New Australian Nursing Sensitive Indicators: Testing Artificial Intelligence (AI) Mediation Tools

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Abstract (174/175 words)

A need has been identified for an Australian Nursing Sensitive Indicator (NSI) registry that reflects outcomes of nursing practice at a unit level. Australian NSI may be derived from merging (mediating) overseas and Australian indicators by identifying semantic similarities. There is potential for nursing to draw from a variety of existing data techniques outside the discipline.

We aimed to test artificial intelligence (AI) mediation tools by constructing two frame based ontologies containing NSI from overseas clinical registries and Australian studies.

The overseas and Australian ontologies were mediated via automatic and manual techniques. A comparison of semantic similarity between term pair mediation approaches was determined.

Analysis revealed 30.71% agreement as to semantic similarity across all techniques. When compared to each other, the two automatic packages agreed 23% while the two manual packages agreed 76.92%. Equivalence was consistently above the .85 I-Sub threshold with manual techniques.

This study suggests AI tools including Boolean truth tables, ontologies and software may be a useful adjunct with traditional measures in evaluating nursing semantic equivalence results across diverse mediation techniques.

Keywords:

Evidence-Based Nursing; Models Nursing; Mediation; Ontology; Nursing Sensitive Indicators; Boolean truth table; semantic similarity.

Introduction

Governments and health care bodies will always require accountability from nurses in the form of accurate and timely clinical data. Nursing Sensitive Indicator research is generating interest in the nursing community because hospitals are being asked to demonstrate efficiency, resource utilisation and value of patient care [1].

As technology progresses, there is a need for a human/machine readable data "capsule" which record nursing structural, process and outcome interactions. The Nursing Sensitive Indicator (NSI) appears to fulfil this function.

The study draws from the realms of nursing and artificial intelligence to mediate frame based ontologies. Mediated indicators may eventually form the basis of a future reusable Australian registry of NSI.

Nursing Sensitive indicators

NSI can reflect the effectiveness of nursing interventions and have the capacity to measure improved function and quality through the effective application of patient centred and effective care [2].

Simply put, NSI can be imagined as a capsule containing data interpreted by humans and computers. The data they contain may describe relationships between the environment the nurse works in, nurse interventions, processes and their effect on patient outcomes. NSI may be organised in conceptual knowledge maps (ontologies) to facilitate diagrammatic comparison.

Ontology

The meaning of the word "ontology" tends to generate confusion primarily because it conveys different meanings per discipline. The term originated in philosophy where it refers to the subject of existence. It is also often confused with epistemology which is concerned with knowledge and knowing [3].

Gruber [4] defines the word "ontology" in the artificial intelligence context to mean a specification of a conceptualisation. That is, ontology is a specification and description of concepts and relationships that can exist for one community of ideas. This community of ideas is often referred to as a "universe of discourse". Ontology's primary purpose is to enable knowledge sharing and reuse between different universes of discourse, or in the nursing context, domains of care.

The problem

Registries of NSI do not exist at unit level in Australia. However, indicators do exist in specific studies but are not used in the wider nursing community to measure clinical processes/outcomes. Duffield, Diers, O'Brien-Pallas, Aisbett, Roche, King and Aisbett [5] observed a one year/researcher expenditure of time and effort producing NSI "on the spot" for research. To alleviate this expenditure the question was asked "can a pool of reusable validated "plug in" NSI be produced that may be used for future research"?

Nursing has recognised ontologies may be used to map between similar terms to address semantic interoperability between disparate domains of care. Poor semantic interoperability between nursing sensitive indicator data sets has been identified as a stumbling block to sharing nursing electronic health information between computer systems [6].

There is strong evidence that ontologies may be used to mediate two similar domains of nurse sensitive indicators (NSI) to produce a third based on semantic similarities [7], [8].

Materials and Methods

Mediation

Definitions of alignment, comparison, and mediation overlap in the literature. Rebstock, Fengel and Paulheim [9] define mediation as the bringing together of two ontologies generating a third by comparison.

Mediation may identify structural similarities and/or like terms by semantic equivalence. Nursing literature has examples of mediating two lists of NSI to produce a third document of like terms to form the basis of a nursing minimum data set. To this end, nursing studies have mediated like terms between varying written and electronic media. Media may include two ontologies [8], terms and definitions in the same ontology [7], two hard copy taxonomies [10] and the outcome of focus groups against nursing documentation [11].

Software used in the test consisted of an ontology editor and three mediation applications. The purpose of the editor is to build two ontologies from two existing hierarchical taxonomies containing lists of NSI terms. The two ontologies are placed in three mediation programmes utilising both automatic and manual semantic equivalence techniques. Semantic equivalence results are compared using a Boolean truth table.

Ontology building, Protégé ontology editing software

Protégé is an ontology editor which uses the Web Ontology Language (OWL) to facilitate frame based ontology building and display. The Protégé platform was chosen as it is the current state of evolution in ontology editing and mapping since Hardiker [7] used the no longer supported open Galen platform and GRAIL language in his early mediation study. Protégé is supported by a global academic community and is free open source software [12].

Two ontologies were constructed from two existing hierarchical taxonomies, one Australian and one American. Hierarchical taxonomies are chosen as they have a similar structure to ontologies [6]. Indicators were derived from well known nursing studies. The Australian taxonomy comprised a list of terms pertaining to indicators identified from the Duffield [5], Chiarella [13] and Chaboyer [14] nursing studies. The American taxonomy was comprised of terms derived from studies using the Collaborative Alliance for Nursing Outcomes (CALNOC) indicators included in studies by Aydin [15], [16] and Patrician [17].

Frame based theory

Marvin Minsky [18] describes a theory of frames based knowledge acquisition common in artificial intelligence literature. Frames represent past known knowledge which can be used as a basis to draw conclusions in a current circumstance. The core of Minsky's [18] theory is that knowledge can be represented by "parent frames" gained by past experience connected by lines of inheritance that spawn new child frames as new information is made available.

Both ontologies are frame based, that is, they have parent classifications and spawn child classifications through inheritance pathways called "slots". Frame theory was chosen as being the best "fit" to display knowledge acquisition techniques common to nursing and technology.

Both ontologies consisted of similar parent classifications containing terms representing NSI. Parent classifications were constructed within Protégé as per the Duffield [5] study. Six structural classifications of Environment, Staffing, Nurse, Patient, Workload and Unit housed their respective indicators in both ontologies. An exception was the Australian Duffield [5] environment classification which did not have an equivalent within the US CALNOC taxonomy and mediation was impossible with that classification.

Within the frame based version of Protégé, the user can add, subtract and modify classifications and connecting slots which combine to form the structure of the ontology. The connecting slots represent lines of inheritance from the parent classification to its children or between classifications. More importantly, slots can represent constraints of range and cardinality thus forming relationships and formal logic between classifications [12].

Once the classifications were entered for the two ontologies within Protégé, simple logic is introduced between them in the form of object and data slots as per frame based structure. For example, nurse and patient categories are joined by an object slot called "cares for". Nurse and Workload were joined by " has a" object slot and Nurse and Unit were joined by "works in".

Mediation software

Mediation software is in its infancy, 7 mediation software packages were identified and four were discounted as they either required unobtainable Java files or could not be compiled and run within our Java/Windows environment. Three experimental mediation software applications were runnable, Falcon, OnAGUI and Prompt. Falcon is strictly automatic; OnAGUI is both automatic and manual. Prompt has an automatic component but was used manually for the test due to linguistic matching algorithm issues. Falcon and OnAGUI are developmental and Prompt has been in existence for some years.

Automated mediation

Falcon automated ontology matching tool

Falcon is a suit of automatic experimental ontology mediating modules which provide fundamental technologies for finding, aligning and learning ontologies. The software provides a graphical user interface showing semantic similarities between two ontologies and a "similarity decimal" derived from an I-Sub linguistic matcher algorithm beside each match [19].

I-Sub linguistic matching algorithm

The I-Sub algorithm was utilised in Falcon and OnAGUI, it compares character strings calculating the number of edits required to form a similarity between terms. The algorithm produces a decimal less than or equal to one, one represents a perfect match. ,Qu., Hu. and Cheng. [20] states that edit distance based string comparison are one of the most commonly used approaches to gain the linguistic similarity in ontology matching.

OnAGUI automatic/manual graphical mediation tool

OnAGUI is a colour coded graphical experimental ontology matching programme where the user can select the I-Sub matching algorithm. Mediation can be automatic, manual or a combination of both. The two ontologies are displayed. Ontology "one" is represented as a colour coded hierarchy on the left of the screen with ontology "two" on the right. The centre pane displays the results of the merge, score, validity, I-Sub decimal and algorithm used [21].

Manual mediation

The Prompt mediation plugin

The Prompt suite is a mediation plugin for Protégé developed by Stanford University's computer science laboratory [22]. Two ontologies were merged manually using Prompt's split screen within the "new operations" tab. This allows the user to select terms which he/she considers semantically similar. The terms may be used to construct a merged ontology. Prompt was used manually because the suit does not generate an I-Sub semantic similarity decimal. With manual mediation a "similarity decimal" similar to the I-Sub was produced by nurse advocates ranking term pairs semantic similarity by Likert scale.

Term pairs

Term pairs consisted of semantically similar terms identified from each ontology. An example of a term pair is "Nurse education level" and "Nurse education academic level".

To generate the term pairs, two ontologies were mediated automatically and manually with the three software packages. This resulted in thirteen pairs of semantically similar/equivalent terms. The automatically mediated term pairs were produced by setting the I-Sub threshold at .85 on Falcon and OnAGUI. The manual threshold of .85 was derived from Sarre and Cooke [23]'s nursing consensus threshold.

For manual mediation, a human approximation of the I-Sub decimal was derived from members of the research team's subjective nursing experience ranking each term pairs semantic similarity from 0 to 9. This method was similar to Sarre and Cooke [23]'s 10-point Likert scales used to identify research capacity indicators for the United Kingdom's national health service. The I-Sub decimal or its manual approximation was placed alongside each of the thirteen pairs to compare the automatic and manual mediation programmes and techniques. Boolean truth tables were used to display comparative outcomes for each technique.

Boolean truth tables

Truth tables display results of Boolean operations such has AND, OR, NOT with either a "true" or "false".

Truth tables may be useful in comparing results between different mediation techniques, particularly displaying patterns of agreement/disagreement between techniques.

Boolean states of true/false were entered against I-Sub decimals. If an I-Sub decimal was present on a term pair, a "true" was entered otherwise "false" was entered representing no match.

Boolean results and I-Sub numbers were tabulated in rows against their respective term pair. Rows were divided by columns representing each mediation method.

Figure 1 displays the Boolean logic flow diagram used in the study. Falcon and OnAGUI true/false automatic mediation results were OR'ed together, OR'ing the results insured that every semantic similarity was flagged. An identical OR'ing process was conducted for the manual results. With manual and automatic OR columns flagging every semantic similarity instance for each term pair it was now possible to compare automatic and manual methods. A comparison could be achieved by AND'ing the manual and automatic OR tables together.

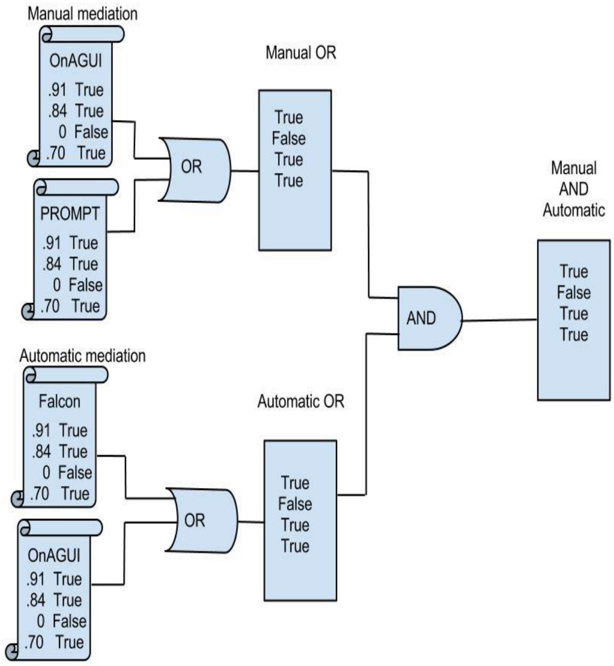

Figure 1: Boolean logic flow diagram

Automatic and manual OR'ed results can be viewed in Table 1. The last column represents a comparison of automatic and manual techniques achieved by AND'ing.

Table 1: Sampling agreement between manual and automatic mediation

Australian Duffield Indicators	American CALNOC Indicators	Automatic "OR"	Manual "OR"	Automatic "AND" Manual
Falls frequency	Falls incidence	F	T	F
Nurse hours per patient day	Nurse staffing direct care hours per patient day	T	T	T
Number of beds	Unit number of beds	T	T	T
Patient	Patient age	T	F	F
Patient LOS	Patient	T	F	F
Patient LOS	Patient stay duration	F	T	F
Nurse education level	Nurse education academic level	T	T	T
Nurse education years of experience	Nurse years of experience	T	T	T
Hours of care re-	Nurse staffing	F	T	F

quired per patient day	direct care			
Pressure ulcer frequency	Pressure ulcer incidence	F	T	F
Medication errors time based	Medication admin errors	F	T	F
Number of planned admissions	Workload intensity admission	F	T	F
Number of planned discharges	Workload intensity discharge	F	T	F

Results

Boolean logic was used to show patterns of agreement across mediation techniques. Descriptive statistics were used to calculate average, percentage and standard deviation across I-Sub and Likert decimals.

I-Sub and Likert scale data were entered into Microsoft Excel™ manually. Cell formulae calculated Boolean "OR", "AND" and descriptive statistics across cells of interest.

Boolean Results

Table 1 reveals sample agreement patterns of semantic similarity for each term pair across mediating techniques.

In both the "OR" columns, a "true" (T) indicates that at least one technique made a semantic match. A "false" (F) indicates no technique made a semantic match.

In the "AND" column a "true" indicates agreement as to semantic similarity across all techniques for that term pair. This occurred four times out of thirteen term pairs (4/13)*100 resulting in 30.71% agreement as to semantic similarity across all techniques.

We were also interested in how the automatic functions of Falcon and OnAGUI compared when viewed together. Their results were AND'ed for each term pair revealing (3/13)*100=23.00% agreement between the two packages.

This is a contrast to AND'ed manual technique results using Prompt and OnAGUI which attained (10/13)*100=76.92% agreement as to semantic equivalence of term pairs.

Descriptive statistic results

We were interested in the percentage of term pairs whose I-Sub numbers were equal to and greater than .85 across mediation techniques. This decimal was the I-Sub threshold set originally in the automatic mediation programmes. It is also the threshold of consensus used in Sarre and Cooke [23]'s study.

The percentage of term pairs reaching .85 or higher was lower in the automatic techniques compared to manual techniques. Falcon automatic mediation (23.076%) was the lowest count. Automatic OnAGUI was second lowest (38.461%). Manual Prompt scored 69.230% of terms higher than .85 and the highest was manual OnAGUI with 76.923%.

Discussion

It was interesting to use Boolean truth tables to display patterns of agreement between mediation technologies. The tables revealed unexpected results. The term pair "falls frequency"-"falls incidence" is a falls related term pair nurses found similar. The similarity is evidenced by the "True" in the manual column but the automatic software did not register any similarity in the term pair, a "False" can be seen in the automatic column.

Similarly, a semantic match for the term pair of "patient LOS"-"Patient stay duration" eluded the automatic software, possibly because the pneumonic "LOS" was meaningless. Given that, an observer may deduce that the word "patient" in both sides of the pair would register a match in the automatic software, but did not.

In contrast, the automatic software discovered semantic similarities in term pairs in which a nurse did not. Term pairs of "patient"-"patient age" and "patient LOS"-"Patient" both registered as semantically similar with the automatic software. Although both terms pertained to the patient, nurses did not see an immediate semantic match.

Inexplicably, the automatic software matched a complex term pair "Nurse hours per patient day"-"Nurse staffing direct care hours per patient day" while rejecting the (to the researchers) simpler term pair of "falls frequency"-"falls incidence".

The two automatic software results when compared had poor agreement (23.07%) with regard to semantic similarities across the same term pairs. Manual mediation fared better (76.92%) this may be because nurses are not restricted to rules of semantic substitution but can draw on experience and past knowledge combining semantic and conceptual rules to determine semantic similarities.

Conclusion

Tools derived from machine-based disciplines such as artificial intelligence may be useful in nursing for displaying patterns of semantic similarities between automatic software and manual mediation techniques.

Software results were inconsistent between the two automatic techniques when processing the same term pairs. The manual mediation techniques demonstrated a greater consistency when selecting term pairs with semantic similarities.

Compared to automatic software, the nurse-operated experimental OnAGUI graphic manual mediation software produced a greater frequency of terms ranking higher than the .85 I-Sub threshold. OnAGUI produced higher rates of term pairs attaining semantic similarities. Higher nurse semantic similarity scoring with graphical manual software may occur because the I-Sub algorithm in automatic software is restricted to calculating semantic similarities by substitution.

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References

[1] Hovenga EJS, Kidd MR, Garde S, Cossio CHL. Health Informatics : An Overview. Amsterdam: IOS Press; 2010. Available from: http://VU.eblib.com.au/patron/FullRecord.aspx?p=557040 .

[2] Naylor MD. Advancing the Science in the Measurement of Health Care Quality Influenced by Nurses. Medical Care Research and Review. 2007;64(2):Suppliment.

[3] Obitko M. Specification of Conceptualization - Introduction to ontologies and semantic web - tutorial. 2012 [cited 2012 9/10]; Available from: http://www.obitko.com/tutorials/ontologies-semantic-web/specification-of-conceptualization.html.

[4] Gruber T. Every Ontology is a Treaty. SIGSEMIS Bulletin: Interview for Semantic Web and Information Systems SIG of the Association for Information Systems. 2004;1(3).

[5] Duffield C, Diers D, O'Brien-Pallas L, Aisbett C, Roche M, King M, Aisbett K. Nursing staffing, nursing workload, the work environment and patient outcomes. Appl Nurs Res. 2011;24(4):244-55. Epub 2010/10/27.

[6] Madsen M. Health care Ontologies: Knowledge models for record sharing and decision support. In: Hovenga EJS, Kidd MR, Garde S, Cossio CHL, editors. Health Informatics : An Overview. Amsterdam: IOS Press; 2010. p. 104-14.

[7] Hardiker NR. Logical Ontology for Mediating between Nursing Intervention Terminology Systems. Methods of information in medicine 2003;42(3):265.

[8] Hardiker NR, Rector AL. Structural validation of nursing terminologies. Journal of the American Medical Informatics Association. 2001;8(3):212.

[9] Rebstock M, Fengel J, Paulheim H. Ontology Engineering

Ontologies-Based Business Integration. Springer Berlin Heidelberg; 2008. p. 97-123.

[10] Goossen W. Cross-mapping between three terminologies with the international standard nursing reference terminology model. International Journal of Nursing Terminologies & Classifications. 2006;17(4):153-64.

[11] Butler M, Treacy M, Scott A, Hyde A, Mac Neela P, Irving K, Byrne A, Drennan J. Towards a nursing minimum data set for Ireland: making Irish nursing visible. Journal of Advanced Nursing. 2006;55(3):364-75.

[12] Protege. Protege ontology editor. Standford University; 2011 [cited 2011 12/6/2011]; Available from: http://protege.stanford.edu/.

[13] Chiarella M, Roydhouse JK. Hospital churn and casemix instability: implications for planning and educating the nursing workforce. . Australian Health Review. 2011;35(1):95-8.

[14] Chaboyer W, Johnson J, Hardy L, Gehrke T, Panuwatwanich K. Transforming care strategies and nursing-sensitive patient outcomes. Journal of Advanced Nursing. 2009;66(5):1111-9.

[15] Aydin CE, Bolton LB, Donaldson N, Storer-Brown D, Mukerji A. Beyond Nursing Quality Measurement: The Nation’s First Regional Nursing Virtual Dashboard. In: ARHQ, editor. Washington DC: US department of health and human services; 2009.

[16] Aydin CE, Bolton LB, Donaldson N, Brown DS, Buffum M, Elashoff JD, Sandhu M. Creating and analyzing a statewide nursing quality measurement database. Journal of Nursing Scholarship. 2004;36(4):371-8.

[17] Patrician PA, Loan L, McCarthy M, Brosch LR, Davey KS. Towards Evidence-based Management: Creating an Informative Database of Nursing-Sensitive Indicators. Journal of Nursing Scholarship. 2010;42(4):358–66.

[18] Minsky M. A framework for representing knowledge. MIT; 1974 [cited 2011 19/9/2011]; Available from: http://dspace.mit.edu/handle/1721.1/6089.

[19] Hu W, Qu Y. Falcon-AO: A practical ontology matching system. Web Semantics: Science, Services and Agents on the World Wide Web. 2008;6(3):237-9.

[20] Qu. Y, Hu. W, Cheng. G. Constructing virtual documents for ontology matching. Proceedings of the 15th international conference on World Wide Web; Edinburgh, Scotland. 1135786: ACM; 2006. p. 23-31.

[21] Mazuel L, Charlet J. SPIM-AlignmentGUI-un logiciel d’aide à la réalisation d’alignements entre ontologies. INSERM UMR. 2009;272(20).

[22] Noy N, Klein M, Kunnatur S. Prompt ontology merging software. Palo Alto California: Knowledge systems laboratory, Stanford university; 2010; 3.3.1:[Available from: http://protege.cim3.net/download/old-releases/3.3.1/full/.

[23] Sarre G, Cooke J. Developing indicators for measuring Research Capacity Development in primary care organizations: a consensus approach using a nominal group technique. Health & Social Care in the Community. 2009;17(3):244-53.

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