise in public settings over the past decade [1],[2]. Advances in robotics and AI now enable these robots to handle increasingly sophisticated tasks, from greeting and guiding visitors to providing information or companionship. Yet, their adoption in open public environments (e.g., hospitals, libraries, malls) remains limited due to unique challenges posed by unpredictable real-world conditions [3]. For example, although the COVID-19 pandemic increased interest in contactless robotic services, real deployments still frequently face significant technical and social barriers [4].

One critical factor influencing successful human–robot interaction (HRI) in these environments is nonverbal communication. Human interactions rely heavily on nonverbal cues (such as facial expressions, body language, tone, and personal space) and these principles are equally vital for robots in public spaces [5]. Robots operating among people are expected not only to complete tasks but also to demonstrate social intelligence through natural interactive behaviors. Studies indicate that robots using appropriate nonverbal behaviors, like maintaining eye contact, gesturing, and respecting interpersonal distance, significantly increase user engagement and trust [6]. For instance, robots that orient their gaze toward people and respond with gestures are perceived as attentive, whereas awkward or unpredictable robot movements can make users uncomfortable and erode their confidence [5],[6]. Another influential factor is user self-efficacy: the confidence individuals have in their ability to effectively interact with robots. High self-efficacy has consistently been associated with better technology adoption outcomes [7],[8]. Users who feel confident with a technology tend to use it more effectively and continuously [9],[10]. However, research indicates that while users often exhibit high self-efficacy in controlled scenarios (such as training sessions or laboratory conditions), their confidence sharply declines in actual public settings [11]. For example, in a pilot study at a higher-education institution, participants trained to use a social robot felt confident during structured training but became uncertain and hesitant when interacting with the same robot in a busy public environment [11]. This gap underscores that technical proficiency alone is insufficient; user comfort and confidence in real-world conditions are critical factors.

Given these challenges, our study investigates the intersection of robot nonverbal behavior and user self-efficacy in real-world public-space HRI, being guided by the following research questions:

- **RQ1:** How do users' levels of self-efficacy differ when interacting with social service robots in controlled environments versus in real-life public spaces?
- **RQ2:** What are the primary barriers and challenges – including those related to nonverbal communication – that end users, collaborators (staff), and robot providers experience when using social service robots in public spaces?
- **RQ3:** What improvements in robot design (particularly nonverbal behaviors), training, or support do these stakeholders suggest to improve user self-efficacy and satisfaction in interactions with social service robots?

By answering these questions, we aim to uncover how the robot's nonverbal behavioral cues and the users' confidence intersect to influence the success of HRI in public deployments, and what can be done to overcome current barriers.

2 Background

Human–robot interaction (HRI) in public spaces typically involves brief, unplanned interactions with diverse users. Unlike structured factory settings, public environments present unpredictable human behaviors and situational variability, complicating robot deployments. Prior studies highlight challenges including technical limitations, user discomfort, organizational barriers, and difficulties managing unstructured interactions like navigating crowds or interpreting informal queries [3],[12],[13]. Social acceptance, significantly influenced by a robot's approachability, politeness, and adherence to social norms, is critical for effective HRI. Robots displaying warm greetings and respectful behaviors consistently attract more engagement compared to mechanically impersonal robots. Additionally, users' preconceived attitudes significantly affect their acceptance: those with positive attitudes interact willingly, while anxious or negative users hesitate [14],[15]. These observations align with broader technology acceptance models emphasizing usefulness, ease of use, and trust. Trust, crucial for interaction, can quickly erode through erratic behaviors, underscoring the need for robots to demonstrate social intelligence alongside functional effectiveness [16],[17].

User self-efficacy, defined as one's belief in successfully performing a task, is strongly linked to effective technology adoption, reduced anxiety, and increased willingness to engage with robots [9],[10]. Studies consistently show higher self-efficacy correlates positively with greater trust and intention to use robots [7],[8]. Conversely, users with lower self-efficacy hesitate, avoid interactions, and often attribute difficulties to personal shortcomings rather than technical limitations. Recent research emphasizes boosting robot-specific self-efficacy through guided mastery experiences, demonstrating that structured training and positive initial interactions significantly enhance user confidence and attitudes [18]. Nonetheless, a common issue persists: users frequently lose confidence transitioning from controlled environments (e.g., structured demos) to unpredictable real-world deployments. For instance, a pilot university study showed participants confident in structured scenarios became hesitant and uncertain in actual busy settings, revealing a notable "*deployment dip*" in user competence [11]. Maintaining user confidence thus requires ongoing support beyond initial training; our study further investigates these moments when user efficacy falters and identifies strategies to mitigate the drop.

Nonverbal communication, encompassing eye contact, facial expressions, gestures, interpersonal distance, posture, and paralinguistic signals, plays a critical role in HRI. In robotics, these human interaction cues translate into design choices such as facial animation, gaze orientation, controlled movement speed, respectful distances, and auditory or visual indicators [5]. Research indicates that appropriate nonverbal robot behaviors strongly influence user perceptions and responses. Robots maintaining eye contact and attentive postures are typically viewed as trustworthy and engaged, while robots ignoring these norms appear inattentive or untrustworthy. Proxemic behaviors (robot–user distances around 0.5–1 meter) significantly impact user comfort: too close causes unease, too far appears impersonal [19]. Similarly, smooth gestures and clear movements increase interaction clarity and comfort, whereas sudden, unexplained motions startle and erode trust. Robot expressiveness through screens or indicators (like smiles signaling task completion) enhances user satisfaction if designed clearly and appropriately. Subtle signals (such as brief tones or blinking lights before movements) also effectively prepare users for robot actions, improving interaction fluidity and preventing confusion [20],[21].

Prior studies consistently indicate nonverbal cues are essential, not supplementary, elements in social robotics, shaping user impressions of robot attentiveness, politeness, and competence. These factors ultimately influence user comfort, trust, and engagement levels. Building on these insights, our study investigates real-world deployments to examine how robot nonverbal behaviors influence user confidence and interaction effectiveness.

3 Methodology

To investigate the research questions, we adopted a qualitative research design centered on semi-structured interviews. This approach allowed us to gather in-depth insights into users' subjective experiences and perceptions of the robot's behavior in real-life contexts. We focused on three stakeholder groups: **end users**, **collaborators**, and **sellers/manufacturers** of the robot.

Participants: We conducted 15 interviews (5 per stakeholder group). *End users* were individuals who directly interacted with the TEMI social service robot as part of their daily environment – for example, library visitors who asked the robot for help, or hospital staff and patients who encountered the robot in hallways. *Collaborators* were people who work alongside the robot or facilitate its use, such as on-site staff at the deployment locations (e.g., librarians or office managers responsible for the robot). *Sellers* (manufacturer representatives) were sales or support personnel from the company providing the robot, who have insight into client feedback and technical issues. All participants had at least some direct experience with observing or using TEMI in its deployment setting. The deployments took place at three sites where TEMI had been introduced: a public library, a hospital lobby, and a corporate office building (5 interviews per site, with one person from each stakeholder group at each site). Participants were recruited via the organizations hosting the robot and through the robot provider's client network. To protect privacy, we refer to interviewees by role (e.g., "*library end user,*" "*office staff collaborator,*" "*seller rep*") rather than by name.

Robot Platform: The robot used in these deployments was the Temi V3 robot (TEMI), a 100 cm tall service robot on wheels with a tablet-like screen as its "*face*" (Figure 1). TEMI is capable of autonomous navigation, greeting and guiding people, and basic spoken dialogue via a voice interface. It is equipped with multiple sensors (cameras, depth sensors, etc.) to detect people and obstacles, and its touchscreen can display information or simple facial animations. In our study, TEMI's typical activities included greeting visitors, answering simple questions (such as providing directions or FAQs), and escorting users to specific locations (e.g., an office or department within the building). This platform was chosen because it is a commercially available social service robot designed for public environments, offering standard capabilities for interaction and navigation.

Fig. 1. The TEMI V3 Robot.

Interview Procedure: Interviews were conducted in person at the deployment sites, usually immediately after the participant had an interaction with TEMI (for end users) or after a period of observing the robot in action (for collaborators and sellers). Each interview lasted approximately 30–45 minutes. We used a semi-structured interview guide covering key topics: the participant's overall impression of the robot and comfort level in interacting with it; specific observations about the robot's nonverbal behaviors (e.g., "*Did the robot's way of moving, looking at you, or keeping distance affect your experience? What did you like or dislike about how it behaved physically?*"); scenarios where they felt confident or hesitant in using the robot, and why; for collaborators, any challenges they noticed users facing and how staff responded, as well as any protocols or training they had for assisting users; for sellers, common feedback from client deployments regarding the robot's nonverbal interaction, reliability, and user support issues; and finally, all groups were asked for suggestions or "*wish list*" improvements to the robot's behavior or design to make it more effective and easier to use. Participants were encouraged to share concrete anecdotes (positive or negative) to illustrate their points. All interviews were conducted in the local language (Estonian for end users and collaborators; English for seller representatives when not local) and audio-recorded with consent, then transcribed and translated to English as needed.

In addition to interviews, we conducted brief non-participant observation at each site to contextualize the interviews. This involved watching how random visitors approached or ignored the robot, and noting any technical issues (e.g., the robot getting stuck or rebooting). These observations were used to inform follow-up questions in the interviews (for example, asking staff about an incident we observed) and to better interpret participants' comments.

Data Analysis: We employed a thematic analysis approach to analyze the interview transcripts. First, two researchers read through all transcripts to get a familiarization with the data. Next, we inductively coded the data, identifying recurring concepts or issues mentioned by participants. The two researchers initially coded transcripts independently, then met to compare and refine the code definitions (creating a codebook). Through discussion, we clustered related codes into broader themes. Key themes that emerged included: *interaction comfort vs. discomfort*, *understanding of robot intentions*, *technical issues*, *user confidence*, *training/support experiences*, and *design suggestions*. Notably, many codes related to the robot's nonverbal communication (e.g., "*eye contact/gaze,*" "*distance,*" "*movement speed,*" "*screen feedback*") as factors influencing both users' emotional responses and the effectiveness of interaction. We grouped certain codes into higher-level categories corresponding to types of nonverbal behavior (informed by prior literature as well as our initial expectations) and categories related to user self-efficacy and adaptation.

To ensure the trustworthiness of our qualitative analysis, we triangulated perspectives from the three stakeholder groups. Where possible, we cross-verified claims – for example, if an end user said they often didn't notice a particular on-screen cue from the robot, we checked whether collaborators (staff) observed users missing that cue as well. We paid attention to any conflicting viewpoints and noted them in our results. We also extracted representative quotes that exemplified each theme for reporting. (Quotes originally in Estonian were translated to English for this paper.) In the results section, we indicate each quote's stakeholder source for context (e.g., *library end user*, *hospital staff collaborator*).

4 Results

4.1 Key Nonverbal Behavior Categories and User Perceptions

From the interviews, several categories of TEMI's nonverbal behaviors emerged as significant: Gaze & Eye Contact, Proxemics (Distance), Gestures & Movement, Posture & Height, Speed of Movement, Expressiveness (Screen & LEDs), and Cultural Sensitivity.

Participants strongly valued the robot's **Gaze & Eye Contact**. TEMI's ability to orient its tablet screen to face users made interactions feel personal and attentive. As one user stated, "*I liked when the robot moved its screen as if it was looking right at me. It made the interaction feel personal.*" Consistent gaze fostered trust, while instances where the robot turned away mid-conversation led users to doubt whether it was attentive or still listening. The robot's **Proxemics** also significantly influenced comfort. TEMI typically maintained around 0.8–1 meter of conversational distance, widely perceived as appropriate. Users noted discomfort if the robot moved too close (less than half a meter), prompting them to instinctively step back, while greater distances sometimes led to uncertainty about engagement. A hospital collaborator noted, "*It kept a polite distance, not too close, not too far, which made people feel safe interacting.*" Regarding **Gestures & Movement**, TEMI's smooth, gentle navigation, such as slowly pivoting while guiding users, was perceived positively, signaling attentiveness and predictability. Conversely, abrupt movements, like sudden swivels to avoid obstacles, alarmed users, undermining perceived reliability. One participant recounted, "*It kind of did a quick turn without warning – I actually jumped back because I didn't expect that.*" For **Posture & Height**, the robot's fixed 1-meter stature was generally acceptable, though some taller users reported having to bend down awkwardly. Participants suggested future adjustments to accommodate different heights or contexts (e.g., wheelchair users), enhancing overall accessibility. TEMI's **Speed of Movement** was typically appropriate, matching a moderate walking pace. However, clearer communication around movement initiation was suggested, as unexpected starts caused confusion. An office user explained, "*It suddenly took off after answering my question, and I wasn't ready – I thought it might stay and wait.*" Participants appreciated TEMI's **Expressiveness** through simplified facial animations and LED signals, as these helped interpret the robot's internal states. For instance, one user enjoyed the animated smile after task completion, noting it encouraged reciprocal positive feelings. Users proposed enhancing the visibility and clarity of these expressive signals, such as using more noticeable facial expressions or subtle audio cues to reassure users during interactions. Finally, **Cultural Sensitivity** influenced user comfort. Local Estonian users appreciated TEMI's reserved style regarding personal space and quiet interactions, aligning with their cultural expectations. International visitors sometimes expected more interactive or familiar gestures, highlighting a potential need for culturally adaptive robot behaviors. A collaborator noted how visitors from Southern Europe or the Middle East often tried to physically engage the robot more closely, suggesting that a uniform approach might not satisfy all users globally.

Overall, well-executed nonverbal behaviors (clear gaze, respectful distance, smooth motion, expressive feedback) fostered trust, comfort, and engagement. Poorly executed or missing cues led to discomfort, distrust, and lower engagement.

4.2 Self-Efficacy in Controlled vs. Real-World Environments

(RQ1) A prominent finding was users' notable drop in self-efficacy when transitioning from controlled introductions (training sessions or demonstrations) to real-world public-space interactions. Initially, most users reported high confidence during guided demonstrations, describing TEMI as "*easy to use.*" However, once interacting independently, their confidence frequently diminished sharply, reflecting a marked "*deployment dip.*"

(RQ2) Interviews highlighted several barriers and challenges contributing to this self-efficacy decline. First, **Unpredictable User Queries** significantly impacted confidence. During controlled sessions, users interacted via scripted questions, but real-world interactions introduced unpredictable scenarios and queries the robot could not handle, leading users to doubt their abilities. An office participant recalled, "*During training, everything was smooth, but when a visitor asked the robot a question it didn't understand, I didn't know what to do.*" Second, **Technical Glitches**, such as intermittent network issues causing robot delays or non-responses, substantially eroded user confidence. Users typically internalized these problems as their own mistakes, exemplified by a participant's comment: "*It didn't always respond as expected, so I began to doubt if I was doing it right.*" Collaborators confirmed users frequently blamed themselves ("*Did I press the wrong button?*"), highlighting a critical link between robot performance and user self-efficacy. Third, **Social Pressure** from bystanders negatively affected user confidence. Users felt hesitant and nervous performing robot interactions publicly, fearing embarrassment from making mistakes in front of others. One participant explained, "*In the demo it was just me and the trainer, but on the floor, I had colleagues watching me. I didn't want to mess up.*" Fourth, **Lack of Immediate Support** in real-world scenarios compounded these issues. Without immediate assistance available, users felt isolated during unexpected robot behaviors, further lowering their confidence. A hospital collaborator noted users frequently sought staff support during issues, but the staff sometimes also felt unsure of how to assist effectively.

(RQ3) Participants proposed several improvements to address these barriers. Enhancements in robot design were strongly recommended, including clearer pre-movement communication cues, improved synchronization between verbal and nonverbal signals, and adaptable interaction styles (professional vs. playful) to suit varied user preferences and contexts. A commonly cited suggestion was for the robot to clearly indicate intentions before initiating action, such as verbally announcing movement ("*Follow me now*") coupled with visual arrows, reducing confusion and increasing user preparedness. Participants also recommended culturally adaptive behaviors (adjusting proxemics, gaze, and expressiveness based on cultural expectations) to support global user acceptance. Moreover, users and collaborators emphasized the need for ongoing training beyond initial introductions, periodic reinforcement sessions addressing common real-world scenarios, and readily accessible troubleshooting resources. Staff training was identified as critical, ensuring frontline personnel could confidently support users encountering robot difficulties. Sellers similarly noted that successful robot deployment required organizational commitment to user and staff training, noting cases where insufficiently trained staff led to underutilization of robots.

Thus, stakeholders consistently highlighted the value of proactive, continuous training and support strategies to bridge the self-efficacy gap observed between controlled introductions and actual public-space deployments.

5 Discussion and Conclusions

This study explored how integrating nonverbal behaviors in social robots influences human interaction and user self-efficacy in public spaces. We found that specific nonverbal cues (including appropriate gaze and eye contact, suitable proxemic distances, predictable and smooth movements, clear expressive feedback such as screen animations, and cultural sensitivity) significantly affected users' trust, comfort, and willingness to engage with the robot. Effective nonverbal behaviors, such as TEMI consistently orienting its screen to maintain eye contact or adjusting its interpersonal distance to around one meter, enhanced interactions by fostering user confidence and reducing uncertainty. Conversely, when nonverbal cues were inappropriate, ambiguous, or absent, for instance, sudden and unexplained robot movements or a lack of clear pre-movement signals, users reported confusion, anxiety, and disengagement. These findings align closely with prior research emphasizing the critical role of social intelligence for robot acceptance [5],[6]. We extend these insights by qualitatively documenting users' real-world experiences, highlighting concrete behaviors that designers should prioritize, such as providing verbal or visual pre-movement cues (e.g., the robot verbally indicating "*I will move now*" or displaying directional arrows) and clearly interpretable emotional feedback (e.g., a smiling face upon task completion).

A notable finding from our deployments was the direct relationship between robot nonverbal behaviors and users' self-efficacy. While users initially demonstrated high confidence during structured, controlled training sessions, their self-efficacy significantly decreased when confronted with real-world complexities like unexpected user queries, technical glitches (particularly delayed robot responses due to connectivity issues), social pressure from onlookers, and the absence of immediate expert assistance. When the robot's feedback was unclear or inconsistent, participants frequently internalized these interaction problems as personal failures, significantly undermining their self-confidence. This suggests that the robot's design and behavior actively shape users' sense of competence, highlighting the need for robot designers to explicitly incorporate reassuring nonverbal cues. Practical implications include adding explicit confirmation signals (such as a reassuring nod or a clear on-screen checkmark to acknowledge commands) and pre-action notices to help maintain and enhance users' confidence during interactions.

Furthermore, our study underscored critical differences between controlled laboratory studies and actual public-space deployments. Observed challenges, including technical reliability issues, unpredictable environments, and diverse user expectations, emphasized the complexity of translating laboratory successes into practical, real-world applications. Stakeholders should thus anticipate a "*deployment dip*" in user self-efficacy, particularly after initial controlled training sessions. To counteract this decline, our results suggest the importance of sustained strategies like ongoing training (e.g., periodic refresher sessions), accessible and easy-to-follow support resources, and opportunities for users to repeatedly engage with the robot. For instance, quick-reference guides or periodic interactive workshops could reinforce user comfort, helping bridge the initial confidence gap over time.

The successful deployment of social robots also relies significantly on effective collaboration among various stakeholders: end-users, support staff, and robot providers. Our findings highlight the importance of viewing robot deployment from a socio-technical perspective. Social robots require not only robust and socially intelligent designs but also trained staff ready to support and guide users when unexpected issues occur. Conversely, manufacturers require continuous and detailed feedback from deployment sites to iteratively improve robot usability. Future deployments could benefit from co-design workshops involving end-users, staff, and developers, helping proactively identify and address potential interaction issues early, ultimately enhancing real-world integration.

Limitations of our study include the relatively small sample size from a single cultural context (Estonia) and reliance on qualitative, self-reported data, limiting the generalizability of findings. Cultural variations could significantly impact user perceptions and preferences regarding nonverbal cues. Future research could complement qualitative data with quantitative metrics (such as interaction durations or proximity behaviors) or employ standardized self-efficacy scales to better quantify user confidence changes and generalize findings across broader contexts and robot designs.

In conclusion, integrating thoughtful nonverbal behaviors into social robots is crucial for enhancing human–robot interaction in public spaces. Robots should be treated as social actors that clearly communicate their intentions and states through consistent nonverbal cues, significantly improving user comfort, trust, and sustained engagement. Recognizing and proactively supporting user self-efficacy (through targeted training, clear and reassuring robot feedback, and ongoing user engagement) will be key to successful and sustained adoption of social service robots in diverse public settings.

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Appendix 7 (GRUSES Scale)

The Guide Robot User Self-Efficacy Scale (GRUSES) is a 9-item instrument used in the dissertation to assess users' perceived capability to interact with a guide robot in public or organizational indoor settings. Responses are recorded on a 7-point scale, and the items are grouped under three dimensions: comprehensibility, effectiveness, and subjective pleasantness.

Table 4. Guide Robot User Self-Efficacy Scale (GRUSES).

Dimension	***Item label***	***Prompt***	***Response anchors***
Comprehensibility	*Complexity*	*Communicating with the robot seemed to you ...*	*Very difficult – Very easy*
Comprehensibility	*Understandability*	*How did you understand the robot's messages or conversations?*	*Very badly – Very well*
Comprehensibility	*Confidence*	*How confident or uncertain did you feel during your interaction with the robot?*	*Very uncertain – Very confident*
Effectiveness	*Effectiveness*	*Did collaborating with the robot help you complete the tasks worse or better?*	*Significantly worse – Significantly better*
Effectiveness	*Comfort*	*How convenient was it for you to solve the tasks in cooperation with the robot?*	*Very uncomfortable – Very comfortable*
Effectiveness	*Speed*	*Did working with the robot make solving the tasks slower or faster for you?*	*Significantly slower – Significantly faster*
Subjective pleasantness	*Safety*	*Did you consider interacting with the robot to be ...*	*Very unsafe – Very safe*
Subjective pleasantness	*Reliability*	*Did you consider the robot as a communication partner for you to be ...*	*Very unreliable – Very reliable*
Subjective pleasantness	*Pleasantness*	*Did you consider the robot as a communication partner for you to be ...*	*Very unpleasant – Very pleasant*

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