Clinical Reasoning and Clinical Decision-Making Systems

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Due to COVID period many people have become recreational runners. Recreational running is a regular way to keep active and healthy at any age. Additionally, running is a popular physical exercise that offers numerous health advantages. However, recreational runners report a high incidence of musculoskeletal injuries due to running. The proposed intelligent system uses data mining algorithms for the rehabilitation guidance of recreational runners with musculoskeletal discomfort. The system classifies recreational runners based on a questionnaire that has been built according to the severity, irritability, nature, stage, and stability model and advise them on the appropriate treatment plan/exercises to follow.

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1. Introduction

Running constitutes a widely adopted modality of physical activity that confers significant contributions to a health-conscious way of life. Moreover, running has emerged as a prominent global pursuit in the domain of exercise, characterized by substantial engagement rates [1], encompassing a heterogeneous and diversified cohort [2]. Additionally, it offers significant health-related advantages, encompassing musculoskeletal robustness, cardiovascular amelioration, the optimization of bodily composition, and the promotion of psychological equanimity [3].

Unfortunately, many recreational runners suffer injuries [4]. The number of injuries is difficult to identify as there are numerous studies that have provided results on the prevalence and incidence of running-related injuries using a variety of measures of association. In recent years, recreational runners have increasingly used technology to record their performance. However, a study [5] of a group of recreational runners in Ireland reported a high incidence of musculoskeletal injuries due to running. Nevertheless, these injuries were not found to be detectable with the available exercise monitoring technology (e.g., smart watches, smart phones) used.

Clinical reasoning refers to the systematic approach employed by a therapist when engaging with a patient. This approach involves gathering information, formulating and testing hypotheses, and ultimately arriving at the most suitable diagnosis and treatment plan based on the gathered data. It has been characterized as “an inferential process utilized by healthcare practitioners to gather, assess data, and make informed decisions regarding the diagnosis and management of patients' issues" [6][7]. This process of clinical reasoning assists healthcare professionals in making well-informed judgments to establish an effective strategy for addressing each patient's injury [8] while also aiding the patient in identifying meaningful goals [9]. Essentially, clinical reasoning is the recording of information given by the patient about his/her injury, after being asked questions by the healthcare professional (the physician, physiotherapist, or rehabilitation trainer) in order to obtain a history at the present moment of the session, in the form of an interview or questionnaire.

The integration of informatics [10] into clinical decision-making systems, while still in its early stages in the United States, is an ever-evolving process that has gained widespread acceptance from both physicians and patients. This integration empowers patients by offering them resources to learn about their health status and actively engage in their healthcare, and it provides easy access to health information. The clinical decision-making system favors reducing the cost of care by seeking alternatives to the evolution of patients' health status. Health-related informatics can facilitate the transition from a disease prevention model centered on the care system to a patient-centered health-promotion approach.

2. Clinical Reasoning

In the past, several studies have highlighted the role of clinical reasoning by focusing on specific points. In [11], the clinical reasoning of experienced musculoskeletal physiotherapists in relation to three different occurrences of pain has been studied and identified five main categories of clinical reasoning: (a) biomechanical, (b) psychosocial, (c) the pain mechanism, (d) temporality, and (e) the irritability/severity of injury. Later, Baker et al. [12] highlighted systematic clinical reasoning in physical therapy (SCRIPT) to guide junior physiotherapists in correctly taking the history of patients with spinal pain. This tool incorporates the severity, irritability, nature, stage, and stability (SINSS) model for clinical reasoning.

The severity, irritability, nature, stage, and stability (SINSS) model is a clinical reasoning construct that offers doctors an organized framework for taking a subjective history in order to choose the best objective examination and treatment strategy and to cut down on errors. The SINSS model aids the physiotherapist in gathering comprehensive data regarding the patient's state, sorting and categorizing the data, ranking their list of issues in order of importance, and choosing which tests to administer and when. This ensures that no information is overlooked and that the patient is not checked or treated excessively [7]. Five points of recording and research are included in the SINSS model:

- The degree of the symptoms, particularly the perceived level of pain, was correlated with the severity of the damage. The level to which the patient's activities of daily living are impacted is a major factor in determining how severe the pain is quantified. Pain can be measured in a variety of methods, including using the Visual Analogue Scale (VAS).

- The degree of activity needed for symptoms to worsen, how bad the symptoms are, and how long it takes for the symptoms to go away can all be used to gauge how irritable the tissue is. The ratio of aggravating to mitigating factors is another way to measure irritability.

- The patient's diagnosis, the sort of symptoms and/or pain, individual traits/psychosocial factors, and red and yellow flags all contribute to the injury's nature.

- The stage of the injury, which refers to how long symptoms have been present. The primary categorizations include the acute phase (spanning less than 3 weeks), the subacute stage (occurring between 3 and 6 weeks), the chronic phase (extending beyond 6 weeks), and the acute stage of a chronic condition (which pertains to a recent exacerbation of symptoms in a condition that the patient has been managing for over 6 weeks).

- The stability of the injury, which refers to the way in which the symptoms develop, where it refers to the improvement, deterioration, and unchanging and fluctuating status of the injury.

Although the above models seem to give a more comprehensive picture of the patient's injury, several studies have applied specific points from the categories of clinical reasoning.

A study [13] used pain severity/irritability in the Maitland construct to study inter-rater reliability among physiotherapists in assessing irritability when applied to patients with low back pain. Additionally, in a study of shoulder irritability, Ref. [14] used the STAR-Shoulder clinical reasoning, which suggests three levels of shoulder tissue irritability with corresponding intervention strategies related to the management of physical stress on shoulder tissues: (a) high irritability (high pain, continuous pain at night or at rest, active less than passive movement, high dysfunction, and pain before full range of motion); (b) moderate irritability (moderate pain, intermittent pain at night or at rest, the same degree of active and passive movement, moderate dysfunction, and pain at full range of motion); and (c) low irritability (low pain, the absence of pain at night or at rest, active more than passive movement, low dysfunction, and minimal pain on application of pressure).

3. Clinical Decision Making

The use of clinical decision support systems in the management of serious injuries in emergency departments is very important [15]. Management errors that occur due to time pressure, inexperience, dependence on memory, multi-tasking, information flow analysis, and failures due to lack of care team coordination, especially during first aid, can be greatly reduced by making use of the decision support system. In the context of clinical medicine, the study [16] mentioned machine learning clinical decision making, which deals with estimating outcomes based on past experiences and data patterns using a computer generated algorithm that combines technical intelligence through visual and auditory data to treat severely injured patients.

Physiotherapists must manage a large amount of information in order to make therapeutic decisions, but they can enhance their practice by using information gleaned from technology, methodical data processing, and expertise

[17]. Frontline staff members can choose the best interventions for patients with musculoskeletal injuries with the aid of clinical decision support tools. These resources are based on online surveys, therapy algorithms and models, clinical prediction criteria, and classification schemes. They are being developed, employ quickly advancing computer technology, and might be of interest to healthcare professionals. Utilizing a decision support system can assist in standardizing data collecting and presenting the steps necessary to apply operational metrics that can be applied across health care disciplines [18].

In [19], the authors evaluated the SIAVA-FIS system based on two modules: a web module where data are entered, configured, and printed and a second module in the form of a mobile device app where different types of graphics are used to present the assessment of patients with musculoskeletal disorders. Through this system, clinical parameters such as vital signs (blood pressure, temperature, heart rate, and respiratory rate), body mass index, goniometry, muscle strength, girth, muscle tone, and pain sensation were recorded.

However, there is also research effort that describes the danger of using one-sided decision support systems for the management of musculoskeletal injuries. In [20], the authors evaluated the validity of a clinical decision support tool—the Work Assessment Triage Tool (WATT)—in relation to physicians' recommendations regarding the choice of treatment for workers with musculoskeletal conditions. Clinicians tended to recommend functional rehabilitation, physiotherapy, or no rehabilitation, while the WATT recommended additional evidence-based interventions, such as workplace interventions. On the other hand, a review study [21] attributed the diversity of existing decision-making systems for the management of musculoskeletal injuries to the complexity of their inherent diagnostic complexity. However, given the multidimensional nature of musculoskeletal injuries, the fuzzy logic that underpins these systems may assist in the design of knowledge bases for clinical decision support systems. A large proportion of these systems were designed for the diagnosis of inflammatory/infectious disorders of bones and joints, and knowledge was extracted by a combination of three methods (expert information acquisition, data analysis, and literature review).

Many coaches and athletes are adopting an increasingly scientific approach to both the design and monitoring of training programs. The appropriate monitoring of training load (frequency, duration, and intensity) can help determine whether an athlete is adapting to a training program and minimize the risk of developing non-functional overuse, illness, and/or injury. In order to understand the function of training load and the effect of load on the athlete, Ref. [22] lists a number of indicators that are available for use via tracking devices (e.g., smart swatch). The main information obtained from these devices refers to the training load (frequency, duration, intensity, etc.), perception of effort and fatigue, recording of sleep and recruitment, and recording of body morphology (body mass index, fat, bone, etc.) and through REST-Q and VAS questionnaires it is possible to record injuries and pain sensation. It seems that in terms of sports activity and monitoring technology, there is no single indicator to guide decision making for injury rehabilitation since the challenge may be due to many interrelated factors.

In [23], the authors studied the modeling of sports-related injuries in twenty-three female athletes at Iowa State University using an inductive approach. The injury suffered by an athlete was set as the target variable for the proposed system. The target variable was structured to represent a discrete binary variable, which indicates whether or not an athlete sustained an injury. The dynamic Bayesian network (DBN) [24], a well-known machine learning method related to athlete health, was used for the research needs. Sports professionals were monitored regularly, throughout the season. Data analysis revealed subjectively reported stress two days before injury, the subjective perception of acute exertion one day before injury, and overwork as expressed by continuous sympathetic muscle tone overload on the day of injury as the main monitoring points with the greatest impact on injury occurrence. Therefore, it is recommended that professionals in the field of sports use the inductive approach to injury provocation to understand the adaptations made in their athletes and to improve their decision making as to the program to follow to prevent the possibility of injury provocation.

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