Improving Pain & Symptom Management for Advanced Cancer Patients with a Clinical Decision Support System

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Abstract. In palliative medicine, healthcare providers aim to provide end-of-life cancer patients with a plan of care to minimize pain and manage symptoms, while providing psychosocial and educational support to patients and their families. Unfortunately, it has been reported that patients often experience unnecessary suffering due to ineffective symptom management as they near end-of-life. Recent advances in health informatics have motivated healthcare institutions to take advantage of clinical decision support systems that assist healthcare providers with evidence-based decision making for pain and symptom management. In this paper, we present a unique clinical decision support system that incorporates case-based reasoning and evidence-based standards of care. It is anticipated that this user-friendly, web-based CBR system will improve decision making for pain and symptom management for end-of-life cancer patients.

Keywords. Care pathways, case-based reasoning, clinical decision support system, end-of-life cancer care, symptom management guidelines

1. Introduction

Cancer is the leading cause of morbidity and premature death in Canada. With a growing and aging population, we can expect the incidence rate of cancer to steadily increase over time, with 38% of women and 44% of men developing cancer during their lifetime [1,2].

Many patients who develop advanced cancer will experience its accompanying symptomatology that precedes death, including physical and psychological suffering [3], and the array of symptoms they contend with will significantly impact their ability to carry out activities of daily living, overall well being, and quality of life [5].

In Canada, palliative care is an integral component of cancer care which can improve the quality of life of patients and their families through the prevention of suffering, symptom assessment, and delivery of effective treatment [3].

In this paper, we present a clinical decision support system (CDSS) to assist healthcare providers with decision-making to improve pain and symptom management in end-of-life cancer care.

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1.1. Symptoms Experienced by Patients with Advanced Cancer

Advanced-cancer patients frequently experience an array of physical and psychosocial symptoms when they near end-of-life; the most common clinical symptoms include pain, dyspnea, nausea, fatigue, anorexia, cachexia, anxiety, and depression [3]. To measure the effectiveness of pain and symptom management, healthcare providers have begun to adopt reliable, validated assessment tools such as the Edmonton Symptom Assessment Scale (ESAS) and the Palliative Performance Scale (PPS).

2. Problem Description

Although assessment tools have been widely adopted in palliative care, 30% of Canadian patients with advanced cancer receive suboptimal, ineffective symptom management; and as a result they continue to suffer unrelieved pain and other cancer-related symptoms as they near end-of-life [1]. According to many studies, effective pain and symptom control can be achieved in 90% of patients with advanced cancer using existing knowledge and resources. Despite the World Health Organization’s widely accepted goal for palliative care, substandard symptom management remains a ubiquitous public health problem which significantly diminishes quality of life for patients with advanced cancer [1].

Recent studies in palliative care have extensively explored barriers to adequate symptom management for patients with advanced cancer, and have found that the majority of these barriers implicate deficits in knowledge and attitude of healthcare providers as main obstacles to effective symptom management. In Canada, the four main barriers impeding excellent symptom management for advanced-cancer patients include: (a) inadequate education and practical training in symptom management and end-of-life care for healthcare providers, (b) inadequate standards of care (CPGs and clinical pathways) and lack of evidence-based practice, (c) fragmentation of palliative care services and limited integration of healthcare providers across the continuum of palliative care, and (d) failure to reliably capture a record of the quality of care delivered to patients with advanced cancer [1-3].

3. Methodology

Clinical practice guidelines and integrated care pathways have been successfully implemented to promote adherence to an accepted standard of care, while encouraging clinical judgement and freedom when deviation from the standard of care is deemed necessary [2]. Several studies have proposed that clinical practice guidelines and integrated care pathways could be similarly applied to palliative care to alleviate the common barriers which currently prevent the delivery of effective pain and symptom management for end-of-life cancer patients [2,3]. Furthermore, healthcare providers have recommended that the barriers which impede the delivery of effective pain and symptom management could be improved when healthcare providers adopt intelligent clinical decision support systems to assist with the complex task of clinical decision making for end-of-life cancer care [6].
3.1. Clinical Decision Making in End-of-Life Care

In the knowledge intensive field of palliative care, a vast amount of information can be derived from clinical experience and archived in a repository for future usage. This collection of information is a priceless asset which can assist healthcare providers with clinical decision making in palliative care; however, managing this volume of information can be overwhelming, and certainly memorizing all the information is virtually impossible. To take advantage of this voluminous information, healthcare providers have begun to implement intelligent clinical decision support systems to support clinical decision making [6].

3.2. Clinical Decision Support Systems

A clinical decision support system presents healthcare providers with an interactive, computerized system that uses data and models to generate information to support clinical decision making. The three main components of a decision support system are a knowledge base, an inference engine, and a user interface. A knowledge base typically contains domain expertise which may be represented as clinical guidelines, decisional rules, and records of past patient cases. An inference engine is a computer program which processes information using systematic inference steps, similar to the decisional steps employed in the human thought process, and uses one or more reasoning methodologies [7].

Case-based reasoning is one such reasoning methodology that is proving to be especially valuable in mitigating error in diagnosis and patient management in palliative medicine. More recent advancements in health informatics, especially in the artificial intelligence (AI) techniques of data mining and case-based reasoning, present an opportunity to improve pain and symptom management through the implementation of case-based reasoning (CBR) medical decision support systems [7].

3.3. Research Objective

Our aim is to develop a CDSS to support clinical decision-making for the delivery of effective pain and symptom management for end-of-life cancer patients. The system will employ case-based reasoning methodology, and serve as a medium from which healthcare providers can leverage knowledge elicited from previously-solved patient cases to assist with the development of effective symptom management care plans for end-of-life cancer care.

4. Case-Based Reasoning System Architecture

The design of the presented case-based reasoning system was motivated by Aamodt and Plaza’s (1994) [8] CBR cycle, whereupon the case-based reasoner must perform four sequential processes: case retrieval, case reuse, case revision, and case retention. To enable these processes, there are four main tasks that must be employed: (1) case representation, (2) case indexing and storage, (3) case retrieval, and (4) case adaptation and learning. Below, we provide the design details of how these tasks were accomplished in our CBR system.
4.1. Case Representation

In this clinical decision support system, CBR was used to support clinical decision making for pain and symptom management in cancer care. Patient cases are represented by several feature attributes that describe a problem (e.g., mild pain) and the solution to the problem (e.g., 200-800 mg ibuprofen). The feature attributes that formed the problem description were: gender, age, cancer type, palliative performance scale (PPS), palliative performance scale-level, and the symptoms that were experienced by advanced cancer patients while in the Victoria Hospice Society palliative care unit.

For this research, simulated case solutions were derived using collaborative care plans and evidence-based symptom management guidelines. These case solutions were vetted by physicians in palliative care services, Capital District Health Authority. The solution attributes (care intervention categories) which formed case solutions were: patient assessment, pharmacological considerations, pharmacological therapy, non-pharmacological therapy, patient activity, psychosocial considerations, and patient/family education.

4.2. Case Indexing and Storage

In our system, patient cases (N = 276) were stored in a MySQL database and MySQL indices were created to speed-up database searching. The primary key of the database was the patient ID number to ensure that every patient record was unique. Indices were also created on the attribute columns to speed-up case comparison and retrieval.

4.3. Case Retrieval

4.3.1. Case Retrieval using the Nearest Neighbor Algorithm

In this CBR system, healthcare providers enter the feature attributes of a new patient case on an electronic web form, then perform a search query to retrieve the four most similar patient cases that are stored in the case library. The resultant set of cases is presented to the user in order of descending similarity. During case retrieval, similarity computation is calculated by applying the nearest-neighbor algorithm, Eq. (1), to find the most similar cases from the case library.

\[
\text{Similarity}(T, S) = \Sigma f(T_i, S_i) x w_i
\]  

In Eq. (1), \( w_i \) is the weighting factor of each individual feature attribute \( (i) \), \( S_i \) represents stored cases of each individual attribute, and \( T_i \) is the target case attributes. Weighting factors \( (w_i) \), or importance values, were determined for each feature attribute using Spearman’s rank correlations and discriminant analysis. Each case has a set of feature weights which is added to produce a weighted sum. The nearest-neighbor algorithm uses a distance calculation to compare the Euclidian distance between two feature vectors (weighted sum of the new query case with the weighted sum of cases stored in the case library) to determine how similar two cases are by comparing their features [9]. Euclidean distances have been determined using confusion matrices (Figure 1).
Table 1. Confusion matrix for pain and dyspnea

<table>
<thead>
<tr>
<th>Pain/Dyspnea ESAS</th>
<th>NONE</th>
<th>MILD</th>
<th>MODERATE</th>
<th>SEVERE</th>
</tr>
</thead>
<tbody>
<tr>
<td>NONE</td>
<td>1</td>
<td>0.75</td>
<td>0.5</td>
<td>0.25</td>
</tr>
<tr>
<td>MILD</td>
<td>0.75</td>
<td>1</td>
<td>0.75</td>
<td>0.50</td>
</tr>
<tr>
<td>MODERATE</td>
<td>0.50</td>
<td>0.75</td>
<td>1</td>
<td>0.75</td>
</tr>
<tr>
<td>SEVERE</td>
<td>0.25</td>
<td>0.50</td>
<td>0.75</td>
<td>1</td>
</tr>
</tbody>
</table>

4.3.2. **Case Retrieval using Inductive Decision Tree/Nearest Neighbor Algorithm**

In the presented system, we developed a second retrieval algorithm whereby we combined an inductive decision tree with a nearest-neighbor algorithm to optimize the efficiency of the CBR system. The inductive decision tree is used to retrieve a selection of indexed cases for subsequent similarity matching by the nearest-neighbor algorithm, which applies a similarity metric to return ranked cases in descending order of similarity to the target case [9].

The ID3 algorithm is used to induce a decision tree by ranking attributes according to their importance in classifying the data. This algorithm ranks attributes using an entropy measure, and is first applied to the complete corpus of cases to determine the attribute with the highest entropy. This attribute becomes the top-most decision point of the tree and is referred to as the root node. Subsequently, this process is applied recursively down the tree until all cases have been classified and indexed in leaves or until there are no further attributes to incorporate [9].

4.4. **Case Adaptation and Learning**

Our presented CBR system currently does not incorporate case adaptation; however, we are exploring the method of compositional adaptation, which is predicated upon combining the most salient solution components from multiple past cases to derive a final composite solution which is more representative of a user’s target case query. In medical case-based reasoning, case adaptation continues to be the main challenge to the development of a clinical decision support system which applies the complete CBR method. In the present system, end-users can store a new case into the case library (case learning) using an electronic web form. Upon submission, this information is stored as a new case in the case library, and so it would be available for future case queries.

5. **Evaluating System Efficacy and Clinical Validity of Case Solutions**

In an external evaluation process, key informants from palliative care examined our simulated case solutions for clinical appropriateness, deficiencies, erroneous care protocols, and whether case solutions represented local best practice and clinical practice guidelines. Future investigation will incorporate an RCT to evaluate the clinical validity of our CDSS in several clinical environments (PCU, ICU, hospice, home palliative care).
6. Concluding Remarks

The Canadian Cancer Society anticipates that death due to cancer will soon surpass cardiovascular disease, to become the leading cause of death in Canada. With this trend, there will be an increasing demand for palliative care services to provide cancer patients with effective relief from pain and other debilitating symptoms that are often experienced near end-of-life. According to WHO, substandard symptom management remains a ubiquitous public health problem, despite the fact that effective symptom management could be achieved for approximately 90% of advanced-cancer patients using existing knowledge such as standards of care.

In this paper, we presented a unique CDSS which incorporates evidence-based standards of care, and takes advantage of case-based reasoning to support clinical decision-making in end-of-life cancer care. Currently, our prototype CDSS is still under development; however, we believe that full implementation of our CBR system could improve clinical decision-making in end-of-life cancer care, ultimately improving symptom management and quality-of-life for end-of-life cancer patients.

Our research warrants further investigation to explore the technique of compositional adaptation, and the feasibility of implementing a clinical decision support system using case-based reasoning to support end-of-life cancer care in palliative care services, Capital District Health Authority, Nova Scotia, Canada.

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References