Towards Safer Mobility: Developing and Evaluating a Fall Detection System for a Smart Walker

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***Abstract*— Fall detection and prevention is a key issue for healthcare in older adults since it prevents the development of multiple cognitive and physical disorders. This study aims to evaluate multiple falls and near-fall detection algorithms to be integrated into a smart walker, which usually comes with an increased risk for falls in case of improper use. A six-axis IMU worn at the user's waist extracts trunk inclination, angular velocity and acceleration. The study employs various fall detection algorithms, such as Kangas and Vertical Velocity, tailored for fall detection, Triangular Feature, Vertical Angle and a Modified Vertical Velocity for pre-fall detection. The experimental protocol involved various Activities of Daily Living (ADLs) and simulated falls, emphasizing participant safety and data usability. The results from this study provide insights into the effectiveness and reliability of the integrated fall detection system in scenarios involving a smart walker.**

I. Introduction

According to the World Health Organization [1], it is estimated that 684.000 individuals die from falls, and 37.3 million falls are severe enough to require medical attention every year. In this scenario, older adults over 60 years old face the highest risk of falls, with 1 in 3 over 65 affected by at least one fall annually, and this increases to 50% for older adults over 80 [2]. The costs of fall-related injuries are consistent [3]. In America, the overall medical costs related to non-fatal fall injuries are 50 billion USD annually [3].

Injuries resulting from falls can range from non-fatal to fatal, with hip fractures being particularly severe among the non-fatal outcomes. Hip fractures are closely associated with a loss of independence, psychological disorders, and an elevated one-year mortality rate [4]. Other non-fatal fall-related injuries include those affecting wrists and the head. Fall risk factors are typically classified as intrinsic or extrinsic. The causes of a fall are often multiple and interconnected [5]. Biological risk factors, in the pathological aspect, play a crucial role. The presence of one or more pathologies elevates the risk of falling [2]. Cognitive and neurological diseases, such as Parkinson's disease or dementia, exert a substantial influence on the falling rates among the elderly, akin to the physical impairments stemming from both normal ageing and specific pathologies [2].

It is important to understand that the consequences of falling are not only related to the mere potential physical disabilities but also to the rise of psychological problems such as fear of falling, anxiety, and depression [6]. In particular, the fear of falling is part of the post-fall syndrome, which leads to severe psycho-motor inhibition, high anxiety symptoms, activity avoidance, loss of self-confidence, and a loss in the general quality of life [6]. Most of the categorizations of falls are related to the factors responsible for them. Other categorizations are linked to the direction of the fall [7] or the position before the fall [8].

Regarding fall detection, especially for older people, the demand for technologies supporting this population has rapidly risen [9]. This can be seen as a shield for the sub-outcomes from falls, such as the financial costs, the demand for medical personnel, and the burden for the patient's caregivers. In this sense, the purpose of a fall detection system is the automatic detection of falls and the enabling of assistance by caregivers if required [8]. A fall detection system should be able to minimize privacy intrusion and obtrusiveness with heavy wearable devices, distinguish between falls and near-fall events from other activities of daily living (ADLs), and minimize false alarms [10].

In this sense, it is important to highlight the difference between falls and near-fall events. Near-falls usually are more frequent and may occur before falls [11]. They can be considered a fall risk prediction parameter when analyzing the fall history for risk assessment. The traditional definition of a near-fall is "*A stumble event or loss of balance that would result in a fall if sufficient recovery mechanisms were not activated*" [11], [12].

In addition to falls detection, walking aids are also required, as they provide cognitive and physical support during ageing [13]. Walking aids can increase safety, maintain walking ability and support balance. The most common devices include canes, crutches, and walkers, and depending on the patient's needs, clinicians might prescribe one for daily use [14], [15]. However, improper use of walking aids is recognized as a potential fall risk factor. This, in turn, contributes to an escalation in the user's fear of falling and exacerbates the spatiotemporal gait pattern [4], [16]. In fact, in 2009, more than 47.000 adults over 65 years old with fall injuries related to walking aids were treated in the US, 87.3% of such falls associated with walkers, 12.3% to canes and 0.4% to both [17]. In particular, the use of a walker not

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only can increase the risk of falls but also modifies the gait biomechanics, and it is important to assess the performance of the fall detection system during walker-assisted gait.

In general, walkers are easy to use while leveraging the user's remaining locomotion capability. However, to overcome the risk of falls associated with walkers and prevent fall events, different technologies have been integrated into conventional walkers. Particularly, advances in robotics make it possible to develop more intelligent/smart walkers by adding sensors, actuators, and high-level processing algorithms for Human-Robot interaction [18]. Smart walkers often provide sensory assistance, cognitive assistance, and health monitoring. Some walkers also focus on sit-to-stand transfers, navigation help, obstacle avoidance, and fall detection [19].

This study aims to integrate an efficient and accurate fall detection system into a smart walker based on a conventional wheeled walking frame. The system is designed as a multi-sensor system composed of a wireless IMU sensor attached to the back of the user and a sensing system designed on the smart walker. This study compares different threshold-based algorithms for fall detection applied to wearable inertial sensors to find the most suitable application on walkers.

II. Related Works

A small literature review was conducted. The article search was conducted across three databases (Pubmed, Scopus, and Ovid MD) during April 2023. To this end, the following search equation was used, along with additional search filters including only articles in English and only articles from the last ten years.

- `\fall detection" OR \falls" OR \fall risk" OR \fall prevention" OR \fall prediction" OR \pre-fall detection" OR \fall-alarm" OR \accidental falls")` AND
- `(\smart walker" OR \smart mobility aid" OR \smart rollator")`

According to this, 14 studies of fall detection systems integrated with walkers revealed that only a limited subset, namely five studies, employed traditional walkers equipped with sensors dedicated to fall detection [9], [10], [20]–[30]. The predominant use of inertial sensors, encompassing IMUs, accelerometers, or gyroscopes, was evident in these investigations, applied strategically to both the user and the walker [21]–[23]. These sensors adeptly extracted nuanced differentials in acceleration and angular velocity. Notably, a prevalent practice emerged involving integrating force sensors into walker handles [10], [20], [23]–[25], [27], [29]. This strategic placement facilitated the analysis of pressure variations on the handles, presenting a pragmatic approach to acquiring dependable data on falls directly from the walker. These methodologies, distinguished by their cost-effectiveness and minimal impact on the user's daily life, contrast the imposition of wearable sensors. While Laser Rangefinder (LRF) sensors were sparingly employed, they emerged as a promising and economical alternative to depth cameras [20]. Their potential extended beyond fall detection, offering insights into leg positioning and user-walker distance. This dual functionality proved instrumental in detecting falls and identifying precursors to loss of balance, thereby enabling the implementation of near-fall detection and preventive measures.

Furthermore, among the studies examined, a diverse array of sensing technologies was employed for fall detection, including seven studies utilizing inertial sensors, two incorporating cameras, 6 deploying pressure sensors, six leveraging LRFs, 1 employing ultrasonic sensors, 1 integrating a smart insole, and 1 utilizing odometry as a distinctive modality for fall detection. In this sense, enhancing the precision of fall detection systems involves the integration of various sensor types, which can be classified as either "homogeneous," utilizing a uniform sensor type such as inertial or ambient sensors, or "heterogeneous," incorporating diverse data sources in a multimodality-based fall detection system. Research findings underscore the substantial advancements achieved by combining multiple sensor types, as this fusion-based approach furnishes comprehensive information on human activities and gait balance characteristics [10], [23], [31].

Systems reliant on a single sensor technology often grapple with accuracy and reliability issues. For instance, ambient and video-based systems face limitations in monitoring field size, installation complexities, maintenance challenges, and adjustments, contributing to increased costs [32]. Wearable-based systems, while providing data over wireless channels, may prove intrusive for users due to prolonged wear periods and potential unreliability. A multisensor-based system offers distinct advantages, permitting adjustments tailored to sensing scenarios (indoor/outdoor), enhancing flexibility to meet user needs, and bolstering reliability by harnessing diverse information sources. Given fall circumstances' intricate and varied nature, the fusion of disparate information emerges as a highly effective strategy.

III. Materials and Methods

A. The BRL Smart Walker

For this study, a conventional four-wheeled walker was used and empowered with multiple sensors and actuators to extract information from the user and the environment. The proposed BRL Smart Walker (SW) uses encoders (AS5600 Magnetic, Osram, Germany) on the rear wheels to estimate the device's movement. An Inertial Measurement Unit (IMU) (BNO080, SparkFun, USA) at the bottom of the seat estimates the SW's orientation. These two sensors provide SW's odometry. The onboard Raspberry Pi 3 Model B 64GB (Raspberry Pi Foundation, UK) runs Debian with the Robotic Operation System (ROS) framework. A camera (Astra S, ORBECC, China) on the backrest records the user's gaze during experiments. The box in the middle of the walker holds all the electronics.

Additionally, from the related works, three additional sensors were chosen for the fall detection system. A wireless IMU sensor (MetaMotionRL - MBIENTLAB) positioned on the waist [10], [23], [33]. A pair of Force Sensing Resistors (FSRs) (Interlink Electronics FSR 402) for each handlebar

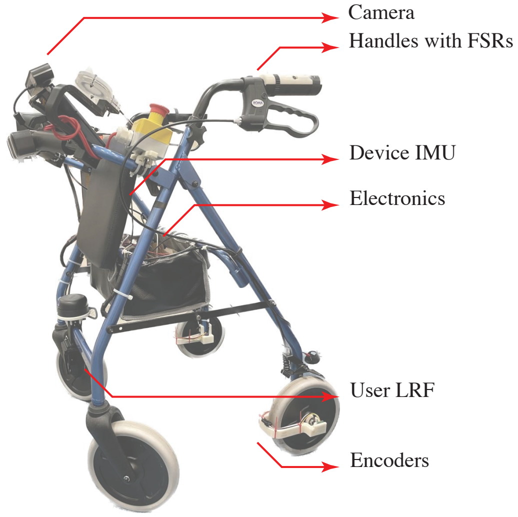

Fig. 1. Illustration of the BRL Smart Walker and the proposed sensors [34].

of the walker [9], [10], [20]. An LRF (URG-04LX-UG01) facing the user legs mounted over the walker [10], [20]. Fig. 1 illustrates the smart walker and the main sensors on it.

B. The Fall Detection System

The system is composed of a wireless IMU sensor, which will be attached to the user's back using a waistband, and the smart walker's sensing system. The sensing system comprises sensing handlebars (on which force sensors are applied to detect the differences in the user's grip force) and an LRF sensor, which can detect the distance between the user and the walker and analyze the gait.

First, the system checks if the handlebars are being held using FSRs. If both are gripped, it moves to the IMU sensor on the user's back, which looks for signs of falls or near-falls based on body movements. Simultaneously, the LRF on the walker focuses on the legs. It checks if they are in a safe position and if the stride length is normal. A warning is sent if the legs are not in a safe position or the stride is unusual. Generally, the handlebars start the check, the back sensor looks for overall body movements, and the walker's sensor watches the legs for any issues. Together, they help detect and warn about potential falls.

From the 6-axis IMU sensor, the acceleration and the angular velocity on the three axes were extracted at a sampling frequency of 100 Hz. The data was analysed using MATLAB R2023a (MathWorks Inc., Natick, MA, USA). The acceleration data has been filtered with a 4-order Butterworth low-pass filter with a cutoff frequency of 10 Hz, and a tilt correction has been applied due to the potential misalignment with the anatomical planes. The angular velocity data instead has been filtered with a 2-order Butterworth low-pass filter with a cutoff frequency of 20 Hz.

The acceleration was then used to calculate the sagittal and coronal plane trunk inclination to decide the detection algorithm. In case of trunk inclinations lower than 60°, pre-fall detection algorithms are applied. In contrast, for trunk inclinations equal to or greater than 60°. Fall detection algorithms are applied. Following the steps of *Ahn et al.* algorithm, the sum vector of the acceleration and the sum vector of the angular velocity was extracted [35].

Fall Detection Algorithms

1) Kangas Algorithm: The algorithm was adapted by incorporating thresholds specific to the waist application and enforcing the trunk inclination restriction of greater than 60°. Initially, the algorithm checks if the vertical axis acceleration is below 0.75 g (first threshold). If met, it identifies the maximum acceleration norm in the subsequent samples, verifying if it exceeds 2g (second threshold). If this condition is satisfied, the algorithm examines the lying posture, assuming that the person will likely stay lying on the floor or other surfaces post-fall. This is determined by evaluating the vertical acceleration within a 2-second interval starting from the sample after the identified impact. A fall is detected if it is below 0.5 g (third threshold). The algorithm demonstrates a sensitivity of 97.5%, and a specificity of 100% [36].

2) Vertical Velocity Algorithm: The Vertical Velocity (VV) feature is determined by numerically integrating the acceleration along the y-axis. A fall is identified if the VV falls below the designated threshold of -1.3 m/s. The algorithm initiates only when the trunk inclination exceeds 60°. In the original study, utilizing the IMU on the trunk, the algorithm demonstrated 100% accuracy, detecting an average of 323 ms before the impact on the trunk [37].

Pre-Fall Detection Algorithms

3) Triangular Feature Algorithm: The Triangular Feature (TF) is determined as the area of the triangle formed by the vector sum of acceleration along the three axes. During standing, the acceleration along the y-axis is 1 g, while the others are 0, resulting in a TF value of 0. Similarly, when lying down, it is the acceleration along the z-axis that is 1 g, leading to a TF value of 0. Thresholds were established by evaluating sensitivity, specificity, and accuracy across various possibilities for acceleration ($Anorm < 0.9g$), angular velocity ($AVnorm > 47.3$ °/s) vector sums, and TF ($TF > 0.19$). The algorithm demonstrated a sensitivity of 100%, specificity of 83.9%, and accuracy of 90.3% on the SisFall dataset. On the study dataset, accuracy reached 100% with a lead time of 427 $\pm$ 45.9 ms. Upon visual analysis of data, a modified Triangular Feature Algorithm was implemented, adjusting the threshold to accommodate the specific conditions of the study (i.e., $Anorm < 0.85g$, $AVnorm > 35$ °/s, and $TF > 0.15$). [35].

4) Vertical Angle Algorithm: The Vertical Angle Feature is derived from sagittal or coronal trunk inclination (trunk), with thresholds applied as follows: $Anorm < 0.9g$, then ($AVnorm > 47.3$ °/s), and finally $trunk <$°. The algorithm was tested on the SisFall dataset, revealing a sensitivity of 100%, specificity of 78.3%, and accuracy of 86.9%. On the study dataset, the accuracy reached 100% with a lead time of 401±46.9 ms. Similarly, for the Vertical Angle Algorithm, thresholds were adjusted to align with the specific characteristics of the current study (i.e., $Anorm < 0.85g$, $AVnorm > 35$ °/s, and $trunk <$°) [35].

5) Pre-Fall Vertical Velocity Algorithm: The *Bourke et al.* Vertical Velocity Algorithm underwent modification to identify pre-falls rather than actual falls. The constraints applied to trunk inclination, acceleration norm, and angular velocity norm in the previous algorithms were incorporated into this one as well, with the addition of the Vertical Velocity feature, calculated through numerical integration of the acceleration along the y-axis. The Vertical Velocity threshold was adjusted from -1.3 m/s to -0.3 m/s, determined through manual analysis of data obtained from the experiments [37]. The final pre-fall vertical velocity threshold underwent a second modification to a more constrained version with a threshold of -0.25 m/s.

Note that the proposed pre-fall algorithms have initial and modified thresholds. This is in the light of finding the best configuration for near-fall events.

C. Experimental Protocol

Initially, an analysis of studies involving fall detection with wearable sensors (EMG electrodes, pressure sensors, and IMUs) was conducted. Protocols in related works focused on two main trial groups: Activities of Daily Life (ADLs) and falls. Common ADLs included standing, sitting, standing up, walking at different paces, and stair ascents and descents. Falls encompassed forward, backwards, left, and right side falls, slipping, and tripping. Safety measures often included the use of mattresses. However, when examining protocols specifically designed for walkers, the number of studies diminished significantly, with unclear protocols often lacking safety measures. Based on the analysis of various studies, an ad hoc protocol was devised, prioritizing both safety and data usability.

The research ethics committee of the University of the West of England Bristol approved the experimental protocol. All experiments were conducted at the BRL laboratory. Participants were briefed on experiment procedures through a participant sheet and practical demonstrations at the laboratory. Participants wore a MetaMotionRL wearable sensor on their back using an instrumented walker. To ensure safety, a Body Weight Support (BWS) system, comprising a vest (RgoSling Ambulating Vest) attached to a mobile suspension (Molift AIR 205), was employed. The BWS or harness served as a critical safety measure. Various ADLs were performed, each for three repetitions, taking approximately 10-15 minutes. The activities included walking at a normal pace, walking fast, stand-to-sit transfer, sit-to-stand transfer, picking up an object from the floor, and standing still.

Near-fall events were conducted, including falls while standing still, falls while walking, and free-falling, each performed with and without the walker. The participants were asked to recover balance without falling to the floor, ensuring a flexed knee and using the walker as support. The participants were asked to conduct the falls in 5 directions (i.e., left, right, forward, backwards, and downward), repeating each fall three times. The time required for near-fall events was approximately 30 minutes. The study recruited young, healthy participants (20-60 y.o.) randomly from both genders, with exclusion/inclusion criteria including no cerebrovascular or neurological diseases, no cardiovascular diseases, no motor impairments, no relevant medical history, and no medication use.

TABLE I
METRICS COMPARING FREE FALLS VS. FALLS WITH SMART WALKER

Algorithms	Sensitivity [%]		Specificity [%]		Accuracy [%]	
	SW	Free	SW	Free	SW	Free
Kangas	100	100	100	100	100	100
Vertical Velocity	100	100	100	100	100	100
Triangular Feature	27.5	9.5	100	100	58.8	52.6
Vertical Angle	41.4	69.4	100	100	64.8	67.6
Pre-Fall Vertical Vel.	28.9	39.5	100	100	58.1	62.9

A total of 6 participants were selected as case studies (30 ± 8.29 y.o., 173 ± 6.66 cm, and with IMU located at 106.33 ± 3.32 cm). All agreed and gave signed consent to take part in the study. Finally, to assess the performance of the algorithms, sensitivity, specificity, and accuracy were calculated as [38]:

$$Sensitivity = \frac{TP}{TP + FN} \tag{1}$$

$$Sensitivity = \frac{TN}{TN + FN} \tag{2}$$

$$Sensitivity = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

True positive (TP) is the number of participants correctly identified as fallers. False positive (FP) is the number of participants incorrectly identified as fallers, True negative (TN) is the number of participants correctly identified as non-fallers, and False negative (FN) is the number of participants incorrectly identified as non-fallers.

IV. RESULTS

An inter-case study analysis was conducted for the six participants, analyzing the performance of the proposed algorithms between free falls conditions and falls during walker-assisted gait[1]. Table I describes the sensitivity, specificity, and accuracy metrics for the proposed falls and pre-falls with the original thresholds. Table II describes the sensitivity, specificity, and accuracy metrics for the proposed falls and pre-falls with the modified thresholds.

All the algorithms were applied to a public dataset comprising eight participants, evenly split between males and females, all in good health and young age. The participants exhibit an average height of 1.7 meters with minimal variability (± 0.1 meters), an average weight of 65.4 kilograms with a slight fluctuation (± 9.2 kilograms), and an average age of 25.1 years with a range of ± 2.9 years. The experimental setup involves a 200x100x40 cm mattress strategically

[1] Raw data is available here

TABLE II
METRICS COMPARING FREE FALLS VS. FALLS WITH SMART WALKER WITH MODIFIED THRESHOLDS.

Modified Algorithms	**Sensitivity [%]**		**Specificity [%]**		**Accuracy [%]**	
	SW	**Free**	**SW**	**Free**	**SW**	**Free**
Triangular Feature	31.2	31.6	100	100	59.2	63.7
Vertical Angle	43.3	83.3	100	100	65.9	74.9
Pre-Fall Vertical Vel.	28.3	68.9	100	100	59.2	77.9

TABLE III
METRICS FOR MODIFIED ALGORITHMS APPLIED ON THE DATASET

Algorithm on Dataset	**Sensitivity [%]**	**Specificity [%]**	**Accuracy [%]**	**Confidence Interval**
Kangas	86.1	100	92.2	[89.69%, 96.31%]
Vertical Velocity	100	39.3.6	73.4	[56.23%, 72.24%]
Triangular Feature	72.2	44.6	60.1	[47.89%, 67.24%]
Vertical Angle	100	28.6	68.7	[49.97%, 74.73%]
Pre-Fall Vertical Velocity	100	14.3	62.5	[55.90%, 71.77%]

positioned on a 40 cm tall wooden structure, with sensors securely attached to the lower back using a belt for precise and consistent placement. The dataset incorporated three distinct protocols: (1) static simulated falls, (2) dynamic simulated falls, and (3) activities of daily living. This dataset was retrieved from an online repository. Table III shows metrics for all algorithms and average confidence intervals for 95% confidence.

V. DISCUSSION

The deployment of fall detection systems incorporating IMU sensors represents a common safety measure for the elderly, with reported statistics typically ranging from 95-99% in existing studies [39], [40]. However, the outcomes of this study reveal notably lower statistics, prompting a critical examination of the limitations introduced by the use of the Smart Walker and the safety system.

The walker's presence during experiments introduces inherent challenges, particularly when simulating falls, creating potentially hazardous scenarios. The bulky design of the walker not only hinders the smooth execution of experimental procedures but also raises safety concerns. Despite the incorporation of a body weight support system, simulating falls induces anxiety in participants, exacerbated by the presence of the walker. These findings align with those of *Pereira et al.*, *Irgenfried et al.*, and *Taghvaei et al.*, [10], [27], [30] were the effects of a young population, and the difference to real scenarios might hinder generalization.

While the harness enhances participant safety, it concurrently imposes significant movement restrictions, introducing more noise and affecting signal detection. Simulating falls or balance loss becomes challenging due to the limitations imposed by the harness, necessitating a delicate balance between safety and the facilitation of natural movements. Notably, the acceleration signal derived from the IMU exhibits considerable noise, potentially stemming from both the use of the walker and constrained body movements. Understanding these nuances in signal characteristics is imperative for refining fall detection algorithms and enhancing the system's reliability, particularly in scenarios involving walker usage.

The metrics analysis concerning simulated falls reveals a substantial reduction in accuracy, specificity, and sensitivity when the walker is present compared to using only the body weight support. This suggests potential challenges or limitations introduced by the walker in the experimental setup, necessitating adjustments for optimal performance. Comparing results between algorithms with original thresholds and their modified versions indicates an increase in metrics attributed to optimized thresholds based on the first participant. Particularly, sensitivity and accuracy increased for all modified algorithms for free and walker falls. Personalizing the system and addressing anxiety during pre-falls could improve performance across different cases.

Testing algorithms on a dataset containing real falls and Activities of Daily Living (ADLs) shows that statistics align with expectations for algorithms designed for real falls. However, despite an overall increase, desired levels have not been attained for other algorithms, potentially due to constraints introduced during fall simulations. A closer examination of implemented constraints is necessary to optimise algorithms for real conditions. Analyzing how these constraints influence algorithm performance can guide modifications, enhancing the system's accuracy and reliability in identifying real falls.

With the proposed modifications to the pre-fall vertical velocity algorithm, the system is able to attain accuracies higher than 70%, which might be complemented with triggered signals from additional sensors such as LRFs and FSRs, during walker-assisted gait. The effects of the walker on the user biomechanical chain affect the measured accelerations at the user waist, and thus lead to lower metrics compared to free-fall scenarios.

VI. CONCLUSIONS AND FUTURE WORKS

This article's proposed fall detection system aims to discern between various scenarios, encompassing Activities of Daily Life (ADLs) like walking or retrieving objects from the floor, pre-falls, and actual falls. The primary objective is to develop a highly reliable system that detects falls and pre-falls to deliver valuable feedback.

Upon detecting an actual fall, the fall detection system should trigger different alarms, such as notifying the caregiver's phone, emitting an acoustic alarm to alert individuals in proximity, and automatically activating the brakes. In the case of pre-fall detection, two distinct scenarios are envisioned: the user momentarily losing balance but recovering, or the loss of balance serving as a precursor to an impending fall or potential injury. In response to the first scenario, the initial feedback entails automatically activating the brakes. Subsequently, the system may display a button on the interface, prompting the user to press it within a designated time frame; failure to do so could result in the activation of alarms associated with an actual fall, including the acoustic alarm and caregiver notification.

Furthermore, the system contemplates integrating a daily pre-fall count feature, allowing for the continuous monitoring of the user's status. This functionality enables the system to notify caregivers of any noteworthy changes in the user's routine, such as a sudden increase in instances of balance loss during specific time intervals throughout the day.

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