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RESEARCH ARTICLE

A Multi-Agent System Approach for Balance Disorder Treatment: Integrating Computer Vision and Gamification

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the ethical committee of the Expert Systems and Applications Laboratory Research Group under Approval Code No. SA-2303/1, and performed in line with the ethical standards of the 1964 Helsinki Declaration.

ABSTRACT This study introduces a pioneering approach for treating balance disorders, integrating advanced computer vision and engaging gamification techniques within a multi-agent system framework. Balancing disorders significantly impair quality of life, manifesting through symptoms like dizziness and muscle weakness. Addressing this, we developed a platform that employs depth imaging and real-time pose estimation to accurately capture and analyze patient movements, enabling personalized and adaptive rehabilitation exercises. The multi-agent system architecture ensures seamless communication and coordination, facilitating the delivery of tailored exercises that cater to the evolving needs of patients, either in person or remotely. Key to our approach is the use of gamification, which transforms rehabilitation exercises into interactive virtual activities, significantly enhancing patient engagement and motivation. Preliminary results demonstrate the platform's efficacy in improving balance, highlighting its potential as a versatile tool for balance disorder treatment. This research advances the technological frontier in balance disorder rehabilitation and offers a blueprint for future telehealth and patient-centric care innovations.

INDEX TERMS Balance disorder, computer vision, gamification, multi-agent system, telerehabilitation.

I. INTRODUCTION

The ability to balance is foundational for humans to remain upright and stable during movement and stationary. It is crucial in facilitating daily activities, from ambulation and running to ascending stairs and handling objects. Declines in balance may arise from aging or a lack of regular physical activity. Furthermore, various chronic conditions like Parkinson's disease, multiple sclerosis, and restless legs syndrome can deteriorate balance and motor capabilities. The World Health Organization (WHO) highlights these conditions as leading contributors to global disability, with projections indicating an uptick in prevalence correlating with demographic aging [1]. Predominantly, impairments in balance and mobility emerge as primary symptoms within these conditions, precipitating reduced independence, increased fatigue perception, and exacerbated disease severity [2], [3].

Enhancing balance necessitates addressing root causes while undertaking rehabilitation to strengthen the neurological and musculoskeletal frameworks. Evidence points towards the benefits of progressive resistance exercises in ameliorating functional capacity, balance, and subjective well-being, including fatigue levels, quality of life, and

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mood [4]. Nonetheless, these interventions typically require direct involvement from specialized professionals.

Emerging needs emphasize the importance of cultivating technologies and systems conducive to managing conditions linked with these challenges. Consequently, Information and Communication Technologies (ICT), alongside innovations like computer vision, sensors, and gamification strategies, have found applications across various medical fields, particularly in enhancing balance and treating associated chronic illnesses [5]. Biometric assessments play a pivotal role by offering precise, quantifiable insights into an individual's balance and movement capabilities, enabling tailored rehabilitation strategies. Moreover, these assessments facilitate ongoing patient monitoring, aiding healthcare providers in identifying progress patterns or necessitating therapy adjustments [6].

In light of the foregoing, this work introduces a supportive platform designed to augment exercises to rectify balance disorders. Leveraging gamification, the platform transports the exercise regimen into a virtual setting to bolster patient engagement. Interaction within this virtual space is mediated through a pose estimation model that discerns the user's physique and potential postural deviations. Virtual environment challenges influence poses executed, affording users visual feedback on their actions and facilitating self-correction of errors.

A sophisticated multi-agent system (MAS) underpins the coordination and communication among all participating entities. This dynamic framework enables the platform to adapt to each patient's specific recovery needs [7]. By distributing resources and capabilities efficiently across nodes, MAS circumvents the pitfalls inherent in centralized systems while its adaptive nature in information retrieval and management augments overall efficiency. Adhering to the Context-Aware framework, the MAS architecture ensures exercises are seamlessly tailored to the individual's unique circumstances, encompassing personal needs, traits, and progression.

This work introduces a pioneering approach to traditional rehabilitation methods for balance disorders, enhancing patient motivation and focusing on ease of use for healthcare professionals. After a detailed review of the state of the literature, the main advantage of this platform over traditional rehabilitation methods is its ability to provide personalized and adaptive exercises based on real-time analysis of patient movements. The work aims to show the scientific community that rehabilitation of balance disorders combined with an interactive experience increases patient motivation, strengthening adherence to the rehabilitation treatment. This system has been designed with simplicity and comfort for the patient (sensor placement, comfort) and the rehabilitation professional (result interpretation, exercise design).

The document is structured into several sections. Section II delves into an extensive review of existing methodologies and technologies for diagnosing and managing balance disorders, emphasizing contributions from artificial intelligence and gamification. Section III outlines the system's architecture alongside the pose detection and analysis approach. Following this, Section IV presents a case study, shedding light on the outcomes achieved with the proposed method, with ensuing discussions in Section V. Conclusively, Section VI offers a comprehensive overview of the findings and forward-looking statements.

II. BACKGROUND

In the realm of rehabilitative medicine, the accurate assessment and treatment of balance disorders present a significant challenge, particularly when these conditions are symptomatic of underlying neurological disorders. Traditional approaches often rely on subjective assessments or require invasive and costly diagnostic procedures that may not be readily accessible in all clinical settings. Moreover, the lack of objective, real-time data to inform therapeutic interventions can hinder the effectiveness of rehabilitation strategies, leading to prolonged recovery times and decreased quality of life for affected individuals. Identifying neurological conditions that impact walking, balance, and body stance is critical for several key reasons in medical practice [8]:

- The risk of repeated falls due to these conditions is a major concern, as falls can cause injuries and are linked to a lower life expectancy.
- Challenges with walking or staying balanced may lead patients to limit their physical activity. Such reductions in activity levels are connected with numerous negative health outcomes, including exacerbation of the primary neurological condition and the onset of secondary health issues (like osteoporosis, diminished cardiorespiratory fitness, constipation, and weight gain).
- Often, particular movement patterns, stability, and posture alteration present themselves early in neurological diseases, sometimes before other symptoms emerge. These patterns can serve as vital diagnostic indicators for the specific neurological disorder.

It is worth noting that this is not solely a problem of diseases, as these disorders occur more frequently in older individuals and are linked to aging [9]. This section will delve into telemedicine's role, multi-agent systems' application, and the techniques and methods used in telerehabilitation.

A. TELEMEDICINE IN NEUROLOGICAL DISORDERS

Telemedicine represents an emerging model for assessing and treating various neurological disorders. It can improve current healthcare processes by minimizing healthcare access disparities and reducing the time between patient follow-up visits [10]. Although increased widespread access to the internet and new wearable technologies provide an opportunity to manage complications associated with chronic diseases in a patient-centered homecare model, many areas still need improvement and development within this context [11].

Following this need, researchers have focused on developing new methods and systems that integrate technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Virtual Reality (VR), among others [12]. Telemedicine has undergone numerous advances and developments, including detecting histological and microscopic elements, early detection of tumors, and diabetic retinopathy [13]. However, telerehabilitation is complex, requiring further study and attention to specific needs. It encompasses process improvement and addressing various challenges, such as the system's capacity to gather user treatment data and encourage active engagement in system utilization for treatment enhancement [14]. Another need is strengthening coordination between the different entities involved in the process. Thus, research is currently trying to find solutions to the many unknowns in this field.

Regarding patient monitoring around recovery or treatment, robots or sensors to monitor patients and assist them in their treatment have been widely studied. It is beneficial in treating these problems [15]. Certain investigations employ robotics and exoskeletal systems to enhance upper limb functionality [16], as well as lower limb performance [17], aiming to advance rehabilitation outcomes for individuals. Some studies show that monitoring patients in their day-to-day lives is beneficial, as monitoring their fatigue or sleep can significantly improve their recovery [18]. Although these tools serve their purpose, they must contact the user. This contact poses a major drawback due to their intrusiveness, which can cause discomfort, restrict mobility, and compromise privacy and autonomy.

B. MULTI-AGENT SYSTEMS IN TELEMEDICINE

Given the need for effective coordination and communication among various entities involved in telemedicine, multi-agent architectures have emerged as a promising solution. These systems improve collaboration and autonomous decision-making among the different actors involved in remote healthcare [19]. Multi-agent architectures model the different system components as autonomous agents able to communicate, cooperate, and coordinate their actions to achieve common goals. The design of these agents represents both healthcare professionals and patients, as well as other relevant actors in the telemedicine process.

Published studies demonstrate the effectiveness of multi-agent systems for the continuous monitoring of patients and in improving their treatment, as seen recently with COVID-19 [20]. For example, one investigation [21] assessed the impact of a rehabilitation program incorporating gamification elements on patients with motor impairments. The outcomes revealed a noteworthy enhancement in the patients' mindset and well-being. Studies like [22] show that MAS in rehabilitation enables better contextualization of scenarios, dealing with uncertainties related to planning and problem-solving, and coordinating distributed information sources. Moreover, a recent study [23] shows how a multi-agent system integrating gamification and portable solutions can improve assessment accuracy and treatment personalization.

Integrating multi-agent systems in telemedicine also extends to promoting physical activity and learning. For instance, the work [24] developed a multi-agent platform to promote physical activity and learning. This platform demonstrates significant potential in educational environments, offering innovative ways to engage users through interactive and gamified experiences.

These examples illustrate the versatility and effectiveness of multi-agent systems in various healthcare applications. By leveraging these advanced technologies, our project aims to enhance patient engagement, improve diagnostic accuracy, and offer personalized rehabilitation programs, thereby addressing key limitations identified in previous studies.

C. TECHNIQUES AND METHODS IN TELE-REHABILITATION

Building patient loyalty to achieve consistent and effective treatment is another critical area. Current studies focus on using gamification techniques to achieve this. Gamification has been recognized for its efficacy in addressing balance or motor skills conditions by integrating technologies like virtual reality [25], [26]. For instance, research conducted by [27] assessed the impact of a gamification-based rehabilitation program on individuals with motor impairments, revealing notable enhancements in their disposition and physical state. Moreover, gamification presents opportunities for crafting individualized therapeutic approaches. As evidenced in a study by [28], the fusion of gamification with an interactive balance platform empowers therapists to tailor training regimens according to each patient's unique balance capabilities and treatment progression. In addition, integrating AR and VR technologies in rehabilitation processes is gaining attention due to their potential to enhance patient engagement and treatment outcomes. According to [29], AR and VR have been effectively used as educational resources, demonstrating significant promise in immersiveness, interactivity, and ease of use. Their findings support the notion that these technologies can overcome traditional barriers, such as limited access to advanced equipment and the need for personalized treatment, by offering more accessible and customizable solutions.

To address this objective, researchers leverage computer vision methodologies due to their non-invasive and cost-effective nature, which facilitates the evaluation of patients' balance and posture, aiding in the diagnosis and treatment of these conditions [30]. Computer vision systems leverage tracking of key points, recognition of patterns, and analysis of images to identify and measure the balance and posture of a patient. Examples of significance include the study by [31], which implements computer vision alongside machine learning techniques to assess ergonomic risks by analyzing workers' postural configurations. In a related vein, the investigation conducted by [32] uses a Kinect sensor combined with machine learning algorithms for assessing posture in individuals with Parkinson's disease, employing indicators such as deviation and velocity of oscillation of the center of mass.

Similarly, physical rehabilitation has significantly integrated these technologies, such as gamification and motion capture systems. In the work [33], they highlighted that, although the use of inertial measurement units and Kinect sensors is prevalent, these systems are often developed independently and do not always fully address the needs for patient motivation and engagement. Furthermore, this study has primarily focused on post-stroke rehabilitation, leaving considerable space to explore other neurological conditions. Similarly, in the work [34], they reviewed the use of Kinect in rehabilitating gait and posture disorders, identifying that although the technology is promising, significant challenges still exist regarding the accuracy of capturing complex movements.

On the other hand, the authors in the work [35] discussed the potential of virtual reality in rehabilitating motor and cognitive functions. However, they pointed out that adopting these technologies is often limited by their high cost and lack of customization. Additionally, recent studies highlight the use of these technologies, emphasizing the need to integrate them with interactive systems that allow for greater personalization and adaptability [36].

These studies highlight the importance and potential of technological advancements in physical rehabilitation but also underscore the areas that need further development, such as accuracy, personalization, and cost, which our project aims to improve.

D. BACKGROUND CONCLUSION

The contribution of our proposed work lies at the intersection of advanced computer vision techniques and gamification, setting it apart from the existing body of research by offering a novel, non-invasive approach to the assessment and rehabilitation of balance disorders associated with neurological conditions. Unlike traditional methods that often rely on subjective assessments or are constrained by the availability of specialized equipment, our system harnesses the power of readily available 3D cameras and custom-developed software to provide real-time, objective data on patient movement. This data-driven approach enhances the accuracy of diagnoses and tailors rehabilitation exercises to patients' needs through an engaging virtual environment. By integrating gamification principles, we address the problem at the beginning of this section and motivate patients to adhere to their treatment plans, thus potentially improving rehabilitation outcomes. Our work represents a significant step forward in making rehabilitative care more accessible and effective, demonstrating how innovative applications of technology can overcome the limitations of current practices.

III. PROPOSED METHOD

This section will describe the architecture designed for the platform and the analysis method used for patient exercise monitoring.

A. SYSTEM ARCHITECTURE

Drawing from identified requirements, the primary aim of this endeavor is to conceptualize and construct a versatile platform capable of delivering tailored detection and rehabilitation exercises, whether administered in person or remotely. These exercises are meticulously crafted to align with the user's unique needs and therapy progression, employing diverse game formats tailored to individual user characteristics and capabilities. The platform meticulously scrutinizes all generated data to dynamically adjust the patient's recovery trajectory in response to their performance and evolution throughout the prescribed exercises. Moreover, the system is augmented by medical experts who provide ongoing monitoring, enabling personalized tracking and supervision for each patient.

The integration of the context-aware framework into a multi-agent system is proposed to achieve the development of this telerehabilitation platform. The context-aware framework [37] allows consideration of the patient's specific context, such as health status, ability level, preferences, and physical limitations. This contextual information allows us to personalize the rehabilitation program, adapting the intensity, duration, and type of exercise to the patient's needs. Another advantage is that the context-aware framework enables continuous monitoring of patient progress and dynamic adjustment of treatments. As the patient progresses through rehabilitation, the system can update goals and challenges to maintain the appropriate level of difficulty and motivation.

The proposed system employs a multi-agent system (MAS) architecture to meet the complex demands of real-time balance disorder rehabilitation. This design choice is grounded in the system's need for high scalability, adaptability, and efficient data handling capabilities. MAS allows for a decentralized architecture where agents operate semi-autonomously, enhancing system resilience and scalability.

This decentralized approach is advantageous for integrating diverse and potentially geographically dispersed data sources, such as sensor types and user input devices. Each agent in the system can independently manage data from its sources, make decisions, and communicate with other agents to provide a cohesive and responsive user experience. This modularity enables easy updates and integration of new technologies without disrupting the system's overall functionality.

Additionally, MAS supports dynamic load balancing, which is crucial for maintaining system performance as the number of users increases. Agents can redistribute tasks among themselves based on current load and resource availability, ensuring that no single point of failure compromises the system's effectiveness or user experience. This capability is particularly important in clinical settings, where system delays or downtime can severely impact patient care and treatment outcomes.

Integrating the context-aware framework into a multi-agent system provides a powerful and flexible solution for telerehabilitation. Agents can interact and collaborate in real time, sharing contextual information and adapting their decisions and actions according to the patient's context. This integration allows further personalized medical care, adjusting exercises and treatments according to the patient's situation and progress and improving the effectiveness and efficiency of remote treatments.

The proposed architecture (Figure 1) stands out for its ability to incorporate new functionalities by adapting to the environment. For optimal performance, the architecture must have well-defined characteristics. To achieve this goal, virtual agents' organizations allow agents to have specific roles and responsibilities and establish relationships with each other. These organizations allow them to share information, coordinate actions, negotiate agreements, and make collective decisions to achieve shared goals. The virtual organization provides a framework for regulating and facilitating agent interaction, promoting cooperation and efficiency in the multi-agent system.

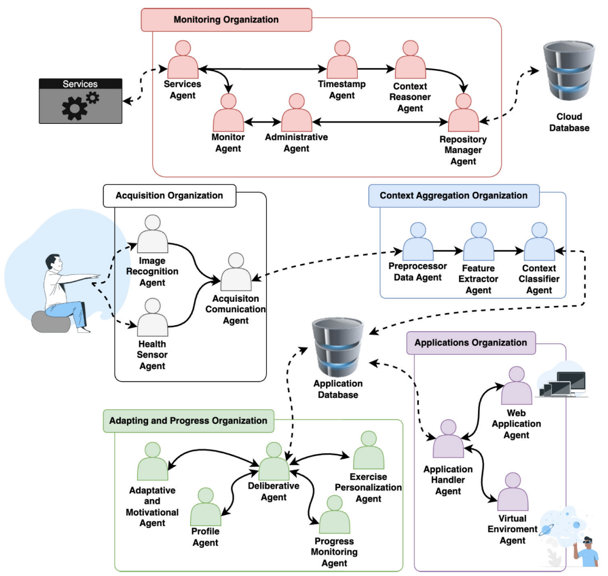

FIGURE 1. Proposed system architecture.

In the architecture, modules, and agents are specialized to fulfill specific objectives or tasks. A primary advantage is its flexibility in replacing agents with similar characteristics while maintaining system performance and consistency. The virtual organizations of agents in the proposed architecture are described below:

1) ACQUISITION ORGANIZATION

This organization allows the incorporation of depth cameras (**Image Recognition Agent (IRA)**) and all possible medical sensors that may be necessary to monitor additional medical parameters (**Health Sensor Agent (HSA)**). The information generated by these devices can be collected via Bluetooth BLE or, in the case of cameras, via RTSP protocol. This allows us to obtain sensor and camera information to understand the patient's context. Finally, the **Acquisiton Communication Agent** (**ACA**) is responsible for sending the information obtained by the multiple data sources of the system for context analysis.

2) CONTEXT AGGREGATION ORGANIZATION

This organization contains a system deployment where the modules for extracting and classifying the characteristics of the data obtained by the agents from the different sources are located. More specifically, the agents that belong to this layer are the following:

- **Preprocessor Data Agent (PDA)**: This agent is a preliminary step to feature extraction and context management. It collects information from dependent devices, such as cameras, and unifies the data they receive as described in Section III-B. It is also in charge of filtering the data and validating and correcting it if necessary.
- **Feature Extractor Agent (FEA)**: This agent is in charge of characterizing the raw information received, which makes it possible to identify the user and his environment. Specifically, this component identifies each of the coordinates in points of interest of the patient's body, as indicated in Section III-B. It also identifies other characteristics, such as the activity performed or the location of the activity.
- **Context Classifier Agent (CCA)**: It is responsible for classifying the previously extracted features, resulting in mid-level information. To do so, it will combine the extracted features, which will allow the identification of deviations in exercise by the patient, the type of deviation, whether or not there is assistance, etc.

3) APPLICATIONS ORGANIZATION

The Applications Organization is vital in adapting system-generated information to the application layer. It enables direct interaction between applications and the system, facilitated by the **Application Handler Agent (AHA)**). Its primary responsibility lies in converting raw system data into human-readable information. Notably, it serves as a point of interaction for both the virtual environment (**Virtual Environment Agent (VEA)**) and medical monitoring applications (**Web App Agent (WAA)**).

4) MONITORING ORGANIZATION

This organization manages and controls the platform's different virtual organizations and agents and the context collected by the rest of the organizations. The agents that make up this organization are:

- **Services Agent (SSA)**: This agent allows the communication of external services with the virtual agent organization. This agent allows the integration of new agents and virtual organizations. Likewise, it manages the system's information, allowing the analysis of the high-level context and the distribution of the global system's information.

- **Monitor Agent (MA)**: This agent periodically checks the system's status. It is responsible for detecting information overload, conflicts between agents, component or resource failures, and inconsistencies in agent states.
- **Administrative Agent (AA)**: The agent is responsible for indicating the available services to all agents in the system. When a new agent seeks to join, it must specify its services to ensure compatibility and communication with other agents.
- **Timestamp Agent (TA)**: This agent is responsible for including date/time information in the data before storing it.
- **Context Reasoner Agent (CRA)**: This agent aims to produce high-level context information from the output obtained by the context aggregation organization. Applying pattern recognition techniques allows them to determine the patient's correct performance of the exercise, its current state, and its progression throughout the exercise. Likewise, it allows us to provide the context with a wider vision, detecting patterns, irregularities, patient needs, etc.
- **Repository Manager Agent (RMA)**: This agent manages all data generated in the system organizations. It functions as an interface between applications and other modules with the database, including all computational needs regarding privacy and information security.

5) ADAPTING AND PROGRESS ORGANIZATION

The Adaptive Organization tailors the user's exercise data and actions to enhance progress and motivation during therapy. It ensures the user is presented with exercises and activities that suit their needs and goals. The agents that make up this organization are:

- **Adaptive and Motivational Agent (AMA)**: This agent collects and analyzes the patient's contextual information, adapts treatments according to the patient's needs, and keeps motivation levels high during rehabilitation.
- **Progress Monitoring Agent (PMA)**: This agent monitors the patient's progress and adjusts treatments based on his progress. This agent uses contextual information to assess patient performance and make informed decisions about the next steps in treatment.
- **Exercise Personalization Agent (EPA)**: This agent adapts exercises and rehabilitation activities according to the patient's contextual information. This agent uses the collected and processed data to design personalized exercise programs, considering other information like the patient's physical ability, preferences, and limitations.
- **Profile Agent (PA)**: This agent plays a crucial role in sharing the user's information with other agents. Additionally, it updates profile values based on the user's progress, ensuring a personalized and adaptive experience.
- **Deliberative Agent (DA)**: This agent is responsible for deciding the next steps in the rehabilitation process. To do so, he considers contextual information, patient preferences, physical condition, limitations, and progress in the rehabilitation treatment. It is the central entity in this organization as, based on the information from the other agents, it can adjust the exercises to increase the patient's progress or, if the AMA agent detects low levels of motivation, our DA agent modifies the focus of the treatments and activities to increase the patient's motivation and engagement.

Concerning inter-agent communication, the designed architecture employs the Advanced Message Queuing Protocol (AMQP) [38]. This standardized messaging protocol provides advanced routing and message queuing features, allowing robust and scalable real-time communication implementation. Furthermore, with various implementations of brokers and libraries, it can be used for communication between agents in different environments, as in the case of this platform.

Moreover, the system relies on multiple databases to ensure proper functioning and scalability. The monitoring organization's database stores essential information about system agents, their services, and their respective tasks. It also records patient context information determined by organization agents. Additionally, the system employs other databases dedicated to storing the case study-specific data.

It's important to know that this architecture uses a hybrid model that integrates decentralized agent interactions and centralized data management, optimizing the treatment process for balance disorders. This approach facilitates real-time adaptive capabilities and leverages robust data handling, which is essential for comprehensive analytical tasks.

The MAS comprises several critical types of agents, including Data Processing Agents and Decision-Making Agents. Data Processing Agents collect and process real-time data from diverse sensors, such as cameras and other devices like accelerometers. Their primary function is to analyze this data to evaluate the user's immediate state and progression in therapy. Decision-making agents use the processed data to make decisions to adjust the rehabilitation exercises dynamically and autonomously. They customize the gamification elements and difficulty levels to match the user's evolving capabilities and therapy requirements.

Integration with a centralized system is crucial for data consolidation and system update coordination. All pertinent user information, including detailed progress metrics and session logs, is consolidated in a centralized cloud database. This centralization ensures comprehensive user data is accessible for session adjustments and longitudinal treatment analysis. The centralized components also facilitate the dissemination of system updates, such as new therapy protocols or software enhancements, ensuring that all agents operate with up-to-date guidelines and functionalities.

The hybrid architectural approach offers significant benefits like scalability and robust data analysis. The central system supports scalability by efficiently managing extensive data across numerous users and therapy sessions. Increasing centralized data analysis capabilities allows for applying advanced computational techniques, which are integral for developing insights that drive continuous improvements in therapy protocols.

This architecture effectively combines the immediate adaptive responses enabled by multi-agent systems with the comprehensive data management and analysis of centralized databases. Such a structure ensures that the platform is responsive to immediate user needs and proactive in adapting to long-term therapeutic trends and advancements.

B. MULTI-REFERENCE SYSTEM FOR POSE ESTIMATION

The process for extracting the patient's skeletal key points by the system is delineated in Figure 2. The process initiates with image acquisition to facilitate pose estimation. Specifically, the proposed system integrates the Intel RealSense Depth Camera D435i [39], chosen for its alignment with platform requisites. Subsequently, utilizing Intel's SDK model [40], the system analyses the acquired images to delineate the skeleton's characteristic points in the form of 3D coordinates within the image space. Consequently, the system leverages these cameras to capture depth images of the patient during exercise sessions. These images are then gathered and transmitted to the local device, where skeletal landmarks are extracted from both perspectives.

In setting up our multi-camera system for pose estimation, all cameras must be precisely time-synchronized to ensure accurate pose reconstruction from the collected data. To achieve this, our system relies on cameras that support the Precision Time Protocol (PTP) [41], a standard for clock synchronization in networked devices. PTP ensures that timestamps of images captured from multiple cameras are synchronized, allowing for coherent data integration and analysis. The camera hardware and network manage this synchronization process independently, requiring no direct intervention within the pose estimation algorithm.

Once the information has been synchronized, we establish a match between the coordinates obtained by the different cameras. For this reason, we create a unified 3D coordinate system using the coordinate transformation method and establish the one given by each camera as a reference for each system. As a result, we get a single coordinate system that allows us to consider a person's perspectives more accurately. Coordinate unification allows us to improve the accuracy of determining the coordinates of a person's skeleton by combining information from multiple coordinate systems and determining human movements in a 3D space.

The iterative closest point algorithm (ICP) [42] achieves a common coordinate system through the coordinates extracted from both cameras. This is achieved by finding the optimal rotation and translation that aligns one set of points with another, which is crucial to unify the coordinates obtained from the different cameras in our system. The main body of this process is shown in Algorithm 1.

Algorithm 1 Iterative Closest Point (ICP) Algorithm

procedure ICP(*CA*, *CB*)
  Initialize R and t with initial values (R = Identity, $t = 0$)
  Initialize *previousError* $\leftarrow \infty$
  Initialize *currentError* $\leftarrow 0$
  Initialize *tolerance* $\leftarrow$ a small positive value ($1e - 6$)
  Initialize *isConverged* $\leftarrow$ False
  while not *isConverged* **do**
    correspondences $\leftarrow$ FindClosestCorrespondences(*CA*, *CB*, R, t)
    $R_{\text{opt}}, t_{\text{opt}} \leftarrow$ OptimizeCorrespondences(*correspondences*)
    currentError $\leftarrow$ CalculateCurrentError(*correspondences*, R_{opt}, t_{opt})
    if $|$*previousError* $-$ *currentError*$|$ $<$ *tolerance* **then**
      isConverged $\leftarrow$ True {Convergence achieved}
    else
      $R \leftarrow R_{\text{opt}}$
      $t \leftarrow t_{\text{opt}}$
      previousError $\leftarrow$ *currentError*
    end if
  end while
  return R, t {Optimal rotation matrix and translation vector}
end procedure = 0

Algorithm 2 Find Closest Correspondences

function FINDCLOSESTCORRESPONDENCES(*CA*, *CB*, R, t)
  correspondences $\leftarrow$ new List()
  for a_i in *CA* **do**
    $b_i \leftarrow$ null
    minimumDistance $\leftarrow \infty$
    for c_j in *CB* **do**
      distance $\leftarrow \|Ra_i + t - c_j\|$
      if *distance* $<$ *minimumDistance* **then**
        minimumDistance $\leftarrow$ *distance*
        $b_i \leftarrow c_j$
      end if
    end for
    correspondences.add(a_i, b_i)
  end for
  return *correspondences*
end function = 0

This process starts from a fixed and equal reference point cloud for both systems, e.g., a fixed object. This way, the point cloud of camera A (C_A) and camera B (C_B) are obtained for the same object. Then, the algorithm transforms C_B to match C_A. To do this, each point in C_B is taken and compared to the nearest point in the set of C_A. This process is repeated until the best correspondence between the two coordinate systems is obtained, i.e., the one that aligns both point clouds. This process is shown in Algorithm 2.

More specifically, the minimization of the distance between the point sets is quantified through the ICP objective function, defined as we can see in 1:

$$E(R, t) = \sum_{i=1}^{n} \|Ra_i + t - b_i\|^2 \tag{1}$$

where:

- a_i represents a point in the point cloud A, and b_i represents the corresponding point in the point cloud B.
- R is the rotation matrix and t is the translation vector that minimize the objective function E.

Once the objective function is defined and understood, the iterative process of the ICP adjusts R and t to minimize E. Convergence to the minimum of the objective function results in obtaining the optimal transformation matrix, which allows for precise correspondence of coordinates from one system to another. The full process is shown in Algorithm 3.

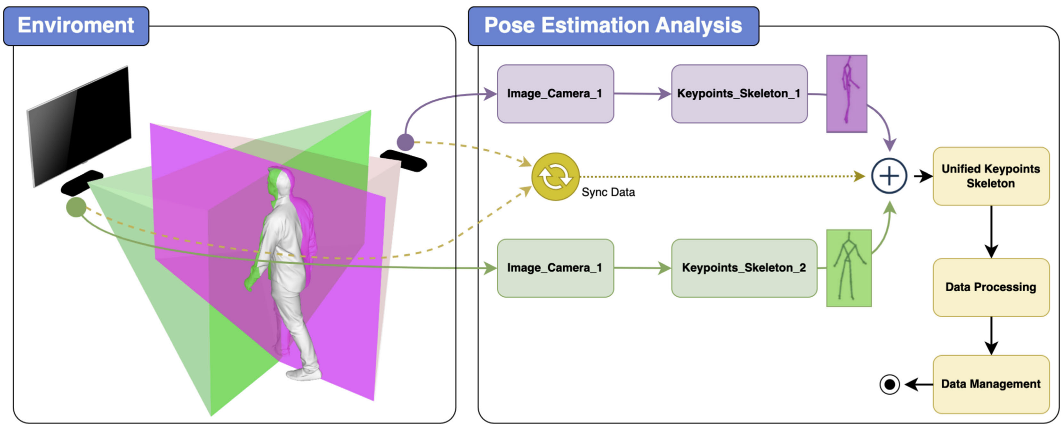

FIGURE 2. Block diagram of pose estimation analysis.

Algorithm 3 Optimize Correspondences

function OPTIMIZECORRESPONDENCES(*correspondences*)
    $R_{\text{opt}} \leftarrow$ Identity, $t_{\text{opt}} \leftarrow 0$
    $E_{\text{min}} \leftarrow \infty$
    converged ← False
    while not *converged* **do**
        $E_{\text{current}} \leftarrow$ CalculateObjectiveFunction(R_{opt}, t_{opt}, *correspondences*)
        if $E_{\text{current}} < E_{\text{min}}$ **then**
            $E_{\text{min}} \leftarrow E_{\text{current}}$
            $U, \Sigma, V^T \leftarrow$ svd(*correspondences*)
            $R_{\text{opt}} \leftarrow V^T U^T$
            $t_{\text{opt}} \leftarrow centroid\_B - R_{\text{opt}} \cdot centroid\_A$
        else
            converged ← True
        end if
    end while
    return R_{opt}, t_{opt}
end function
function CALCULATEOBJECTIVEFUNCTION(R, t, *correspondences*)
    error ← 0
    for each (a_i, b_i) in *correspondences* **do**
        $transformedPoint \leftarrow Ra_i + t$
        $error \leftarrow error + \|transformedPoint - b_i\|^2$
    end for
    return *error*
end function = 0

Algorithm 4 Multi-Reference Pose Estimation Process

procedure MULTIREFPOSEESTIMATION(*cameras*, R, t)
    allKeyPoints ← new List()
    for all *camera* in *cameras* **do**
        image ← *camera*.getImages() {Images are already synchronized}
        keyPoints ← *model*.AnalyzeImage(*image*)
        if *index* ≠ *baseCameraIndex* **then**
            keyPoints ← ApplyTransformation(*keyPoints*, R, t)
        end if
        allKeyPoints.Add(*keyPoints*)
    end for
    unifiedKeyPoints ← UnifyPoints(*allKeyPoints*) {Unify to a single point per position}
    return *unifiedKeyPoints*
end procedure
function APPLYTRANSFORMATION(*keyPoints*, R, t)
    transformedKeyPoints ← new List()
    for all *point* in *keyPoints* **do**
        $transformedPoint \leftarrow R \cdot point + t$ {Apply rotation and translation}
        transformedKeyPoints.Add(*transformedPoint*)
    end for
    return *transformedKeyPoints*
end function = 0

Once the transformation matrix is available, each time the coordinates identified by each camera are received, the key points of the skeleton identified in B are transformed to the A system so that those points not identified by A will be identified by B and, in this way, the information of the system for the user's pose will allow us to have greater precision about the user's posture. With this information, it is possible to know more precisely the person's key points that determine a person's upright posture and its possible deviations. This analysis will show the deviations from the correct posture for each patient. More specifically, the pseudocode of the process can be found at Algorithm 4.

It is important to highlight that the precision and reliability of pose estimation within our system critically hinge upon effective error management and the quality of data procured by the cameras. Intrinsic challenges, such as fluctuations in environmental illumination, partial occlusion of subjects, and disruptions caused by loose-fitting attire, necessitate a robust strategy to safeguard data integrity. In response to these challenges, we have included extended preprocessing and filtering mechanisms, like the normalization of illumination, which enhances the quality of images before pose estimation. Furthermore, the dynamic selection of key points, predicated on reliability and visibility across various captures, facilitates the mitigation of potential detection inaccuracies, thus ensuring a more accurate and consistent depiction of user movements.

C. GAMIFICATION AND TRANSFER TO THE VIRTUAL ENVIRONMENT

Integrating gamification techniques into rehabilitation represents a significant advancement in treating balance disorders. Gamification leverages both intrinsic and extrinsic motivation to foster active patient participation. In our proposed system, gamification transforms traditional rehabilitation exercises into interactive and engaging activities conducted within a virtual environment. This approach enhances

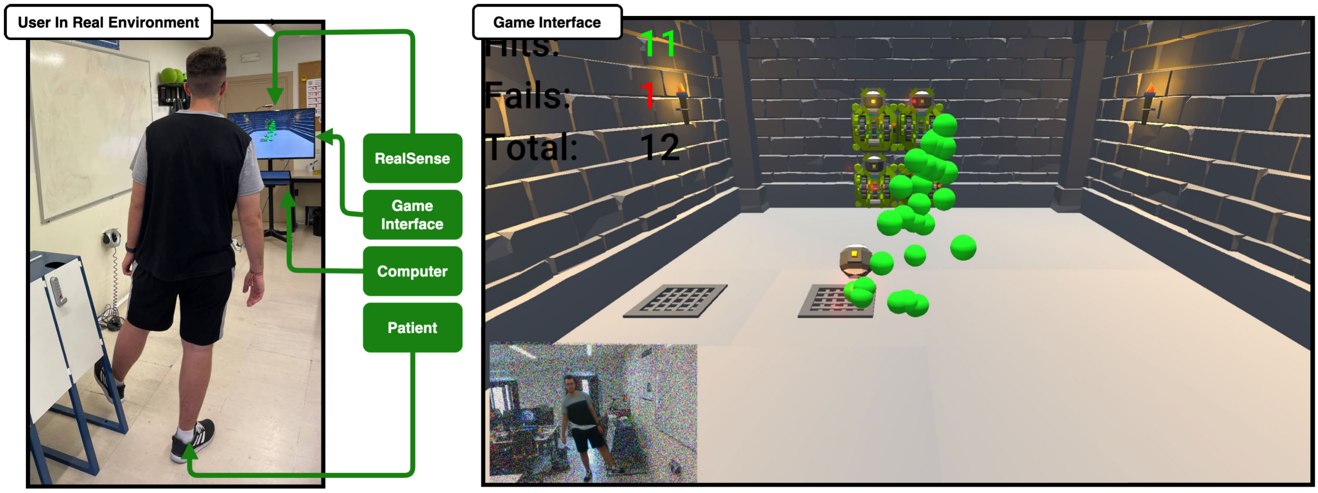

FIGURE 3. Game example alongside the user employing the system.

treatment adherence and allows for detailed monitoring of patient progress.

The system maps the user's physical movements to actions within the game or virtual environment using real-time estimated pose data. This is achieved through a gamification engine that interprets accuracy, speed, and range of motion in the context of playful challenges designed to simulate specific therapeutic exercises. The games employed by the system require users to reach or strike moving targets with different parts of their bodies, promoting coordination and agility. For instance, one game challenges the user to maintain a specific posture to interact with virtual balls thrown toward them, incentivizing the correction of improper postures through immediate visual and auditory feedback. The need to return balls in different directions compels users to perform a variety of movements, fostering a dynamic and adaptive rehabilitation experience that enhances the user's autonomy in postural correction. Figure 3 shows an example of this.

The user's visual representation in the form of an avatar composed of key points allows for detailed visualization of posture and movements, facilitating self-correction of improper postures. Additionally, the system enables integration with proprioception equipment, intensifying rehabilitation and toning of critical areas, promoting autonomous movements and adaptation to different postures necessary for interacting with the game.

Achievements, virtual rewards, and scoring systems reflect the user's progress, incentivizing continuous improvement and persistence in treatment. Gamification allows for the customization of exercises based on the user's skill level and specific rehabilitation needs, automatically adjusting the difficulty and objectives of the games based on observed progress. This adaptive system ensures a constant challenge, promoting faster and more effective recovery without causing frustration or excessive fatigue.

IV. RESULTS

The current study presents results from an initial prototype testing phase designed to integrate computer vision and gamification to treat balance disorders. It is important to note that this prototype is in the early stages of development, and the results discussed herein are preliminary. The primary aim of this phase has been to test the technical feasibility of the proposed system and gather initial data on its performance and user interaction. As such, these results do not indicate clinical efficacy but rather demonstrate the system's potential and guide further refinements.

A month-long experiment was conducted to validate the system's real-world performance, involving four patients receiving treatment for balance disorders. The testing process adhered to the ethical principles outlined in the 1964 Helsinki Declaration for Medical Research Involving Human Subjects [43]. The detailed statistics and analysis of these results have been included in the revised manuscript, providing a clear and data-driven narrative of the benefits and impact of the gamified treatment protocol.

This study involved 4 participants, selected based on specific inclusion criteria that reflect the typical characteristics of individuals suffering from balance disorders. The patients included two with age-related balance issues (Patient_1 and Patient_2), one with Parkinson's disease (Patient_3), and one with Multiple Sclerosis (MS) (Patient_4).

The exercises performed for the assessment belong to the basic static balance test, which is performed for people with a balance disorder [44]. The Four Stages Balance Test [45] was used where patients perform four standing positions that become progressively more difficult to maintain:

- Stand with feet side by side (30 sec).
- Place the instep of one foot to touch the other foot's big toe (30 sec).
- Place one foot in front of the other, with the heel touching the toes (30 sec).
- Stand on one foot (30 sec).

FIGURE 4. Example of system use.

The test aimed to evaluate the patients' balance and establish a monitoring guideline for improvement through exercises. Over the month, users performed exercises prescribed by the system to enhance their condition. Each session involved analyzing various parameters, such as deviations and time. With this in mind, the gamification-based system conducted experiments to test its performance. Figure 4 shows an example of the system.

A. EVALUATION OF SYSTEM PERFORMANCE

An initial validation was conducted during the first session to assess the system's performance in detecting patient postural errors. Two experts were tasked with visually identifying posture errors as patients completed a series of balance exercises. Concurrently, the system's automated detection was recorded to compare its efficacy against the expert clinicians' observations. Table 1 presents a detailed comparison of postural errors detected by the expert clinicians versus those identified by the system during the first session across four different exercises.

TABLE 1. Comparison of errors detected for all patients in the first session.

	Ex. 1	Ex. 2	Ex. 3	Ex. 4	Total
Expert	57	76	54	62	249
System	46	60	44	51	201
True Positives	42	56	38	45	181
False Positives	4	4	6	6	20
False Negatives	15	20	16	17	68

As indicated in the table, expert observations identified 249 errors across all exercises, with the highest number of errors noted in Exercise 2 (76 errors) and the lowest in Exercise 3 (54 errors). The system detected a slightly lower total of 201 errors, reflecting discrepancies in error detection capabilities between human observers and the automated system.

The breakdown of true positives, where the system successfully identified errors, which the experts also noted, shows reasonably high detection accuracy, with 181 out of 201 possible true errors being detected. However, the system registered false positives (errors detected by the system but not confirmed by experts) uniformly across the exercises, amounting to 20 instances, indicating a potential over-sensitivity or misinterpretation of data by the system. False negatives, representing the errors missed by the system but noted by the experts, totaled 68 across all exercises.

To comprehensively assess the system's performance in detecting posture errors, we used a set of well-established metrics commonly employed in classification tasks. These metrics provide a robust framework for evaluating the precision and reliability of the detection algorithms used in the system:

- **Accuracy:** This metric represents the system's overall effectiveness in identifying correct and incorrect postures. It indicates the proportion of total predictions that were accurately identified, which is critical for understanding the general performance of the system.
- **Recall:** Also known as sensitivity, recall measures the system's ability to detect all relevant instances (true positives). High recall is important in medical or therapeutic settings as it ensures that most problematic postures are identified and corrected, reducing the risk of untreated issues.
- **F1-Score:** By combining precision and recall, the F1-score provides a single metric that balances the system's accuracy and recall. This is useful when comparing two systems with different strengths and weaknesses regarding precision and recall.

The results summarized in Table 2 show how these metrics manifest in actual system performance, providing a clear and quantitative insight into its capabilities and areas for improvement.

The results of the system's performance in detecting errors across various exercises demonstrate a notable level of accuracy and precision. With an overall accuracy of 72.7%,

TABLE 2. Evaluation metrics of the system.

Metric	Value
Accuracy	0.727
Precision	0.900
Recall	0.727
F1 Score	0.804

the system correctly identifies errors in nearly three-quarters of all cases compared to expert detections. This level of accuracy indicates that the system is reliable for consistent error detection, but there is still room for improvement to reach higher standards. The system's precision has a result of 90.0%, which means that a significant amount of errors detected by the system are indeed actual errors. This high precision is important for maintaining user trust, as it minimizes the number of false positives, ensuring that the feedback provided is accurate and actionable.

However, the recall metric, which stands at 72.7%, highlights an area that could benefit from enhancement. While the system is adept at correctly identifying errors when detected (high precision), it misses about 27.3% of the true errors (false negatives). This gap suggests that while the system accurately detects, it is not capturing all potential errors. The F1 score, which balances precision and recall, is 80.4%, reflecting a solid overall performance.

B. TEST RESULTS

As a preliminary step to the tests, the researchers accompanied the patients in the first session, explaining the method for using the tool. During each day, the patients performed the corresponding exercises, and before the end, they performed the evaluation exercises, using the tool to collect the necessary metrics. In this way, at the end of the testing period, these metrics were used to evaluate the evolution in their ability to maintain balance. One of the results obtained, the evolution of the users' ability to maintain a posture, can be seen in Figure 5.

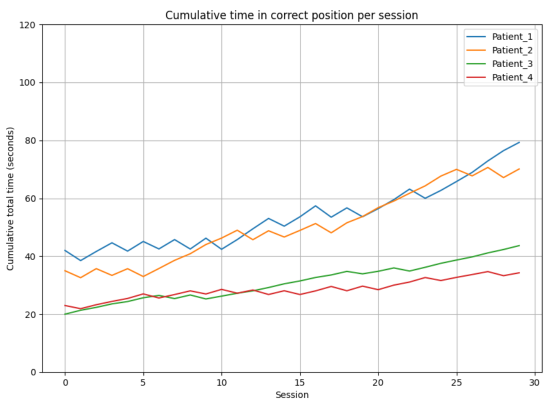

FIGURE 5. Evolution of the time accumulated by the patient maintaining a posture in each session.

All patients have improved their ability to maintain their posture throughout the test. More specifically, the volunteers with a balance disorder due to old age (Patient_1 and Patient_2) are the ones who improve the most in comparison to those with Parkinson's disease (Patient_3) and Multiple Sclerosis (Patient_4). Specifically, they are the most improved (with 37 and 35 seconds, respectively) compared to the other two patients (24 and 12 seconds, respectively). This situation is expected as Patient_1 and Patient_2 possess similar potential for improvement compared to the other patients, as any specific disease does not cause their balance disorders. This implies that physical and neurological limitations associated with specific diseases do not affect them. Therefore, the potential for improvement depends on various factors, but Patient_1 and Patient_2 are not subject to such limitations. Despite this, improvements can be observed in all subjects since the performance of these exercises usually involves coordinated movements, positions through the muscles, and the perception of the body itself, so the performance of these exercises helps to stimulate and strengthen the vestibular and motor systems, which are responsible for the balance of our body. The developed platform helps reinforce these factors, so the progress they achieved through these exercises is supported and boosted. This improvement process is not linear, where both the response of each patient and the adaptation process of the exercises influence each patient in different ways. However, by observing the starting and endpoints, the improvement of all of them is certified.

On the other hand, if we consider the evolution of the mean deviations detected per session, which can be seen in Figure 6, all participants improved their stability when performing the postures. However, the magnitude of the improvement varies between volunteers, similar to what has been observed previously. The improvement in stability can be understood as a reduction in the deviation of the key points from the ideal balance position. This description means that, after performing the postures, all volunteers could maintain their balance position more precisely and more stable, reducing body oscillations that could lead to a loss of balance.

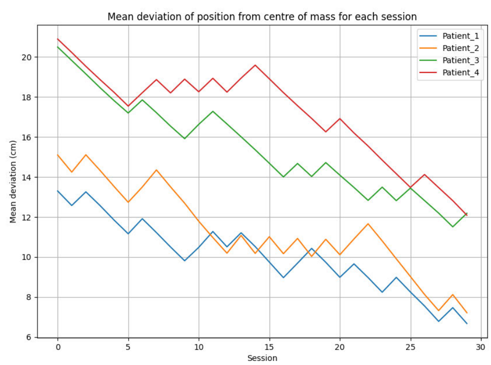

FIGURE 6. Mean deviations in postures for each of the sessions.

Initial participant feedback in the prototype testing phase has provided important insights into the system's user experience and effectiveness. The overall response has been positive, with participants noting a significant increase in motivation. Users have appreciated the real-time feedback on their balance, stating that it aids significantly in taking immediate corrective actions.

The engagement level was notably high among users, who reported that the system made the exercises more enjoyable and less tedious. These findings suggest that integrating gamification and interactive feedback mechanisms has successfully enhanced user adherence to therapeutic regimes. The positive reception is crucial for the platform's ongoing development, focusing on enhancing the precision of movement detection and broadening the gamification elements to cater to diverse user preferences.

C. STATISTICAL RESULTS

This study employed a sequence of statistical tests to analyze two critical metrics: "Correct Position", the average time subjects can maintain a correct posture, and "Mean Deviation", the average deviation from the center of mass. We selected a sequence of statistical tests to rigorously analyze the data obtained from our intervention to improve balance and posture through a gamified platform. The rationale behind each test selection is deeply rooted in the unique characteristics of our dataset and the specific objectives of our analysis.

We initiated our statistical exploration with the Shapiro-Wilk test for normality. This choice was driven by the test's robustness in assessing the normal distribution of small to medium-sized datasets, which is pivotal for determining the appropriate subsequent analytical techniques. Given the critical nature of assuming normality in many parametric tests, establishing or refuting this assumption was paramount. Our dataset, characterized by posture maintenance and deviation measurements, warranted this preliminary step to guide the accurate selection of further analysis methods.

The Shapiro-Wilk test results (Table 3) indicated that the data's normality varies across sessions, influencing the selection of non-parametric methods for further analysis. The test yielded Shapiro statistics ranging from 0.7946 to 0.9962 and p-values between 0.0004 and 0.9866. This wide range of results demonstrates a mix of sessions that align well with a normal distribution and others that diverge to a greater extent. For instance, sessions with Shapiro statistics close to 1 and p-values greater than 0.05 suggest that the data are typically distributed, allowing parametric tests. Sessions with lower Shapiro statistics and p-values less than 0.05 indicate non-normal distributions, allowing non-parametric tests. These variations highlight the importance of selecting appropriate statistical methods based on the specific characteristics of each session's data.

TABLE 3. Summary of the Shapiro-Wilk test results.

Metric	Shapiro Statistic		p-value	
	Min	Max	Min	Max
Correct Position	0.7946	0.9962	0.0004	0.9866
Mean Deviation	0.7798	0.9962	0.0004	0.9866

The observed variability and the approximation to normality in several sessions, supported by Shapiro statistics close to 1 and non-significant p-values, indicate that while some sessions show typical distribution characteristics, others do not. This finding is crucial as it directs non-parametric tests for those sessions that do not fit the normal distribution.

Upon establishing the normality or non-normality of our data distributions, we proceeded with the paired samples t-test. This decision was contingent on the Shapiro-Wilk test results and the paired nature of our data—pre and post-intervention measurements for the same subjects. The paired samples t-test was deemed the most suitable method for evaluating the effectiveness of our intervention due to its sensitivity in detecting changes within subjects over time. This test allowed us to quantify the impact of our gamified platform on improving participants' balance and posture by comparing their performance metrics before and after undergoing the intervention.

The results of the paired samples t-test are presented in Table 4. These results show the mean difference, standard deviation, t-statistic, degrees of freedom, and p-value for both "Correct Position" and "Mean Deviation" metrics. A significant t-statistic and a p-value less than 0.05 indicate a statistically significant difference between the pre-intervention and post-intervention measurements, suggesting that the intervention had a meaningful impact. Specifically, a positive mean difference in "Correct Position" suggests improving the ability to maintain correct posture. In contrast, a negative mean difference in "Mean Deviation" indicates a reduction in deviations from the center of mass. These findings support our gamified platform's effectiveness in enhancing participants' balance and posture. The detailed results in Table 4 help to quantify these improvements and provide a robust statistical basis for our conclusions.

TABLE 4. Results of the paired samples t-test.

Metric	t-Statistic	p-value
Correct Position	16.93	< 0.001
Mean Deviation	-4.49	0.021

Finally, we employed Ordinary Least Squares (OLS) regression analysis to explore the relationship between the "Correct Position" and "Mean Deviation" metrics. This analysis was conducted to determine how improvements in maintaining correct posture might influence the precision of balance, as indicated by deviations from the center of mass. The results of the OLS regression analysis are presented in Table 5.

Table 5 shows the regression coefficient, standard error, t-statistic, and p-value for the predictor variable "Correct Position." The regression coefficient for "Correct Position" is negative and statistically significant ($p < 0.05$), indicating that as the time maintaining a correct posture increases, the average deviation from the center of mass decreases. This negative relationship suggests that improving correct posture

TABLE 5. Summary of the results of the OLS regression analysis.

	Value	Interpretation
Metrics:		
R-squared	0.866	86.6% of the variability explained
Adj. R-squared	0.844	Adjustment for the number of predictors
F-statistic	38.88	Global significance of the model
Prob (F-statistic)	0.000787	Probability of F-statistic
Coefficients:		
Constant	93.4870	Value of Y when X=0
x1 (Correct Position)	-3.7107	Change in Y per unit of X
$P > \|t\|$ (Constant)	< 0.001	Significance of the constant
$P > \|t\|$ (x1)	< 0.001	Significance of x1

is associated with better balance control. The R-squared value of 0.866 indicates that approximately 86.6% of the "Mean Deviation" variability can be explained by "Correct Position," demonstrating a strong link between these two metrics.

The coefficients in the OLS regression reveal that for each unit increase in "Correct Position," "Mean Deviation" decreases. This indicates a negative relationship between the metrics, consistent with the previously identified negative correlation, and underscores how improvements in posture corrections negatively influence the average deviation from the center of mass. The statistical significance of these coefficients, as indicated by the P > |t| values, further supports confidence in these findings.

Overall, the OLS regression analysis results support the hypothesis that enhancing correct posture through our gamified platform reduces deviations, thus improving overall balance. This robust statistical analysis adds credibility to our findings and reinforces the intervention's value in clinical practice.

V. DISCUSSION

Within neurological rehabilitation, traditional methods for addressing disorders that impact balance, gait, and posture have predominantly relied on professionally guided physical therapies. These therapies often encompass balance and strengthening exercises, gait retraining techniques, and mechanical aids. Although effective, these strategies exhibit limitations, such as challenges in sustaining patient motivation over the long term, the subjectivity of progress assessment, and reliance on the availability of trained specialists.

The proposed system addresses these limitations by incorporating computer vision and gamification into rehabilitation. Unlike traditional methods, our approach enables an objective and real-time evaluation of patient movement, surpassing the subjectivity of human observations. Moreover, we enhance treatment adherence by transforming rehabilitation exercises into interactive games within a virtual environment. This strategy captures the patient's interest and active participation through entertainment and progressive challenges. Also, it facilitates detailed and continuous monitoring of progress.

Furthermore, our system's customization capability ensures that exercises are tailored to the user's skill level and specific rehabilitation needs, a feat that can be challenging to achieve in traditional therapy sessions due to time and resource constraints. The automatic adaptability of the system to the patient's improvement ensures a consistent challenge, promoting faster and more effective recovery.

Implementing statistical analyses in our study reinforces the validity of these assertions. The Shapiro-Wilk test established the normality of the distributions for our metrics, enabling the use of paired sample t-tests. These tests confirmed significant improvements in posture maintenance abilities and reductions in postural deviations among our subjects. The OLS regression analysis highlighted a negative association between the time of maintaining the correct posture and the average deviation from the center of mass, demonstrating tangible improvements in posture over time.

The evaluation metrics used to assess the system's performance detecting posture errors provide a quantitative measure of its effectiveness. The accuracy, precision, recall, and F1-score, as calculated, indicate that the system performs well in real-world settings with some limitations. The results suggest that the system can reliably identify errors, yet it misses specific errors due to occlusions or the presence of loose clothing. This underscores the need for improvements in sensor accuracy or alternative strategies to enhance detection capabilities. One approach to address these limitations could be integrating more advanced sensor technologies, such as depth-sensing cameras or infrared sensors, which may be less susceptible to common visual obstructions. Additionally, enhancing the algorithm's capability to interpret complex or partially obscured human forms could significantly reduce the rate of false negatives.

The evaluation metrics used to assess the system's performance detecting posture errors provide a quantitative measure of its effectiveness. The accuracy, precision, recall, and F1-score, as calculated, indicate that the system performs well in real-world settings, albeit with some limitations. The results suggest that the system can reliably identify errors, yet it misses specific errors due to occlusions or the presence of loose clothing. This underscores the need for improvements in sensor accuracy or alternative strategies to enhance detection capabilities. One approach to address these limitations could be integrating more advanced sensor technologies, such as depth-sensing cameras or infrared sensors, which may be less susceptible to common visual obstructions. Additionally, enhancing the algorithm's capability to interpret complex or partially obscured human forms could significantly reduce the rate of false negatives.

Our decision to develop a bespoke algorithm rather than employ traditional posture detection models stems from the need to provide a more flexible, accurate, and robust solution for the real-world application of balance disorder rehabilitation. The performance metrics from our initial tests, particularly the high precision and reasonable recall rates, affirm the efficacy of our approach. The algorithm's ability to discern true posture errors represents a significant advancement over conventional methods, often limited by rigidity and lack of adaptability to diverse patient conditions.

To further enhance the capability of our posture detection system, ongoing efforts are directed toward refining the algorithm to handle occlusions more effectively and improving its sensitivity to subtle postural deviations. These enhancements are expected to further boost the system's accuracy and reliability, ensuring that it not only matches but exceeds the performance of traditional posture detection methodologies.

This study introduces an innovative approach to treating balance disorders associated with neurological conditions, combining the precision of computer vision with the allure of gamification techniques. Our findings indicate that applying this system enhances the accuracy of balance disorder assessments and significantly boosts patient motivation and adherence to treatment. This aligns with previous research, such as [46], which suggests the effectiveness of gamification and immersive virtual reality (IVR) in rehabilitative contexts. The study by [47] also leverages computer vision to assess gait in patients with Parkinson's disease, employing a computer-vision-based method to objectively quantify gait characteristics from videos recorded with mobile devices in clinical settings. Their system achieved significant correlations between model estimations and clinical ratings, providing an objective way to estimate the severity of gait disorders in Parkinson's disease. Like our study, [47] emphasizes the importance of objective evaluations and the potential to integrate these technologies into regular clinical practice without additional equipment or specialized setups.

However, there are key differences between these studies. While [47] focuses on Parkinson's disease and quantifying the severity of gait disorders through UPDRS scores derived from extracted gait features, our system encompasses a broader range of neurological disorders. It combines gait assessment with gamification elements to enhance patient motivation and engagement in treatment. Furthermore, our emphasis on customizing and adapting the system to the specific rehabilitation needs of the patient and improving treatment adherence through gamification provides added value beyond merely objective gait evaluation.

Moreover, whereas the study [46] is limited to patients with chronic stroke, our approach seeks to generalize the system's applicability to a broader array of neurological disorders, thereby increasing its potential for implementation in various clinical scenarios. Despite similarities in the use of IVR, our study stands out for its ability to personalize and adapt exercises to the patient's specific needs, promoting faster and more effective recovery.

Comparing our system with previous works, including [46] and [47], it becomes evident that while we share similar objectives of enhancing the assessment and treatment of neurological disorders through advanced technologies, our project is distinguished by its unique capability of integrating objective evaluation with an enriched rehabilitation experience through gamification. This approach addresses the limitations of conventional methodologies. It sets new directions for future research and clinical practice, supporting a more personalized and contextualized use of technology in diagnosing and treating movement disorders.

Furthermore, it is crucial to continue innovating and developing more precise and adaptive measurement techniques that can be seamlessly integrated into daily clinical practice. Our study aligns with prior research efforts and expands their application, suggesting future directions for using technology in clinical and research contexts.

VI. CONCLUSION AND FUTURE WORK

Throughout this document, we have demonstrated that our project has achieved its goal of developing a balance training platform that is finely customized to meet the individual needs of each user. This platform features a range of exercises and games designed specifically to enhance patient balance, which can be accessed both in-person and remotely. A key strength of the platform is its adaptability, mainly due to its innovative architecture based on a multi-agent system integrated within the Context-Aware framework. This adaptability ensures the training is personalized and effective, adjusting dynamically to each patient's progress and changing needs. Moreover, including gamification elements in the exercises significantly increases patient engagement and adherence to the treatment regimen.

The technical evaluation of our platform focused on assessing the accuracy of the computer vision algorithms and the effectiveness of the gamification strategies in promoting user engagement. The initial tests highlighted the system's capability to track and analyze user movements accurately in real-time, thanks to the integration of the dual-camera setup. Precisely detecting postural deviations has proven effective in providing users with actionable feedback.

Despite the promising results, the evaluation also identified areas for improvement, particularly in enhancing the system's responsiveness and the diversity of exercises available. To address these issues, it's necessary to increase the gamification elements to include a wider variety of challenges and rewards in future works. To substantiate the system's performance, we have incorporated standard evaluation metrics such as accuracy, precision, recall, and F1-score in our assessment. The results from these metrics underscore the system's reliability in real-world settings and highlight potential areas for enhancement. Improvements to address these areas include integrating more advanced sensor technologies and refining the algorithm to handle occlusions more effectively, which are expected to improve detection capabilities further.

Furthermore, a structured clinical trial is needed to ensure the platform's clinical efficacy. This trial will quantitatively measure the improvements in balance and posture through standardized tests, providing a robust dataset to analyze the system's therapeutic benefits. This extensive research will allow for a comparative analysis of patient progress based on diagnosed pathologies, shedding light on the platform's effectiveness and broader applicability in managing balance disorders.

The study design for this project was tailored to match the initial development stage of our innovative platform, which integrates computer vision and gamification to treat balance disorders. Given the nature of this system, the primary objective at this phase was to evaluate the technical feasibility, user interaction, and the immediate impact of the gamification elements on user engagement.

The selected evaluation methods were intended to provide insights into the system's operational effectiveness and user acceptance. These methods allow quick adjustments and iterative improvements based on real-time interactions and experiences.

While the platform's clinical efficacy is an essential component, the initial focus on technical validation and user experience is essential to establish a strong foundation. This approach ensures the platform is optimized for user interaction and technical robustness before conducting extensive clinical trials. It is anticipated that the insights gained from this preliminary study will guide the design of a comprehensive clinical trial, which will rigorously evaluate the system's clinical outcomes and therapeutic benefits.

Finally, future work will focus on enhancing the system by incorporating a cutting-edge fixed platform designed to accurately detect the pressure exerted by users in various postures. This improvement is expected to provide more detailed information about the user's center of gravity, thereby increasing the system's precision.

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