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Survey paper

Knowledge discovery in clinical decision support systems for pain management: A systematic review

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ABSTRACT

Objective: The occurrence of pain accounts for billions of dollars in annual medical expenditures; loss of quality of life and decreased worker productivity contribute to indirect costs. As pain is highly subjective, clinical decision support systems (CDSSs) can be critical for improving the accuracy of pain assessment and offering better support for clinical decision-making. This review is focused on computer technologies for pain management that allow CDSSs to obtain knowledge from the clinical data produced by either patients or health care professionals.

Methods and materials: A comprehensive literature search was conducted in several electronic databases to identify relevant articles focused on computerised systems that constituted CDSSs and include data or results related to pain symptoms from patients with acute or chronic pain, published between 1992 and 2011 in the English language. In total, thirty-nine studies were analysed; thirty-two were selected from 1245 citations, and seven were obtained from reference tracking.

Results: The results highlighted the following clusters of computer technologies: rule-based algorithms, artificial neural networks, nonstandard set theory, and statistical learning algorithms. In addition, several methodologies were found for content processing such as terminologies, questionnaires, and scores. The median accuracy ranged from 53% to 87.5%.

Conclusions: Computer technologies that have been applied in CDSSs are important but not determinant in improving the systems' accuracy and the clinical practice, as evidenced by the moderate correlation among the studies. However, these systems play an important role in the design of computerised systems oriented to a patient's symptoms as is required for pain management. Several limitations related to CDSSs were observed: the lack of integration with mobile devices, the reduced use of web-based interfaces, and scarce capabilities for data to be inserted by patients.

1. Introduction

According to the International Association for the Study of Pain [1], pain is an unpleasant sensory and emotional experience related to past or potential tissue damage, and patients may describe their pain in these terms. Its occurrence accounts for billions of dollars in annual medical expenditures [2]. Negative impacts on quality of life and decreased worker productivity contribute to indirect costs [3–5]. When the pain has a relatively short duration, it is known as acute pain, whereas pain that persists over a long period of time is regarded as chronic pain [6]. Furthermore, pain is the fifth vital sign for indicating basic bodily functions, health and quality of life [7], along with blood pressure, body temperature, pulse rate and respiratory rate. However, unlike the first four vital signs, pain does not represent an objective measurement, but it is considered an emotional status that happens inside the mind of each individual, making it harder to produce an assessment that leads to the proper treatment course. In line with this, clinical decision support systems (CDSSs) face additional challenges when applied to patients with symptoms of pain. These systems are widely applied in healthcare processes, such as triage, early detection of diseases, identification of changes in health symptoms, extraction of patient data from medical records, in-patient support, evaluation of treatment, and monitoring. However, despite the subjectivity and more difficult assessment of pain management, CDSSs should be developed to ensure the acquisition of knowledge from the data collected by patients or health care professionals.

This review aims to examine computer technologies used for CDSSs for patients that suffer from either acute or chronic pain.

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It focuses on methodologies that produce knowledge from clinical data to support clinical decision-making.

2. Methods

2.1. Research questions

The primary questions of this review were as follows: (RQ1) Which computer technologies have been used in CDSSs applied to pain? (RQ2) What is the overall accuracy resulting from the application of these technologies? (RQ3) Which technologies can improve a physician's decision-making process?

2.2. Inclusion criteria

Studies measuring and assessing pain using CDSSs were included in this review if they met the following criteria: (1) constituted a decision support system, (2) were related to acute or chronic pain complaints, (3) included data about pain values or (4) produced results based on the detection of pain occurrences, (5) used computerised systems, (6) were published between 1992 and the 31st of December, 2011, and (7) were written in English. There were no age or disease restrictions. Participants could be adults or children, chronic pain patients, healthy individuals with pain complaints, or individuals experiencing an episode of acute pain.

2.3. Search strategy

The team searched for studies meeting the inclusion criteria in the following electronic databases: CiteSeerx, IEEE Xplore, ISI Web of Knowledge, Mendeley, Microsoft Academic Search, PubMed, Science Accelerator, Science.gov, ScienceDirect, SpringerLink, and The Cochrane Library. One study was published online (November, 2011) [8] while the team was researching the electronic databases and was therefore included in this review. The study was subsequently published in February 2012.

Every study was independently evaluated by two reviewers (NP and PA), and its suitability determined with the agreement of both parties. A third reviewer was available to adjudicate any differences of opinion but was not required because a consensus was reached in all cases. The studies were also examined to identify and isolate clusters that report the same data to avoid the risk of selection bias [9]. When different studies reported the same CDSS, they were considered independently because they considered different symptoms and approaches (e.g., the studies [10,11], relative to the CDSS of [12–17]).

Additionally, the references cited by the studies were analysed for any additional CDSS studies applied to pain. The abstracts and/or full text papers of these studies were subsequently evaluated by both reviewers, following the same criteria they applied to the database searches.

2.4. Extraction of study characteristics

The following data were extracted from the studies and tabulated (see Table 1): year of publication, clinical information that includes clinical condition, pain setting (the duration of pain: acute or chronic), clinical care (emergency care, primary care, and secondary or tertiary in-patient and out-patient care), environment (single or multiple centre), and the clinical task (varying among diagnosis, screening, treatment and risk assessment). Finally, the main decision, the collected and/or computed data related to pain, the improvement in practitioner diagnosis, and the detailed information about the computerised system architecture are also presented.

As shown in Tables 2 and 3, the included studies were clustered into machine learning (ML) and content processing (CP). The ML group comprises rule-based algorithms (RBAs), artificial neural networks (ANNs), nonstandard set theory (NST), and statistical learning algorithms (SLAs). The CP group encompasses terminologies, questionnaires, and scores. The described characteristics of the ML techniques include: study identification, year of publication (the earliest year in cases of studies reported from the same dataset), healthcare condition, number of learning/training/testing records, and accuracy. The CP characteristics include study identification, year of publication, clinical condition, number of records and type of content used. Each study and its content can be referenced across a diverse range of ML and CP topics.

Notably, the accuracy is the percentage of records that are correctly predicted by the model, and this accuracy is defined by the ratio of correctly predicted cases to the total number of cases.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (1)$$

where TP is the number of true positive cases, TN is the number of true negative cases, FP is the number of false positive cases, and FN is the number of false negative cases.

In addition, the correlations between the independent variables presented in Tables 1 and 2 were determined using Spearman's correlation coefficients (r_s), and the normality of the data was computed by the Shapiro–Wilk test.

3. Results

As illustrated in Fig. 1, our review identified 1245 citations, of which 75 duplicates were excluded. The remaining 1170 citations were evaluated in terms of title, abstract, and keywords, resulting in the exclusion of 1081 citations. Full text evaluation of the remaining 89 papers resulted in the exclusion of 57 papers that did not match the defined criteria. In addition, seven additional papers were included from the cited reference tracking. In summary, our review examined 39 papers that represent 31 unique studies (some studies reported the same data and were clustered to avoid selection bias).

As shown in Table 1, the clinical symptoms were segmented into abdominal pain (ten studies (32%)), chest pain (eight studies (26%)), lower back pain, and palliative care (three studies each (10%)). These four symptoms represented 78% of the dataset. The remaining symptoms comprise of knee pain (two studies), cancer pain, myofascial pain, post-operative pain, rheumatoid arthritis pain, and scrotal pain (one study each). Only ten studies are related to chronic pain (32%). Moreover, nine of the thirty-one studies (29%) included in this review were published by the end of 2000. Of the remaining 22 studies, only seven were published by the end of 2005 (23%). Finally, 15 studies (48%) were published between the beginning of 2006 and the end of 2011. Emergency care (EC) and primary care (PC) are presented in sixteen studies (52%) and six studies (19%), respectively. Secondary/tertiary care, which includes in-patient care and out-patient care, were both reported in three studies (19%). Two studies presented in-patient and out-patient care combined, whereas combined PC and out-patient care was suggested by one study. The clinical tasks were clustered into diagnosis (17 studies (55%)), treatment (six studies (19%)), screening (five studies (16%)), and risk assessment (three studies (10%)). This review uncovered three variables related to pain, namely, location, severity, and duration considered in twenty-tree studies (74%), fourteen studies (45%), and four studied (13%), respectively.

Applying the Shapiro–Wilk test to the quantitative information based on the data presented in Tables 1 and 2 revealed that the data significantly deviate from a normal distribution ($p < .05$). Then, analysing these data, a strong correlation between the duration of