international journal of medical informatics 82 (2013) 875–881

journal homepage: www.ijmijournal.com

Application of a model based on fuzzy logic for evaluating nursing diagnostic accuracy of students

Maria Helena Baena de Moraes Lopes[a,*], *Rodrigo Jensen*[a], *Diná de Almeida Lopes Monteiro da Cruz*[b], *Fabiana Gonçalves de Oliveira Azevedo Matos*[c], *Paulo Sérgio Panse Silveira*[b], *Neli Regina Siqueira Ortega*[b]

[a] *University of Campinas, Campinas, SP, Brazil*
[b] *University of São Paulo, São Paulo, SP, Brazil*
[c] *State University of West Paraná, Cascavel, PR, Brazil*

ARTICLE INFO

Article history:
Received 16 September 2012
Received in revised form
24 April 2013
Accepted 30 April 2013

Keywords:
Nursing diagnosis
Educational technology
Decision support techniques
Fuzzy logic

ABSTRACT

Purpose: To describe a model for assessing nursing diagnostic accuracy and its application to undergraduate students, comparing students' performance according to the course year.
Methods: This model, based on the theory of fuzzy sets, guides a student through three steps: (a) the student must parameterize the model by establishing relationship values between defining characteristic/risk factors and nursing diagnoses; (b) presentation of a clinical case; (c) the student must define the presence of each defining characteristic/risk factors for the clinical case. Subsequently, the model computes the most plausible diagnoses by taking into account the values indicated by the student. This gives the student a performance score in comparison with parameters and diagnoses that were previously provided by nursing experts. These nursing experts collaborated with the construction of the model indicating the strength of the relationship between the concepts, meaning, they parameterized the model to compare the student's choice with the expert's choice (gold standard), thus generating performance scores for the student. The model was tested using three clinical cases presented to 38 students in their third and fourth years of the undergraduate nursing course.
Results: Third year students showed superior performance in identifying the presence of defining characteristic/risk factors, while fourth year students showed superior performance in the diagnoses by the model.
Conclusions: The Model for Evaluation of Diagnostic Accuracy Based on Fuzzy Logic applied in this study is feasible and can be used to evaluate students' performance. In this regard, it will open a broad variety of applications for learning and nursing research.
Limitations: Despite the ease in filling the printed questionnaires out, the number of steps and fields to fill in may explain the considerable number of questionnaires with incorrect or missing data. This was solved in the digital version of the questionnaire. In addition, in more complex cases, it is possible that an expert opinion can lead to a wrong decision due to the subjectivity of the diagnostic process.

* *Corresponding author at*: Rua Conceição, 552, apto. 25, CEP 13010-050 Campinas, SP, Brazil. Tel.: +55 19 3521 8831; fax: +55 19 3521 8822.
E-mail addresses: mhbaena@fcm.unicamp.br, mhbaenaml@yahoo.com.br (M.H.B.M. Lopes).

1386-5056/$ – see front matter

http://dx.doi.org/10.1016/j.ijmedinf.2013.04.010

1. Introduction

Nurses are legally responsible for nursing diagnosis (NDx) and treating human responses [1]. It has been demonstrated that NDx identification can improve the quality of interventions and the results achieved in patient care [2].

NDx is defined as "a clinical judgment about individual, family, or community response to actual or potential health problems/life processes. A nursing diagnosis provides the basis for selection of nursing interventions to achieve outcomes for which the nurse is accountable" [3].

Although it provides for better assistance, NDx is complex and prone to low accuracy due to its inherent subjective interpretations [1]. It is important, however, for the correct identification of signs and symptoms to support diagnostic reasoning, to establish diagnostic etiology, and to improve diagnostic accuracy [2].

In addition to some methods that have already been proposed to evaluate diagnostic accuracy [4,5], other methods are also required to teach diagnostic reasoning to students. The Lunney Scoring Method for Rating Accuracy of Nursing [4] consists of a seven-point scale designed to assess the "accuracy of the interpretation of clinical findings" of nurses. It is guided by the principle of sufficiency of data appropriateness of diagnosis and context in which they occur. The Nursing Diagnoses Accuracy Scale (NDAS) [5] was created based on the Lunney's scale. It also aims to assess the "accuracy of the interpretation of clinical findings" of nurses. It has four items that assess the presence, relevance, specificity and coherence of cues (defining characteristics) of the diagnosis. This scale was refined recently by its authors, and called NDAS – Version 2 [5].

Here, we present the application of one of these methods that is based on the theory of fuzzy sets [6]. Fuzzy logic allows for the construction of a linguistic model that provides a more natural way for students to learn clinical reasoning by using verbalization of all steps that are taken from a patient's signs and symptoms to their relationships to diagnostic possibilities.

This paper presents an application of fuzzy modeling, which is an approach to evaluate the performance of nursing students during the diagnostic process, this is, a tool of education assessment and training performance. This new method parameterizes fuzzy models through linguistic transformations from lexical expressions to categorical values. Then, the results of student diagnoses are aggregated through max–min composition and compared to those obtained by nursing experts.

In the present study, we used the Model for Evaluation of Diagnostic Accuracy Based on Fuzzy Logic presented previously in a nursing conference [6] and applied this to undergraduate students in their third and fourth years of the nursing course. Their abilities to correctly parameterize the model and their performance obtained from comparisons with those provided by nursing experts are also included, besides comparing students' performance according to the year of course.

2. Methods

2.1. Theoretical background

Artificial Intelligence has pursued the reproduction of human intellect capabilities with the use of computational systems. In this context, expert systems must be designed to represent human knowledge and, based on decision rules, to support decision-making; this is useful for standardizing nomenclature and improving the concordance among specialists. Using this type of system in the case of health care, it is expected that a professional can provide data from a patient and interact with a program that is able to indicate the most plausible diagnosis and, perhaps, also provide treatment suggestions, as if the system could act as a consulting specialist [7].

Although the application of fuzzy logic in the area of nursing remains limited, some studies have highlighted fuzzy logic in decision-support models in nursing practice [8,9]. The present study is representative of this use of fuzzy logic, although it also has implications for nursing teaching.

The theory of fuzzy sets (TFS) was developed during the 1960s by Lofti Zadeh [10]. This theory is based on the concept of partially true values that allows for the treatment of uncertainty, which is the case with NDx. While classical logic incorporates clearly delineated sets, fuzzy logic treats the boundaries between sets as gradual transitions. This introduces the concept of degrees of membership, whose values may vary from 0 to 1.

For example, while fever is either absent or present in classical logic, in fuzzy logic there is a gradual transition from a gradually decreasing membership to the non-fever state to a gradually increasing membership to the fever state with increasing temperature. Thus, this allows a model to be a guide to the correct diagnosis without regard for no-fever/fever, which is particularly interesting for clinical cases that present with low or intermittent fevers. By means of a symbolic system, models based on TFS can work with linguistic terms to describe the uncertainty of a phenomenon, such as *always*, *frequently*, *sometimes*, *rarely*, or *never* [10]. Thus, this approach can apply a mathematical treatment to human language and turns the interaction of a health professional with a model for diagnostic support into a straight forward task.

In addition, the notion of the 'degree of membership' allows for the reinterpretation of concepts. Rather than taking health and disease as opposites, where disease is the lack of health and vice versa, in fuzzy logic, these concepts are complementary and the passage from health to disease is gradual. In this way, a patient may present with either a progressive deterioration or a steady recovery to health, which is much more in agreement with reality [11].

Formally, if U is a set that represents the Universe, a fuzzy subset A of U is associated with the function μ_A: $U \rightarrow [0,1]$, which is usually called the membership function. The idea is that, for each $x \in U$, the $\mu_A(x)$ element indicates the degree to which x is a member of subset A, which indicates how much x is compatible with the characteristics that comprise A [12].

Classical set operations can be extended to the fuzzy sets, which also have membership degrees that are in the interval [0,1]. Thus, if it is assumed that A and B are two fuzzy subsets of U, their union is a C fuzzy set of U, denoted by $C = A \cup B$, such that for each x in U:

$$C(x) = \max[A(x), B(x)] = A(x) \vee B(x).$$

The intersection between A and B is another fuzzy subset of U, denoted by $D = A \cap B$, such that for each x in U:

$$D(x) = \min[A(x), B(x)] = A(x) \wedge B(x),$$

where the symbols $\vee$ and $\wedge$ denote, respectively, the maximum and minimum operators[13].

Another important concept related to fuzzy sets is *fuzzy relations*. A fuzzy relation R between two non-fuzzy sets X and Y, where $x \in X$ and $y \in Y$, may be defined as a fuzzy set given by

$$R = \{\mu_R(x, y)|(x, y)\}.$$

for each $(x, y) \in X \times Y$ (the Cartesian product), where $\mu_R(x, y)$: $X \times Y \rightarrow [0,1]$ is the membership function of R, $\mu_R(x, y) \in [0,1]$ is the relational degree of $x \in X$ and $y \in Y$ in R. Because this basic type of fuzzy relation is defined by the Cartesian product of two sets, it is called a fuzzy binary relation. However, this concept can be generalized to a fuzzy *n-dimensional* relation [14].

Fuzzy relations can express a partial or imprecise relationship among set elements. In the same manner as pertinence degrees, the value of fuzzy relations gradually varies from 0 (when the relationship does not apply) to 1 (when the relationship is complete). When working in a discrete dimension space, fuzzy relations may be represented by a matrix to simplify the composition of fuzzy relational methods [14].

Among others, the maximum–minimum composition (max–min) is one of the most useful composition methods. The max–min composition of two fuzzy relations, R in $X \times Y$ and S in $Y \times Z$, is defined as

$$\mu_{R \circ_{\max-\min} S}(x, z) = \max_{y \in Y}[\min(\mu_R(x, y), \mu_S(y, z))]$$

for each $x \in X$, $y \in Y$, and $z \in Z$. This mathematical operation is similar to matrix multiplication [13].

In fact, the choice of the use of a composition of fuzzy relationships among many other possibilities is arbitrary. However, this choice is made through the mathematical characteristics of the chosen function and characteristics of the phenomenon analyzed. The max–min composition works as a process of extrapolation between the data, this is, it does not require for each input data of the test bank the model provides as output the exact diagnosis associated with that input data, which would be related to an interpolation process (as occurs, for example, with the Gödel type compositions). In view of the inherent uncertainties in the diagnostic analysis we believe that the max–min composition becomes more adequate to promote the mapping input/output of the model.

2.2. *Model development*

As mentioned in Section 1, the Model for Evaluation of Diagnostic Accuracy Based on Fuzzy Logic proposes to reproduce a specialist's process of decision making and to make possible the evaluation of the students' performance using the same process.

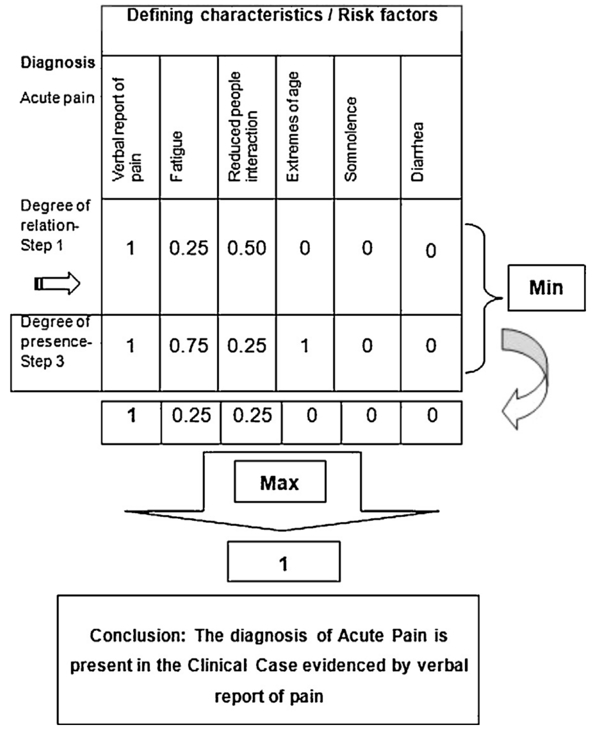

Fig. 1 – Example of diagnosis determination using a maximum–minimum fuzzy composition (min = minimum value; max = maximum value).

The student activity was structured in three steps, the same performed by the specialists, as follows:

Step 1: The student was asked to define relation values (membership degrees) between each defining characteristics (that is, subjective or objective signs/symptoms) or risk factors (DC/RF) and each NDx related to a clinical case. Some DC/RF and NDx that were not present in the clinical case were also included to increase the complexity of the activity. At this point, the student was unaware of the clinical case in such a way that the performance at this step depended on the student's knowledge of how each NDx is manifested. Membership degrees could vary from 0 (for DC/RF that was not related to a given NDx) to 1 (for DC/RF totally related to a NDx). The student did not treat the membership degree numerically. Instead, an interface presented the alternatives as linguistic terms associated with respective hidden values as follows: strongly related, SR = 1; related, RE = 0.75; moderately related, MR = 0.5; weakly related, WR = 0.25; and not related, NR = 0 (Fig. 1).

Step 2: In this step, a reading of the clinical case was presented. This reading was only offered in the second step of the activity so as not to influence the previous step.

Step 3: The student was asked to indicate the degree of certainty that the DC/RF is present in the clinical case (membership degrees). Some DC/RF's not present in the clinical case were also included, as in the first step, to increase the complexity of the activity. Again, the student was unaware of the hidden numerical values, and only assessed the linguistic terms: present, PR = 1; possibly present, PP = 0.75; I do not know, DK = 0.5; possibly absent, PA = 0.25; and absent, AB = 0 (Fig. 1).

A fuzzy max–min composition was applied to establish final diagnoses. For this inference process, the max–min composition was similar to the operation of matrix multiplication, in which multiplication was replaced by the minimum operator and summation was replaced by the maximum operator.

For each DC/RF, minimum values were selected among membership degrees established by the student in the first step of the activity and the respective membership degrees of the third step. Then, for each NDx presented in step 1 of the activity, the maximum value was selected from among all of these minima, ending with fuzzy possibility degrees for each diagnosis (Fig. 1). Here, positive diagnoses where taken as all diagnoses that achieved values of 1 or, if none achieved possibilities equal to 1, the diagnoses with the maximum values were considered positive. Thus, the model may have indicated more than one possible diagnosis.

2.3. Performance scores

In order to attribute a performance score to the student, the student's answers were compared with those determined by the specialists. Three scores were presented to the student: (a) performance when establishing a relational degree between DC/RF and NDx (at step 1); (b) performance in recognizing the presence of DC/RF in the clinical case (at step 3), and (c) performance in NDx determined by max–min composition, which depended on the student's correctness when parameterizing the model during step 1 and when recognizing the degree of certainty that the DC/RF is present in the clinical case during step 3.

Performance scores for the students were given by:

$$p_k = 1 - \frac{1}{q}\sum_{i=1}^{q}\left|\left(d_{k(i)} - d^*_{(i)}\right)\right|$$

where $k = 1, 2, \ldots, K$ (K was the total number of enrolled students), $d_{k(i)}$ is the membership degree established by student k for item i, $d^*_{(i)}$ is the membership degree established by specialists for item i; q is the number of diagnoses.

Thus, p_k provided a similarity measure between student k and the specialist responses, ranging from 1 (total agreement) to 0 (total disagreement). If $d_{k(i)} = d^*_{(i)}$ for all i items, then $p_k = 1$, which reflected total agreement between the values suggested by the student and by the specialists. In contrast, if $d_{k(i)} \neq d^*_{(i)}$, then p_k corresponded to the average of mistakes, which reflected how much the values suggested by the student differed from those of the specialists. This function for score computation can be thought of as an aggregation operation [15].

For example, consider a clinical case presenting four diagnoses to which values given by a max–min composition based on a student's parameterization were 0.75, 1, 0.75, and 0, while for the same diagnoses, the specialists attributed values of 1, 0.75, 0.75, and 0, respectively. The computed score function is:

$$p = 1 - \frac{1}{4}(|1 - 0.75| + |0.75 - 1| + |0.75 - 0.75| + |0 - 0|) = 0.875$$

In this example, a student's score performance was 0.875, which demonstrates how close the student was to the specialists' reasoning.

2.4. Model implementation

This study was conducted during the first semester of 2008 with nursing students that were enrolled in nursing diagnosis classes, which was available as an option for an undergraduate course in a public university of São Paulo State, Brazil. Three case studies, which were previously validated [5], were offered for the students' evaluations. From these case studies, an activity was elaborated that was based on the NANDA International (NANDA-I) taxonomy, 2007–2008 version, translated into Brazilian Portuguese [16].

Before the electronic implementation and application to the students, the activities were structured as printed questionnaires and tested by participants of a NDx research group who followed the steps that a student should take. These were nurses with the following highest academic degrees: a Ph.D. in Nursing with research in NDx ($n = 1$), doctoral students who develop studies on NDx ($n = 3$), a doctoral student in Nursing ($n = 1$), a Master's in Education ($n = 1$), a Master's student in Nursing ($n = 1$), nursing experts ($n = 2$), and a nursing undergraduate student ($n = 1$). Through the interactions among these research group members, a consensus was established regarding the relationship values between DC/RF and NDx and the degree of certainty that the signs and symptoms (DC/RF) were present in the clinical case. This generated relation matrices that parameterized the model. These relations established by the specialists' opinions were compared to the students' opinions in order to generate performance scores. Both students and specialists were allowed to consult the NANDA-I taxonomy.

The protocol for this research was approved by the ethics committee on research of our institution. Although all of the students that were enrolled in nursing diagnosis classes performed all of the activities for these case studies, only those who signed a study agreement were considered for analysis.

The incorrect fill of the questionnaire was considered as exclusion criterion. Both, the ambiguity in the response (to select two fields of the same item) or not to complete the item (no response on the item) were considered as incorrect fill.

2.5. Statistical analysis

Questionnaire data from specialists and students were stored and transferred to worksheets for statistical analysis. SPSS version 15.0 (IBM, Somers, NY) was used to analyze data referring to sample characterizations. The performance scores from the two groups of students (third and fourth year nursing school undergraduates) were compared by a Mann–Whitney U test [17], with the significance level set at 5% ($p < 0.05$) for all analyses.

3. Results

Thirty-eight of the 45 students enrolled in nursing diagnosis classes agreed to participate in this study (84.4%), which included 25 in the 3rd year and 13 in the 4th year of undergraduate nursing. Case studies were presented in class on three different days. The number of students participating in each activity and the number of questionnaires excluded due to missing data for each clinical case are reported below.

All of the details of these case studies are not shown here, as they have been published elsewhere [5], although a brief summary of each case is presented below. Each case study was structured in sections: patient's hospital data (suppressing personal identification data), interview, and physical examination. The interview was structured into 13 domains: health promotion, nutrition, elimination and exchange, activity/rest, perception/cognition, self-perception, role relationships, sexuality, coping/stress tolerance, life principles, safety/protection, comfort, and growth/development.

3.1. *Case study 1*

The first case study was from a 76-year-old woman's clinical history on her first day of hospitalization with medical diagnoses of systemic arterial hypertension, diabetes mellitus, congestive heart failure, and chronic pancreatic insufficiency. She presented NDx of acute pain, chronic pain, imbalanced nutrition: less than body requirements, impaired walking, risk for falls, fatigue, risk for impaired skin integrity, bowel incontinence, and urinary incontinence. The false diagnoses shown to the student were sexual dysfunction, disturbed sleep pattern and ineffective breathing pattern.

This activity was performed by 38 students (100%). Eight questionnaires (21%) were excluded from the analysis and the remaining 30 questionnaires (79%) were analyzed. The average student age was 22.6 (±1.9) years and they were predominantly females (96.7%) and students from the 3rd year (60%).

The average students' performance for determining the relation between DC/RF and NDx was 0.79 (±0.06); the average for indicating the degree of presence of DC/RF in the clinical case was 0.85 (±0.06); and the average for indicating diagnoses generated by max–min composition was 0.91 (±0.03).

There was a greater performance by the 3rd year students for indicating DC/RF presence degree in the clinical case compared to the 4th year students ($p = 0.03$, Fig. 2).

3.2. *Case study 2*

This case study was for a 57-year-old woman on her fifth day of hospitalization with a medical diagnosis of acute myocardial infarction. She presented NDx of imbalanced nutrition: more than body requirements, ineffective therapeutic regimen management, activity intolerance, risk for impaired skin integrity, and risk for trauma. The false diagnoses shown to the student were bathing/hygiene self-care deficit and low self-esteem.

This activity was done by 36 students (95%). Eight questionnaires (22%) were excluded for missing data and analysis was done for the remaining 28 (78%). For the students who were included for the analysis of case study 2, their average age was 22.8 (±1.9) years, and were predominantly female (93%) and students in the 3rd year (53.6%). The average students' performance for determining the relation between DC/RF and NDx was 0.77 (±0.09); the average for indicating the degree of presence of DC/RF in the clinical case was 0.80 (±0.13); and the average for indicating diagnoses generated by max–min composition was 0.83 (±0.06).

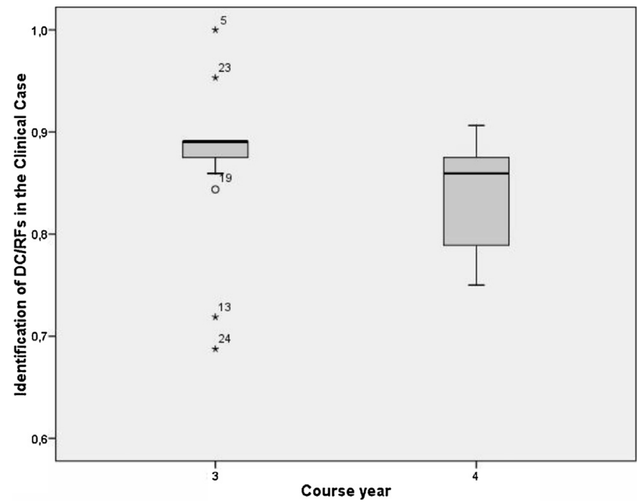

Fig. 2 – Students' performance in step 3 of case study 1 and by course year, showing that 3rd year students' median performance was superior to that of 4th year students. Legend: DC (defining characteristic), RF (risk factor).

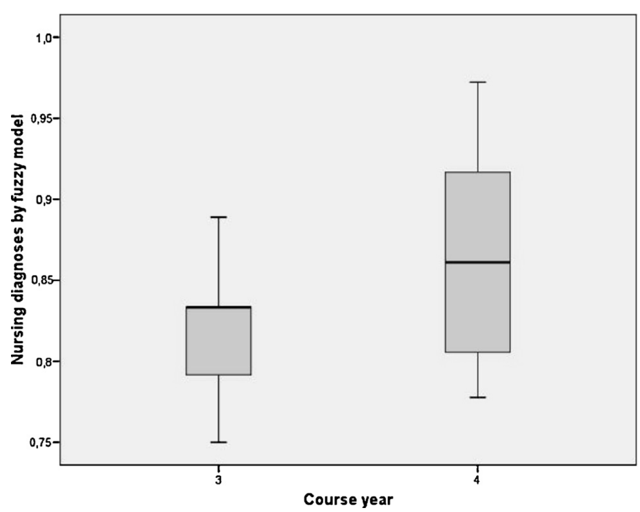

Fig. 3 – Students' performance in diagnosis indicated by maximum–minimum fuzzy composition for case study 2 and course year, showing superior 4th year students median performance in comparison with students of the 3rd undergraduate year.

Students in the 4th year had greater performance in the diagnosis generated by max–min composition than the students in the 3rd year ($p = 0.03$, Fig. 3).

3.3. *Case study 3*

This was a report for a 57-year-old woman on her first day of hospitalization with a medical diagnosis of bronchopneumonia. She presented NDx of acute pain, chronic pain, activity intolerance, imbalanced nutrition: more than body requirements, and ineffective breathing pattern. The false diagnoses shown to the student were impaired gas exchange and social isolation.

The activity was performed by all 38 students (100%), with 15 questionnaires (39%) excluded and 23 (61%) questionnaires analyzed. The students' average age was 22.7 (±2.1) years and they were predominantly females (100%) and students from the 3rd year (65%).

The average performance for determining the relation between DC/RF and NDx was 0.74 (±0.07); the average for indicating DC/RF presence degree for the clinical case was 0.83 (±0.07); and the average for indicating diagnoses generated by max–min composition was 0.94 (±0.02). There was not a significant difference between the performances of the students from the 3rd and 4th year.

4. Discussion

It was possible to identify that 3rd-year students had better performance and were more homogeneous in the identification of DC/RF in clinical case study 1. The 4th-year students had a superior average performance in the diagnosis indicated by max–min composition in case study 2. However, students in their 3rd year were also more homogeneous. Other possible explanations are that the students of this university are taught in the 3rd year of the course the practice use of nursing diagnoses in the hospital, so the students are continually exposed to the use of nursing diagnoses in practice. The students of the 4th year of the course have a big load of academic activities in the hospital. As the classes were taught at night the tiredness of the 4th year students may have generated a lack of attention in filling.

Because students' performances were computed using comparisons with the parameters and diagnoses previously provided by nursing experts, a student whose parameterization approached that of the specialists in the determination of membership degree between each DC/RF and each NDx exhibited better theoretical knowledge of the phenomena (NDx), while a student who could correctly identify the existence of DC/RF from a clinical case exhibited better practical ability to recognize them, this is, better ability to diagnose by using the theory and the information provided in the case.

The complexity of the false diagnoses and elements included in the step 1 and 3, was ranged from low to high in all the three cases. Diagnostic and elements that were chosen, in the most cases, could be present but were not conclusive without more information (data). So, the different complexity of the cases could not explain these differences.

It is interesting to consider the metacognition aspects involved in this kind of model. Metacognition is the self-acknowledgment by an individual of her/his own cognition. That is, it may be defined as the knowledge of an individual's own mental operations, including their identification, the way they are processed, the awareness of alternative strategies, and which factors may help or interfere in their mental operations [18]. The structure of the model presented here may, therefore, have stimulated the students' abilities of metacognition, as it created a scenario to consider all steps that led to certain diagnostic decisions. The feedback to the students from the model by comparisons with specialists' performance may also induce the students to reflect on their own performance, thus instilling investigation and thinking to pursue better abilities to reach the correct NDx.

The first score reflects the step 1 where the student shows his knowledge of the phenomenon of the diagnosis, *i.e.*, how much is a symptom associated with a diagnosis. The second score reflects the third step of the activity, where the student indicates the presence of symptoms in the case clinical. The third score reflects the reasoning that the student performed during the activity. From the values assigned by students in steps 1 and 3 the diagnostic decision of the student is generated by the model maximum–minimum fuzzy These diagnoses generated by the model are understood as reflecting the diagnostic reasoning process of the student that is indicated in the third score. Being consistent in these steps the student will perform well in the diagnosis generated by the model, *i.e.*, in the third score.

In addition, this model can also help nursing teachers, as it is an objective method of assessing students regarding their knowledge related to nursing phenomena and how much each DC/RF contributes to diagnosis determination.

This proposed activity was developed using printed questionnaires that were filled-in by the students. Despite the ease in filling them out, the number of steps and fields to fill in may explain the considerable number of questionnaires with incorrect or missing data. How the items were presented in a list, we believe that the fields with no answer are not associated with a student's ignorance about the item, but by a lack of attention when the student performed the item.

Based on this model, an electronic version, a software, has been developed for use as an educational tool for NDx learning. The software interface is available via the Internet. It was designed to reduce the time spent by the student on an activity, to minimize questionnaire filling-in errors, and to provide immediate feedback to the students by showing their performance and, thus, contributing to their learning. In addition, the students can review their mistakes, make corrections, and retry until they reach the correct diagnosis, which reinforces the proposed model as an educational tool for the student's refinement of nursing diagnosis reasoning.

Fuzzy logic has a great potential for the development of models that are designed to support decision-making and for systems capable of knowledge-acquisition of specialists. By contributing to both education and research, the use of fuzzy logic in areas related to health sciences is a relevant research path that will increase nursing practice quality. Due to its easier approach to uncertainty and imprecision, fuzzy logic offers theoretical and methodological bases for dealing with complex nursing phenomena [19].

5. Conclusion

The Model for Evaluation of Diagnostic Accuracy Based on Fuzzy Logic applied in this study is feasible and can be used to evaluate students' performance when establishing relational degrees between DC/RF and NDx, for identifying the certainty degree of DC/RF in clinical cases, and for determining the correct NDx. In this regard, it will open a broad variety of applications for learning and nursing research.

Summary points

What was already known on the topic

- The theory of fuzzy sets, in nursing, has significantly contributed to the understanding of subjects related to imprecision or the need of an expert.
- This theory has been used by nurses in the development of models to support decision-making.

What this study added to our knowledge

- To the best of our knowledge, the "Model for Evaluation of Diagnostic Accuracy Based on Fuzzy Logic" is the first objective method to measure the accuracy of each step of the diagnostic process.
- The theory of fuzzy sets has a great potential in the teaching of diagnostic reasoning.
- The structure of this model stimulates the students' abilities of metacognition in the diagnostic process.

Authors' contributions

Maria Helena Baena de Moraes Lopes: (1) was primarily responsible for the conception of the original idea, the conception and design of the study, acquisition of data, analysis and interpretation of data, (2) drafting the article, (3) final approval of the version to be submitted.

Rodrigo Jensen: (1) the conception and design of the study, acquisition of data, analysis and interpretation of data, (2) drafting the article, (3) final approval of the version to be submitted.

Diná de Almeida Lopes Monteiro da Cruz: (1) the conception and design of the study, (2) revising the article critically for important intellectual content, (3) final approval of the version to be submitted.

Fabiana Gonçalves de Oliveira Azevedo Matos: (1) the conception and design of the study, (2) revising the article critically for important intellectual content, (3) final approval of the version to be submitted.

Paulo Sérgio Panse Silveira: (1) acquisition of data, analysis and interpretation of data, (2) revising the article critically for important intellectual content, (3) final approval of the version to be submitted.

Neli Regina Siqueira Ortega: (1) the conception and design of the study, analysis and interpretation of data, (2) revising the article critically for important intellectual content, (3) final approval of the version to be submitted.

Conflicts of interest

None of the authors have any conflicts of interest to declare.

Acknowledgments

We would like to thank Prof. Dr. Fernando Gomide and the Research Team for the study of Nursing Classifications (DIREnf – School of Nursing, University of São Paulo, Brazil).

Financial support was received from the São Paulo Research Foundation (Fundação de Amparo à Pesquisa do Estado de São Paulo – FAPESP) and from the National Council for Scientific and Technological Development (Conselho Nacional de Desenvolvimento Científico e Tecnológico – CNPq).

REFERENCES

[1] M. Lunney, Critical Thinking and Nursing Diagnoses: Case Studies and Analysis, NANDA International, Philadelphia, 2001.

[2] M. Müller-Staub, M.A. Lavin, I. Needham, T.V. Achterberg, Nursing diagnoses, interventions and outcomes – application and impact on nursing practice: systematic review, J. Adv. Nurs. 56 (5) (2006) 514–531.

[3] NANDA. International, Nursing Diagnoses: Definitions and Classification 2009–2011, NANDA International, Philadelphia, 2009.

[4] M. Lunney, Accuracy of nursing diagnosis: concept development, Nurs. Diagn. 1 (1990) 12–17.

[5] F.G.O.A. Matos, D.A.L.M. Cruz, Development of an instrument to evaluate diagnosis accuracy, Rev. Esc. Enferm. USP 43 (S) (2009) 1088–1097.

[6] M.H.B.M. Lopes, Model for evaluation of diagnosis accuracy based on fuzzy logic, in: Poster Presented at NANDA International Conference November, 13–15; Miami (EUA), 2008.

[7] R.M.E. Sabbatini, Use of computer support in medical diagnosis, Rev. Inform. 1 (1993) 5–11.

[8] I.R. Marques, S.F. Barbosa, A.L.O. Basile, H.F. Marin, Decision-support guideline in obstetrical nursing: application of fuzzy logic technique, Rev. Bras. Enferm. 58 (3) (2005) 349–354.

[9] M.H.B.M. Lopes, N.R.S. Ortega, E. Massad, H.F. Marin, Model for differential nursing diagnosis of alterations in urinary elimination based on fuzzy logic, Comput. Inform. Nurs. 27 (5) (2009) 324–329.

[10] L.A. Zadeh, Fuzzy sets, Inform. Control 8 (1965) 338–353.

[11] K. Sadegh-Zadeh, Fundamentals of clinical methodology: 3. Nosology, Artif. Intell. Med. 17 (1999) 87–108.

[12] E. Massad, N.R.S. Ortega, L.C. Barros, C.J. Struchiner, Fuzzy Logic in Action: Applications in Epidemiology and Beyond, Springer, New York, 2008.

[13] W. Pedrycz, F. Gomide, An Introduction to Fuzzy Sets: Analysis and Design, MIT Press, London, 1998.

[14] M.A.M. Reis, N.R.S. Ortega, P.S.P. Silveira, Fuzzy expert system in the prediction of neonatal resuscitation, Braz. J. Med. Biol. Res. 37 (5) (2004) 755–764.

[15] W. Pedrycz, F. Gomide, Fuzzy Systems Engineering: Toward Human-Centric Computing, Wiley Interscience, New Jersey, 2007.

[16] NANDA. International, Nursing Diagnoses: Definitions and Classification 2007–2008, NANDA International, Philadelphia, 2007.

[17] S. Siegel, Non Parametric Statistics, McGraw-Hill, São Paulo, 1979.

[18] L.F. Ferreira, Cognitivism × Constructivism [Internet]. 2010 [cited 2012 Ago 7], 2010, Available from: http://penta.ufrgs.br/~luis/Ativ1/CogXCon.html

[19] E.-O. Im, W. Chee, Fuzzy logic and nursing, Nurs. Philos. 4 (1) (2003) 53–60.