Decision Support System for Automatic Adjustment of Rehabilitation Routines for Stroke Patients

Sergio Martínez[1], Cristian Gómez[1], Vanesa Herrera[1], Javier A. Albusac[1], José J. Castro-Schez[1] and David Vallejo[1]

[1]Department of Computer Science, University of Castilla-La Mancha, Paseo de la Universidad 4, 13071 Ciudad Real, Spain

Abstract

The ability of new Artificial Intelligence (AI) models to assist humans in performing tasks is creating new business models and transforming existing ones at breakneck speed. One of the application areas benefiting from this technology is healthcare. The work presented in this article falls within this domain. In this sense, our work focuses on how AI can be used to facilitate the work of therapists responsible for the physical rehabilitation of stroke patients. In particular, we present a decision support system integrated in a global remote rehabilitation system composed of two interconnected applications: the one used by the therapist to define routines and monitor patients and the one used by the patient to perform rehabilitation exercises autonomously. The decision support system is based on the use of fuzzy logic, which significantly increases its scalability and interpretability. The proposed system is capable of automatically suggesting personalised modifications to the rehabilitation routine assigned to a patient by the therapist, based on the patient's performance. In addition, this system integrates aspects of Explainable Artificial Intelligence (XAI) by being able to justify why it suggests such modifications, so that the therapist has more information when validating or not validating the modifications proposed by the artificial system. The paper discusses a case study describing how a stroke patient's routine is automatically adjusted by the system.

Keywords

Decision Support Systems, Remote Rehabilitation, Explainable AI, Soft Computing, Health.

1. Introduction

Cerebrovascular accidents, also known as strokes, are among the leading causes of death and disability worldwide. This condition is characterised by the loss of cerebral tissue, mainly caused by circulatory deprivation within the brain. Projections for the year 2030 postulate that strokes will account for eight million fatalities annually. Stroke is the second leading cause of death and disability in Europe, costing the European Union more than 30 billion [1]. A significant hindrance to the execution of effective stroke care is

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*Corresponding author: David.Vallejo@uclm.es (D. Vallejo)
0009-0009-8976-4974 (S. Martínez); 0000-0002-9603-9481 (C. Gómez); 0000-0002-6187-4794 (V. Herrera); 0000-0003-1889-3065 (J. A. Albusac); 0000-0002-0201-7653 (J. J. Castro-Schez); 0000-0002-6001-7192 (D. Vallejo)

the scarcity of suitable transportation and competent stroke specialists. This condition manifests a predilection for the aged population. Stroke symptoms present considerable heterogeneity amongst patients, with potential impacts on both their physical and cognitive faculties. Convalescence following a stroke can take several months; however, to mitigate the resulting disabilities, the implementation of perpetual monitoring by health care professionals throughout this period is imperative [2].

The primary focus of stroke rehabilitation centres around physical recuperation. Physiotherapists aid patients in undertaking physical rehabilitation exercises designed to restore mobility and autonomy. A particular type of these exercises, named functional exercises, involves patients performing routine tasks autonomously within their home environment. These exercises can be implemented independently by patients at home. Their principal benefit is the ability to simultaneously increase strength, speed, stamina, and precision, thereby endowing the patient with a higher degree of independence. The duration of the rehabilitation process may span from a few weeks to several months.

Recently, home rehabilitation has evolved into a practical substitute for conventional rehabilitation methods. Telerehabilitation facilitates the treatment of stroke and other ailments via the execution of rehabilitation exercises within a domestic setting. Several research efforts have been focused on technology-assisted physical rehabilitation performed at home [3]. A subset of technologies, widely embraced for home rehabilitation, is comprised of immersive technologies that encompass virtual reality, augmented reality, and mixed reality. By employing these technologies, home rehabilitation systems are capable of instructing patient movements whilst they independently conduct rehabilitation exercises. A novel technological application within the realm of physical rehabilitation involves the use of decision support systems [4], which aid therapists in determining the appropriate rehabilitation routine for each individual patient, taking into account variables such as the specific exercises to be performed by the patient and the required number of repetitions for each exercise. The automation of the physical rehabilitation routine alleviates therapists from this workload. Thus, therapists can accommodate more patients or they can allocate more quality time to their existing patients, increasing therapy effectiveness and personalisation [5].

Our proposal involves the integration of a Decision Support System (DSS) with a home rehabilitation system for stroke. The rehabilitation system guides the movements of the patients while performing the exercises using augmented reality. The data collected during the exercise execution are used by the DSS to adjust the rehabilitation routine. The primary objective is to maintain motivation of patients by adapting the routine to an appropriate level of difficulty. If the rehabilitation routine were too difficult then patients would feel discouraged and frustrated, whereas if it were too easy then patients would feel bored. This adaptation is achieved through a Fuzzy Inference System (FIS), which incorporates an explainability module that provides therapists with explanations of the decisions taken by the system. Being provided with explanations enhances their trust on the DSS and facilitates its integration into their workflow.

2. Related work

2.1. DSSs for physical rehabilitation

Physical rehabilitation is an important part of the recovery process of stroke patients. An alternative way of performing physical rehabilitation is home rehabilitation, which is gaining prominence both as a viable complement and as a replacement for conventional physical rehabilitation [6]. Among the main challenges encountered in home rehabilitation faces is that therapists are generally less involved in the patients' rehabilitation than in on-site rehabilitation. One of the tasks affected by reduced participation is adjusting the patient's routines. Therefore, in order to fully implement home rehabilitation it is highly advisable to automate the process of adjusting the routines according to the evolution of patients. Automating the adjustment of the routine is not a trivial task, and several DSSs using different AI techniques have been designed.

One technique used for automatically adjusting the difficulty of rehabilitation exercises is state machines. While state machines do not fall under the category of AI, they are a simple approach to automate the adjustment of physical rehabilitation routines. Pinto et al. [7] used state machines to implement dynamic difficulty adjustment in their upper extremity rehabilitation system. Their system consisted of a set of exergames, each with a discrete number of predefined difficulty levels. The state machine would be responsible of determining whether the difficulty level should be increased, decreased or maintained.

Schulze et al. [8] used Bayesian networks to adjust difficulty in a COPD rehabilitation system based on a stationary bicycle. One major advantage of Bayesian networks applied to physical rehabilitation is its ability to handle incomplete data effectively. This is important in a medical context, since medical knowledge is often uncertain [8]. The probabilities of the network were obtained through clinical knowledge and through unsupervised learning models.

Capecci et al. [9] used a Hidden Semi-Markov Model for assessing rehabilitation exercises. Their system extracted features related to the trajectories of the joints using a RGB-D camera. The features were selected using expert knowledge. The HSMM is then able to provide Clinical Scores for the execution of the exercises according to said features. HSMM can be used because the problem satisfies the Markov property; possible future postures only depend on the current posture [9].

Karime et al. [10], used a FIS for adapting a rehabilitation routine in the context of wrist rehabilitation. Their system used sensors to measure the performance of patients. The inputs of the FIS, which are the reach angle, the angular velocity and the jerkiness, are extracted from the data measured by the sensors. A major advantage of applying fuzzy logic to the medical field is that it is able to handle uncertainty.

2.2. Explainable AI

XAI is a branch of AI focused on producing results that humans can easily understand [11]. XAI models, also known as glass-box models, differ from black-box models in that they offer transparency and interpretability. By providing explanations, XAI engenders trust in the suggested solutions. Consequently, AI can be applied to a broader array of domains, such as medicine [12]. It is worth noting the trade-off that there is between the performance and the explainability of the AI method to be used when designing an XAI model [13].

XAI methods can generally be classified into five categories: interaction and importance of features, mechanism of attention, reduction of dimensionality of data, distillation of knowledge and extraction of rules, and models intrinsically interpretable. Furthermore, XAI methods can also be categorized according to how the interpretation is performed. The interpretation of a XAI method can either be intrinsic, where the interpretation is an inherent part of the AI model, or posthoc when it is an additinal step performed on the model. The interpretation can also be global when it applies to the logic of the model or local when it only applies to a particular decision for an instance. Finally, interpretations can be model-specific or can be agnostic of the model used [14].

Gandolfi et al. [15] used Machine Learning (ML), and in particular Random Forest (RF), to predict the upper limb functional recovery of patients. In addition to creating the RF model, they incorporated four different XAI approaches to determine the most relevant features of the model. Since RFs are not inherently explainable, the XAI techniques are post hoc XAI techniques. The techniques used were RF Feature Importance, where the decrease in node impurity in a node and the probability of reaching the said node are used to determine the importance of features, Permutation Feature Importance, based on changes in the prediction error when randomly changing the value of a single feature, LIME (Local Interpretable Model-agnostic Explanations), which consists in perturbing data samples and training local surrogate models for individual predictions, and SHAP, which is based on game theory Shapley values.

Prentzas et al. [16] developed a framework for combining ML with symbolic reasoning, and applied it for stroke predictions. Their framework can be applied on top of any ML technique amenable to rule-generation algorithms (such as RFs and Decision Trees). It is based on the Gorgias argumentation framework, a logic programming framework that is able to combine preference reasoning and abduction. The framework consists in extracting rules from the trained model, processing the resulting rules with Gorgias, and allowing users to query Gorgias about the reasons behind the decisions of the system. On the other hand, Settoui et al. [17] applied neuro fuzzy c-means classifiers in the context of diabetes diagnosis. They are a combination of a fuzzy c-means classifier, which is highly interpretable but cannot be trained, and neural networks, which are not interpretable but can be trained. Combining both approaches enables automatic adjustment of fuzzy rules by representing them in a neural network.

3. Architecture

3.1. General overview

Figure 1 provides a global vision, at an architectural level, of the proposal put forward in this work. As can be seen, there are two applications that communicate with each other through cloud infrastructure. On the one hand, the therapist's application allows the monitoring of patients and includes functionality for user management and the creation

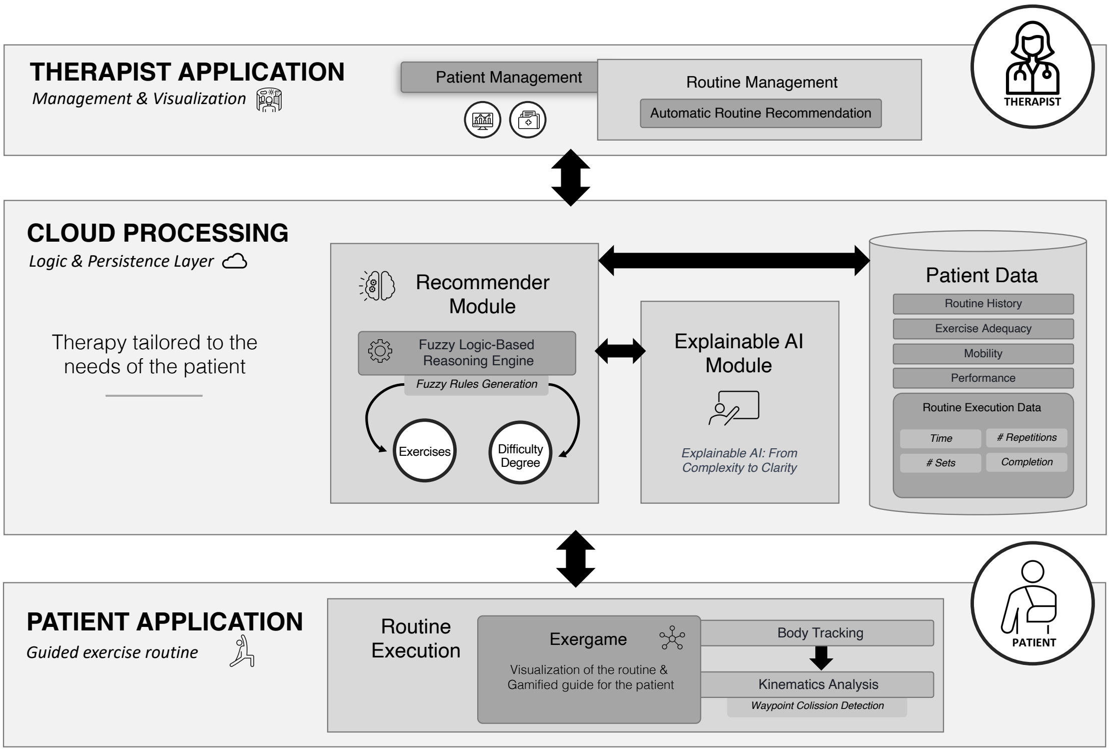

Figure 1: High-level overview of the proposed architecture.

of rehabilitation routines. On the other hand, the patient application allows the patient to perform rehabilitation exercises autonomously from home, according to the routine previously assigned by the therapist.

As the focus of this paper is on the decision support system designed to automatically adapt rehabilitation routines, the main aspects of its design are discussed below. In particular, Section 3.2 discusses the technical aspects of the routine recommendation module, which is based on our previous work [18]. Section 3.3 then describes how the automatic explanations associated with the module are generated.

3.2. Recommender module

The recommender module has been implemented using a Fuzzy Inference System [19]. Fuzzy logic is a particular case of infinite-valued logic, in which truth values range from 0 to 1 [20]. It was created in 1965 by Lofti Zadeh, and aims to achieve computing with words [21]. A notable advantage of fuzzy logic is its ability to tolerate uncertainty. Being able to deal with uncertainty is important in our proposal because joint tracking is imprecise, and it is not possible to know all the data about the patient with precision. Fuzzy logic is also highly interpretable, since it is based on rules that follow an if-then structure. Interpretability is also relevant in our proposal because it facilitated the incorporation of XAI. The FIS consists in a set of fuzzy variables, which may either be input or output variables, and an algorithm that employs the fuzzy variables to generate a new routine from the data collected from the execution of the previous routine by the patient (see Algorithm 1).

The input variables of the FIS and their descriptions are as follows:

- time: This variable represents the duration of the daily exercise, ranging from 0 to 300 seconds.
- completion: This variable indicates the percentage of exercises completed compared to the scheduled exercises in the routine being adjusted. It ranges from 0 to 100.
- reps: This variable represents the number of repetitions of a specific exercise performed daily, with a maximum limit of 50 repetitions.
- sets: This variable represents the number of sets of an exercise performed daily, with a maximum of 10 sets.
- performance: This variable reflects the overall patient's performance level and is used to summarise past performance. Unlike time or repetitions, it is not tied to a specific physical metric. It is scaled from 0 to 100 for simplicity, with an initial value of 50 that can be modified by subsequent recommendations.
- mobility: This variable indicates the general level of mobility perceived by the therapist. Similarly to performance, it ranges from 0 to 100 and is not tied to specific physical metrics.
- exergame_diff: This variable complements the execution data when analyzing parameters of exergames. It ranges from 0 to 100 and follows the same principles as performance and mobility. Fuzzy rules are used to determine the difficulty based on predefined waypoints within a unitary square that guides the patient's movements.
- waypoint_number: This variable represents the number of waypoints for each repetition of an exercise, ranging from 2 to 10.
- waypoint_distance: This variable represents the average distance between consecutive waypoints for a given exercise. It ranges from 0 to 1.

The output variables of the FIS and their descriptions are as follows:

- rep_incr: This variable represents the adjustment to the number of scheduled repetitions for a specific exercise. A positive value indicates an increment, while a negative value indicates a decrement. The use of increments avoids abrupt changes in the routine. It ranges from -40 to 40.
- set_incr: This variable represents the adjustment to the number of scheduled sets for a specific exercise. It ranges from -3 to 3.
- time_incr: This variable represents the adjustment to the allocated time for the execution of an exercise. It ranges from -120 to 120.
- performance_incr: This variable represents the contribution of an exercise to the adjustment of the overall performance. Total adjustment is the average of the contributions of all exercises. It ranges from -20 to 20.

- adequacy_incr: The adequacy variable indicates how suitable an exercise is for the patient and ranges from 0 to 100. It is used in the creation of personalised routines for the selection of exercises. The adjustment range is from -20 to 20.
- exergame_number: This variable represents the number of exercises included in the personalised routine and ranges from 1 to 10.

In order to completely define the FIS, it is also necessary to define the fuzzy sets of each variable. A systematic approach known as fuzzy partitioning was employed to define the fuzzy sets. For each fuzzy variable, five fuzzy sets were established: VL (very low), L (low), M (medium), H (high), and VH (very high). The membership function for all of these fuzzy sets follows a cone shape, where there is a specific value at which the membership is 1. From that point on, the membership decreases linearly in both directions until it reaches a membership level of 0. The fuzzy sets are evenly distributed, with the VL set centred around the lowest possible value for the variable, and the VH set centred around the highest possible value.

The main guideline while defining the fuzzy rules of the FIS was to maintain the motivation of the patient. If the routine is too easy then the patient feels bored, while if the routine is too difficult then the patient feels frustrated [7]. The success of physical rehabilitation depends on the amount of physical activities as well as the patient's commitment to the therapy [22]. Listed below are some sample rules. The full list of rules (a total of 118) and the inference system, coded in R, is available for the reader[1].

- fuzzy_rule(time %is% VL && completion %is% VH, rep_incr %is% VH)
- fuzzy_rule(time %is% VL && completion %is% M, performance_incr %is% H)

One of the major challenges faced during the design of the FIS was that it deals with two problems simultaneously: choosing the exercises that comprise the routine and adjusting the parameters of the exercises. To solve this problem, rules have been designed with one of the following goals in mind: adjusting a parameter of an exercise, determining the adequacy of an exercise for a patient and choosing the number of exercises in the routine. Additionally, rules were added to determine the difficulty of the exergame. Algorithm 1 describes in detail how these rules are used to adjust the routine. The main advantage of this algorithm is that it simplifies the design of the fuzzy rules, which are only focused on one goal, while enabling the FIS to achieve both goals simultaneously.

3.3. Explainable AI

The XAI algorithm used is based on the extraction of rules from the model. Since this method is based on FIS, it is an intrinsic model-specific method. Additionally, this XAI algorithm is a local method because it is focused on providing explanations for specific decisions of the system rather than for the global logic of the model. Our approach to extracting rules was to analyse the rules that were activated during the inference and select the most relevant rule for the decision of the system. The most relevant rule

[1] https://www.esi.uclm.es/www/dvallejo/AIXIA2023/DSS_inference_system.R

Algorithm 1 Automatic generation of the personalized routine.

Input execution history, patient data, current routine
Output new routine, updated performance

$performance\_acc \leftarrow 0$
$exergame\_number \leftarrow$ inference of exergame number(patient data)
for each exercise execution in exercise execution history; exergame parameters in current routine **do**
    $exergame\_increments \leftarrow$ fuzzy inference of exergame data(exercise history)
    $exergame\_parameters \leftarrow exergame\_parameters + exergame\_increments$ ▷ The increments are applied to the parameters of the exercise
    $performance\_increment \leftarrow$ fuzzy inference of performance increment(exercise history)
    $performance\_acc \leftarrow performance\_acc + performance\_increment$
end for
$sorted\_exergames \leftarrow$ Sort exergames according to their new adequacy
$new\_routine \leftarrow$ Pick the top $exergame\_number$ exergames from $sorted\_exergames$
$updated\_performance \leftarrow performance\_acc/number\_of\_exercises$

is determined using the membership function of the output fuzzy set after performing inference. This is because rules with a higher membership will have more relevance during the defuzzification process. However, it is necessary to summarise the membership function into a single value to be able to compare the membership of different rules. This was achieved by calculating the area under the curve of the membership function. Algorithm 2 details how the explanations are generated.

Algorithm 2 Generation of the explanation for the decisions.

Input rules, inference input
Output relevant rule

max relevance $\leftarrow -\infty$
$relevant\_rule \leftarrow null$
for each rule in rules **do**
    $fuzzy\_set \leftarrow fuzzy\_inference(rule, inference\_input)$
    $relevance \leftarrow area\_under\_the\_membership\_function\_of\_the\_output\_of\_the\_rule$
    if $relevance > max\_relevance$ **then**
        $max\_relevance \leftarrow relevance$
        $relevant\_rule \leftarrow rule$
    end if
end for

Since this algorithm depends on the inherent explainability of the model, it is also necessary to consider the interpretability of the FIS while designing it. The main quantifiable factors that contribute to the explainability of a FIS are the number of rules in the system and the number of variables per rule. The lower the number of rules and variables, the higher the explainability of the model. However, a lower number of rules and variables tends to impact the effectiveness of the model; there is a trade-off between explainability and performance [13].

4. Results

This section aims to show how our proposal works by defining a basic rehabilitation routine and its subsequent automatic adaptation by the DSS integrated into the overall system. In this sense, details of the system's reasoning for such adaptation will also be included. However, before discussing this case study, the following subsections provide details of the two interrelated applications that make up the overall rehabilitation system: (i) the patient application and (ii) the therapist application. The DSS is actually a software module of this second application.

4.1. Patient's application

Figure 2 shows the visual aspect of the application used by the patients through different views. In particular, the application offers a number of tips on how to use the application (see Figure 2.b), as well as incorporating information on safety use. Currently, the application offers two main modes: i) routine mode, where the patient performs the exercises of the routine previously assigned by the therapist, and ii) autonomous mode, where the patient can choose which exercise to perform (see Figure 2.c).

On the other hand, the view in which the patient performs rehabilitation has been designed with usability as a fundamental element. To this end, virtual spheres are used, which are numbered so that the user knows which joint of his body must pass through which area of physical space, always in a predefined order. The reference joint for each exercise is marked with a small white circle containing a green dot. In addition, it is possible to set fixed joints so that the patient does not compensate for the lack of mobility with other parts of the body. For example, Figure 2.d shows how the patient must fix his elbow (joint marked with a green cross) at a certain point in the space (pink grid) in order to perform the exercise correctly.

It is worth noting that the patient's application is gamified, i.e. it includes a series of simple mechanics to motivate the patient to perform the exercises. In addition to a score and timer, the application renders visual effects and plays sounds according to the patient's correct (or incorrect) performance.

Finally, the application uses a machine learning model to track the patient's skeleton[2]. This design choice is different from other existing commercial applications, as our system can run on any computer or mobile phone with a standard webcam. In this sense, it is able to work directly on 2D images without the need to use specific hardware devices that calculate positions and orientations in 3D space. This choice greatly increases the

[2]https://github.com/google/mediapipe

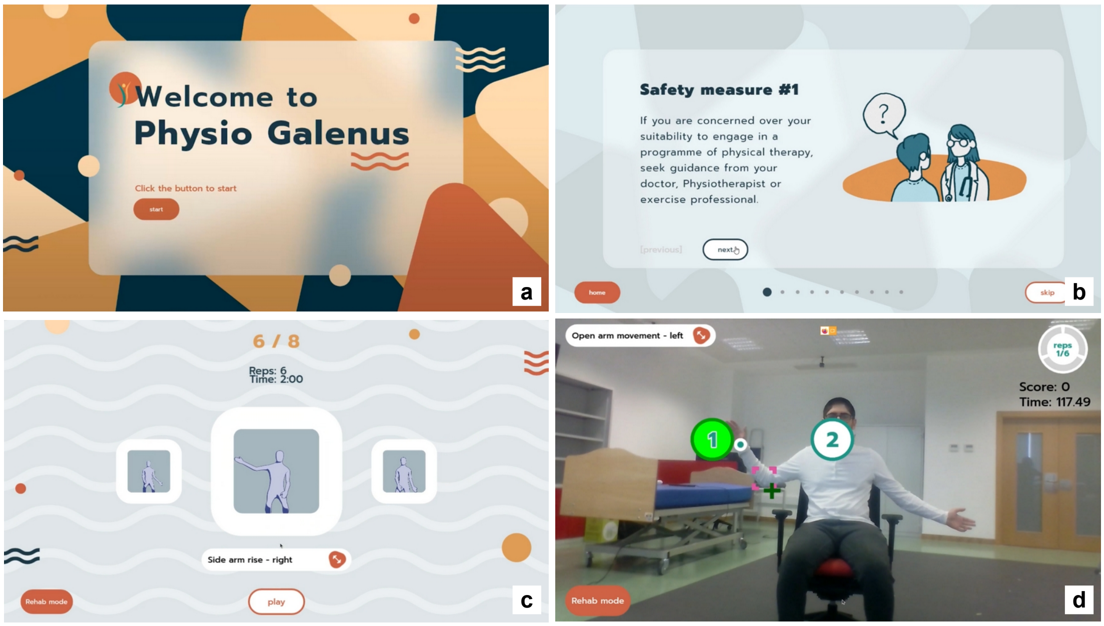

Figure 2: Screenshots taken from the patient's application. a) Presentation screen. b) Example of a screen that is part of the initial tutorial on usability and security. c) Rehabilitation exercise selector (stand-alone mode). d) Main screen for performing physical rehabilitation.

accessibility of technological solutions for physical rehabilitation, as no specific hardware (such as those with integrated depth sensors) is required. However, the recognition of certain types of exercises (e.g. joint rotations) is a technical challenge.

4.2. Therapist's application

In order for the patient to be guided through a rehabilitation routine, it must first be defined by a therapist. Our proposal includes a second application that allows both the definition of routines and the automatic adaptation by the DSS. The two applications are connected via web technology. In particular, the therapist application is a web application deployed in the cloud. This choice was made with the scalability of the system in mind, as the therapist does not need to install any software on his computer.

Figure 3 shows the routine editing screen. A routine is an ordered sequence of exercises. Each exercise has a number of sets associated with it, structured in repetitions. The therapist can also define the maximum time to complete an exercise and the rest time between sets.

The therapist's application provides the ability to automatically adjust a patient's assigned routine at the click of a button. The therapist simply clicks a button to generate the new routine. The visual result is shown in Figure 4.a and consists of the sequence of exercises previously assigned by the therapist, but with new values associated with sets, repetitions, maximum time and rest time between sets. Before validating or rejecting the

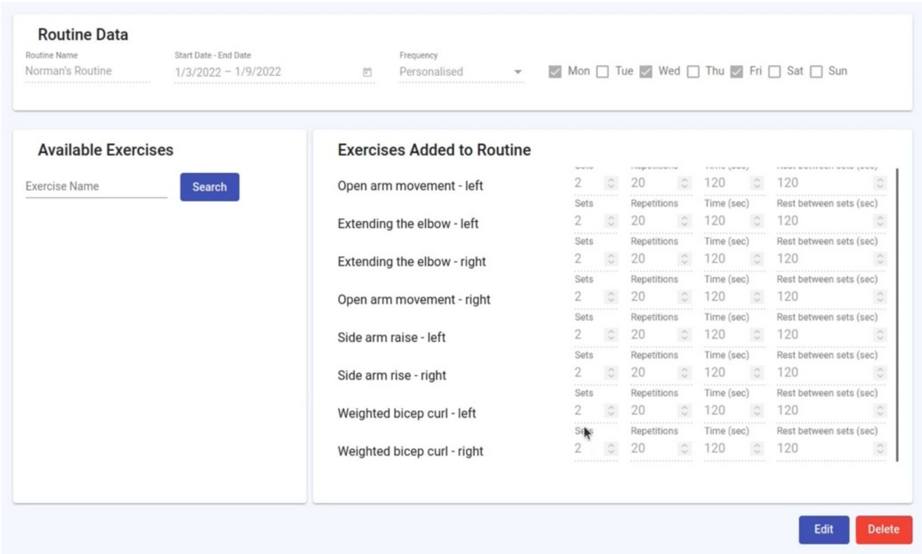

Figure 3: Therapist application routines edit view.

adjustments proposed by the DSS, the therapist can consult the explanations provided by the DSS that motivated the automatic modification of the routine according to the patient's performance. These explanations are also visual and can be seen in the Figure 4.b.

4.3. Case study: automatic adjustment of a routine for stroke patients

This section presents a concrete case of automatic adaptation, considering a simple rehabilitation routine assigned to a stroke patient. The aim is to show how the DSS works for a representative example and what information it provides to motivate the automatic adaptation of the routine. The result of the inference process from three samples is included to better illustrate the model of the DSS. All examples refer to the execution data of the same routine: a reference routine that starts on 03-06-2023 and ends on 09-06-2023. The routine is executed every Monday, Wednesday and Friday and the daily target is 2 sets of 20 repetitions for each exercise in the system (8 in total). The exercises included in the original routine are open arm movement, elbow extension, side arm raise and weighted bicep curl.

The sample execution data can be seen in Table 1. Each row represents a sample (column Number). Columns Mobility and Performance represent the patient's data for each sample. Mobility and performance were defined in section 3.2. Columns Sets, Repetitions and Time represent how each patient sample executed the reference routine previously assigned. This reference routine (2 sets and 20 repetitions per exercise) is the same for all samples. For example, sample 3 represents a patient that spent 120 seconds making 1 set of 5 repetitions per exercise (instead of 2 sets of 20 repetitions each).

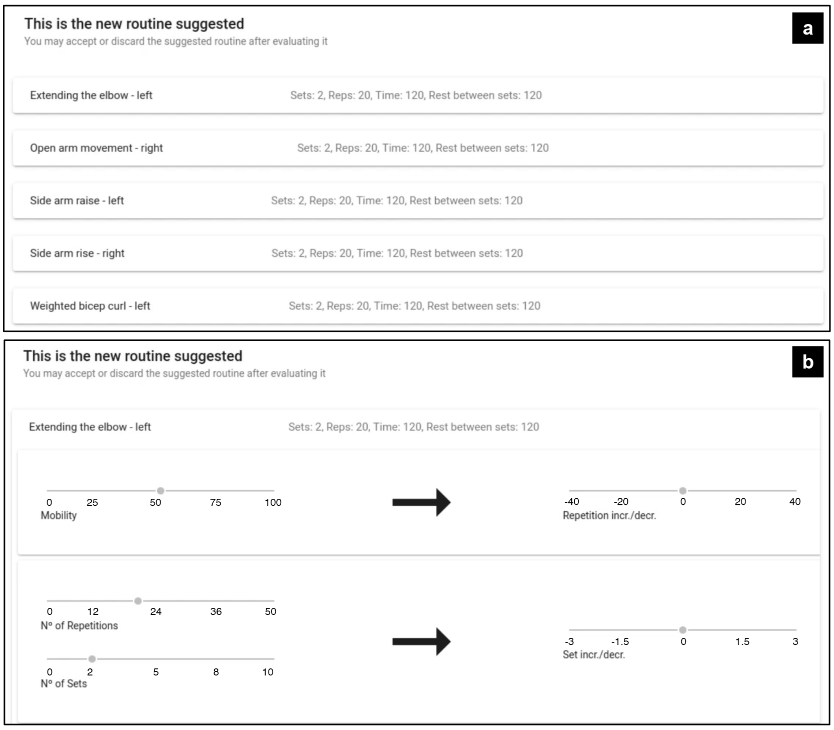

Figure 4: Automatic modification of exercises by the DSS. a) Modified routine. b) Visual justification of the modification generated by the DSS.

Number	Mobility	Performance	Sets	Repetitions	Time	New Sets	New Reps.	New Time
1	50	50	2	20	120	2	30	120
2	90	90	2	40	60	5	55	100
3	10	10	1	5	120	2	15	170

Table 1
Sample execution data of the case study.

On the other hand, columns New Sets, New Repetitions and New Time represent the output of the DSS after adjusting the routine depending on the patient's performance, that is, after the patient made the reference routine for the first time. The recommended routine generally corresponds to the expected output. In sample number 1 (first row), the execution data was average and no major changes were made. In sample number 2 (second row), the execution data was pretty good and the difficulty was increased (more sets, more repetitions and less time). Finally, in sample number 3 (last row), the execution data is poor and the difficulty is decreased. The changes made in the third example can be seen graphically in Figure 4. In this case, the DSS maintains the number of sets regarding the reference routine (2 sets), but the difficulty is actually decreased by reducing the number of repetitions and increasing the time.

4.4. Limitations of the study

So far, the proposal has been reviewed by a physiotherapist who has validated the system of rules that is part of the recommendation module previously discussed in section 3.2. We have also shown the system as a whole, i.e. the two applications, to several therapists in Spain and the UK, in order to validate the functionality currently offered by the system. In parallel, we defined an arbitrary number of rehabilitation routines and simulated the progress of several fictitious patients in order to verify the adequacy of the recommendations and explanations offered by the therapist's application. This testing and debugging process allowed us to fine-tune the recommendations module.

Moreover, while our initial focus has been on stroke rehabilitation, the only component of the system that is specific to stroke is the list of exercises that can be assigned to patients. With the appropriate selection of exercises, the system could be adapted to support the physical rehabilitation of other neurological diseases. Additionally, the recommendation module is able to select the most adequate exercises for the patient according to how they perform each exercise. This adaptability facilitates the integration of exercises for different neurological diseases into the system.

However, a preliminary clinical evaluation is necessary to assess both the patient's application, in terms of remote exercise performance, and the therapist's application as a whole. With regard to the latter, it is essential to compare the recommendations made by the system with the ones that the physiotherapist could make when working with patients. In this sense, we intend to face this clinical evaluation with the Hospital Nacional de Parapléjicos de Toledo (Spain), entity with which we are currently collaborating in the development of Virtual Reality (VR) solutions for the rehabilitation of upper limbs in patients with Spinal Cord Injury (SCI) [23].

5. Conclusions and future work

In this paper, we have presented the design of a DSS capable of automatically generating and justifying modifications to physical rehabilitation routines previously assigned by a therapist to his patients. The ability of the DSS to provide visual explanations falls within the scope of Explainable AI. This DSS is integrated into a system composed of two interlinked applications that allow both the monitoring of patients and the remote execution of rehabilitation exercises by them. The DSS is based on the use of fuzzy logic and, in particular, consists of fuzzy rules that govern its behaviour. The choice of fuzzy logic significantly increases the scalability and interpretability of the system. The DSS is able to simultaneously adjust the parameters of the exercises and select the exercises that make up the modified routine.

The completion of this work opens up a number of research lines. One is related to the ability of the DSS to automatically generate the explanations. Although the current approach to generating is effective, it does not treat all cases equally. If there is only one rule that contributes significantly to the output of the system, it is selected as the explanation. However, if there are many rules that contribute significantly to the output, only one of these rules is selected. This could be improved by generating an explanation as a combination of similar rules, or by selecting multiple rules as the explanation.

On the other hand, the current version of the DSS does not accept any information from the therapist other than the patient's level of mobility. If therapists had a greater degree of influence, they could better handle edge cases. For example, if the therapist felt that the patient needed to do a particular exercise, the DSS would include that exercise in the routine, despite the level of appropriateness of that exercise.

Finally, the current version of the DSS is passive; a suggestion is only made if the therapist requests it. This is because changing patient's rehabilitation routine without the therapist's supervision is not without risk. However, there are other tasks in monitoring the patient's progress where the system could play a more important role where the system could take a more proactive approach. For example, if the routine does not do enough repetitions, the system could inform the therapist of this situation.

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