IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 8 June 2024, accepted 5 July 2024, date of publication 11 July 2024, date of current version 23 July 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3426476

RESEARCH ARTICLE

Making Medical Prescription Automatic: The Case of Prescribing Therapies in Ankle Fracture Rehabilitation by Means of a Computer-Aided System

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This work was supported by the Program for Scientific and Technological Research, Universidad Autónoma de Nuevo León (UANL), under Grant IT1797-21.

ABSTRACT Automated decision support systems are computational tools that have been applied in clinical practice and have many benefits in processes, such as the diagnosis of diseases. Scientific and technological advancements in this area have led to the development of systems for other decision-making processes including medical prescriptions. In this study, we aimed to automate medical prescription making by designing a computer-aided system based on the experience of clinicians. In this case study, we automated the prescription of therapies for ankle fractures in a physical rehabilitation program. The database of the computer-aided prescription systems comprised a set of clinical records, from which the input variables were signs and symptoms related to ankle fracture rehabilitation, and the output variables represented rehabilitation therapies that may be prescribed by clinicians. The system was clinically validated, and its performance was quantified using confusion matrix metrics: 97.4% accuracy, 98.7% precision, 96.6% recall, 98.4% specificity, and 97.6% F-score. Therefore, the proposed system could be a useful tool in decision-making processes as prescription therapies that could contribute to the later motivation regarding traditional physical rehabilitation programs which is the optimization of resources for both patients and physical rehabilitation centers, while rehabilitation objectives are achieved.

INDEX TERMS Computer-aided prescription, decision support systems, computer-aided diagnosis, physical rehabilitation, ankle fracture.

I. INTRODUCTION

More than 20% of lower limb injuries are ankle fractures [1], [2], representing the highest rate of incidents related to fractures in emergency departments [3]. After emergency care, each fracture case is referred to a trauma specialist for appropriate treatment. Owing to the high incidence rate of ankle fractures, they represent a high percentage of the workload of these specialists [4]. Commonly, treatments recommended by trauma specialists to treat ankle fractures

The associate editor coordinating the review of this manuscript and approving it for publication was Donato Impedovo.

include a physical rehabilitation program (PRP) to recover motor function [3]. Traditional PRPs comprise a set of therapies that must be executed over a certain period of time. The objective of PRPs is to regain the motor skills lost because of fractures. In general, PRP therapies have two modalities: (i) mobility and strength exercises, and (ii) physical means. The objective of mobility and strength exercises is to recover the optimal range of motion (ROM) of the injured joint and muscle strength through passive exercises, in which the patient requires the help of a physiotherapist, or active exercises in which the patient must perform the exercises on their own. There are also active assisted exercises, in which the patient requires partial help from a physiotherapist. In contrast, the objective of physical means is to relieve pain and reduce edema of the affected area through the application of lasers, ultrasound, thermal changes, and interferential therapy [5]. Traditional PRPs are illustrated in Figure 1.

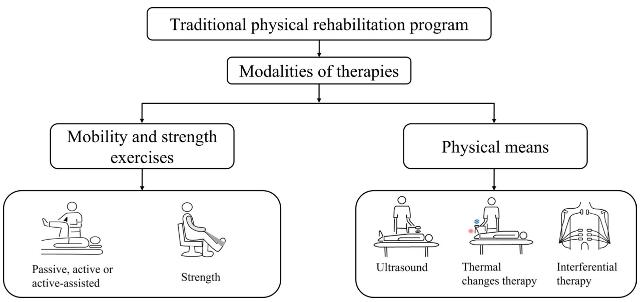

FIGURE 1. Two modalities of therapies executed in traditional PRPs: mobility and strength exercises and physical means. The first modality (left side) includes passive exercises and active or active-assisted exercises. The second modality (right side) includes the application of laser, ultrasound, thermal changes, and interferential therapy. These therapies are recommended to patients to regain motor skills after an ankle fracture [5].

In clinical practice, PRP is part of the rehabilitation cycle recommended by trauma specialists to regain motor skills [6]. This is an iterative process of executing therapies based on clinical assessments to achieve the rehabilitation goals. At each iteration, the decision to continue or complete PRP depends on the progress assessment of the patient's functional abilities. For traditional PRPs, such assessments are evaluated using objective and quantitative criteria, including the clinician's judgment to rate the patient's performance [7]. If a decision is made to continue PRP, clinicians usually prescribe a specific selection of therapies based on the progress of the patient. These recommendations are made according to available clinical guidelines, such as the Massachusetts General Hospital protocol for rehabilitation of ankle fractures with ORIF [8], or in accordance with the clinical practices of a particular health center. These characteristics of traditional PRPs lead to the question of whether this decision can be made automatically. To address this question, we propose a computer-aided system for automated prescription of specific therapies required by patients enrolled in PRP. The aim was to develop a computational methodology to process data from the clinical records of patients and to represent the clinical acknowledgment of physicians, which is the basis of automated prescription. A later motivation regarding traditional PRPs is that automation can promote the optimization of resources for both patients and physical rehabilitation centers while rehabilitation objectives are achieved.

II. RELATED WORK OF MEDICAL DECISION SUPPORT SYSTEMS

There are a wide variety of computational tools for automated decision making by clinicians, which are known as decision support systems. Based on their functions, these systems are classified into two areas: computer-aided diagnosis and computer-based treatment. Computer-aided diagnosis deals with the automated classification of the health status of a patient based on the recording and processing of information related to signs and symptoms that form the basis of disease diagnosis, whereas computer-based treatment deals with two main stages: the clinical prescription and execution of prescribed therapies.

Computer-aided diagnosis is the most advanced [9], and many studies have been conducted to diagnose diseases such as different types of cancer, including lung and colorectal [10], breast [11], and prostate cancer [12]; different types of tumors [13], [14], [15]; diabetic complications such as diabetic foot [16] and retinopathy [17], [18]; and cardiac pathologies such as atrial fibrillation and visual diseases such as glaucoma [19], coronary artery disease [20], and diagnosis of Covid-19 [21].

Regarding treatment, in specific cases of physical rehabilitation, some systems have been reported to automate the clinician's decision. For example, Maddison et al. [22] reported an automated program to deliver prescriptions for regular exercise, technical support, and behavioral strategies (goal setting, exercise scheduling, and overcoming barriers) based on the American College of Sports Medicine guidelines, focusing on cardiac rehabilitation. Although the article reported the results of applying their program, it did not report information on the computational methodology that managed the clinician's knowledge. Similarly, Klein et al. [23] reported a study on rehabilitation for anxiety disorders and claimed full automation of treatment programs, including a computer-aided diagnosis system called e-PASS, evaluation using a set of questionnaires, and five fully automated self-help cognitive behavior e-therapy programs, depending on the anxiety disorder and its symptoms. This program included automatic delivery of e-mail alerts to follow the prescribed program. Nevertheless, as in the case of Maddison et al. [22], algorithms for automated clinician knowledge have not yet been reported. Gross et al. reported a clinical decision support tool based on a machine learning algorithm to prescribe interventions for patients with musculoskeletal disorders [24]; in fact recently, they applied this methodology in clinical trials, showing that the accuracy of the algorithm for selecting successful rehabilitation programs was less accurate than human clinical recommendations [25]. This revision of the state-of-the-art shows us that research on computer-aided prescription systems is an early field, with several scientific and technological challenges regarding both development and clinical validation.

With respect to evaluation, automated measurement of exercise execution in rehabilitation programs, as well as the supervision and remote feedback of clinicians, has become popular in recent years. For example, Moral-Munoz et al. [26] presented a review in which the most common studies focused on stroke, cardiac disease, balance impairment, and joint/limb rehabilitation. This study reviewed smartphone-based software to facilitate patient caregiver communication, progress management, easy interaction, and clinical tests. Another review of software for mobile applications by Nussbaum et al. [27] included a large set of injuries and diseases, such as musculoskeletal, spinal cord injury, traumatic brain injury, pulmonary and neurological diseases, cancer, pain, non-specific issues, and general rehabilitation programs. There are algorithms for evaluating the performance of exercises based on metrics established by clinicians. Liao et al. [7] presented a comprehensive review focusing on machine learning algorithms that automatically evaluate a patient's performance and can be useful in supporting traditional rehabilitation assessments performed by trained clinicians and in promoting home-based rehabilitation. Figure 2 shows the main applications of decision-support systems in medicine.

In the specific case of PRPs for ankle fractures, the treatment involves two stages. In the first stage, patients visit the clinical center for physical assessment, and the clinician prescribes a set of therapies (mobility and strength exercises and physical means) that they must perform to restore functional abilities. The second stage is the performance of these prescribed therapies by the patient, according to the schedule provided by the clinician. In traditional PRPs, the first stage is a subjective decision that depends on the clinician's experience and skills. In the second stage, the performance of therapies is limited to hospital facilities and home-based performance is conducted at the patient's home without the supervision of a therapist. Thus, it is challenging to develop automated decision support systems in both stages of PRPs to improve the selection of therapies and assess the performance of exercise execution. Currently, most automation research in rehabilitation is concentrated in the second stage, mainly on the automatic measurement of movement variables and evaluation of the performance of prescribed exercises [28]. For this reason, there is also an interest in developing decision support systems to automate the determination of which therapies a patient must perform at each iteration of the rehabilitation program to restore functional abilities. Thus, in this study, we propose a computer-aided prescription system to automate the clinician knowledge based on patient data and prescriptions based on medical guidelines of the injury or disease.

III. METHODOLOGY

The proposed computer-aided prescription system is based on the execution of traditional PRP for ankle fractures and is composed of clinical records and a set of therapies, meanwhile, the rules are based on the clinician's knowledge. Figure 3 illustrates the proposed system, and the following subsections describe it in detail, including the traditional PRP for ankle fractures represented as an iterative process to be automated.

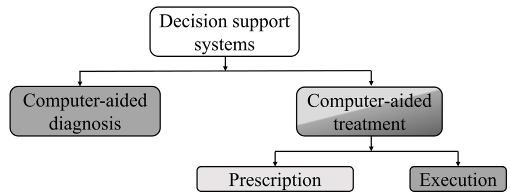

FIGURE 2. Decision support systems have two main applications in medicine: diagnosis (computer-aided diagnosis) and treatment (computer-aided treatment). Computer-aided diagnosis is the most mature area (dark-gray box), whereas for treatment, most research has been focused on automating the execution of therapies (dark gray box). The automation of prescriptions is an early research field (light gray box).

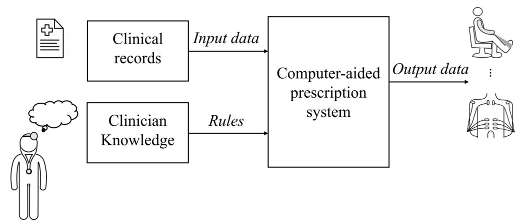

FIGURE 3. Block diagram of the proposed computer-aided prescription system. The database includes the clinical records (the input variables) of patients suffering from an ankle fracture and the set of therapies prescribed (the output variables). The rules of the systems are defined by the experience and knowledge of clinicians. The system provides the prescribed therapies, which belong to a subset of the full set of therapies.

A. TRADITIONAL PRPS FOR ANKLE FRACTURE

In traumatology, the conventional treatment for ankle fractures includes two approaches. (i) Conservative treatment consists of a cast immobilizer (other materials can also be used) covering the foot and shank just below the knee, or if required, other external tools can be used. (ii) Treatment based on surgery consisting of open reduction and internal fixation with osteosynthetic materials. Regardless of the selected approach, treatment of the fracture is followed by a period of leg immobilization to allow bone healing. Immobilization has short-term consequences such as muscular atrophy, deep vein thrombosis, joint stiffness, and edema as well as long-term consequences such as gait abnormalities, persistent leg weakness, and a permanent deficit in joint abilities that the patient had before the fracture [4], [29].

The process of regaining biomechanical capabilities after a fracture is as follows: Trauma specialists evaluate the biomechanical capabilities of the patient; if such capabilities are not optimal, the patient must attend the PRP. At the beginning of PRP, the patients' clinical records were assessed

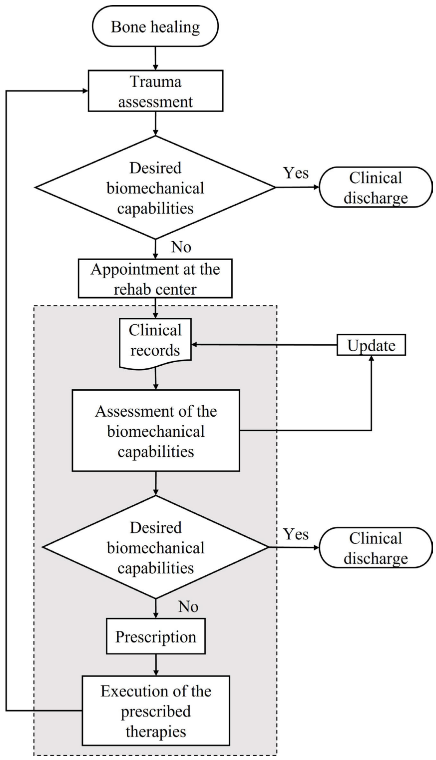

FIGURE 4. Flux diagram of a conventional treatment to recover biomechanical capabilities after an ankle fracture. The gray box highlights the process of a traditional PRP.

by clinicians at the rehabilitation center. Subsequently, muscular and joint functions are estimated or measured, and if such functions are not optimal, clinicians prescribe a set of rehabilitation therapies [5]. The prescription includes the time period of execution (e.g., 10 or 15 days) and the number of series or repetitions that the patient must execute daily for each therapy. After the execution period, the patient returns to the trauma specialist for reassessment of the biomechanical capabilities; if these are in the optimal range, then the patient is discharged. Otherwise, the patient returned to PRP. Thus, PRPs are iterative processes that end when patients regain biomechanical capabilities. Figure 4 depicts the main steps of the traditional treatment of ankle fractures, and the specific steps followed during PRP are shown in the gray box. According to Figure 4, the main elements of the iterative cycle of a PRP are clinical prescription, execution of therapies, and assessment of biomechanical capabilities; being the first one the element of interest to be automated in this work.

B. COMPUTER-AIDED PRESCRIPTION SYSTEM

A system dealing with this challenge requires the automatic acquisition of data on the biomechanical capabilities of the patient, management of the clinician's knowledge, and a computational method to integrate these elements. With this in mind, the proposed computer-aided prescription system has a database based on the clinical records of patients who suffered an ankle fracture and the set of therapies prescribed for the clinician. Clinicians' knowledge is based on the medical conventions for ankle fracture rehabilitation reported in the medical literature, as well as their experience as specialists in physical rehabilitation. These elements are described as follows.

1) DATABASE

The database of the computer-aided prescription system, designed to automate the clinical prescription of PRP, was formed using two sets of data. The first dataset contained clinical records reporting the patient's condition. The second dataset contained the therapies that the clinician must prescribe to patients according to the condition registered in the clinical records. Next, we describe the two sets in detail.

Conventionally, the clinical records of patients with ankle fractures contain data from trauma and rehabilitation centers. This record was updated at each PRP iteration until the desired biomechanical capabilities were achieved. Clinical records contain quantitative and qualitative data. The quantitative variables were the main joint movements, including dorsiflexion, plantarflexion, inversion, and eversion; these variables are measured in degrees (^{o}) and it is desirable that their values are into the optimal ROM. The remaining variables are qualitative. The first qualitative variable was muscular strength, defined using the Lovett and Daniels scale, which registers six levels of strength: none, poor, deficient, regular, good, and normal. The second variable was movement limitation, which was estimated in two states: with and without limitation. The third variable was the pain condition, estimated using the visual analog scale in four levels: no pain, mild pain, moderate pain, and severe pain. The fourth variable was edema, which was recorded using the Godet technique at four levels: no edema, mild, moderate, and severe. The fifth variable was contracture, which was estimated in two states: the occurrence or absence of contracture in the patient's ankle. The sixth variable was the wound, indicating adherence to the deep planes of the skin. The seventh variable was trophic change, which was estimated in two states: with or without trophic changes. The eighth variable was sensitivity, which indicate the presence of sensitivity. The ninth variable was gait, which considered two types of patterns: the desired pattern (called eubasic) and a pattern that is not desired (called dysbasic). The 10th variable was joint stability, which was estimated in two states, whether or not there was stability. The last qualitative variable was bone healing, which was estimated in two states: presence or absence of bone healing. The ranges and scales of these variables were estimated according to standardized scales reported in the medical literature [5]. Table 1 summarizes the clinical records of patients with ankle fractures.

Mobility exercises, which are dorsiflexion, plantarflexion, inversion, and eversion, are the most relevant therapies for regaining the ROM of joint movements. Depending on the patient's development, these exercises can be passive, active, or assistive. As joint movements recover, it is important to promote muscular strengthening by executing isometric, isotonic, stretching, and proprioception exercises. Once a

TABLE 1. Description of variables registered in the real clinical records of patients who have suffered an ankle fracture. The states, values, or scales correspond to medical conventions reported in the literature [5].

Description	Type	State	Values/scale
Joint Movements	Quantitative	Dorsilflexion	10° to 20°
		Plantarfelxion	20° to 45°
		Inversion	10° to 35°
		Eversion	10° to 25°
Strength	Qualitative	None	0
		Poor	1
		Deficient	2
		Regular	3
		Good	4
		Normal	5
Movement Limitation	Qualitative	If present	1
		Not present	0
Pain	Qualitative	Not present	0
		Mild	1 to 3
		Moderate	4 to 7
		Severe	8 to 10
Edema	Qualitative	No edema	0
		Mild	x
		Moderate	xx
		Severe	xxx
Contracture	Qualitative	If present	1
		Not present	0
Wound	Qualitative	Adhered	1
		Not adhered	0
Trophic changes	Qualitative	If present	1
		Not present	0
Sensitivity	Qualitative	Altered	1
		Not altered	0
Gait	Qualitative	Dysbasic	1
		Eubasic	0
Stability	Qualitative	If present	0
		Not present	1
Bone healing	Qualitative	If present	0
		Not present	1

patient can walk, walking exercises are prescribed for gait re-education and to improve equilibrium. If necessary, and if pain is not present, a set of massages could be prescribed, such as anti-adherent massage for the scar, anti-edema massage, and relieving massage. Physical means also support mobility exercises to return ROM to the joints; for example, the application of ultrasound or thermal exchange therapy, which consists of the alternate application of cold and heat. Interferential therapy is recommended for: pain, edema, and bone healing. In summary, Table 2 shows 14 therapies organized by type, including their conventional prescription, nine therapies for mobility and strength, while five therapies for physical means. Data from the clinical records and therapies summarized in Tables 1 1 and 2, respectively, are the two sets of information required to determine the prescription of PRP. Next, we discuss the conventional agreement to prescribe therapies for PRP based on the clinical records of patients.

TABLE 2. Set of therapies for PRPs in ankle fracture rehabilitation. There are two modalities of therapy: mobility and strength exercises, and physical means. The conventional prescription for each therapy is in accordance with medical conventions [5]. *Reps, repetitions.*

Therapy	Prescription
Mobility and strength exercises	
Mobility exercises:	
Dorsiflexion	A daily set of 10 reps
Plantarflexion	A daily set of 10 reps
Inversion	A daily set of 10 reps
Eversion	A daily set of 10 reps
Isometric exercises	A daily set of 8 to 10 reps
Isotonic exercises	A daily set of 8 to 10 reps
Stretching exercises	A daily massage for 5 min
Proprioception exercises	A daily set of 10 reps
Gait exercises	A daily series of 10 to 15 laps on a 3 m track
Anti-adherent massage	A daily massage for 5 min
Anti-edema massage	A daily massage for 5 min
Relieving massage	A daily massage for 5 min
Physical means	
Shallow depth ultrasound	A daily session 3 MHz for 5 min
Thermal change therapy	A daily hot and cold session alternately for 15 min
Interferential therapy for edema	A daily application 0 to 200 Hz for 15 min
Interferential therapy for pain	A daily application 80 to 150 Hz for 15 min
Interferential therapy for bone healing	A daily application 100 Hz for 15 min

2) CLINICIAN'S KNOWLEDGE

As shown in Figure 4, in traditional PRPs, the prescription of rehabilitation therapies is determined by clinicians. This decision is based on the biomechanical capabilities registered in the clinical records, functional assessment of the patient, and experience and knowledge of the clinicians. If some biomechanical capabilities are not in the desired range, then therapies are prescribed; otherwise, the desired outcomes are achieved, and the patient is discharged. Thus, because the decision-making process for the prescription of PRP therapies involves conditional rationale, the direct method to automate this process is based on IF THEN rules that relate input and output variables are described in Tables 1 and 2, respectively. The elements and structure of each rule depend on the clinician's knowledge; these elements are listed in Table 2. The input variables are related to the outputs and the structure is defined by functions that represent the rationale of the clinician. The different states that an input variable can take (third column of Table 1) determines the possible combination defined by the rule.

IV. RESULTS

To illustrate the proposed methodology, we consider PRP for ankle fracture rehabilitation as a case study. This procedure was prescribed by clinicians at the Department of Sports Medicine and Rehabilitation, hospital "Dr. José Eluterio González", University of Nuevo León, Monterrey, Nuevo León, Mexico.

A. DATA COLLECTION

To populate the database, a retrospective longitudinal study was conducted to collect input and output data from patients who had been enrolled in PRP at this hospital between 2017 and 2019. According to the clinical practice of the hospital, a full set of therapies was prescribed to patients at each assessment appointment during the rehabilitation process. At each appointment, an observation sheet was generated about the patient's condition (input and output variables) and with the prescription made by the physician. These data were registered at each patient appointment to assess the recovery of the biomechanical capabilities. Because this relationship between the input and output variables prescribed according to the physician's knowledge and experience is of interest to automate, the observation sheet that is generated when a patient attends an appointment is called a real clinical record. The inclusion criterion to consider a real clinical record eligible was as follows: each record must be from an adult patient of either sex with an ankle fracture. The type of fracture could be Weber types A, B, or C. The exclusion criterion was the use of lower limb prostheses.

In this study, 34 real clinical records met the inclusion and exclusion criteria and were collected from 10 patients with different numbers of appointments (mean age, 39.4 yrs; standard deviation, 10.9 years) who suffered an ankle fracture (four categorized as Weber B, three as Weber C, and three as not specified). The selected clinical records were analyzed by a collaborative team of clinicians specializing in physical rehabilitation. Relevant information of the real clinical records was extracted corresponding to the clinical conditions defined in Table 1 and the clinical prescriptions described in Table 2. An example of the information extracted from the four real clinical records is presented in Table 3.

Each series of input variables consists of the 12 variables described in Table 1 and is represented by the vector $\boldsymbol{x} = [x_1 \ \dots \ x_{12}]^T$, where each element of $\boldsymbol{x}$ is a binary variable defined as follows: x_1 represents joint movements, x_2 is strength, x_3 is movement limitation, x_4 is pain, x_5 is edema, x_6 is contracture, x_7 is wound, x_8 is trophic changes, x_9 is sensitivity, x_{10} is gait, x_{11} is stability, and x_{12} is bound healing. From the values and scales reported in Table 1, the registration of the input variables in the clinical record depends on the medical rationale. For example, x_1 has a scale for each of the four angular joints. Nevertheless, when a clinician performs a joint movement, they only consider

TABLE 3. Example of information extracted from four real clinical records of the database of this study. The clinical conditions were registered according to the scales and values reported in Table 1.

Clinical condition	Clinical record			
	1	2	3	4
Joint movements	Incomplete	Incomplete	Incomplete	Complete
Strength	4/5	4/5	4/5	4/5
Movement limitation	Yes	Yes	Yes	Not
Pain	3/10	3/10	2/10	0
Edema	x	x	x	x
Contracture	Yes	Yes	Yes	Yes
Wound	Not adhered	Not adhered	Not adhered	Not adhered
Trophic changes	No	No	Yes	No
Sensitivity	Not altered	Not altered	Not altered	Altered
Gait	Dysbasic	Dysbasic	Dysbasic	Dysbasic
Stability	Not	Yes	Yes	Yes
Bone healing	Yes	Yes	Yes	Yes

whether the ROM is complete. In practice, x_1 represents two states: the patient has achieved ROM of the four joint movements. This implies that x_1 is a dichotomous variable, and thus, $x_1 \in \{0, 1\}$. Regarding x_2, this variable takes values from 0 to 5 according to the scale reported in Table 1; however, conventionally, the scale is discretized to represent four states, that is, $x_2 \in \{00, 01, 10, 11\}$. Double zero (00) represents level 0, 01 represents the range from 1 to 3, 10 represents 4, and 11 represents level 5 on the strength scale; thus, x_2 is a binary polytomic variable. x_4 is also a polytomic variable, that is, $x_4 \in \{00, 01, 10, 11\}$. This is reported to be between 0 and 10 according to the Lovett and Daniels scale, but the scale is conventionally grouped by clinicians into four states; that is, the scale is discretized representing 00 for the 0 level of the scale, 01 for the 1-3 level, 10 the for 4-7, and 11 for the 8-10 level. x_5 is also a polytomic variable representing four states on the Godet scale: $x_5 \in \{00, 01, 10, 11\}$, where 00 represents no edema, 01 represents the x level, 10 represents xx, and 11 represents xxx. The remaining variables, $x_3, x_6, \dots, x_{12}$, are dichotomous, according to the possible values they represent as reported in Table 1. Table 4 summarizes the types, numbers of bits, and possible combinations that can be used to represent the different clinical conditions, scales, and values reported in Table 1. The definition of the type and states of variables is in accordance with medical rationale, in which the input variables are registered as binary data. An example of binarization of the input variables corresponding to the clinical records reported in Table 3 is presented in Table 5.

TABLE 4. Discretization of input variables.

Input variable	Type	Number of states	Combinations		Clinical conditions
x_1	Dichotomous	2^1	0		Complete ROMs
			1		Incomplete ROMs
x_2	Polytomic	2^2	D1	D0	Strength
			0	0	No strength
			0	1	Mild strength
			1	0	Regular strength
			1	1	Normal strength
x_3	Dichotomous	2^1	0		No movement limitation
			1		Movement limitation
x_4	Polytomic	2^2	D1	D0	Pain
			0	0	No pain
			0	1	Mild pain
			1	0	Moderate pain
			1	1	Severe pain
x_5	Polytomic	2^2	D1	D0	Edema
			0	0	No edema
			0	1	Mild edema
			1	0	Moderate edema
			1	1	Severe edema
x_6	Dichotomous	2^1	0		No contracture
			1		Contracture
x_7	Dichotomous	2^1	0		No adhered wound
			1		Adhered wound
x_8	Dichotomous	2^1	0		No trophic changes
			1		Trophic changes
x_9	Dichotomous	2^1	0		No altered sensitivity
			1		Altered sensitivity
x_{10}	Dichotomous	2^1	0		Eubasic gait
			1		Dysbasic gate
x_{11}	Dichotomous	2^1	0		Stability
			1		No stability
x_{12}	Dichotomous	2^1	0		Bone healing
			1		No bone healing

The computer-aided system provides a clinical prescription that depends on the input variables registered in clinical records. Thus, the output variables of this system were the 14 therapies reported in Table 2, and each output variable was defined as follows: y_1 represents mobility exercises (full set including dorsiflexion, plantarflexion, inversion, and eversion), y_2 isometric exercises, y_3 isotonic exercises, y_4 stretching exercises, y_5 proprioception exercises, y_6 walking exercises, y_7 anti-adherent massage, y_8 anti-edema massage, y_9 relieving massage, y_{10} shallow-depth ultrasound, y_{11} thermal therapy, y_{12} interferential therapy for edema, y_{13} interferential therapy for pain, and y_{14} interferential therapy for bone healing. In the conventional rationale for clinical rehabilitation, depending on the values of the 12 input variables, the clinicians recommend therapy; therefore the output variables y_1 to y_{14} are binary and dichotomous, assigning 0 for not executing the therapy and 1 for executing the therapy. Thus, the output variable of the computer-aided prescription system is the vector $\boldsymbol{y} = [y_1 \ \cdots \ y_{14}]^T$, where each y_i, for $i = 1, \ldots, 14$ can be 0 or 1. In summary, the result of the data collection process is the database of the computer-aided prescription system, which includes input and output data $\boldsymbol{x}$ and $\boldsymbol{y}$ respectively. Both variables are binary and can be used to relate the clinical condition of the patient and the prescriptions of therapies based on the clinician's knowledge, represented by the relationships described in the next subsection.

TABLE 5. Example of discretization of input variables reported in the clinical records analyzed in Table 3.

Input variable	Clinical records 1	2	3	4
x_1	1	1	1	0
x_2	10	10	10	10
x_3	1	1	1	0
x_4	01	01	01	00
x_5	01	01	01	01
x_6	1	1	1	1
x_7	0	0	0	0
x_8	0	0	1	0
x_9	0	0	0	1
x_{10}	1	1	1	1
x_{11}	1	0	0	0
x_{12}	0	0	0	0

B. REPRESENTATION OF THE CLINICIAN'S KNOWLEDGE

As described in Section II, a computer-aided prescription system was proposed to automate the prescription of therapies in PRP for ankle fractures. The mathematical representation of a clinician's knowledge comprises a set of functions. This representation was selected for two reasons: (i) the binary nature of the database, and (ii) the rationale for clinicians to decide on prescriptions based on the clinical condition of the patient. Because the prescription is represented by $\boldsymbol{y}$, its 14 components are functions that depend on the components of the input variable $\boldsymbol{x}$; thus, the clinician's knowledge is represented by 14 functions.

- *Mobility exercises (y_1).* This therapy includes a set of four exercises to recover ROM in dorsiflexion, plantarflexion, inversion, and eversion. y_1 is prescribed if the joint movements (x_1) are incomplete, ($x_1 = 1$)

OR $(+)$ if the movement limitation (x_3) is present $(x_3 = 1)$. Thus, the decision is represented by the following equation.

$$y_1 = x_1 + x_3. \quad (1)$$

- *Isometric exercises (y_2).* This therapy is recommended when clinical assessment indicates that joint strength (x_2) is limited. $D0$ is defined as the least significant bit (LSB) and $D1$ is the most significant bit (MSB) of a binary variable. Therapy is prescribed when $x_2'D1 = 1 OR x_2'D0 = 1$, where $(')$ represents the **NOT** operator of a variable. Thus, according to Table 4, the prescription is as follows.

$$y_2 = x_2'D1 + x_2'D0. \quad (2)$$

- *Isotonic exercises (y_3).* This therapy also depends on x_2, and this condition is prescribed when the joint strength is reported to be normal. Then, according to Table 4, the condition is prescribed when $x_2D1 = 1$ **AND** $(\cdot)$ $x_2D0 = 1$; thus, the function is as follows:

$$y_3 = x_2D1 \cdot x_2D0. \quad (3)$$

- *Stretching exercises (y_4).* This therapy is prescribed if joint movements (x_1) are incomplete, or if both movement limitation (x_3) and contracture (x_6) are present.

$$y_4 = x_1 + x_3 + x_6. \quad (4)$$

- *Proprioception exercises (y_5).* This therapy is prescribed if clinical assessment reports movement limitations, altered sensitivity, dysbasic gait, or instability. This relationship is as follows:

$$y_5 = x_3 + x_9 + x_{10} + x_{11}. \quad (5)$$

- *Gait exercises (y_6).* These exercises are prescribed when dysbasic gait is reported in the clinical records. This function is expressed as follows:

$$y_6 = x_{10}. \quad (6)$$

- *Anti-adherent massage (y_7).* If the clinical assessment reports that the wound of the affected joint is adherent, this therapy is prescribed. The corresponding functions are as follows.

$$y_7 = x_7. \quad (7)$$

- *Anti-edema massage (y_8).* This therapy depends on two polytomic variables: pain (x_4) and edema (x_5), the discretization of which is shown in Table 4. The therapy was prescribed only if there was no pain or very mild pain and if edema was moderate or severe. Considering all possible combinations of x_4 and x_5, the function representing y_8 is defined, and a simplified version of the function that satisfies the above conditions is as follows:

$$y_8 = x_4'D1 \cdot x_5D1, \quad (8)$$

where x_4' represents the opposite condition of the discrete variable x_4.

- *Relieving massage (y_9).* This therapy depends on the polytomic variable x_4 and dichotomous variable x_6, the discretization of which is shown in Table 4. It is recommended if there is no pain or mild pain and if there is contracture. The simplified expression for this function is as follows:

$$y_9 = x_4'D1 \cdot x_6. \quad (9)$$

- *Shallow-depth ultrasound (y_{10}).* This therapy is prescribed if moderate or severe pain is reported in the clinical assessment, considering the discretization of x_4 in Table 4.

$$y_{10} = x_4D1. \quad (10)$$

- *Thermal changes (y_{11}).* This therapy is prescribed if any state of pain, edema, or trophic change is present in the clinical assessment. Based on the discretization of x_4 and x_5 in Table 4, the function is as follows:

$$y_{11} = x_4D1 + x_4D0 + x_5D1 + x_5D0 + x_8. \quad (11)$$

- *Interferential therapy for edema (y_{12}).* This therapy was prescribed for any level of edema (see discretization of x_5 in Table 4).

$$y_{12} = x_5D1 + x_5D0. \quad (12)$$

- *Interferential therapy for pain (y_{13}).* This therapy is prescribed when pain is registered as moderate or severe, which has over five labels in clinical practice. According to the discretization of x_4 in Table 4, the function can be expressed as follows:

$$y_{13} = x_4D1 \cdot x_4D0. \quad (13)$$

- *Interferential therapy for bone healing (y_{14}).* This therapy was prescribed when bone healing (x_{12}) is not present. Thus, the relationship is expressed as follows:

$$y_{14} = x_{12}. \quad (14)$$

The set of mathematical functions given by (1)-(14) defines the core of the proposed computer-aided prescription system.

C. NUMERICAL IMPLEMENTATION

The computer-aided prescription system defined in (1)-(14) was implemented in MATLAB 2021a. Algorithm 1 was tested using a database collected at the hospital, as described in section III-A. Figure 5 shows the results of the evaluation of the system for all the collected clinical records. The first column includes the total number of clinical records, and the remaining columns illustrate the clinical prescriptions recommended by the system. Each therapy (y_i for $i = 1, \ldots, 14$) is represented by a cell, which is colored dark gray if the computer-aided system recommends the prescription of therapy ($y_i = 1$); otherwise, the cell remains white ($y_i = 0$). To analyze the recurrence of the prescribed therapies, Figure 6 presents a histogram of the prescription frequency for each therapy.

Algorithm 1 Computer-Aided System to Automate Prescription of PRP Therapies

Begin: Input data representing clinical condition of patient.
1: $\boldsymbol{x} = [x_1\ x_2\ x_3\ x_4\ x_5\ x_6\ x_7\ x_8\ x_9\ x_{10}\ x_{11}\ x_{12}]^T$.
Declaration of input variables:
2: $X(1) = x_1$; $X(2) = x_2D1$; $X(3) = x_2D0$; $X(4) = x_3$; $X(5) = x_4D1$; $X(6) = x_4D0$; $X(7) = x_5D1$; $X(8) = x_5D0$; $X(9) = x_6$; $X(10) = x_7$; $X(11) = x_8$; $X(12) = x_9$; $X(13) = x_{10}$; $X(14) = x_{11}$; $X(15) = x_{12}$;
Prescription functions:
3: $y_1 = X(4)$ **OR** $X(1)$;
4: $y_2 = X(2)'$ **OR** $X(3)'$;
5: $y_3 = X(2)$ **AND** $X(3)$;
6: $y_4 = X(1)$ **OR** $X(4)$ **OR** $X(9)$;
7: $y_5 = X(4)$ **OR** $X(12)$ **OR** $X(13)$ **OR** $X(14)$;
8: $y_6 = X(13)$;
9: $y_7 = X(10)$;
10: $y_8 = X(5)'$ **AND** $X(7)$;
11: $y_9 = X(5)'$ **AND** $X(9)$;
12: $y_{10} = X(5)$;
13: $y_{11} = X(5)$ **OR** $X(6)$ **OR** $X(7)$ **OR** $X(8)$ **OR** $X(11)$;
14: $y_{12} = X(7)$ **OR** $X(8)$;
15: $y_{13} = X(5)$ **AND** $X(6)$;
16: $y_{14} = X(15)$;
Return: Output data representing the prescribed therapies.
17: $\boldsymbol{y} = [y_1\ y_2\ y_3\ y_4\ y_5\ y_6\ y_7\ y_8\ y_9\ y_{10}\ y_{11}\ y_{12}\ y_{13}\ y_{14}]^T$.

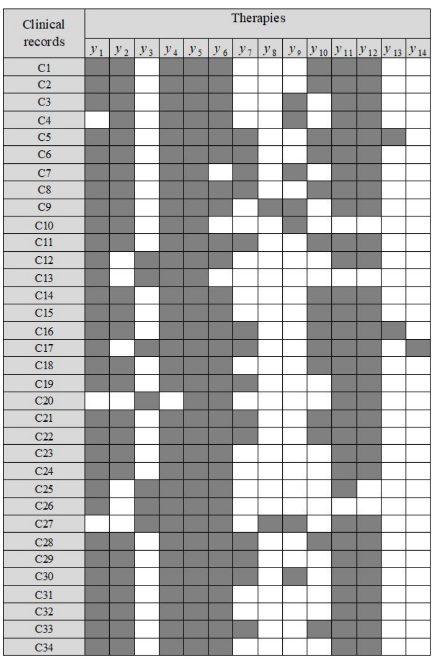

FIGURE 5. Evaluation of the computer-aided prescription system defined by (1)-(14). The system is tested using input data the clinical records (first column). In the remaining columns, the cell of each therapy is colored in dark gray if the computer-aided prescription system recommends prescribing the therapy ($y_i = 1$); otherwise, the cell remains white ($y_i = 0$).

D. VIRTUAL CLINICAL RECORDS

The database was supplemented with a set of virtual clinical records to validate the performance of the proposed computer-aided prescription system. The goal was to generate 90 virtual clinical records sharing statistical features with the 34 real clinical records selected according to the procedure described in the data collection subsection. The procedure used to generate virtual clinical records was as follows:

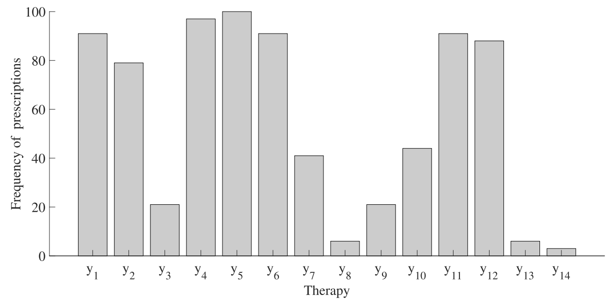

FIGURE 6. Frequency of prescription of therapies for 34 clinical records evaluated with the computer-aided prescription system.

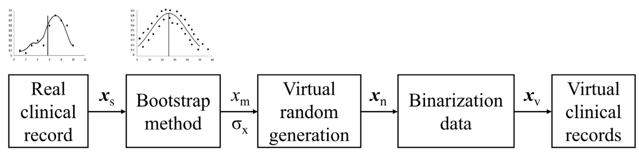

FIGURE 7. Procedure to generate virtual clinical records. Virtual clinical records were generated from: (i) the dataset of real clinical records, (ii) using the bootstrap method to obtain a resampled population, (iii) a random data generator defined in (15), and (iv) a binarization process considering the threshold for each component of $\boldsymbol{x}_v$ according to Table 4.

The set of 34 real clinical records is used as starting data and forms a skewed distribution, and each element of this set is represented by ($\boldsymbol{x}_s$). The aim was to generate virtual input variables ($\boldsymbol{x}_v$) sharing the mean and standard deviation with the set of real clinical records. The bootstrap method [30] is used to resample a set of real clinical records with replacement to obtain a set of random variables with a normal distribution. In this case, a population of 10,000 random variables ($\boldsymbol{x}_r$) with a normal distribution was generated, and the method provided the mean (x_m) and standard deviation (σ_x) for the new set which includes the real $\boldsymbol{x}_s$. Using these statistics, new virtual data ($\boldsymbol{x}_n$) are generated from $\boldsymbol{x}_r$ according to the following expression:

$$\boldsymbol{x}_n = \boldsymbol{x}_r\sigma_x + x_m. \tag{15}$$

As previously mentioned, the real input variable $\boldsymbol{x}_s$ is binary; thus, $\boldsymbol{x}_n$ from (15) must be binarized. The binary threshold for each component $x_{v,i}$ for $i = 1, \ldots, 12$ depends on the scales defined in Table 4 as illustrated in Figure 7. Thus, 90 virtual variables $\boldsymbol{x}_v$ were selected in a random manner to form a set of virtual clinical records. Then, for validation purposes, a database consisting of 10 real clinical records and 90 virtual records generated using the previous methodology was considered, with a total of 100 clinical records.

TABLE 6. Validation of a virtual clinical record. The value "Incomplete" of x_{v1} in the third column was changed to "Complete" to maintain congruence with the typical clinical condition of a patient.

Virtual clinical record			Clinical adjustment
Condition	Symbol	Value	
Joint movements	x_{v1}	Incomplete	Complete
Strength	x_{v2}	4/5	-
Movement limitation	x_{v3}	Not present	-
Pain	x_{v4}	2/10	-
Edema	x_{v5}	x	-
Contracture	x_{v6}	Present	-
Wound	x_{v7}	Not adhered	-
Trophic changes	x_{v8}	Not present	-
Sensitivity	x_{v9}	Not altered	-
Gait	x_{v10}	Eubasic	-
Stability	x_{v11}	Present	-
Bone healing	x_{v12}	Present	-

V. CLINICAL VALIDATION

A. VALIDATION OF VIRTUAL CLINICAL RECORDS

The virtual clinical records generated by the procedure depicted in Figure 7 were validated by a clinician at the Department of Sports Medicine and Rehabilitation, hospital "Dr. José Eluterio González", University of Nuevo León, at Monterrey, Nuevo León, México. The clinician analyzed the input variables $\boldsymbol{x}_v$ for each virtual clinical record. When there was inconsistency (i.e., differences between the data generated by the virtual method and the clinician's knowledge), the clinician recommended adjustments to the non-congruent data. An example of this procedure is presented in Table 6. It presents data from a virtual clinical record, where the value of x_{v1} represents incomplete joint movement. This value was revised by a clinician who reported no congruence with the eubasic gait and movement limitations. In this case, the clinician's suggestion was to change the value of x_{v1} from incomplete joint movements to complete joint movement, to be congruent with the clinical record.

From the full set of clinical records, only 15 (16.6%) were inconsistent. Inconsistencies were observed in x_{v1}, x_{v3}, x_{v9}, x_{v10}, and x_{v11}. The frequency of the inconsistencies per virtual input variable is shown in Figure 8.

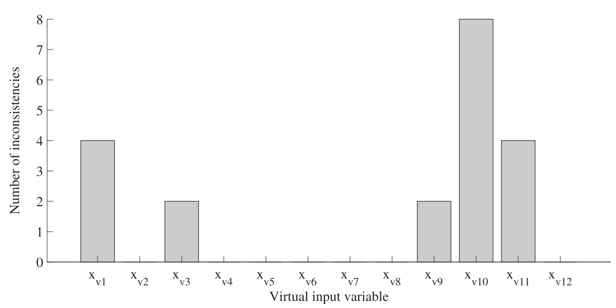

FIGURE 8. Virtual input variables presenting inconsistencies in the validation process of the virtual clinical records.

B. VALIDATION OF THE COMPUTER-AIDED PRESCRIPTION SYSTEM

The validation of the proposed system consisted of comparing data from medical prescriptions made by a clinician with the automated prescription computed by the system. In both cases, the input data comprised the full set of clinical records. Clinical prescriptions were administered by one clinician for three months. Prescriptions were collected in sessions during which the clinician accessed the database and prepared prescriptions as a function of the data registered in each clinical record. The full database was shown to the clinician using single-referenceless randomized selection. Automated prescriptions were computed using Algorithm 1, which was fed using the same input database provided to the clinician.

The computer-aided prescription system was validated using a confusion matrix (C.M.), which is commonly used to measure the accuracy of an algorithm. To complement these metrics, we included the F-score. The C.M. is an error table that serves as a statistical tool for analyzing observation pairs [31], and the F-score is a metric for evaluating the accuracy of a binary classification model [32]. This includes the calculation of the metrics for accuracy, precision, sensitivity, and specificity [33]. The elements of C.M. were computed from the results of the clinical and automated prescriptions. Considering the full set of clinical records (100) in the database and the 14 different therapies to be prescribed ($\boldsymbol{y} = [y_1 \ \ldots \ y_{14}]^T$), a total of 1400 prescriptions were made by the clinicians, and the same number of prescriptions were computed by the computer-aided prescription system. The total number of cases for each element of the C.M. is listed in Table 7, which includes 759 true positives (TPs), 10 false positives (FPs), 27 false negatives (FNs), and 604 true negatives (TNs). From this data, we used conventional metrics to validate the computer-aided prescription system [34], with the following results: 97.4% accuracy, 98.7% precision, 96.6% recall (sensitivity), 98.4% specificity, and 97.6% F-score. The data are summarized in Table 8.

TABLE 7. Cross-referencing of automated and clinical prescriptions.

		Clinical prescription		
		Positive	Negative	Total
Automated prescription	Positive	759	27	786
	Negative	10	604	614
	Total	769	631	1400

TABLE 8. Metrics to validate the computer-aided prescription system.

Metrics	Indices
Accuracy	97.4%
Precision	98.7%
Recall	96.6%
Specificity	98.4%
F-score	97.6%

The reliability index of the computer-aided prescription system was also included in validation. It was computed by considering the number of agreements and inconsistencies between pairs of clinical and automated prescriptions. Figure 9 shows the number of inconsistencies between the clinical and automated prescriptions for each therapy, where y_2, y_3, y_5, y_6, y_7, y_{11}, y_{12}, and y_{14} had no inconsistencies.

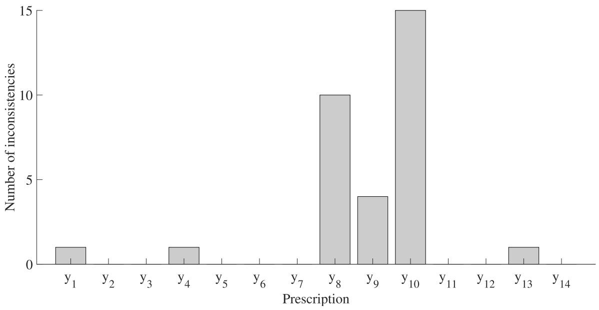

FIGURE 9. Number of inconsistencies between automated and clinical prescriptions considering the full dataset of clinical records.

The remaining prescriptions accumulated 32 inconsistencies, accounting for 2.29% of 1400 prescriptions. Thus, the reliability index of the computer-aided prescription system is 97.71%.

VI. DISCUSSION

As discussed in Section II, there is a current challenge in the development of computer-aided prescription systems. Therefore, this study seeks to contribute to the systematization and quantification of the decision-making process of clinicians in rehabilitation programs for ankle fractures. The contributions of this work are as follows: (1) The analysis of retrospective data from the clinical records of patients enrolled in an ankle fracture rehabilitation program. (2) Quantitative representation of clinicians knowledge regarding the prescription of therapies. (3) Development of a computational methodology that synthesizes the information from previous points to automate the prescription. These three points are illustrated in the block diagram in Figure 3. The above provides a general computational methodology, which could be useful in the design of computer-aided prescription systems for therapies in different types of conditions, with the appropriate definition and quantification of input and output variables, as well as the definition of rules based on clinician' knowledge. In the case study, the database was obtained from the analysis of the clinical records, and it provided the input and output variables $\boldsymbol{x}$, $\boldsymbol{y}$ (Tables 1 and 2). The quantification of the clinician's acknowledgment resulted in the relationships defined by the functions in (1)-(14). Algorithm 1 presents the proposed computational methodology. The results of the algorithm evaluation allowed us to calculate the prescription frequency of each therapy (Figure 6) showing that some therapies are less frequently prescribed; for example, isotonic exercises (y_3) and reliving massage (y_9) were prescribed in 21% of the clinical records; anti-edema massage (y_8) and interferential therapy for pain (y_{13}) were prescribed 6% of the time; and inferential therapy for bone healing (y_{14}) was prescribed in just 3% of cases. This demonstrates a difference between the clinical prescription and computer-aided prescription, which gives us the opportunity to identify key elements of the process to optimize it and could help plan the use of resources at a rehabilitation center in terms of equipment and specialized personnel availability.

To validate the computer-aided prescription system, virtual clinical records were proposed and validated by a clinician to confirm their agreement with the real records might look like. 75 virtual clinical records (83.4%) were congruent with real patient conditions. The remaining 15 clinical records presented inconsistencies in specific variables, which are summarized in Figure 8, where gait (x_{v10}) was the variable that most often presented inconsistencies during clinical validation. Using the full database, we validated the performance of the computerized prescription system. Inconsistencies between automated and clinical prescriptions were quantified for each therapy, as illustrated in Figure 9. The largest number of inconsistencies were observed for anti-edema massage (y_8), relieving massage (y_9), and ultrasound (y_{10}); this is because these therapies depend on the input variable pain (x_4), in clinical practice, pain levels are highly subjective, which increases the variability in the prescription. By summarizing the full set of prescriptions and quantifying the agreements and inconsistencies between automated and clinical prescriptions, we found that the computer-aided prescription system was 97.71% reliable.

Additionally, C.M. was used to quantify the accuracy (97.4%), precision (98.7%), sensitivity (96.6%), specificity (98.4%), and F-score (97.6%) of the computer-aided prescription system. The results of the computer-aided prescription system proposed herein are consistent with previously reported computer-aided systems in medical applications. For example, Polat et al. presented a computer-aided system for diagnose diabetes which had a 89.47% accuracy [35]. Other studies have reported computer-aided systems to diagnose breast cancer with 97% specificity and 76% sensitivity [36], coronary artery disease with 93.3% accuracy, 93.3% specificity, and 93.2% recall [33], thyroid disease with 89% accuracy [37], leukemia with 94% accuracy, and musculoskeletal disorders with 86.7% accuracy [38]. Therefore, previous works mainly reported the accuracy of computer-aided systems, and the value of our approach is in these reported accuracy ranges. Specificity and sensitivity were reported in only two studies [33], [36], and their values were comparable with the results of the computer-aided prescription system reported in this work.

VII. CONCLUSION

The consolidation of computer-aided diagnosis has led to the development of computer-aided systems in other areas of decision making in clinical practice, such as the prescription of therapies and treatments. In the case of PRP, identifying the structure and elements of the prescription process, including sources of information and the rationale of clinicians, allowed us to propose a computer-aided prescription system to automatically prescribe rehabilitation therapies. This prescription is based on data on the biomechanical conditions of patients registered in clinical records.

The scope of this study was to synthesize the procedure of a physical rehabilitation program as an iterative process and define the elements of a computer-aided prescription system that can be used as a computational tool to support medical decisions. Our system has an acceptable performance according to the metrics reported in the literature for computer-aided systems in other medical applications for decision-making. This case study could be the basis of a system for automatic learning that specifies and improves clinical prescriptions based on information provided by clinicians. As stated in the discussion section, the system was validated with virtual clinical records; thus, the next challenge of this research could be the study of the system's performance in actual clinical trials, including inpatient/outpatient tests, with patients starting their physical rehabilitation programs.

DECLARATION OF COMPETING INTEREST

The authors declare that this research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

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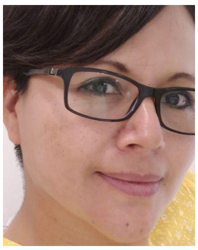

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