A Framework for Assessing Gait Modulation and User Experience in Social Robot Guidance: the R1 Robot as a Lobby Assistant*

Giulia Bodo[+1], Ettore Landini[+2], Francesco Brand[2], Andrea Piccardo[1], Leonardo Gori[2], Carlos Beltran[3], Matteo Laffranchi[1] and Lorenzo Natale[2]

Abstract— **The development of assistive technologies is becoming increasingly important due to demographic trends highlighting the growing number of frail individuals requiring support and the simultaneous shortage of caregivers. In this context, the integration of smart environments and social robots within the Ambient Assisted Living (AAL) paradigm is attracting increasing research interest. While several studies have already demonstrated the potential of human–social robot interaction for guidance and assistance tasks, further work is needed to develop standardized approaches for monitoring and evaluating the impact of robotic guidance on human gait. This study proposes a testing framework based on a navigation and interaction model that enables the use of the R1 robot as a lobby assistant, integrating sensorized insoles to monitor gait parameters during both free and robot-guided walking. In addition, questionnaires were administered to evaluate system usability, wearable comfort, and the perceived applicability of robotic guidance in clinical settings.**

I. INTRODUCTION

Identifying novel technological solutions to support older adults and individuals with disabilities is becoming an increasingly urgent societal challenge [1]. Demographic projections for the next two decades indicate a substantial increase in the dependency ratio, that is, the relationship between the number of individuals requiring care and the number of available caregivers [2]. This trend highlights the critical need to develop technologies capable of supporting people throughout the aging process and assisting individuals with functional impairments. Within this framework, Ambient Assisted Living (AAL) has emerged as a rapidly expanding research field [3] , integrating environmental and wearable sensors with robotic platforms, including social robots designed to interact naturally with users and provide personalized assistance [4]. The use of social robots for guidance and assistance has already been explored in several application domains. For example, robotic systems have been employed to guide visitors in museums [5], demonstrating the feasibility of socially interactive navigation support and how social robots can effectively interact with humans at both emotional and social levels. Several studies have also explored the use of social robots as side-by-side companions to support safe and natural ambulation [6]. In the field of rehabilitation, social robots have been implemented as tools for patient engagement and motor correction [7], for example, previous work has shown that patients can follow and mimic the robot's posture and movements, leading to improvements in walking patterns and motor performance [8]. In clinical contexts, however, human–robot interaction (HRI) requires particular attention, as the behavioral and functional effects of interacting with a robot must be carefully considered [9].

In this study, the authors propose a novel application for the R1 robot [10] as a lobby assistant and guide in unfamiliar indoor environments. The ultimate goal of this development is to enable the robot to accompany patients across different hospital departments, facilitating safe ambulation while reducing stress and difficulties in reaching target locations.

The proposed framework integrates wearable technologies, specifically sensorized insoles, to monitor gait parameters during both free walking and robot-guided walking. The objective is to investigate the relationship between robotic guidance and gait modulation. An interaction and navigation model was developed and evaluated in a laboratory setting, supporting the navigation across multiple areas of a building floor. The system was tested on a sample of 15 healthy participants to assess both the quality of the dialogue interaction and the effects of following the robot on gait patterns. Participants wore sensorized insoles to collect spatiotemporal gait parameters, enabling evaluation of whether robotic guidance influences physiological gait characteristics, particularly in terms of symmetry and balance. The study aimed to determine whether structured guidance, through predefined walking paths and controlled speed, could potentially contribute to fall risk reduction. The findings may, in future work, inform the refinement of the robot's locomotion parameters to promote safer ambulation. In addition to quantitative gait analysis, questionnaires were administered to evaluate the usability of the robotic system, the comfort of the wearable setup, and the perceived applicability of robotic guidance in clinical contexts. Both standardized questionnaires (Technology Acceptance Model, TAM; System Usability Scale, SUS) and ad hoc surveys were used to gather participants' feedback on human–robot interaction and the insole-based monitoring approach.

Overall, the proposed framework provides a structured methodology for assessing the biomechanical and experiential impact of robotic guidance, contributing to the de-

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+ Co-first authors, equal contribution

[1]Rehab Technologies Laboratory at Istituto Italiano di Tecnologia, Genova, Via Morego 30, 16163, Italy.

[2]Humanoid Sensing and Perception Laboratory at Istituto Italiano di Tecnologia, Genova, Via S. Quirico, 19d, 16163, Italy.

[3]Pattern Analysis and Computer Vision at Istituto Italiano di Tecnologia, Genova, Via Enrico Melen 83, 16152, Italy.

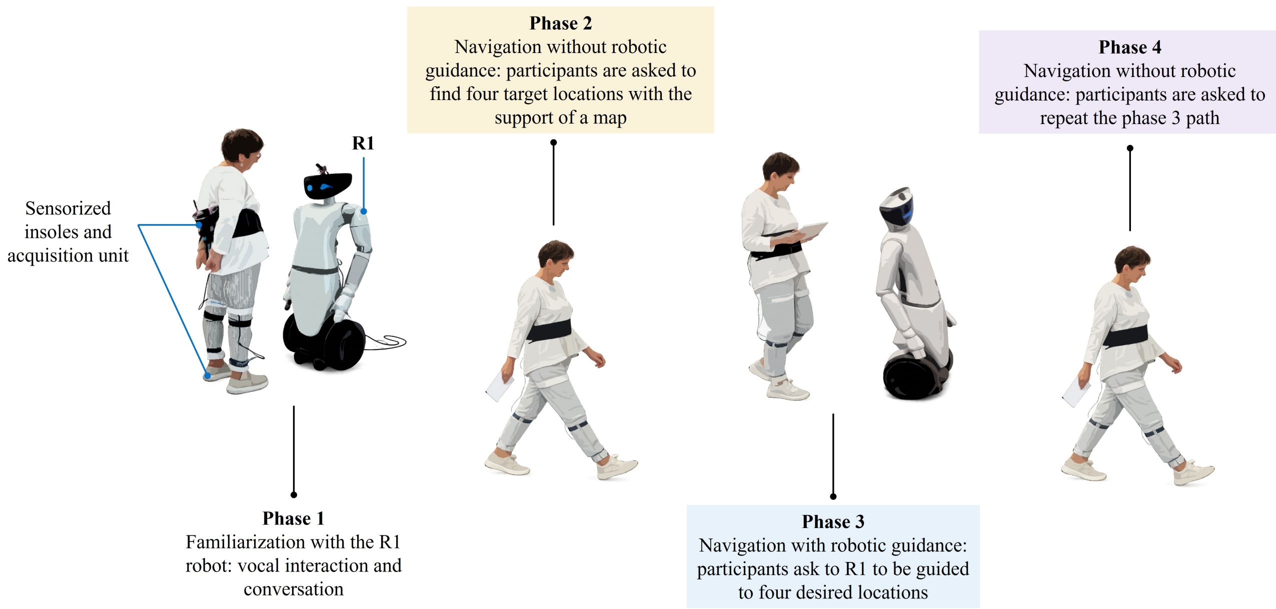

Fig. 1. Schematic representation of the experimental procedure followed during data acquisition on healthy participants. At the beginning of the session, a familiarization phase with the R1 robot was conducted. Subsequently, the participant, equipped with a map of the laboratory floor, was asked to autonomously reach a sequence of unknown target locations. In the second phase, the participant requested guidance from the R1 robot to reach selected destinations. Finally, the participant autonomously repeated the same path previously performed under robotic guidance. During all walking phases, the instrumented insoles continuously recorded plantar pressure data.

velopment of more effective assistive robotic solutions for healthcare and assisted living environments.

II. Materials and Methods

A. Experimental protocol

The experiment was conducted in accordance with the procedure described in the IIT_RAISE2_SENSE protocol and was approved by the local Ethics Committee (N. CET - Liguria: 292/2024 - DB id 14006).

Healthy participants (mean age 46.4 years, range 25–74) were recruited to evaluate the effectiveness of the R1 robot as a guide in an unfamiliar indoor environment and to assess its impact on physiological gait parameters.

During the experimental session, participants wore sensorized insoles (Pedar system by novel.de) to collect spatiotemporal gait and balance data.

The experimental protocol, detiled in Fig. 1 consisted of four phases: (i) Familiarization with the R1 robot: participants were introduced to the robot and received instructions on how to activate it (via keyword) and interact through voice commands. A familiarization period of 5–10 minutes was provided to allow participants to gain confidence with the system. During this phase, participants were free to converse with the robot on any topic, without specific constraints. (ii) Navigation without robotic guidance: participants were provided with a schematic map of the experimental floor, in which specific target locations were highlighted. They were asked to identify and reach four predefined areas while walking at a natural, comfortable pace, ensuring safe but purposeful ambulation. (iii) Navigation with robotic guidance: after consulting the map, participants were asked to autonomously select a sequence of four target locations. For each destination, they verbally requested guidance from the R1 robot and followed it to the selected area. Participants were instructed to walk behind the robot during navigation. (iv) Repetition of the guided path without the robot: participants were asked to repeat the same path followed in Phase iii, this time without robotic assistance.

At the end of the experimental session, participants completed standardized questionnaires: Technology Acceptance Model (TAM) and System Usability Scale (SUS), along with ad hoc questionnaires designed to assess the overall user experience and perceived usability of both the robotic system and the insole-based monitoring approach.

B. R1 Robot

R1 is a robotic platform developed by the Italian Institute of Technology. It is a wheeled humanoid unit with 8 Degrees Of Freedom (DOF) arms, a 2 DOF head, 4 DOF torso. It is equipped with a Realsense D435 RGB-D camera and two RPLIDAR A3s. It has an LED Matrix display in the head, used to show the robot's face and easy the communication with humans. Four different computing units are responsible for controlling it different parts. One in the robot base (Intel i7 7th gen) running standard Ubuntu 24.04, two in the torso (Nvidia Jetson TX2), running a version of ubuntu customized by NVidia and one in the robot's head (Xilinx ZynQ based board), running again a custom version of Ubuntu. At a last directional microphone and a speaker, both mounted on the robot's head for vocal communication. The main software platform running the robot is the middleware YARP [11], which controls the the robot's HW and most of its more

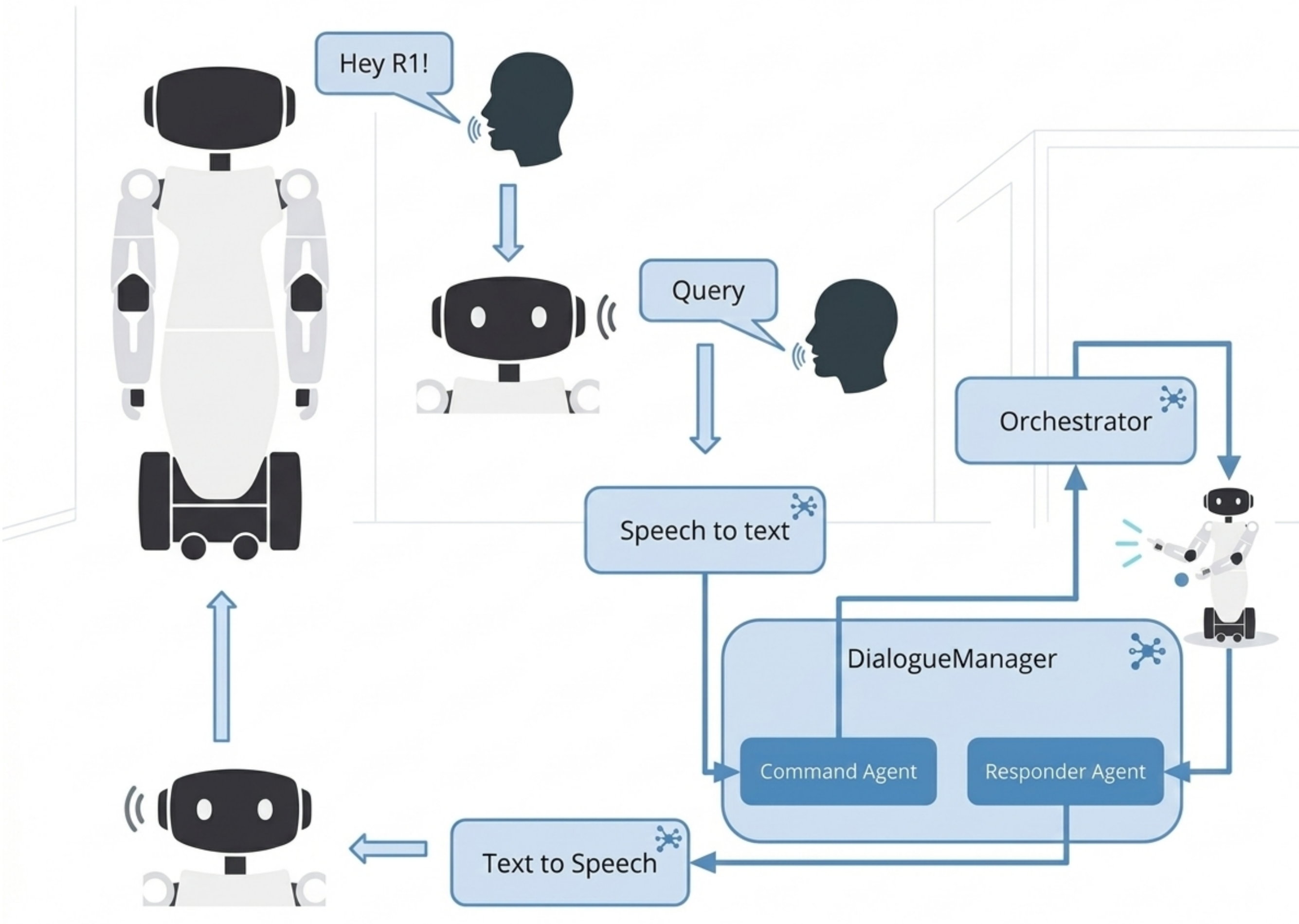

Fig. 2. Schematic representation of the pipeline managing subject-robot interaction

advanced features. For autonomous navigation, authors relied on the ROS2 navigation 2 stack (from here on Nav2) [12] [13]. Thanks to our software plug-ins that allow to interface YARP and ROS2, it was possible to easily integrate the Navigation 2 stack into our software. The floor map was created using the robot lidars and the Slam toolbox utilities and then determined a set of fixed locations .

C. Interaction model

To manage the interaction between R1 and the subjects, it was developed a modular software pipeline that could allow to easily test different Natural Language Processing (NLP) models and tools and also easy to monitor, debug and restart in case of unexpected failures (Fig. 2). The last aspect was particularly important since, during a test, being able to quickly recover from a failure allows us to not end a test abruptly. The pipeline contains, except for the obvious components for audio acquisition from the robot microphone and audio generation from R1 speakers, six different modules: wake-word detection; voice activation detection (from here on "VAD"); speech to text transcription; Large Language Model (LLM) based agent to interpret incoming text (from here on "command agent"); LLM based agent to generate human understandable replies and diagnostic messages (from here on "responder agent"); text to speech synthesis. The first module uses the open wake word model [14] trained on our custom phrase "Hey R1". This module allows us to keep the robot microphone recording without risking it to react to random conversations. Our module, once it detects the wake-word lets the the audio pass through and reach the rest of the pipeline. The second one uses the Silero voice activation detection library [15] is used to detect the part of the input audio that contains human speech and cuts when a pause longer than a certain threshold is detected. The speech to text module and the text to speech one use Google Cloud Services to transcribe the audio received from the VAD and to synthesize the responses from the LLM agents. The two LLM agents rely on a GPT-4o model queried using Azure-OpenAI APIs wrapped by an open-source library called "liboai" [16]. Both of them are managed by a software module (from here on "dialogue manager") that acts as a man in the middle between the vocal interaction part and the module that actually manages the tasks that the robot is supposed to perform (from here on "orchestator").

The command agent receives the transcription of the user speech and interprets it in order to fill a JSON structure (i.e. {"m_type":"command type", "m_params": [param_1, param_2, ...], "m_language":"language code"}) used to identify the instruction to send to the orchestrator. This agent is also responsible for filtering wrong queries. The responder agent is used by both the dialogue manager and the orchestrator in order to provide vocal feedback to the user every time a question is asked or an event is triggered by the modules managed by the orchestrators (e.g. target location reached, task aborted, hardware issue etc...). It receives messages with the same JSON structure mentioned before, containing also, the original user query ad a comment that explains the feedback a little better. This helps the responder craft a more useful feedback for both the subject and for us.

A little digression on the orchestrator module is needed to understand how the pipeline handles the tasks that the robot is supposed to perform. This module manages a state machine that dictates how the system has to react to different commands. The orchestrator receives input from the dialogue manager, the navigation stack and, when active, the object search pipeline. The orchestrator, can, at any given time, pause an ongoing task, start a new task in the middle of the ongoing one and stop it if something wrong happens or if the user asks for it. Most of the modules (dialogue manager excluded) can run independently and have their own internal state machine to define their behaviour. This creates a little redundancy on some communications, but it allows to easily debug each of them when needed, without having the entire structure running.

D. Plantar Force Data Acquisition and Processing

The Pedar system was used to automatically extract, from the plantar pressure map, the vertical component of the force computed at the center of pressure (CoP). Force signals from both the right and left insoles were processed to: detect the number of steps and their duration, compute stance and swing phase durations within the gait cycle, estimate gait cadence, evaluate weight shift distribution between limbs.

Force-Based Step Detection: Step detection was performed using a threshold-based algorithm applied to the vertical force profile. A high threshold (T_H) was used to identify the stance phase, while a lower threshold (T_L) was used to detect the swing phase.

Initially, a step was considered to begin when the vertical force exceeded T_H, indicating foot contact and the onset of the stance phase. Once the stance phase was detected, the algorithm monitored the force signal for a drop below T_L, corresponding to the swing phase. When the force remained below T_L for a predefined number of consecutive samples (10 samples threshold was set to avoid false detections), the step was considered completed and its timing was recorded.

Step Duration and Cadence: Step timing was analyzed to evaluate potential modulation of mean step duration induced by the guidance of the R1 robot. For each detected stance–swing sequence, the overall single-leg step duration was computed as the time interval between two consecutive step events of the same foot.

Cadence was calculated as the ratio between the total number of detected steps and the overall task duration, and subsequently converted by proportional scaling into steps per minute (steps/min). The task duration was defined as the time interval between the first and the last detected step events.

Step Phase Characteristics: For each detected step, stance and swing phase durations were computed from the number of samples above and below the predefined force thresholds, respectively. These phase durations were then normalized to the total step duration in order to obtain the percentage contribution of stance and swing within each gait cycle.

According to gait analysis literature, physiological walking is typically characterized by an approximate 60% stance phase and 40% swing phase distribution within the gait cycle [17]. Deviations from this proportion were evaluated to assess potential alterations of gait dynamics induced by following the R1 robot.

Weight-Shift Distribution: Weight-shift distribution was evaluated by comparing the vertical force signals recorded from the right and left insoles. Under symmetrical gait conditions, a near 50%–50% distribution between limbs is expected over time. Persistent deviations from this distribution could be interpreted as indicators of asymmetric loading, potentially reflecting imbalance or fall risk during walking.

E. Statistical analysis

The collected metrics were evaluated by comparing the three experimental conditions: (i) autonomous participant navigation in an unknown environment while reaching preassigned target locations (Unknown), (ii) navigation guided by the R1 robot, during which the participants selected the area to be guided to (R1 Guided), and (iii) autonomous navigation along the same path previously experienced in the R1 Guided condition (Known).

For the statistical analysis, the considered metrics correspond to the mean values computed over the entire acquisition period, thus providing a representative descriptor of each walking trial. Swing–stance phase percentages, step duration, step count and cadence were calculated using data from both left and right insoles.

The total number of steps was compared exclusively between the R1 Guided and Known conditions, as these two scenarios involved the same walking path, thereby ensuring direct comparability of the locomotor demand.

To ensure statistical validity, the normality of the data distribution was assessed for each variable under the three experimental conditions using the Lilliefors test.

Excluding the total number of steps, a one-way repeated-measures ANOVA (omnibus test) was conducted to assess differences among the three testing conditions for variables that satisfied the normality assumption. When the ANOVA revealed a significant main effect, post hoc pairwise comparisons were conducted. Specifically, paired-sample t-tests were applied for normally distributed variables.

Regarding the total number of steps, data collected in the Unknown condition were excluded from the comparative analysis, as the walking path in this scenario differed from the other two conditions and was therefore expected to result in a different total step count. For this reason, the total number of steps was not included in the repeated-measures ANOVA. Instead, step counts recorded in the R1 Guided and Known conditions, performed along the same path, were directly compared using a paired-sample t-test.

The resulting p-values were corrected for multiple comparisons using the Bonferroni correction, computed as:

$$p_{\text{bonf}} = \min\left(p_{\text{raw}} \cdot m,\ 1\right) \tag{1}$$

where m=3, corresponds to the number of pairwise comparisons per variable (Unknown vs R1 Guided, Unknown vs Known, R1 Guided vs Known). Statistical significance was assigned according to the following convention: results were considered highly significant for $p<0.01$, significant for $p<0.05$, and marginally significant for $p<0.1$. Values not meeting these thresholds were considered not significant.

F. Questionnaires

At the end of the experimental session, participants were asked to complete a set of questionnaires. An ad hoc questionnaire based on a 5-point Likert scale (1–5) was developed to assess multiple domains. Specifically, it investigated the overall experimental experience, the usability of the wearable insole sensor, and aspects related to data privacy, data processing, and trust, with a focus on potential adoption in the healthcare domain. In addition, the TAM and the SUS, both administered using a 5-point Likert scale, were employed to evaluate participants' perception of the R1 robotic platform. The TAM questionnaire assessed the following constructs: Perceived ease of use, attitude toward using, future intention of use, trust, and social perception of the R1 robot. The SUS questionnaire provided a more detailed evaluation of perceived usability, particularly from the perspective of first-time users.

III. Results

From the gait analysis prospective different metrics have been evaluated to detect possible modulations introduced by the robotic guidance. The computed gait metrics from the acquisitions of 15 subjects have been analysed and results are presented in the next sections.

A. Statistical analysis

The Lilliefors test confirmed that all variables of interest followed a normal distribution. The gait metrics computed under the three testing conditions were analyzed using a repeated-measures omnibus ANOVA. The results are reported in Tab. I. Significant effects of the testing condition were found for Total Steps, Cadence, Mean Step Duration, and the mean percentage duration of Swing and Stance phases within the gait cycle. No significant differences were observed for balance-related metrics (percentage of weight distribution on right and left legs).

TABLE I
Repeated-measures ANOVA results across the three testing conditions.

Variable	F-value	p-value
% Balance Right	0.437	0.650
% Balance Left	0.437	0.650
% Swing Phase	9.688	0.001
% Stance Phase	9.688	0.001
Mean Step Duration	327.140	<0.001
Cadence	421.605	<0.001

Pairwise comparisons were subsequently performed only for the variables that showed a significant effect in the ANOVA. Paired-sample t-tests were conducted, and the resulting p-values were adjusted using the Bonferroni correction.

The Bonferroni-adjusted p-values are reported in matrix form in Tab. II, where rows and columns represent the three testing conditions (Unknown, R1 Guided, Known).

TABLE II
Bonferroni-adjusted p-values for pairwise comparisons across testing conditions. Test phases are compared as follows: 1–Unknown, 2–R1 Guided, 3–Known.

	p-values		
Variable	1 vs 2	1 vs 3	2 vs 3
% Swing Phase	0.018	1.000	0.016
% Stance Phase	0.018	1.000	0.016
Step Duration	<0.001	0.399	<0.001
Cadence	<0.001	0.253	<0.001
Total Steps	-	-	<0.001

The distribution of the variables is shown as boxplots in Fig. 3. Statistical significance was indicated using a star-based convention (*** highly significant, ** significant, * marginally significant).

B. Questionnaires

The different investigation domains were evaluated by participants using 5-point Likert-scale rating scores. Participants were asked to express their level of agreement with a series of statements, ranging from 1 (completely disagree) to 5 (completely agree). The statements addressed multiple aspects, including the overall experimental experience, the usability of the wearable insole device, and issues related to data privacy, data processing, trust, and the potential application of the technology in the healthcare domain.

The TAM questionnaire was used to investigate the perceived usefulness and perceived ease of use of the R1 robot, as well as participants' attitude toward its adoption, trust, and social perception aspects. The responses obtained for each domain were averaged across participants. Mean values and standard deviations computed over the 15 participants are reported in Fig. 4.

Additionally, the usability of the R1 robot was further assessed using the SUS. The average SUS score across the 15 participants was 77.5 ± 15.60, indicating good perceived usability.

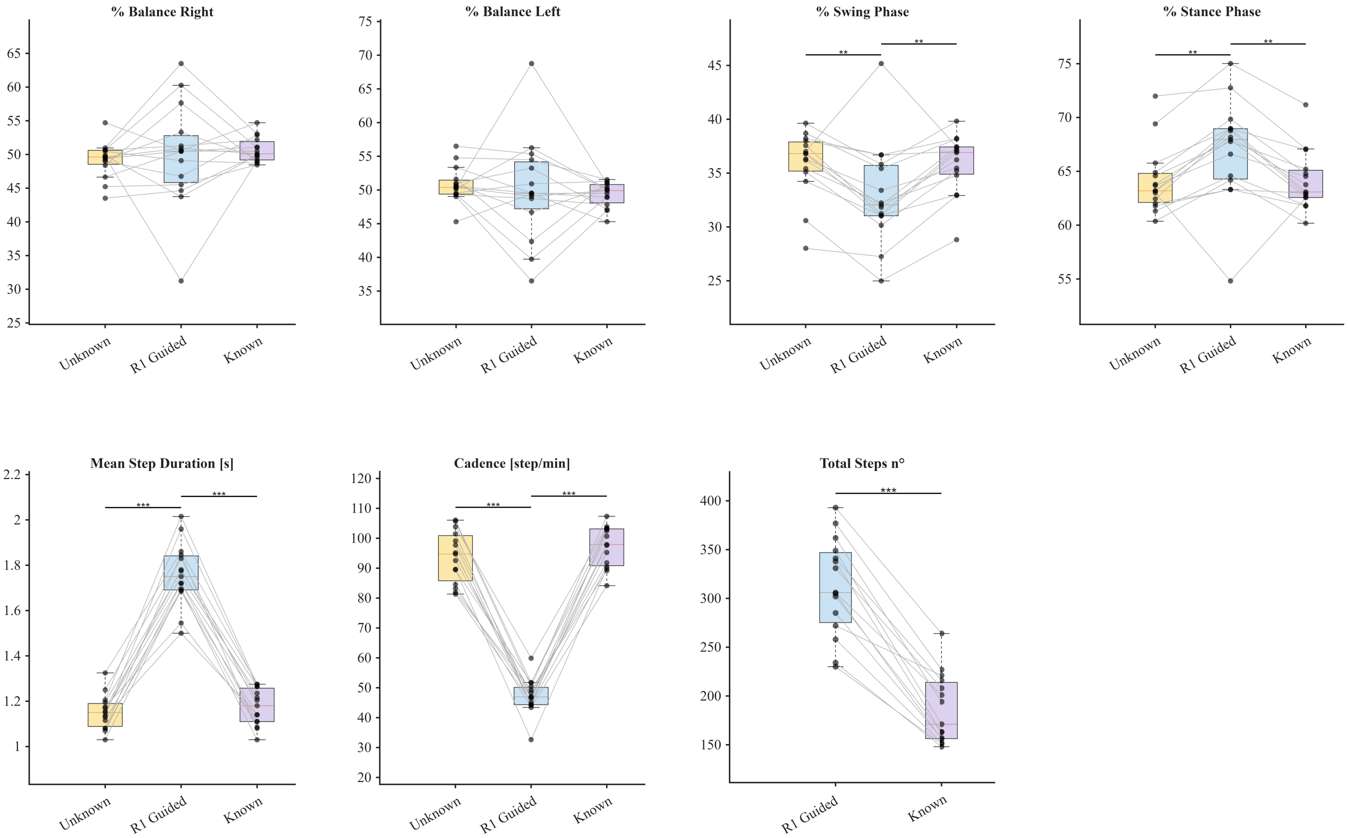

Fig. 3. Gait was evaluated under three experimental conditions: autonomous navigation toward assigned targets in an unknown environment, navigation guided by the R1 robot, and autonomous repetition of the previously guided path (now familiar). Results of the statistical analysis of gait metrics, computed across both lower limbs, are shown. Mean values of the right and left limbs were used for gait phases, step durations, and cadence, while the total number of steps corresponds to the sum of right- and left-limb steps. The analysis shows that R1 guidance does not significantly affect balance-related parameters but does enable modulation of gait cadence and step duration. Correlation analysis was performed across the investigated variables, with relevant correlations highlighted (*** highly significant, ** significant, * marginally significant).

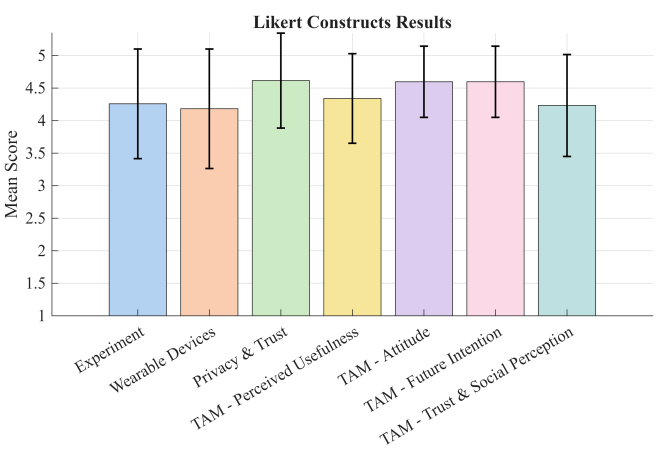

Fig. 4. Mean Likert-scale scores (1–5) across the investigated domains. Error bars represent the standard deviation across the 15 participants.

IV. Discussion and Conclusion

This work proposes a novel approach to investigate and assess human–robot interaction during an accompaniment task, in which participants requested guidance from a robot while navigating an unfamiliar environment. The project was developed with the prospective aim of deploying the R1 robot in clinical settings, for example as a lobby assistant providing guidance to geriatric or mobility-impaired individuals. In such contexts, it is essential to verify that robotic guidance does not induce imbalance or alter physiological gait patterns, particularly in relation to fall-risk prevention.

To assess this aspect, sensorized insoles were adopted to monitor gait parameters under three different scenarios: autonomous navigation in an unknown environment, navigation guided by the R1 robot, and autonomous navigation along a previously guided (known) path. The evaluated metrics across the three conditions are reported in Fig. 3.

The statistical analysis revealed no significant modulation of weight distribution between the two limbs during walking. The balance remained centered around an approximately 50–50 distribution in all conditions, suggesting that R1 guidance does not negatively impact static or dynamic balance. However, slightly increased inter-subject variability was observed in the guided condition. This finding is coherent with the experimental observations: several participants tended to walk faster than the robot's nominal speed and, in order to adapt to it, modified their natural gait pattern. Specifically, subjects often performed a higher number of shorter steps, characterized by reduced swing duration and increased stance duration, resulting in an overall modulation of cadence and step timing.

The prolonged stance phase observed in the guided condition may also explain minor variations in limb loading distribution. Depending on limb dominance, some participants tended to shift weight preferentially toward one side during the longer stance phase, although this did not result in statistically significant asymmetries.

R1 guidance also led to a reduction in cadence variability across participants, indicating a regularizing effect of the robot on walking rhythm. Inter-subject variability was expected, given the heterogeneous age range of the recruited participants. Nevertheless, consistency of the metrics trend across subjects was observed for most of the analyzed gait parameters.

The correlation analysis further demonstrated that robotic guidance significantly influences cadence and temporal gait parameters. This information is particularly relevant for optimizing the robot's navigation parameters, especially its walking speed. The present results suggest that the robot's default navigation speed may have been slightly lower than the participants' preferred walking speed, thereby inducing a less natural gait pattern characterized by an increased number of steps and altered stance–swing phase distribution. The adoption of instrumented insoles proved to be a valuable tool for optimizing the robot's control parameters, providing a standardized and quantitative method to assess the impact of robotic guidance on gait modulation. None relevant differences were statistically observed when comparing the known and unknown conditions. Therefore, both scenarios produced comparable results from a statistical perspective.

Ad hoc, TAM, and SUS questionnaires were administered to collect feedback aimed at improving the R1 platform for assistive guidance. The results showed that, despite the heterogeneity of the participants in terms of age, the technology was overall well appreciated. The wearable setup highlighted the need for slight improvements in terms of comfort, but was appreciated for its potential in supporting gait analysis in a minimally invasive way. Robotic guidance was generally considered a valid form of support, and its potential application in clinical settings was positively evaluated.

Although the robot was described as friendly, easy to interact with, and useful as a guide, most participants expressed a preference for human assistance rather than robotic support. Nevertheless, participants demonstrated trust and openness toward the adoption of monitoring systems and AI-based robotic approaches in clinical environments.

The SUS evaluation indicated a very positive perception of system usability. Out of the 15 participants, 7 rated the system with excellent usability (SUS score < 80), 7 reported good usability (SUS score between 68 and 80), and only one participant expressed dissatisfaction with the robotic platform (SUS score < 50).

Beyond the present study, the experimental setup highlights potential applications in assistive and rehabilitative contexts. In future developments, instrumented insoles could be integrated into a closed-loop control strategy. If the robot were deployed as a gait-training assistant, it could adapt its navigation speed and behavior in real time according to the patient's performance, thereby promoting safer and more physiological gait patterns while continuously monitoring locomotor parameters.

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