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An Adaptive Fatigue Detection Model for Virtual Reality-Based Physical Therapy †

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Abstract: This paper introduces a fatigue detection model specifically designed for immersive virtual reality (VR) environments, aimed at facilitating upper limb rehabilitation for individuals with spinal cord injuries (SCIs). The model's primary application centers on the Box-and-Block Test, providing healthcare professionals with a reliable tool to monitor patient progress and adapt rehabilitation routines. At its core, the model employs data fusion techniques via ordered weighted averaging (OWA) operators to aggregate multiple metrics captured by the VR rehabilitation system. Additionally, fuzzy logic is employed to personalize fatigue assessments. Therapists are provided with a detailed classification of fatigue levels alongside a video-based visual representation that highlights critical moments of fatigue during the exercises. The experimental methodology involved testing the fatigue detection model with both healthy participants and patients, using immersive VR-based rehabilitation scenarios and validating its accuracy through self-reported fatigue levels and therapist observations. Furthermore, the model's scalable design promotes its integration into remote rehabilitation systems, highlighting its adaptability to diverse clinical scenarios and its potential to enhance accessibility to rehabilitation services.

Keywords: upper limb; rehabilitation; virtual reality; serious games; fatigue detection; Box-and-Block Test

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1. Introduction and Context

Despite technological advancements aimed at improving treatment efficacy, upper limb rehabilitation continues to present notable challenges [1]. These injuries frequently lead to a diminished quality of life and heightened reliance on healthcare services, which are often limited in availability, particularly in resource-constrained environments. Although rehabilitation aims to enhance mobility, flexibility and alleviate pain, its initiation is frequently delayed due to the extensive time commitment required from therapists, thereby postponing essential care. The early phases of rehabilitation are especially demanding, with variations depending on the injury's severity. This complexity has driven the investigation of virtual reality (VR) as a supportive intervention, demonstrating its potential to serve as a complementary modality [2].

VR is a technology that allows users to immerse themselves in interactive digital environments [3], creating an immersive experience that simulates real-world situations. In

recent years, there has been a strong development and expansion in the use of headsets, consisting of a viewer and controllers, which has allowed its application to be extended to multiple fields, including the field of rehabilitation.

Rehabilitation of upper extremity injuries poses significant challenges that persist despite technological advances that improve the effectiveness of treatment [4]. These injuries often significantly reduce patients' quality of life and increase their dependence on health services, which can be scarce in resource-limited settings [5,6]. Although the goals of rehabilitation include improving mobility, flexibility and pain relief, initiation of treatment is often hampered by the amount of time therapists must devote to each patient, delaying the provision of essential care. The early stages of rehabilitation are particularly rigorous and vary according to the severity of the injury, which has led to the exploration of VR as a facilitating tool.

A major advancement in VR has been the use of direct hand tracking systems [7], eliminating the need for controllers. This new way of interacting with the virtual environment was particularly relevant for spinal cord injury (SCI) patients, who in many cases suffer from spasticity, limited grasping and other functional challenges [8,9]. These conditions have prevented the use of VR devices due to difficulties in grasping controllers and correctly using buttons or joysticks.

In addition, motivation plays a crucial role in the rehabilitation of SCI patients, as the process is lengthy and the exercises performed are repetitive [10]. VR combined with gamification makes rehabilitation more engaging and fun, which increases patient participation. For example, games that reward the achievement of specific goals have been shown to significantly improve adherence. Adherence helps overcome emotional barriers that patients often face, such as boredom or frustration. In addition to psychological benefits, VR allows for the personalization of therapy [11]. Virtual environments can be tailored specifically to the needs of each patient, adapting to the level of injury and its evolution over time.

Finally, VR provides valuable support for the clinical analysis and objective measurement of patient performance [12]. Using this technology, specialists can monitor exercise execution, evaluate trajectories performed and analyze key kinematic elements such as range of motion or speed of execution. These data allow them to accurately identify areas for improvement, providing an evidence-based approach for optimizing personalized rehabilitation for SCI patients.

In response to the pressing demand for novel rehabilitation methods, we collaborated with a hospital specializing in SCI to create the Rehab-Immersive (RI) framework [13]. This framework delivers a data-driven, customizable virtual environment that supports the simulation of hand movements and incorporates therapeutic activities, such as the Box-and-Block Test, to enhance both patient engagement and therapeutic results. By enabling precise kinematic analysis, the system empowers therapists to monitor patient progress accurately. Additionally, it equips developers with versatile tools for designing adaptive and creative VR applications, addressing the technical requirements and therapeutic goals essential for effective patient rehabilitation.

On the other hand, healthcare professionals play a critical role in rehabilitation, traditionally requiring their physical presence to oversee and adjust patient treatments. This necessity places considerable strain on resources, inherently restricting the number of patients who can be managed effectively. To address this limitation, it is crucial to develop a system that offers remote access to comprehensive patient reports, enabling therapists to optimize their workload and extend their capacity to manage larger patient groups. Such a solution would enhance the efficiency of rehabilitation services, allowing therapists to broaden their impact without necessitating a proportional increase in personnel.

Within this context, this study aims to create a scalable and comprehensive model for evaluating patient performance within a VR-based rehabilitation setting, with an emphasis on measuring muscle fatigue following therapeutic exercises. Muscle fatigue, defined as the gradual decline in a muscle's ability to produce force, is central to this research work [14]. The model utilizes data extracted from the RI framework to generate a measurable fatigue indicator, enhancing the clarity and interpretability of patient progress evaluations. A significant contribution of the model is its scalability, which allows for the integration of additional variables or sensor inputs to refine fatigue assessments over time. Furthermore, the design accommodates the inclusion of new rehabilitation games without requiring modifications to the foundational algorithms.

To address the uncertainties and imprecision associated with muscle fatigue measurements, our model employs fuzzy logic to calculate fatigue levels for individual metrics [15]. This approach leverages fuzzy sets to manage inherent ambiguities effectively. For aggregating these metrics, we utilize ordered weighted averaging (OWA) operators [16], offering a flexible mechanism for combining information. By adjusting aggregation weights, this method accommodates varying levels of significance and consistency across metrics, allowing for either an optimistic or pessimistic interpretation of the data. This adaptability ensures a customized and precise assessment of fatigue levels tailored to the specific context.

Experimental results were considered from three different perspectives. First, a preliminary evaluation focused on functional verification to ensure that the fatigue detection model was consistent with its intended design. This step included testing with healthy participants. Next, tests were conducted with patients from the National Hospital for Paraplegics in Toledo (Spain). These trials aimed to analyze real data collected during rehabilitation exercises using the VR-based RI framework. Finally, the integration of the model into a second system designed to support remote rehabilitation of neurological patients was also addressed.

The main technical contributions of our research work are the following:

1. A fatigue detection model has been developed that is based on data fusion and fuzzy logic. The model under discussion combines OWA operators with fuzzy logic. This model is proposed for use in the assessment of patient fatigue in virtual reality environments. This approach allows for a flexible and personalized assessment of muscle fatigue. It addresses the uncertainties inherent to the measurement of this phenomenon in rehabilitation.
2. The integration of the model into an immersive VR rehabilitation environment has been addressed. The model has been developed within the RI framework, a platform designed specifically for the rehabilitation of patients with spinal cord injuries. This integration enables the system to adapt to the needs of patients, thereby minimizing the risks associated with interaction with immersive technology.
3. The model's adaptability and scalability to other rehabilitation scenarios has been considered from the design point of view. The proposed solution is sufficiently flexible to be extended to other contexts, such as augmented reality (AR) rehabilitation environments. This property enables the model's implementation with diverse hardware and software configurations without the need for significant alterations to its underlying algorithms.

The rest of the article is organized as follows: Section 2 provides an overview of the related literature. In Section 3, the proposed fatigue detection model is detailed, including the metrics employed, the data fusion approach and the underlying architectural design. Section 4 presents the experimental findings and their analysis. On the other hand, Section 5 presents a brief discussion after the research work has been presented and the experiments

have been carried out. Lastly, Section 6 summarizes the work and highlights potential directions for future research.

2. Related Work

VR is rapidly establishing itself as a groundbreaking tool in medical rehabilitation [17]. Its flexibility in customizing exercises and therapies to meet the specific requirements of individual patients significantly amplifies its impact. This innovation signifies more than the adoption of advanced technologies; it marks a fundamental shift in rehabilitation methodologies. Beyond traditional approaches, VR redefines the rehabilitation experience by transforming routine exercises into immersive, engaging activities. This evolution not only exemplifies technological progress but also fosters increased patient motivation and active participation in therapy [18]. By embedding immersive elements, VR elevates rehabilitation from a procedural task to an interactive and stimulating journey for patients.

VR offers significant potential for advancing upper extremity rehabilitation by incorporating gamification elements and leveraging immersive technologies to enhance patient engagement and therapeutic outcomes [19]. By creating dynamic and interactive virtual environments, VR transforms traditionally monotonous rehabilitation exercises into more enjoyable activities, alleviating their repetitive nature. Within these safe and controlled virtual settings, patients can perform intricate movements while receiving high-quality multimedia feedback. This feedback, which incorporates multi-sensory responses, is vital for ensuring the precise execution of therapeutic tasks. Furthermore, VR facilitates the implementation of home-based rehabilitation programs, improving accessibility and promoting greater adherence to therapy schedules. The expanding body of research underscores the positive impact of VR on upper limb rehabilitation and its potential to revolutionize conventional therapeutic approaches [20].

In stroke recovery, VR has emerged as a versatile tool, supporting both cognitive and motor rehabilitation [21]. The real-time feedback it offers during therapy sessions enables dynamic adjustments to treatment plans, enhancing their overall effectiveness. Its unparalleled accessibility allows VR to be utilized virtually anywhere and at any time, making it a flexible solution for patient rehabilitation. This adaptability not only streamlines the recovery process but also plays a crucial role in enhancing patients' quality of life. Moreover, VR extends its benefits beyond physical rehabilitation by mitigating pain perception during therapeutic exercises [20]. Through immersive and comfortable experiences, VR addresses both the physical and emotional aspects of recovery, supporting a comprehensive and patient-centered approach.

In parallel, related studies emphasize the crucial role of external sensors in improving the accuracy of fatigue performance measurements. A high level of fatigue decreases the effectiveness of physical rehabilitation, and it increases the risk of injury [22]. Wang et al. [23] use external devices such as electromyography (EMG) and heart rate variability (HRV) to measure fatigue. For the detection task, an understanding of the metrics that lead to fatigue detection is encouraged [24]. In addition, in [25], Bartels et al. suggest a link between muscle fatigue and muscle strength, using the widely used Box-and-Block Test implemented in RI for verification. Jiang et al. [22] introduced a predictive model for fatigue detection using motion data from inertial measurement units and force plates. Using machine learning techniques, such as convolutional neural networks and random forests, they achieved high accuracy in correlating motion data with self-reported fatigue levels.

Surface electromyography (sEMG) has been extensively studied for its ability to capture muscle fatigue non-invasively during the execution of exercises and for its low cost. Montoya et al. [11] explored the application of bio-cybernetic adaptation in VR rehabilitation. They used sEMG signals to monitor fatigue in real time and adapt game challenges

accordingly. This approach not only reduces perceived fatigue but also improves performance, highlighting the synergy of VR with physiologically aware systems. Karthick et al. [26] also used sEMG for evaluating the fatigue level of patients performing rehabilitation exercises. They focused on analyzing sEMG signals specifically during dynamic contractions, using high-resolution time-frequency methods and machine learning to differentiate between fatigued and non-fatigued states. They employed multiple time–frequency analysis methods, such as the Stockwell transform, in combination with machine learning algorithms like support vector machines (SVMs), achieving a 91% classification accuracy. Furthermore, in [27], Roldán et al. employed sEMG in combination with the accelerometer sensor in a smartphone to quantify fatigue. Their study was centered on a 30 s sit-to-stand test, where they applied machine learning algorithms, such as support vector machines, to differentiate between fatigued and non-fatigued states during dynamic contractions.

Nasirzadeh et al. [28] proposed a novel approach to fatigue detection for real-time monitoring in rehabilitation. Their framework uses the entropy and statistical analysis of heart rate signals for detecting physical fatigue. Key features were extracted, ranked and classified using machine learning algorithms, achieving over 90% accuracy. Finally, Moniri et al. [29] introduce the application of adaptive machine learning algorithms for real-time forecasting of muscle fatigue. Using sEMG sensors in trunk muscles, shallow models were employed in conjunction with concurrent neural networks to forecast muscle fatigue up to 25 s in advance. Although sEMG features vary between subjects, with this approach, they are able to forecast fatigue levels accurately.

While existing research provides valuable insights, there is still a gap in immersive VR applied to rehabilitation and the fatigue detection methods using these metrics. This paper attempts to fill this gap by presenting a reliable approach to fatigue detection within the constraints of using only data accessible from the RI software (version 1.0.1) without relying on external devices.

Our Approach

Despite the growing interest in the use of VR for rehabilitation purposes, the prevailing approaches primarily emphasize enhancing mobility through the repetition of motor exercises, neglecting an accurate assessment of the patient's fatigue level. Existing studies have explored the use of external sensors, such as surface electromyography (sEMG) or heart rate variability (HRV), to measure fatigue during rehabilitation. However, these approaches introduce additional complexity and costs. In fact, patients afflicted with SCI frequently encounter substantial challenges in adhering to the integration of hardware sensors, increasing the complexity and cost associated with experimental setups analogous to those outlined in this proposal. However, few works have dealt with fatigue detection based solely on data captured by the VR system itself, without relying on external hardware. The present study proposes a novel approach to address this critical gap by developing a fatigue detection model that integrates internal data from the VR environment with fuzzy logic. This model enables customized assessments that do not need the use of additional devices. Thus, our approach not only detects fatigue but also presents it visually to therapists, thereby facilitating real-time decision-making and enhancing the adaptability of rehabilitation sessions.

3. A Model for Fatigue Detection

Our model generates a single fatigue output value by employing a multi-step process. Initially, several fatigue metrics are derived from the extracted data. These metrics are subsequently combined using data fusion techniques to produce a unified fatigue indicator. In particular, the aggregation relies on OWA operators, which form the foundation of the

model's fatigue detection framework. The design prioritizes flexibility and scalability, enabling the seamless addition or removal of metrics to accommodate new data or previously unconsidered factors.

The Oculus Quest 3 (OQ3) VR device was utilized to capture high-quality data, which serve as the foundation for our fatigue detection model. The collected data include hand and head positions, rotations and hand speed. Additionally, RI has introduced specific indicators, such as the timing of object grasping and the force exerted by the fingers. A comprehensive overview of the data recorded by both the OQ3 and RI is provided in Table 1.

Table 1. Data captured by the model for fatigue detection through Oculus Quest 3.

Variable	Data Type	Range of Values	Description
Frame number	Integer	0 to n	The frame number at the start of the exercise
Time	Float	0 to n seconds	The time measured in seconds
Head position	Vector	x, y, z coordinates	3D position of HMD in space
Head rotation	Vector	x, y, z coordinates	Head rotation value in every direction
Hand detection	Boolean	True or false	Detection of hand (detected or undetected)
High confidence	Boolean	True or false	Confidence hand tracking; if true, then the confidence level is high
Hand position	Vector	x, y, z coordinates	3D position of hand in space
Hand rotation	Vector	x, y, z coordinates	Hand rotation value in every direction
Hand velocity	Vector	x, y, z coordinates	Hand velocity value in every direction
Wrist twist force	Float	0 to 360	Degree of hand rotation relative to the wrist
Pinch detection	Boolean	True or false	Detection of a pinch
Palmar grasp detection	Boolean	True or false	Detection of a palmar grasp
Autogrip	Boolean	True or False	Autogrip mode
Strength	Float	0 to 1	Strength value from thumb to each finger and from palm to each finger
Grab identifier	String	36 bytes identifier	Identifier for the box being grabbed at each moment
Moved correctly	Boolean	True or False	The user moved the box correctly

3.1. Data Extraction

As previously noted, our model focuses on the Box-and-Block Test. This task is characterized by a highly consistent movement pattern: each cycle starts with the user grasping a block, transferring it to the opposite compartment and then retrieving another block to repeat the process. This repetitive sequence offers a reliable evaluation of manual dexterity and hand–eye coordination. Once the series is divided into individual repetitions, the following data are extracted:

Time: Difference between the first and last timestamp.

Velocity: Given the three components of the vector space representing speed, the scalar magnitude is calculated at each instant. The mean scalar value over the duration of the repetition is then used as its representative metric.

Grip strength: As there are different types of grips, we only count the fingers of the hand that apply force and calculate the average.

Head position: In this case, we simply take the head position on the three axes without any pre-processing.

Hand trajectory: Only key points relevant to our estimations are considered: the picking point (y-axis), the highest point (y-axis) and the leaving point (x-axis, y-axis).

Block drops: A metric generated by the RI identifies the block being manipulated. If a break is detected where the user picks up a block, sets it down and then picks it up again, this event is counted as a drop.

Incorrect movements: Check the relevant data without pre-processing.

3.2. Data Fusion

OWA operators play a vital role in handling decision-making processes under conditions of uncertainty. Mathematically, an OWA operator of order n is defined as a mapping $F : R^n \rightarrow R$ associated to a vector of weights W of length n. $W = [w_1, w_2, .., w_n]$, where $\sum_{i=1}^{n} w_i = 1$.

An OWA operator provides a mechanism for information fusion, allowing for a spectrum of consensus ranging from optimistic to pessimistic. Unlike traditional weighted averages, where weights are assigned directly to specific inputs, OWA operators distribute weights based on the rank or order of the inputs rather than their actual values.

In our research, a pessimistic consensus was adopted. This choice, informed by the findings presented in Section 4, aimed to derive values closely reflecting the user's perceived fatigue. After testing various parameters, the pessimistic approach was identified as the most suitable for our objectives. A pessimistic approach in the context of fatigue detection refers to giving more importance to higher fatigue values over lower ones in the aggregation process. This is implemented by giving higher weights to the higher ranks and lower weights to the lower ranks in the OWA operators. In this way, the final fatigue estimation prioritizes worst-case scenarios, ensuring that higher fatigue levels have a more significant impact on the aggregated result.

To enhance adaptability, we implemented an automatic re-weighting mechanism for the OWA weights, adjusted dynamically based on specific conditions. When a fatigue metric reports an unusually high value, the weights are adjusted such that ranks with higher fatigue levels are given a higher weight than they would otherwise have. This mechanism ensures a balance between typical and abnormal scenarios, recognizing the importance of outlier metrics.

Following the approach described in [30], the Sugeno method was applied for automatic re-weighting. In this method, the degree of normality $N_i \in [0, 1]$ is calculated for each concept, which, in this study, corresponds to the fatigue value. Then, the degree of abnormality is then defined as $A_i = 1 - N_i$, quantifying the deviation of each fatigue value from normality. Finally, the difference between the degree of abnormality and the degree of normality $\Delta(A - N)_i = A_i - N_i$ is used for dynamically adjusting the weights. Weights increase when this difference is greater than zero, following the weight adjustment function f:

$$f(\Delta(A - N)_i, w_i) = \begin{cases} w_i & \text{if } \Delta(A - N)_i \leq 0, \\ w_i + \Delta(A - N)_i & \text{if } \Delta(A - N)_i > 0. \end{cases}$$

As the addition of all the weights may be larger than 1, the final weights must be normalized:

$$w_i' = \frac{f(\Delta(A - N)_i, w_i)}{\sum_{j=1}^{n} f(\Delta(A - N)_j, w_j)}$$

For example, consider the fatigue values $[0.8, 0.5, 0.3, 0.3, 0.2]$ and the corresponding OWA weights $[0.5, 0.3, 0.1, 0.05, 0.05]$. If the degrees of normality are taken as the complement of the fatigue values, they become $[0.2, 0.5, 0.7, 0.7, 0.8]$. The resulting differences

between abnormality and normality degrees are $[0.6, 0.0, -0.4, -0.4, -0.6]$. In turn, the weights before the normalization are $[1.1, 0.3, 0.1, 0.05, 0.05]$, and after normalization, they become $[0.688, 0.187, 0.062, 0.031, 0.031]$.

This method demonstrated effectiveness by balancing the detection of abnormal situations and mitigating their recurrence for the same patient in subsequent evaluations.

3.3. Fatigue Computation

In this model, a specific fatigue output is determined for each patient based on their individual performance data. Initially, comparative data are defined for each repetition to assess the decline in the patient's performance, which serves as the basis for calculating fatigue on a per-patient basis.

For patients performing an exercise with RI for the first time, the comparative data are derived from the initial 20% of repetitions in the exercise. Conversely, when historical data are available, the comparative data incorporate these records, excluding the top 20% and bottom 20% of values for each indicator, which are treated as outliers.

Because rehabilitation is a prolonged process, greater significance is assigned to historical data that are closer to the date of the new therapy session. To achieve this, a weighted average is employed, with weights being defined by the formula: $P_i = \frac{n-i+1}{\sum_{j=1}^{n} j}$. The initial values in the weight calculation correspond to the most recent dates, ensuring that newer data are prioritized. Once the comparative data have been defined, the fatigue calculation for each metric is performed based on this weighted dataset.

Time and velocity and grip strength: The worse the performance, the higher the fatigue will be. Fuzzy logic has been used for calculating the fatigue (see Figure 1).

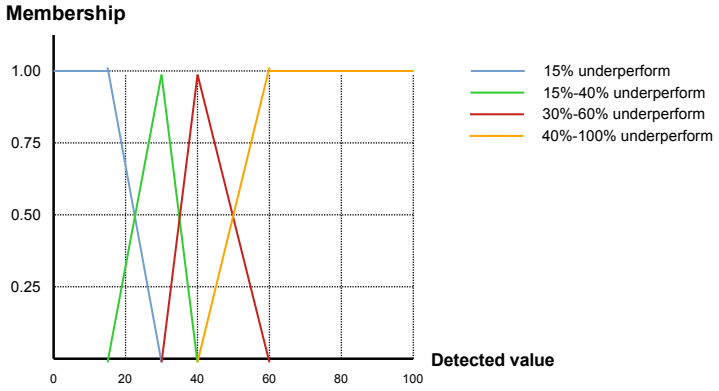


Figure 1. Fuzzy sets to represent the patient's performance decline.

Head position: Based on the comparative data, a positional boundary for the head has been defined. When patients exceed this boundary, it suggests an attempt to compensate for reduced mobility by moving their torso, which is interpreted as a sign of compensation and, consequently, fatigue.

Hand trajectory: Two key points are analyzed for comparison. The first is the highest point on the y-axis during the trajectory; a reduction in this height indicates an increased level of fatigue. The second point corresponds to the position where the block is released. When the release occurs closer to the center of the box, it signifies a higher degree of fatigue.

Once the fatigue indicator values have been computed, the OWA operator described in Section 3.2 is applied to determine the fatigue level for each repetition. Errors are then penalized: if the box is dropped, the fatigue value is increased by 15%, and if the movement is performed incorrectly, it is increased by 10%.

In the second step, the overall fatigue value for the entire exercise is calculated. To achieve this, the lowest 20% of the values are discarded, and the average is computed from the remaining data points.

Patients who engage in exercises over extended periods accumulate fatigue from previous sessions, which must be accounted for in the final analysis. To address this, the accumulated fatigue from prior sessions is incorporated, reflecting its influence on current results. Fuzzy sets have been utilized to illustrate the relationship between rest intervals and fatigue, as outlined in [31], providing a clearer understanding of this dynamic.

To enhance interpretability, fatigue values, repetition counts and series data are standardized against historical records. This process allows for the classification of fatigue into four distinct categories [32], offering therapists a visual representation of patient fatigue levels: low, moderate, high and very high fatigue.

3.4. Architecture

Figure 2 illustrates the overall architecture of the RI framework, which incorporates the fatigue detection model within the AI layer component of the kernel layer. This architecture supports a multi-layered system designed to deliver personalized and immersive rehabilitation. At its center is the patient, who engages in exergames using a VR headset. These gamified rehabilitation scenarios, selected from a tailored menu, are customized to align with each patient's individual profile.

The system's functionality is structured across several layers, including presentation, sensor integration and common utilities such as body tracking and environmental adaptation. A cloud-based platform underpins the framework, enabling data storage, integration with medical records and remote access for therapists. This cloud infrastructure allows for real-time monitoring and dynamic adjustments to the rehabilitation plan.

The fatigue detector, an essential sub-module within the system's AI layer, implements the previously discussed model to analyze kinematic data and user interactions, identifying indicators of muscle fatigue during VR exercises. This sub-module plays a critical role in customizing the intensity and duration of rehabilitation sessions to align with each patient's endurance. By ensuring that therapeutic activities strike a balance between avoiding overexertion and providing adequate challenge, it supports effective recovery.

The outputs generated by the fatigue detector are invaluable for therapists, enabling them to fine-tune VR exercises, and for developers, assisting in the optimization of serious games. This adaptability enhances the overall rehabilitation process, ensuring it remains both effective and responsive to the patient's evolving condition.

The fatigue detector employs a structured procedure to evaluate fatigue levels across a series of exercises. The process begins with data acquisition, focusing on the last 50 iterations of a consistent exercise performed by a single user. Once the data are collected, chronological processing is initiated. Each series undergoes sequential analysis through the instantiation of a BBT class, which executes multiple steps: extracting data for individual series, performing comparative metric analysis to infer fatigue and calculating fatigue at both repetition and series levels. This iterative process continues until the dataset is fully processed, followed by a normalization step, provided there are at least two exercise sessions.

The final stage synthesizes the results into multiple outputs. A summary file is generated, listing the date of each series and its corresponding fatigue level. Additionally, detailed files are created for each series, including fatigue metrics for individual repetitions, along with specific recommendations to address identified errors or significant fatigue peaks in the patient's performance. This comprehensive approach not only quantifies fatigue but also delivers actionable insights aimed at enhancing patient care.

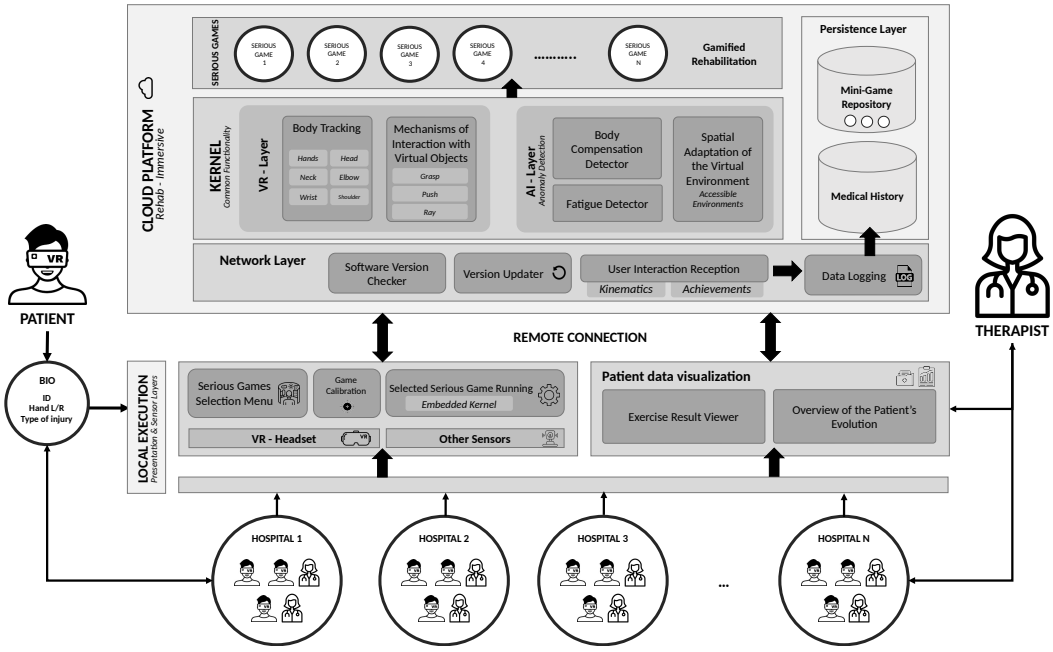


Figure 2. Global architecture of the Rehab-Immersive system. The AI layer includes the module for fatigue detection.

4. Experimental Results

This section describes the tests performed to validate the fatigue detection model in immersive virtual reality-based environments. These tests were approached from three angles. Firstly, a preliminary validation was carried out, focusing on functional aspects in order to assess whether the module behaves as expected, in line with the design of the module. This first validation, discussed in Section 4.1, took the form of a set of tests with healthy participants. Secondly, another set of tests was carried out with patients from the National Hospital for Paraplegics in Toledo (Spain), as described in Section 4.2. In this sense, and after the functional validation of the fatigue detection model, the objective was to handle real data from patients performing physical rehabilitation exercises with the VR-based framework Rehab-Immersive [13]. Finally, Section 4.3 deals with the integration of the fatigue detection module in another virtual reality system developed by the authors of this work in order to facilitate remote physical rehabilitation of patients suffering from neurological diseases [33].

4.1. Preliminary Functional Validation

In a controlled study designed to assess the accuracy of the system in evaluating patient fatigue, six healthy and physically active participants were recruited (refer to Figure 3). Prior to the experiment, participants were given detailed instructions on how to use the virtual reality technology and perform the Box-and-Block Test. The participants were divided into two groups: one group completed the exercise sequence ten times with brief rest periods of less than 30 s, while the other group performed the sequence five times with rest intervals of two minutes.

During the study, participants sat on a standard chair and used their dominant arm to complete the exercises, each lasting 60 s. An initial trial was conducted for the participants to become familiar with the virtual environment. After completing each set of exercises, the participants filled out a questionnaire to self-report their perceived fatigue levels, selecting from a range of options from low to very high. This approach aimed to capture real-time fatigue levels as experienced by the participants and to evaluate the system's capability in accurately measuring these fatigue indicators.



Figure 3. Healthy participants testing the fatigue detection module.

The source code of the proposed model, along with the data collected during the experiments, has been made publicly accessible on GitHub (https://github.com/AIR-Research-Group-UCLM/Fatigue-Detector-Rehab (accessed on 22 December 2024)). Readers are invited to explore the recorded tests, which can be found in the ExperimentalData directory.

The study included six healthy participants with a mean age of 24.5 years, representing a diverse mix of genders and varying levels of familiarity with rehabilitation and VR. One-third of the participants had prior experience with rehabilitation, though none for upper limbs, and the majority had some acquaintance with VR technology. To evaluate fatigue levels within the VR program, the Hamming distance (traditionally used in coding theory to compare code words) was adapted to quantify deviations between observed and expected fatigue levels. This provided an empirical means of assessing the VR program's accuracy by comparing participant-reported fatigue with performance metrics. Figure 4 illustrates the comparison of perceived fatigue levels from three participants against the fatigue values inferred by the automatic detection model.

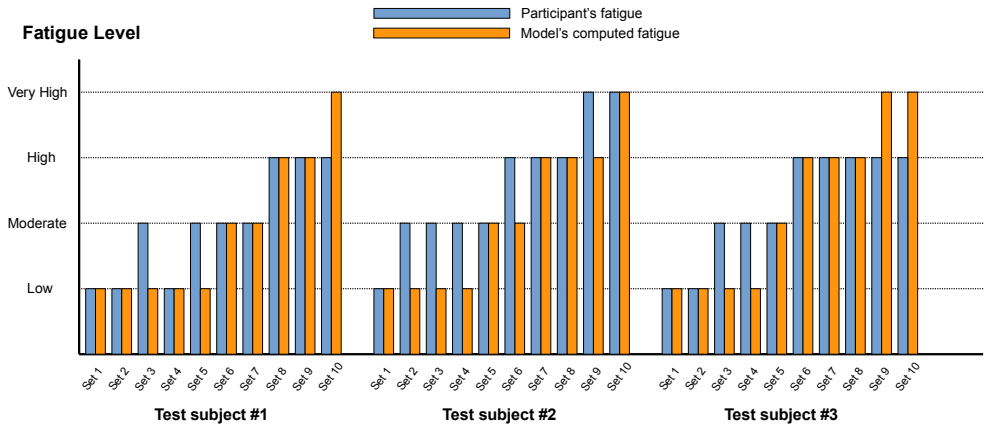


Figure 4. The comparison between the fatigue levels perceived by three test subjects and those automatically calculated by the model is illustrated. On the y-axis, the fatigue levels are categorized as low, moderate, high or very high. The x-axis corresponds to the set numbers assigned to each test subject.

Participant fatigue was classified into four categories (low, moderate, high and very high) to evaluate the alignment between self-reported fatigue levels and model predictions. By adapting the Hamming distance, numerical values were assigned to each category, enabling an assessment of the model's accuracy through percentage error calculations. This allowed us not only to measure the correctness of predictions but also accounted for the magnitude of deviations from participants' perceived fatigue, with larger discrepancies being penalized to ensure a more precise evaluation of the model's performance.

To improve the accuracy of the fatigue assessment, the model's parameters were fine-tuned based on their sensitivity, and the error margins were identified using the Hamming

distance. An iterative calibration process was employed to align the parameters with empirical data, systematically reducing discrepancies. Once the parameters minimizing the error were established, the model's predictive performance was analyzed in detail.

We find that the evaluated model achieves an overall error rate of less than 15%, with notable differences observed between the two participant groups. For participants who completed 10 exercise series, the error rate was 13%, whereas it increased to 17% for those who performed 5 series with longer rest intervals. This variation suggests that the model's predictive accuracy improves as the amount of exercise data increases, demonstrating that greater interaction with the model enhances its ability to estimate fatigue levels. These results underscore the critical role of data volume in optimizing the predictive accuracy of models, particularly in applications like physical rehabilitation.

4.2. Tests with Patients

The performance of the fatigue detection model was also evaluated through a series of Box-and-Block Tests with patients at the National Hospital for Paraplegics in Toledo (Spain) undergoing VR-based recovery therapy. In particular, the tests were carried out with the RI platform [13]. In this sense, the patients who participated in the experiment are familiar with the use of immersive technologies in the hospital itself.

The left side of Figure 5 shows a patient performing the Box-and-Block Test. The same figure, but on the right, shows one of the alerts generated by the fatigue detection module. This alert is associated with a decrease in the patient's performance, which is in turn associated with the output of the fatigue detection module. It is important to note that this alert is primarily intended for the therapist supervising the patient's rehabilitation, so that they can use this information, together with the real-time feedback provided by the patient, to know when the patient should take a break (or stop the rehabilitation to avoid injury).

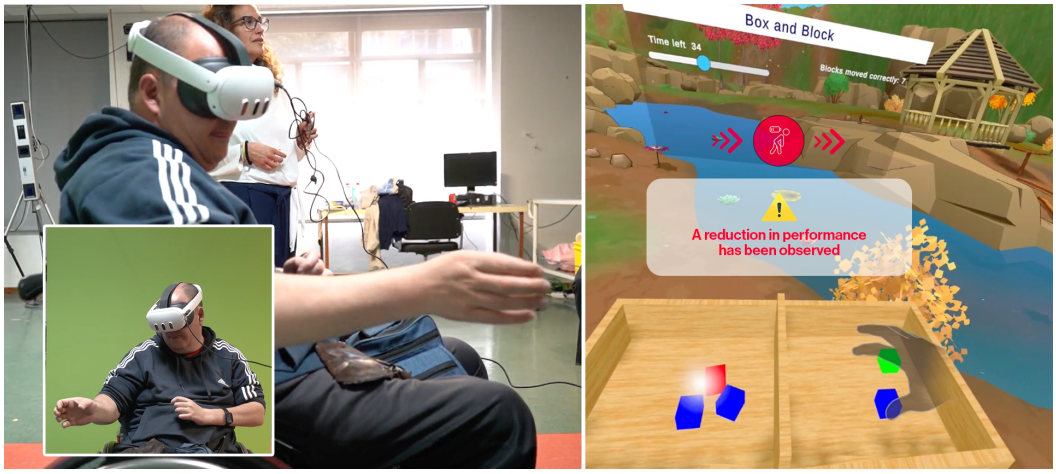


Figure 5. (**Left**) Test subject using the Rehab-Immersive platform. (**Right**) Screenshot taken from the video recorder to show when the module for fatigue detection raised an alert.

The tests were carried out in the hospital thanks to the participation of nine patients who were supervised at all times by an occupational therapist. Although all the patients have SCIs, each patient's condition is different, so the tests did not set a fixed number of sets to be performed (as we did in Section 4.1). Instead, in consultation with the therapist, a reference range of between two and four sets was established, so that each set consisted of a 1 min Box-and-Block Test and a 1 min rest between sets.

Figure 6 visually shows the level of fatigue perceived by the fatigue detection module for each patient in each set. Colors closer to red represent high levels of fatigue, while colors

closer to green represent low levels of fatigue. As can be seen, there are four patients (H006, H007, H008 and P006) who only performed two sets, one patient (P010) who performed three sets and four other patients (H009, H010, P001 and P009) who performed four sets.

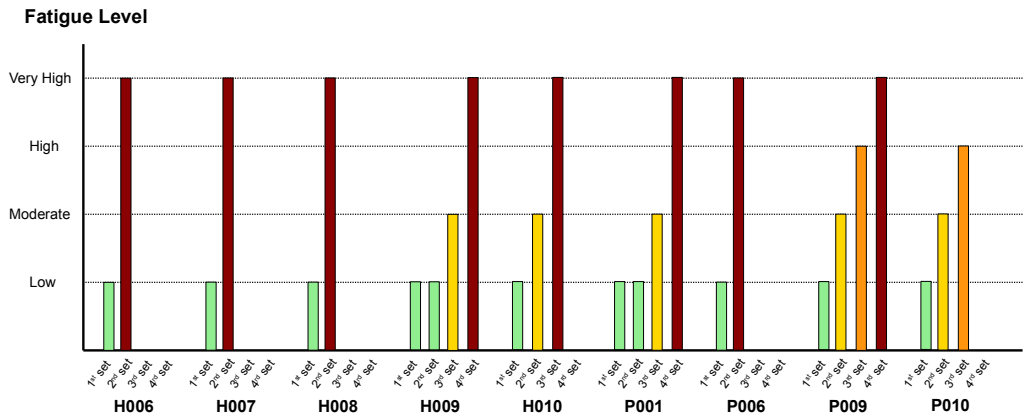


Figure 6. Visualization of the level of fatigue automatically computed by the model after running the tests at the National Hospital for Paraplegics with 9 patients that attended VR-based physical therapy. The number of sets performed varies from patient to patient.

With regard to the patients who performed two sets, it is noteworthy that in the first set, the fatigue detection module showed a low level of fatigue, whereas in the second set, this level shot up to a very high value. We believe that this abrupt change is related to the physical condition of these patients and their situation in the physical rehabilitation process, in which mobility is gradually regained at the same time as adaptation to physical rehabilitation therapy takes place. Due to the marked change in the level of fatigue detection and the therapist's observations, it was decided to stop the experiment without a third set.

On the other hand, the remaining patients showed a level of fatigue detection that increased progressively with the number of sets performed. In this sense, this group of patients became increasingly tired as they repeated the Box-and-Block Test.

Overall, we believe that the result obtained by the fatigue detection module is consistent for patients who, like the first group, tire too quickly and for patients who, like the second group, are able to perform more physical rehabilitation exercises because their ability to adapt has gradually improved. In this respect, there were no situations in which the level of fatigue detected decreased significantly after a set had been performed, which would have been exceptional in this type of test. Moreover, the results obtained automatically by this module are in line with the feedback given by the patients and the therapist herself.

4.3. Scaling the Fatigue Detection Module

The fatigue detection module proposed in this research work has also been integrated into a larger remote rehabilitation system to assess its flexibility and scalability. The integration into this system shows that the approach described in this article is sufficiently general to be applied to other systems with different hardware. This system consists of a home rehabilitation system based on AR that guides the movements of patients as they perform the exercises [33,34]. It consists of three main components: a client application for the patient, a client application for the therapist and a server that connects the two. The system's interface is presented in Figure 7. Additionally, the system includes a decision support system (DSS) [35] that is able to automatically suggest adjustments to the rehabilitation routine based on the data captured during the exercise execution. This module was developed to automate part of the rehabilitation process and reduce the workload of therapists. By reducing the time therapists devote to reviewing and adjusting the rehabilitation

routine, they are able to spend more quality time with patients. The fatigue detected by the module has been included as part of the data used for the adjustment of the routine. The DSS employs a fuzzy inference system [36], whose behavior is determined by a set of rules. This approach was chosen because it is inherently interpretable, as fuzzy rules follow a IF–THEN structure that can be easily understood by humans. Interpretability is relevant in the context of healthcare because the output of the DSS can impact patient wellbeing. Additionally, fuzzy logic is able to handle the vagueness and imprecision of the data provided by the sensors, which makes the DSS more robust. The structure of these rules is shown below. For instance, the first rule implies that if the time for a given set is very high and the actual number of repetitions that were executed is very low, the scheduled number of repetitions will be decreased.

- `IF time IS Very High AND completion IS Very Low THEN rep_incr IS Very Low.`
- `IF mobility IS Very Low AND time IS Medium AND completion IS Very Low THEN adequacy_incr IS Low.`
- `IF time IS Medium AND completion IS Very Low THEN performance_incr IS Low.`

Unlike the VR device used in the rest of the article, the system uses a regular RGB camera with no depth perception to implement the AR functionality. The video stream is processed to estimate the pose of patients as they perform the exercises. This approach was used because the system addresses different needs: because it is focused on home rehabilitation, ease of use and costs are relevant factors. VR headsets are significantly more expensive than a standard webcam, and patients unfamiliar with VR technology may need help using the VR headset. However, it is worth noting that the precision of the data is lower, and fewer variables can be calculated.

Because the system has fewer variables describing the movements of patients, the fatigue module had to be adapted. The main revision consisted of changing the metrics used by the fatigue detection algorithm. The metrics used by the adapted algorithm are the time, velocity, number of incorrect movements and trunk compensation level:

- Time refers to the time spent executing each set.
- Velocity represents the average speed of the joints involved in the exercise.
- The number of incorrect movements quantifies how often the patient deviates from the trajectory of the exercise.
- Trunk compensation level estimates the degree of compensatory movements that use the trunk.

These metrics are calculated using only the estimated pose data. For instance, the trunk compensation is calculated based on changes in the trunk's angle as the exercise progresses. This integration highlights the flexibility and scalability of the fatigue detection module. A key aspect of the design of the fatigue detection module is the smooth integration of new fatigue metrics. This capability enables the usage of the module with rehabilitation exercises other than the Box-and-Block Test. Furthermore, as the fatigue metrics can be computed with different sensor data, it can be used in systems with different hardware capabilities. For instance, data from accelerometers and gyroscopes could be used in a wearables-based system for evaluating the fatigue.

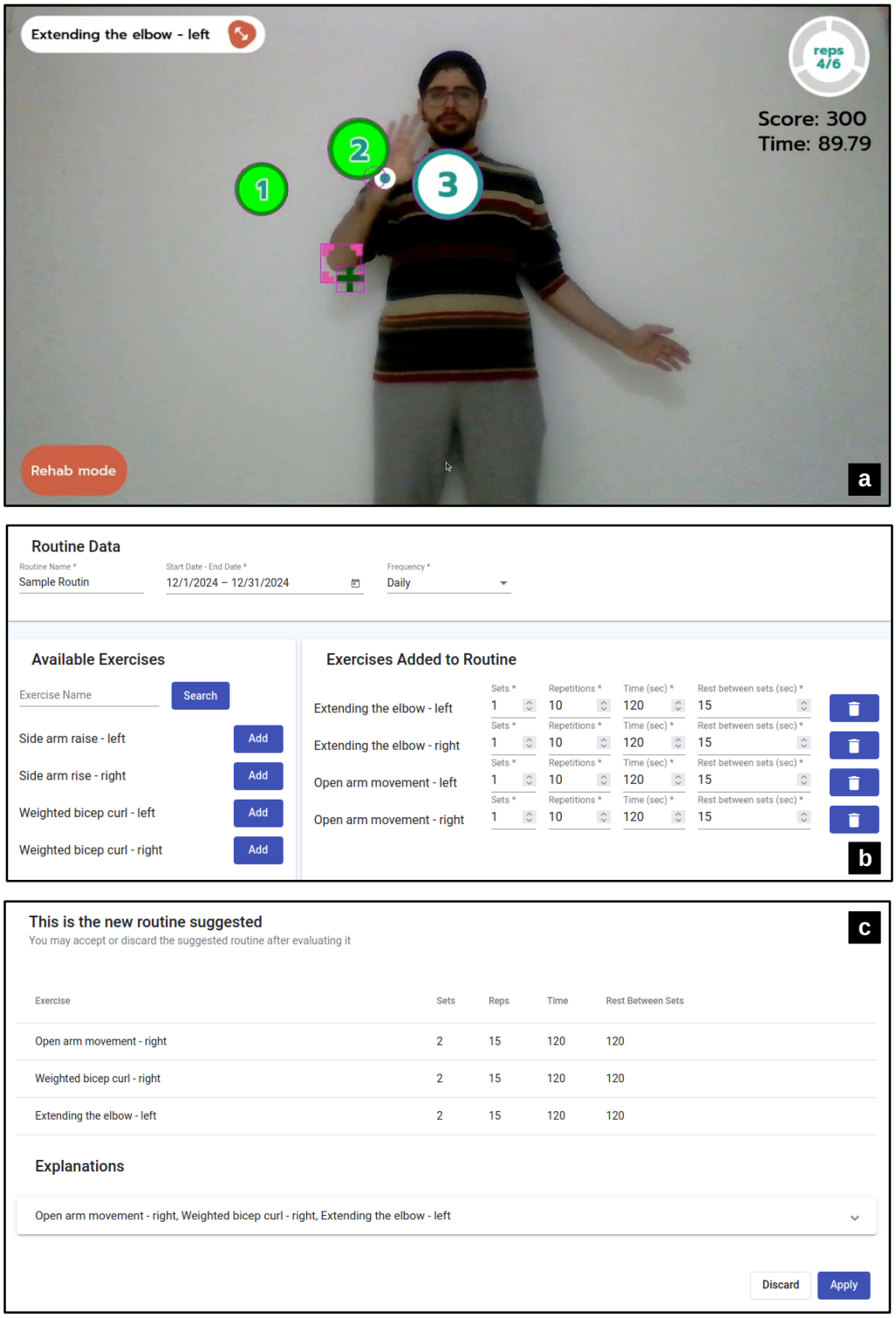


Figure 7. User interface of the system the fatigue module was integrated in. (**a**) Screenshot of the system in operation. (**b**) Patient's routine data. (**c**) Routine information automatically suggested by the system.

Once the module calculates the fatigue level, the result is used as an input for the DSS. This DSS employs fuzzy logic to adapt the assigned rehabilitation routine based on the variables extracted from the pose data. The fatigue level has been incorporated as an additional fuzzy variable for the DSS. The system uses this variable to modify relevant parameters in the routine. These include the number of repetitions per set and the number of exercises included in the routine. These parameters were chosen because they determine

the workload of the patient. Additionally, some variables are calculated as references for future adjustments to the routine, such as the level of performance and the adequacy of the exercise for each patient. The effect that the fatigue has on the DSS can be seen in Table 2. The routine remains unchanged at low fatigue levels, but as the fatigue level increases, the value of the routine parameters is reduced progressively. The rules within the DSS are designed to respond appropriately to fatigue levels. For example, if an excessive level of fatigue is detected, the DSS reduces the routine's difficulty to ensure patient safety and adherence to the rehabilitation. Some example rules using the fatigue level are shown below. For example, the third rule indicates that if the level of mobility by the patient (specified by the therapist) is low and the fatigue level detected by the module is high, then the estimated performance of the patient will be reduced. The performance is updated with every execution of the DSS, and it is used as an input for future inferences.

- `IF mobility IS Medium AND fatigue IS High THEN rep_incr IS Very Low.`
- `IF mobility IS High AND fatigue IS Medium THEN adequacy_incr IS Very Low.`
- `IF mobility IS Low AND fatigue IS High THEN performance_incr IS Low.`

Table 2. Effect of fatigue level on the adjusted routine. The table shows the detected fatigue level, the adjusted number of repetitions per set, the adjusted number of exercises, the detected performance level and the adequacy of the exercise for the patient.

Fatigue (%)	Reps/Set	No. of Exercises	Performance (%)	Adequacy (%)
0	20	5	50	64
10	20	5	50	64
25	15	4	50	38
50	15	3	44	38

5. Discussion

Although the number of people involved in this initial functional validation is not significant (see Section 4.1), it serves as a reference to check that the system works as it should and that it meets both the functional and non-functional requirements initially set. This testing phase is very useful before the system is used with patients in a hospital as it reduces the number of potential bugs and improves certain aspects of the user interface and user experience.

It is also important to highlight a question regarding the potential generability of the model proposed in this research. On the one hand, the number of patients involved in the experiment with patients (see Section 4.2) may be relatively small. This is due to several factors, including the difficulty of selecting patients who can safely perform tests such as those presented in this section and the difficulty of coordinating the schedule with occupational therapists (who tend to have very heavy workloads). On the other hand, as we have just seen, each patient is different and presents a situation and a state in the rehabilitation process that condition the performance of tests that are as homogeneous as possible in terms of hypothesis generation and validation. We are aware that aspects such as these may limit the generability of the proposed model.

On the other hand, the integration of the model into an immersive VR environment specifically designed for the rehabilitation of SCI patients has proven effective in reducing some of the risks associated with the use of this technology in clinical contexts. These risks include ergonomic issues arising from the incorrect execution of exercises and the complexity of interactions in virtual environments. To address these limitations, the

RI system has been developed with a patient-centered approach, incorporating specific adaptations to minimize these risks.

Adaptations include the design of intuitive interactions and the use of visual and auditory elements carefully configured by rehabilitation specialists. In addition, the positioning of objects in virtual space has been calibrated to ensure an accessible, ergonomic and safe experience, promoting a rehabilitation environment suitable for patients with different levels of mobility.

A critical aspect of the system's development is the potential discomfort associated with the use of immersive technologies, such as dizziness, disorientation and oculomotor fatigue. Preliminary results show good patient tolerance of VR devices, which supports the feasibility of their implementation in clinical settings. These findings are supported by recent studies such as the one discussed by Herrera et al. [37], which highlight the effectiveness and acceptability of these technologies.

Furthermore, the flexibility of the proposed model makes it possible to extend its application to augmented reality (AR) scenarios. This technology offers a complementary and potentially transformative approach to rehabilitation, allowing patients to interact directly with real objects. In the case of upper limb rehabilitation, this could provide additional benefits such as experiencing tactile sensations and applying force to perform exercises that simulate tasks from traditional rehabilitation methods. These capabilities could facilitate a smoother transition to everyday activities, contributing to more comprehensive and effective rehabilitation.

6. Conclusions and Future Work

This article introduces a fatigue detection model developed for upper limb rehabilitation within the RI platform, offering healthcare professionals a robust and dependable tool for monitoring patient fatigue. The model is designed to be scalable, supporting the integration of additional variables and metrics as patient needs evolve. It also generates comprehensive fatigue-related information and provides visual feedback on patient performance, facilitating result interpretation and enabling informed decisions about rehabilitation routines. This visual feedback complements traditional assessments, such as the Box-and-Block Test, contributing to a holistic evaluation of patients' motor skills and progress.

Preliminary validation of the model with healthy participants revealed its accuracy in assessing functional metrics, showing a strong correlation between model-inferred fatigue levels and participant-reported fatigue. Trials with patients further confirmed its potential applicability in real-world rehabilitation scenarios, with consistent fatigue detection under the supervision of occupational therapists. These results were robust across a diverse range of patient profiles, reflecting the model's versatility. Additionally, the successful integration of the model into another remote rehabilitation system underscores its scalability and adaptability, paving the way for broader applications across various platforms and patient needs.

This fatigue detection model serves as a foundation for further research. The flexibility of its architecture enables the incorporation of additional parameters, leveraging advanced sensors to provide more precise insights into patient fatigue. The approach could also be expanded to include other rehabilitation games within the RI framework, broadening its scope.

Future research will focus on enhancing the interpretability of the model's outputs for therapists. While alerts are currently provided for abnormal metric values, integrating explainable AI (xAI) techniques or advanced tools such as a chatbot could streamline therapists' workflows and support more efficient decision-making processes.

One of the main challenges identified in our model is the dependence on a reference value for the maximum fatigue of each patient, which may affect its applicability in diverse clinical settings. To address this limitation in future versions of the system, we consider the integration of an adaptive approach based on machine learning. This would allow for dynamic updating of the fatigue threshold by continuously analyzing performance patterns across multiple rehabilitation sessions. In addition, the integration of progressive personalization techniques, where the system adjusts the threshold according to the patient's performance and evolution, could improve the reliability of the model without requiring manual calibrations.

Another line of future work will focus on conducting a clinical trial with a larger cohort of patients to assess the impact of the system in the medium term. This will not only increase the statistical robustness of the results but also allow for the further analysis of the scalability and adaptability of the system to different patient profiles and rehabilitation contexts. We aim to examine the sustainable benefits of the system, particularly in terms of therapeutic outcomes and patient adherence, and to identify opportunities for optimization.

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Institutional Review Board Statement: The tests carried out on patients in the hospital are part of the research study with ID #919, certified by the Clinical Research Ethics Committee of the National Hospital for Paraplegics in Toledo (Spain).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Existing datasets will be made available on request.

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