Introducing Social Robots to Assess Frailty in Older Adults

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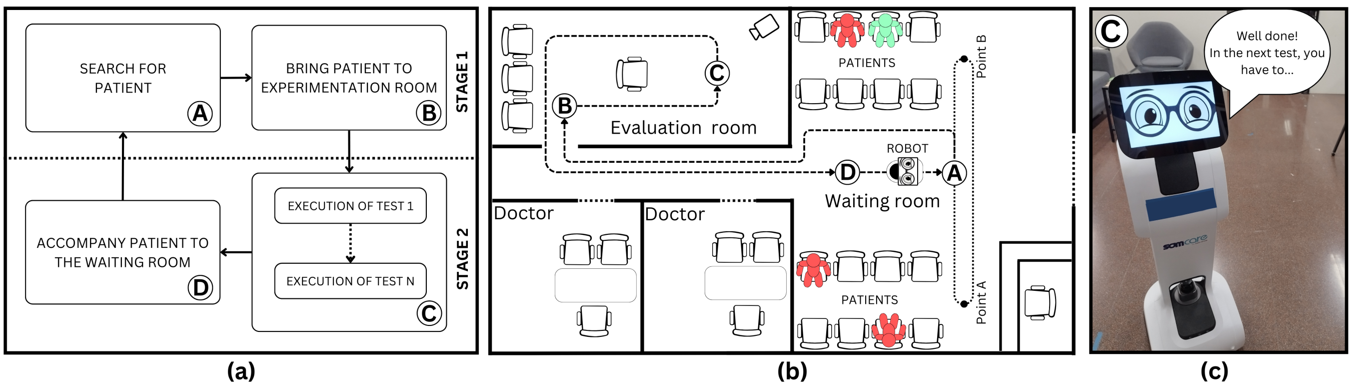

Figure 1: In (a), the workflow of actions expected to be performed by the robot, divided into two stages. In step A, the robot searches for a new patient in the waiting room. In step B, it brings the patient to the evaluation room. In step C, the patient performs the tests with the instructions of the robot. In step D, the robot accompanies the patient back to the waiting room. In (b), an illustration of an ambulatory floor with the locations of the above-mentioned steps: the robot is currently at step A and it needs to find the patient in green. In (c), an example of feedback provided by the Temi robot during step C.

ABSTRACT

Frailty is a crucial indicator in determining the well-being of older adults in terms of their health. With the growing number of elderly people, the demand for geriatricians is increasing, which means that they have less time to spend with each patient. The current methods for frailty assessment use simple tests that are time-consuming and do not require specific medical expertise. To address this issue, this paper proposes the use of social robots to assess frailty autonomously. It presents a practical proposal that defines the robot's behavior and explains the design and implementation concepts. Finally, it discusses some of the challenges that may arise from introducing social robots as frailty evaluators.

CCS CONCEPTS

• **Information systems** → *Test collections*; • **Applied computing** → **Health care information systems**.

KEYWORDS

Frailty Assessment, Healthcare, Social Robots, Behavior Trees

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1 INTRODUCTION

The aging population is growing rapidly [22], and it has become a major concern for health organizations worldwide [28]. This demographic shift has resulted in an increased demand for healthcare services by older adults. As a consequence, healthcare resources such as personnel, time, space, and technology must be expanded to effectively meet this rising demand. In addressing the challenges

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associated with the aging population, one critical aspect is frailty. Frailty is a geriatric syndrome that commonly affects older adults, leading to a decline in their physical and mental health [17]. It makes them more vulnerable to illnesses, disabilities, and mortality due to a decrease in their physiological reserve and adaptive capacity. Studies have shown that a person's frailty profile is a better predictor of treatment tolerance and survival than their chronological age [21, 30].

To address the challenges associated with frailty in the aging population, the World Health Organization (WHO) has developed the framework of Integrated Care for Older People (ICOPE)[1]. The ICOPE framework, which employs questionnaires and validated scales, comprises six key components: cognitive impairment, mobility, nutrition, vision, hearing, and mood. By addressing these areas, the ICOPE framework aims to enhance the health and well-being of older individuals and alleviate the burden on healthcare systems.

Concerning mobility, there are some standardized tests to evaluate this dimension, such as the Timed Up and Go (TUG) [27] and the Short Physical Performance Battery (SPPB) [20], amongst many others [15]. However, while these tests are simple and require minimal effort on the part of the patient, they are time-consuming for both patients and healthcare professionals. In this context, robots can be valuable tools in facilitating mobility assessments, ensuring they are conducted more efficiently and accurately, augmenting therapist effectiveness, and lessening their burden. Indeed, robots have been proven to be very effective in repetitive tasks e.g., physical and cognitive training [5]. Furthermore, robots can provide additional information than the current gathered by professionals at sight. Despite the significance of frailty assessments, only a limited number of studies have tackled the challenge of autonomously administering these tests using computer vision techniques [14, 18, 19, 33] or physical sensors [29, 31] and even fewer studies involved robots. For instance, Olde *et al.*[25] used a social robot to explain different physical exercises to diminish people's frailty, but a healthcare professional delivered the tests.

While recognizing the positive impact of a robot's social presence in improving patient engagement [32] and reducing dropout rates[13], our central goal is to advance beyond Olde's work and develop a more sophisticated system. The main contribution of this work is the definition of a new framework for robotic frailty assessment co-designed with healthcare professionals, in which the robot serves as a social facilitator for the medical staff. The framework consists of two stages. In the first stage, the robot locates patients in the waiting room and brings them to the evaluation room. In the second stage, the robot guides them through a series of well-established tests to assess their level of frailty. We present the framework and discuss the need to address various aspects of human-robot interactions (HRIs), including patient identification, effective communication, motivation during the tests, and ensuring understanding, among other factors.

2 PROPOSED APPROACH

In this section, we will discuss the framework for automatic frailty assessment and its two main stages (see Fig. 1(a)). We will explain the procedures and implementation for each of the two stages, as well as the challenges we anticipate needing to address to successfully achieve our objective. It is worth noting that we have already started working on the second stage and we will be sharing some preliminary results. However, the first phase is still in its early stages and the primary building blocks still need to be implemented on the robot.

2.1 Stage 1: Seeking for patient

Aiming to lessen the healthcare personnel's workload, an important stage that shall be automatized in the frailty assessment process is the patients' localization. At this stage, the robot's goal is to locate the patient, who is next in line, in the waiting room. The robot will then accompany them to the evaluation room, which corresponds to steps A and B in Fig. 1(a).

Procedure. The first step for the robot is to check for new patients to serve. The patient list is retrieved from the hospital database queue, which is updated every time a patient registers at the entry.

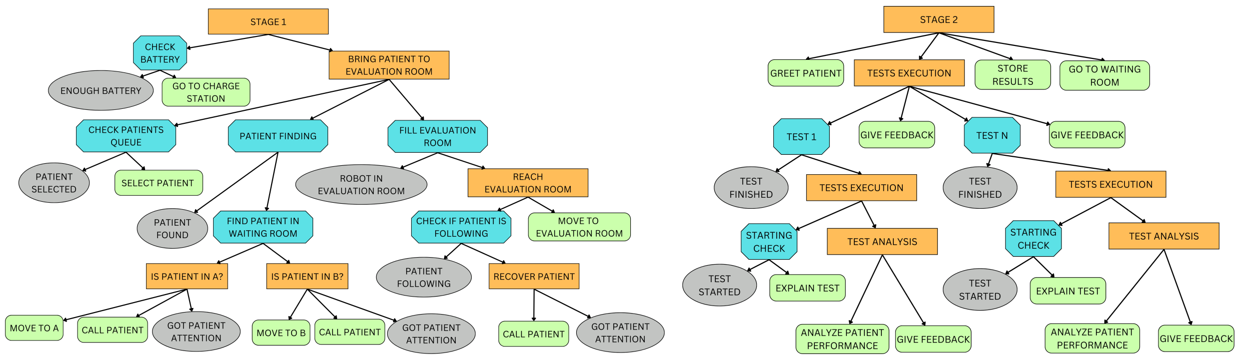
Once the robot detects that a new patient is available, it will move to predefined positions in the waiting room. In the example in Fig. 1(b), the robot can move to points A or B. During the navigation, the robot calls the patient using synthesized speech and also with its name written on the screen to grab their attention.

The last step consists of guiding the patient to the evaluation room while the robot ensures that the patient is following. If the robot can't locate the patient within a time set, it will proceed to the next one in the queue.

Implementation. There are different methods for designing the architecture of a social robot in the current context. These methods include Finite State Machines (FSM) and Behavior Trees (BTs). The use of BTs in social robot applications in dynamic environments has been documented in the literature as they offer more advantages over FSM [11], such as higher flexibility, responsiveness, and modularity.

Therefore, in our work, the robot's software architecture is based on BTs. Those offer the possibility to modify the actions of the robot, for example adding a new test or condition, without increasing the complexity of implementation. This makes the framework easily adaptable to the specific needs of each healthcare center.

In Fig. 2(a), we can see the structure of the BT. The robot begins the stage with a sequence that first ticks in a sanity check selector to ensure there is enough battery for both stages. Next, it moves to the sequence branch in charge of bringing a patient into the evaluation room. This sequence is split into three selectors. First, the robot looks for a new patient in the database queue, then it searches for them, and finally, they proceed to the evaluation room together. The selector in charge of checking the patients in the queue first checks if a patient has already been selected. If not, it then checks if there are any patients in the queue. If there are, the first patient in the queue is marked as selected. The BT then moves on to the next sequence branch, which is finding the patient. When searching for a patient, the BT first checks a conditional variable to determine if the patient has already been found. If the patient has not been found, the next node in the BT is a selector. Each branch of the selector checks if the patient is in a specific location. When the robot arrives at the search location, it calls out to the patient and



(a) (b)

Figure 2: Behavior trees for stage 1 (a) and stage 2 (b). The blue octagons are selector nodes, the orange rectangles are the sequence nodes, the green rounded squares are the action nodes, and the grey ovals are condition nodes.

tries to get their attention. If the patient does not respond, the robot moves to another search location and repeats the process. If the patient is found, the system moves to the final branch of the tree, which involves bringing the patient to the evaluation room. In this last branch, the robot needs to ensure that both itself and the patient reach the evaluation room. To do so, the robot constantly checks that the patient follows it until they both reach the evaluation room. If the patient is not following, the robot calls out to the patient and verifies if they have their attention. If the robot succeeds in getting the patient's attention, it will keep moving to the evaluation room.

To make the framework more user-friendly for caregivers, the robot will have a touchscreen menu to turn on, shut down, or modify the application. Additionally, it will include an application for building a map of the ambulatory.

Challenges. In this stage, we have identified the following challenges: (i) How to grab the patient's attention and identify them? (ii) How to understand the patient?

The first challenge involves understanding the most effective social cues that best fit the patient's physical and cognitive impairment to gather their attention. In ambulatory and hospital contexts, therapists usually call out the patient's name and wait for them to show up in front of them. If that does not work, then they search for them around the waiting room and finally, they identify the patient if they are in the room. While this task seems quite straightforward for humans it is not trivial to implement that on a robot. A possible solution would be to replicate the above-mentioned therapist's behavior. However, instead of navigating around to seek the patient, the robot tries either another interaction modality (speech, gesture, or acoustic cues) or moves to a different point on the map. To identify the patient, one obvious solution would be to use facial recognition. However, that could raise privacy issues as the robot would need to record patient's images. This solution is also challenging from a technological point of view as automatic facial recognition systems struggle to work with older adults due to a limited sample representation of them in the training set [8]. A viable solution that can address these limitations would be using QR codes or RFID technologies to identify each patient.

Understanding the patient verbal and non-verbal interaction is an additional challenge. Humans are naturally good at understanding each other and adapting to different situations. In our context, we will primarily concentrate on verbal interactions, since it is preferred over other communication channels by older adults [6], and those that can arise from the tablet. To accomplish this, we require an Automatic Speech Recognition (ASR) system that can recognize the patient's intentions using, for instance, rasa [7]. This will enable the robot to engage in small talk conversations with the patients. Moreover, the tablet can be used to support the interactions and clarify what the robot has understood, making the overall interaction more transparent to the patient. It is important to note that ASR, like face recognition systems, suffers from the same issue. Therefore, we need to refine the current speech recognition models to include a more representative older population in the training set [9].

2.2 Stage 2: Test performance

At this stage, the robot's objective is to perform the frailty assessment through the tests and then bring the patient back to the waiting room. In Fig. 1(a) it corresponds to steps C and D.

Procedure. To begin with, the robot greets the individuals who have entered the evaluation room. It then directs the patient to a designated area of the room where the tests will be conducted. Once the patient reaches the designated area, the robot provides a detailed explanation of each test and displays a demonstration video on the screen. The explanations of the tests are presented both visually and audibly. The robot explains each test to the patient and monitors the start and end times of each test. Ultimately, it stores the results in the clinical history database and brings the patient back to the waiting room.

Implementation. This stage is also developed using BTs (see Fig. 2(b)) to offer a flexible and reactive service. The robot starts with a sequence for gathering data. The latter consists of another sequence (test execution) and various actions. First, the robot greets the patient using text-to-speech and visual cues on the touchscreen. Then, it proceeds to execute the tests. The robot activates the camera with a 3D skeleton pose tracking algorithm to detect the patient.

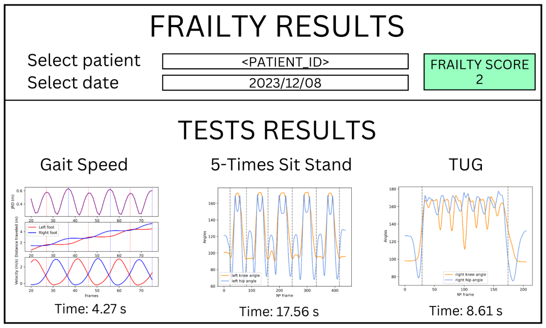


Figure 3: Example of visualization of the tests' results. As it can be noted, besides the time to complete them, doctors can access and visualize additional information.

The skeleton is used to identify the start and end of each test in real-time, as well as the patient's performance. The tests start with an explanation describing how they must be performed. Then the movements of the patient will be analyzed to detect the moment when the patient completes each of the tests. The robot will not only deliver them but also will be able to detect unexpected behaviors of the patients (e.g., cheating or leaving the room before the end of the tests, or not performing correctly the test). Additionally, the robot provides personalized feedback during the tests. The type of feedback to be given and when to give it is decided to ensure a comfortable and motivating interaction. Fig. 1(c) provides an example of feedback and an explanation of the next test.

We are collaborating with the hospital doctors to define an initial set of tests. The tests that have been implemented are the following: i) standing balance, ii) 5 times sit-stand, iii) gait speed; and finally, iv) timed Up and Go. While doctors only collect the time to perform each test, by introducing a robot we can gather additional measures. For example, the stride and step lengths and velocities during the walk, the balance during the walk, and the stability during the balance test, amongst others. We evaluated the feasibility of our system to monitor the users and measure their performance both in our lab with a convenient population and in the healthcare facility with older adults [26].

After conducting the tests, the subsequent step involves storing the results in the database and formatting them in a way that doctors can easily visualize them. This allows the doctor to access the results during the visit, as shown in Fig. 3. Finally, the robot accompanies the patient to the waiting room and the robot switches to stage 1 of the BT.

Challenges. We identify the following challenges: (i) What kind of techniques could we use to provide personalized interaction, and how do we provide feedback to them? (ii) How can we detect unexpected patient behavior, and how should a robot react to it? (iii) How can we ensure that patients trust the robot to manage their data?

Concerning personalization, research has demonstrated that tailoring a robot's behavior to an individual's preferences can significantly increase trust and acceptance, particularly during prolonged interactions [23]. This is especially pertinent when dealing with older adults, as their physical and cognitive abilities necessitate a personalized approach [24]. However, collecting data on each individual can pose a challenge. To address this, we propose implementing a system akin to Andriella [4] whereby therapists can impart prior knowledge about the patient and specify their initial preferences. This approach would expedite the learning process and ensure that the robot's behavior aligns with the patient's needs from the outset. Therefore, incorporating expert prior knowledge into behavior adaptation techniques could be valuable [10].

Exploring when to offer feedback is an important aspect to consider. In this regard, we will examine research on proactive robot behavior [2, 12]. Finally, regarding what human-like features the robot shall be endowed with, previous work suggests that personality behavioral patterns would be relevant to consider in a motivational feedback robot [3, 16].

In terms of detecting unexpected behavior from humans, our focus will be on identifying whether patients are performing their tests correctly. While it may be possible to recognize these types of events, we acknowledge that how to address them is still an area of ongoing research. There are a few potential options, such as having the patient redo the test, providing feedback to the robot about the situation, or skipping to the next test and notifying the doctor.

One last hurdle is to ensure that it can explain its data management, which includes disclosing the information that has been processed and giving patients the ability to exercise control over it. One possible solution could be to obtain the patient's informed consent, while also explaining how the data that has been gathered will be utilized by the doctor. Additionally, the patient can agree or disagree on what data to be shared.

3 CONCLUSION AND FUTURE WORK

This article discusses the feasibility of using social robots to conduct frailty assessments in healthcare systems. The framework for automatic frailty assessment is divided into two main stages, for each of which we sketched the procedure, implementation, and the main challenges. Some of those challenges still have no specific solution, but they are great research opportunities that we aim to investigate in the near future.

Our next objective is to automate the assessment of tests and detect the start and end of each test in real-time. This will allow us also to identify unexpected patient behavior as well as to react to them. Additionally, we will continue collaborating with healthcare professionals using a co-design approach to develop our technology.

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