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Using Formal Knowledge to Support Episodic Evidence-Based Nursing Care

Shai JAFFE[a,b1] , Bruria BEN SHAHAR [c], Yuval SHAHAR[c], Ayelet GOLDSTEIN [d], Erez SHALOM[c], Maya SELIVANOVA[e], Ephraim RIMON[d] and Odeya COHEN [a,b]

[a] *Department of Nursing,Faculty of Health Sciences, Ben-Gurion University of the Negev, Israel*

[b] *Nursing Informatics lab, Faculty of Health Sciences, Ben-Gurion University of the Negev, Israel*

[c] *Department of Software and Information Systems Engineering, Ben-Gurion University of the Negev, Israel*

[d] *Computer Science Department, Hadassah Academic College, Israel*

[e] *Herzfeld Geriatric Rehabilitation Medical Center, Israel*

ORCiD ID: Shai Jaffe 0009-0000-9996-0367, Bruria Ben Shahar 0009-0003-2631-9132, Yuval Shahar 0000-0003-0328-2333 Ayelet Goldstein 0000-0003-0794-3653, Erez Shalom 0000-0002-3471-3143, Odeya Cohen 0000-0002-2427-6381

Abstract: Applying evidence-based medicine prevents me*dica*l errors highlighting the need for applying *Clinical Guidelines* (CGs) to improve patient care by nurses. However, nurses often face challenges in utilizing CGs due to patient-specific needs. Developing a *Clinical Decision Support System* (CDSS) can provide real-time context-sensitive CG-based recommendations. Therefore, there is a need to acquire and represent CGs in a machine-applicable manner. Also, there is a need to be able to provide recommendations *episodically*, only when requested, and not continuously, and to assess previous *partial* performance of evidence-based actions on a continuous scale. This study evaluated the feasibility of acquiring and representing major nursing CGs, in a machine-applicable manner for episodic use. Using data from an Israeli geriatric center, the results suggest that an episodic CDSS effectively supports the application of formalized nursing knowledge.

Keywords. Nursing Protocols, CDSS, Clinical Guidelines, Formalization

1. Introduction

Nurses work under pressure, expected to meet patients' needs with high quality care[1,2]. Integrating best-practice medical knowledge with individualized *electronic medical records* (EMR) facilitates appropriate treatment for each patient[3]. Exploiting evidence-based nursing (EBN)[2] and implementing a system recommending care per current guidelines could ease nurses' burden, enhance care quality and cost-effectiveness[1,4].

In practice, *clinical guidelines* (CGs) are mostly available in free text and need transformation into a computer interpretable format for automated support[3]. This process, called *formal knowledge representation*[4] has led to the development of

[1] Corresponding Author: Shai Jaffe; E-mail: shaija@post.bgu.ac.il.

Computer-Interpretable Clinical Guidelines (CIGs)[5]. Applied by *Clinical Decision Support Systems* (CDSSs), CIGs can assist clinicians in evidence-based monitoring and treatment[6,7]. While most CDSSs support *continuous* decision making, medical and nursing care often benefit more from *episodic* consultation mode, allowing a nurse to use the system only when requiring assistance. In addition, actions are often performed partially, considering the patient's clinical manifestation to accommodate clinical ambiguity.

Picard is a continuous CG-application engine, developed[3] and evaluated extensively[5, 7-9]. We extended Picard to *e-Picard* by adding an episodic mode for CG-based CDSS, allowing nurses to consult the framework in a non-continuous manner. We represented partial action performance and achievement of [care] process, and [patient] outcome goals, using *fuzzy (temporal) logic*[10]. The knowledge acquisition process (Figure 1) includes: 1) eliciting the CG's *declarative* knowledge (*What is?*) focusing on time-dependent diagnostic, therapeutic patterns and goals based on the CG[6-9,11]. This is achieved using our *Temporal Abstraction Knowledge* (TAK) language, which is based on the *Knowledge-Based Temporal-Abstraction* (KBTA) method and on its ontology[6]. 2) eliciting the CG's *procedural* knowledge (*How to?*) represented by *Asbru* CG specification language[11], allowing partial performance, with *fuzzy logic*. We use a semi-automated graphical knowledge-acquisition tool, previously developed for that purpose, named *GESHER*[10], and 3) acquiring the Quality Assessment (QA) knowledge defining the treatment intentions, conditions for complete or missed actions and QA scores for each action, as will be further detailed in the methods.

Our project's objectives were: 1) Formally represent several key nursing CGs at a large geriatric medical centre. 2) Assess the quality of these CGs' representation, using the e-Picard engine.

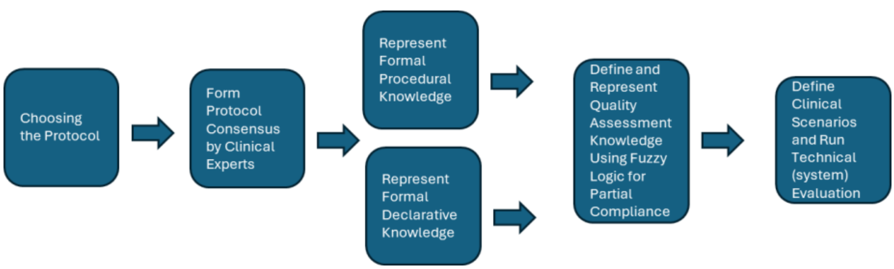

Figure 1. Steps to formalizing the CGs in a computer comprehensible format.

2. Methods

2.1. Medical Knowledge-Engineering Methods

We use the Asbru language[8,11] for CG procedural knowledge, the KBTA ontology[3] and its TAK language for CG declarative knowledge, and the GESHER graphical knowledge-representation tool[9], to formally represent CGs. Additionally, acquiring and representing *Quality Assessment* (QA) knowledge is essential for *episodic* CG application. This involves understanding from the EMR [1] what *was* performed according to the CG, [2] *to what extent* (i.e., partially) and [3] the conditions under which an action, if not performed or insufficiently performed, is still relevant. The last requirement proved the most challenging.

Clinical protocols were initially presented in a decision tree and verified by the hospital's senior nursing and medical staff for accuracy. After reaching consensus, we formalized the nursing CGs' procedural knowledge (e.g., plans, and actions) using the GESHER tool and the DeGel library[9,11]. Declarative knowledge (e.g., eligibility conditions, outcome intentions) was acquired using the TAK language.

To support QA knowledge representation, we developed a methodology to convert *procedural* knowledge (i.e., taking a patient's temperature) into *declarative* knowledge (i.e. *what* temperature range is defined as a fever, and *what pattern* of temperature measurements indicates a correct performance of the CG) to define temporal patterns that should be discoverable in the patient's data if the therapy plan was correctly applied, thus formally representing quality-assessment knowledge, using fuzzy logic to assign quantitative scores to partial performance of actions and subplans (see Figure 1).

Uncertainties in clinical decision-making make fuzzy logic valuable, offering a flexible framework for managing ambiguity and partial truths in complex scenarios. The scenarios, verified by senior clinical staff for accuracy, serve as a gold standard of care. The CDSS should recommend actions as a senior staff nurse would, using the patient's past and present data, the CG, and sufficient time.

2.2. Study Population

We focused on protocols for *pressure ulcer* (PU) and for diabetes management, due to their prevalence in geriatrics, nursing relevance, and clinical decision-making complexity, supporting nursing care and follow-up decisions.

This IRB-approved study (#0114-21-KMC) involved 4000 patients from five departments at the Herzfeld Geriatric Medical Center, including two critical care wards. For the technical evaluation of the represented CG knowledge and of its application by e-Picard, we focused on 50 PU patients, hospitalized on average 38 days, and 10 diabetes patients with a 14-day average stay. We are expanding the patient cohort.

2.3. The Technical Evaluation

Quality assessment used two metrics: *Correctness*, evaluating the soundness of e-Picard's recommendation given the CG and patient data, determined by the percentage of e-Picard's correct recommendations out of all the recommendations it provided; and *Completeness,* assessing the percentage of the CG's recommendations that were actually suggested by e-Picard, given the CG and patient data, calculated by the number of recommendations given by e-Picard out of the total CG's context-sensitive recommendations. These metrics, expressed as percentages from 0 (none correct) to 1 (all correct), have proven highly useful in previous studies[4].

To measure Correctness and Completeness, we conducted the technical evaluation in several iterations, starting by validating the CG's procedural and declarative knowledge semantics with domain experts. Key clinical scenarios from nursing CGs were approved by experts. A random sample of 50 patients meeting PU and Diabetes CGs (five and two, respectively) criteria gauge scenario accuracy. The *e-Picard* engine's recommendations' correctness and completeness were calculated and validated through manual comparison with full EMRs. For the PU CG, a 2 to 4 weeks period per patient was evaluated, while the Diabetes CG required a shorter period to assess blood glucose levels (BGL) during hospitalization.

3. Results

Representing two nursing CGs revealed protocol variations among units often diverging from the original CG. An impartial expert helped achieve consensus in such instances. The application of fuzzy logic for assessing quality healthcare delivery provided valuable insights for quality optimization. To represent *declarative knowledge* (often part of various procedural conditions), we created 162 raw concepts, such as numeric blood glucose levels and nominal diagnoses: 35 for Diabetes CG and 127 for PU GC. We also created 103 state abstraction concepts from raw concepts (i.e. patient repositioning instances per week within the context of follow-up in the PU CG). Table 1 details the declarative knowledge represented for each CG.

Table 1. Distribution of TAK files for the two nursing CGs

Clinical Guideline	Raw concept	State	Pattern	Context	Event\ Attributes	Intentions	Total TAK files:
Diabetes	35	25	40	25	4\16	6	145
PU	127	78	122	30	N\A	8	365

To represent *procedural knowledge*, we created 388 concepts: 280 for PU CG and 108 for diabetes CG. Both had four main "monitor" plans (i.e., patient continuously monitored by system within plan context; satisfying activation conditions as long as they have a PU needing management). Each CG required a hierarchy of actions. Table 2 details the procedural knowledge represented for each CG.

Table 2. Distribution of plan types for the two nursing CGs

Clinical Guideline	Monitor Plans	Actions	Pt.DE	Procedure	DA	Cyclic plans	Not.	Ref.	Ed.
Diabetes	4	38	N/A	23	18	21	1	2	1
PU	4	72	19	130	N/A	51	N/A	1	3

Pt. DE – Patient Data Entry; DA – Drug Administration; Not. – Notifications; Ref. – Referral; Ed - Education

The e-Picard algorithm was run on all of the 50 patient records, generating a report for each with QA performance scores for past CG actions, and CG-based recommendations for present therapy. It successfully applied 13 chosen scenarios for both CGs, generating quality assessments and recommendations whose Correctness and Completeness were meticulously manually validated against full longitudinal data, demonstrating that complex nursing CGs can be formally represented while capturing their key semantics.

4. Discussion

Clinical critical thinking requires a broad outlook on patient health, addressing multiple issues simultaneously given medical decision-making nuances[1,3]. Achieving expert consensus was challenging but essential. Nursing support must consider the *episodic* nature of consultations and *partially performed* actions or actions that need to be *repeated*. Fuzzy temporal logic functions handle CG ambiguities, particularly with timing and value-based decisions. For example, in the Diabetes CG, BGL testing must occur at a set time before breakfast, followed by insulin administrations. Deviations lower compliance score. This study demonstrates the viability of applying an episodic CG-based CDSS in a geriatric setting, laying the groundwork for large-scale retrospective quality assessments and real-time nursing decisions. A current limitation is e-Picard's inability to interpret free-text nursing reports, relying solely on structured EMR. Future work may include natural language processing. In the next phases, we will assess retrospective data, and deploy a real-time CG-based CDSS in the geriatric medical centre to support nurses in daily care.

5. Conclusions

We demonstrated that two critical nursing CGs could be fully acquired from the literature and clinical experts' feedback and represented using distinct formal languages for the specification of procedural and declarative knowledge, while considering both the episodic nature of the consultations and the possibility of partial action performance. Using the formally represented CIGs, the e-Picard CG-application engine applied two different CIGs, to generate episodic retrospective quality assessments and therapy recommendations, generating reports that aligned with the established nursing protocols.

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