Model for Differential Nursing Diagnosis of Alterations in Urinary Elimination Based on Fuzzy Logic

MARIA HELENA BAENA DE MORAES LOPES, PhD
NELI REGINA SIQUEIRA ORTEGA, PhD
EDUARDO MASSAD, PhD
HEIMAR DE FÁTIMA MARIN, PhD

Urinary problems are common in the general population. Urinary incontinence (UI) has a high prevalence among women, mainly elders. The psychosocial effect of UI can be more devastating than the health consequences, with multiple and broad-reaching effects that influence social interactions, daily activities, and self-perception of health status.¹

The prevalence of UI ranges from 10% to 40% in women from 40 to 70 years of age.² This wide variation can be explained by the use of different definitions and methods for UI assessment and by the characteristics of the population. In general, the number of individuals with UI increases with the increasing age of the population.³ However, many of the cases remain undiagnosed because of different reasons, particularly the fact that some individuals do not seek treatment and that health professionals are frequently not well prepared to deal with this situation.

In 1988, the International Continence Society (ICS) defined UI as “involuntary loss of urine, which is objectively demonstrable and a social or hygienic problem.”⁴(p5) Ten years later, an international group of experts on UI that...
assembled in Monte Carlo initiated an attempt to finally have UI recognized as a disease in the World Health Organization’s *International Classification of Diseases*; until then, IU was considered merely a symptom. The ICS has recently changed the definition to “the complaint of any involuntary leakage of urine.”

The North American Nursing Diagnosis Association (NANDA) considers UI and other problems associated with the alterations in urinary elimination as nursing diagnoses.

The differential diagnosis of UI could be difficult for a nonexpert, as the diagnosis involves the assessment of health history, clinical examination, and urodynamical testing. To deal with this problem, some expert systems have been developed to assist not only urologists and gynecologists but also general practitioners.

Expert systems are models designed in a specific area of knowledge, which make it easier to implement and codify knowledge base more restrictively. Knowledge representation, rules of decision, and data supporting the decision can be clearly defined by an expert system. These systems therefore decipher problems that are normally solved only by specialists, that is, professionals who accumulate knowledge and expertise, which enable them to solve the more difficult problems.

The expert systems may be used in two different ways: decision support, when the program helps the professional to make a decision (the most commonly used in medicine), and decision making, when the system makes the decision for someone (most commonly used in many industrial and financial systems, but now also used in medicine).

Moreover, expert systems in the healthcare area must consider the frequent uncertainty present in the diagnostic process. Fuzzy logic was developed based on the concept of partially true values, varying from “completely true” to “completely false,” and has become a powerful instrument for managing imprecision and uncertainty. This instrument is used in diagnostic systems, image analysis, and, more recently, in epidemiology and public health.

Zadeh introduced the theory of fuzzy sets in the 1960s as a means to model the uncertainty within natural language (eg, “ever,” “frequently,” “sometimes,” “rarely,” and “never”). The theory of fuzzy sets considers that a set could have members that belong only in part to the set. Such fuzzy sets have imprecise boundaries, and therefore, a gradual transition from membership to non-membership of an element in the fuzzy set is observed. The ambition of fuzzy sets is to interact natural language and numerical models.

In the literature review, three decision support systems for differential diagnosis of UI were identified: a rule-based system, a system based on fuzzy logic, and a machine learning system that is used as a genetic algorithm to discover the rules for an expert system from databases.

These systems were based mainly on urodynamical testing and on some anamnesis data. A system constructed in this way could be more restrictive for clinical use in primary care, for example, where it is frequently not possible to perform the urodynamical testing immediately but the patient requires orientation and adequate intervention to minimize the symptoms while a diagnosis is not yet defined. In addition, the decision support system is built to help the health professional who is not an expert; this professional uses the system to reach an initial diagnosis and to refer, if necessary, to experts for a more accurate diagnosis.

In nursing, there are few specialist nurses in this area; therefore, an expert system could be useful in practice or teaching. Thus, in this study, we present a model based on fuzzy relations to obtain the differential nursing diagnosis associated with alterations in urinary elimination based mainly on anamnesis data and using an international classification: the NANDA taxonomy. A system using the nursing terminology could be more adequate for nursing practice, especially in health institutions where the NANDA taxonomy is used electronically.

## METHODS

In the present study, NANDA taxonomy version 2001–2002 translated into Portuguese was used. The following diagnoses are defined by NANDA taxonomy: impaired urinary elimination, stress UI, reflex UI, urge UI, functional UI, total UI, risk for urge UI, and urinary retention.

As the model must be able to make the differential diagnosis of actual urinary problems, the nursing diagnosis risk urge UI was not included in the analysis. The diagnosis of impaired urinary elimination was not included in the analysis because it is either very unspecific or common to all cases of alteration in urinary elimination. Thus, the model considered six diagnoses: stress UI, reflex UI, urge UI, functional UI, total UI, and urinary retention.

To obtain an actual nursing diagnosis, defining characteristics including subjective and objective signs or symptoms must be applied in a cluster; that is, they must appear together. All the defining characteristics approved by NANDA were used in the analysis. As suggested by some authors, “decreased frequency” as a defining characteristic was added. The defining characteristics “inability to voluntarily inhibit or initiate voiding” and “small, frequent voiding or absence of urine output” were divided into two parts and considered as two different symptoms. “Bladder contracture/spasms” may be a sign (observed by urodynamical testing) or a symptom (some people complain of spasms before
involuntary loss of urine); therefore, these were considered as two different defining characteristics. For calibration purposes, the defining characteristic “incontinence” was excluded because it is common to all diagnoses, including urinary retention (the overflow incontinence can occur in some cases of urinary retention). As a result, 39 defining characteristics were considered for analysis.

To construct the system model, the composition of fuzzy relations called max-min composition was used. First, an explanation about fuzzy sets and max-min composition becomes necessary.

If we assume that X is a set serving as the universe of discourse, a fuzzy subset A of X is associated with a characteristic function:

\[ \mu_A : X \rightarrow [0, 1] \]

which is generally called membership function. The idea is that for each \( x \in X \), \( \mu_A(x) \) indicates the degree to which \( x \) is a member of the set \( A \). This membership degree indicates the compatibility degree of the assertion “\( x \) is \( A \)”.

The classical set theory operations can be extended to fuzzy sets, which have membership grades that are in the interval \([0, 1]\). So, if we assume that \( A \) and \( B \) are two fuzzy subsets of \( X \), their union is a fuzzy subset \( C \) of \( X \), denoted \( C = A \cup B \), such that for each \( x \in X \):

\[ C(x) = \max[A(x), B(x)] = A(x) \lor B(x) \]

It is a common practice to use \( \lor \) as the max operator.

In addition, their intersection is another fuzzy subset \( D \) of \( X \), denoted \( D = A \cap B \), such that for each \( x \in X \):

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

It is also common practice to use \( \land \) as the min operator.

Another important concept on fuzzy sets is fuzzy relations. A fuzzy relation \( R \) between two (nonfuzzy) sets \( X \) and \( Y \), with \( x \in X \) and \( y \in Y \), is defined as a fuzzy set in the Cartesian product \( X \times Y \), that is:

\[ R = \{ \mu_R(x, y) / (x, y) \} \]

for each \( (x, y) \in X \times Y \), where \( \mu_R(x, y) : X \times Y \rightarrow [0, 1] \) is the membership function of the fuzzy relation \( R \), and \( \mu_R(x, y) \in [0, 1] \) gives the degree to which the elements \( x \in X \) and \( y \in Y \) are related in relation \( R \) to each other. Because this basic type of fuzzy relation is defined in the Cartesian product of two sets, such a fuzzy relation is sometimes called a binary fuzzy relation. However, this concept could be generalized to \( n \) dimensions of fuzzy relations.

A fuzzy relation could express a partial or imprecise relationship between elements of some sets, as opposed to a precise one in the case of a crisp relation in which any element can either be related or not. In the fuzzy relation, there are gradual relationships that vary from 1, for being fully in relation, to 0, for not being in relation at all, through all intermediate values. If \( X \) and \( Y \) are discrete spaces, then the fuzzy relation \( R \) could be represented in a matrix form.

The max-min composition of two fuzzy relations \( R \) in \( X \times Y \) and \( S \) in \( Y \times Z \), written as \( R_{\text{max-min}} S \), is defined as a fuzzy relation in \( X \times Z \) such that

\[ \mu_{R_{\text{max-min}} S}(x, z) = \max \{ \min(\mu_R(x, y), \mu_S(y, z)) \} \]

for each \( x \in X \) and \( z \in Z \). The mathematical operation expressed above is similar to a multiplication of matrix, where each matrix represents a fuzzy relation.

Based on the above statements, a fuzzy relational matrix was constructed (relational matrix) with six columns (diagnoses) and 39 lines (defining characteristics). The relational matrix provides the association between each defining characteristic (sign or symptom) and each diagnosis, through fuzzy relation value. These fuzzy degrees of association could vary from 0 (no relation) to 1 (total relation).

A second matrix (case matrix) was constructed, containing 195 cases/patients (lines) with urinary problems that were obtained from the database of a previous study and their relation with the defining characteristics (columns). The presence of each defining characteristic was evaluated considering the following values: 0 = absent or not available, 0.25 = absent but not sure, 0.75 = sometimes present, and 1 = present. Each line of the case matrix represents the health status vector of the patient, considering the 39 chosen defining characteristics (a matrix type \( 1 \times 39 \)).

The model was based on the fuzzy max-min composition. Figure 1 shows an example of the max-min composition structure for a hypothetical case analysis. The decision process is similar to a matrix multiplication, changing the algebraic sum operator by the max operator and the multiplication by the min operator. Thus, consider a patient in which the defining characteristic frequency is present; nocturia is sometimes present; dysuria, hesitancy, and retention are absent; and urinary urgency is present, resulting in the health status (1, 0.75, 0, 0, 0, 1). These defining characteristics can be associated to the diagnosis of urge incontinence through the relational matrix expressed in the matrix (0.75, 0.75, 0.5, 0.3, 0.3, 1), in which the first element is the fuzzy degree of the relation between the defining characteristic frequency and the diagnosis of urge incontinence; the second element is the fuzzy degree of the relation between the defining characteristic nocturia and the diagnosis of urge incontinence, and so on. Applying the max-min fuzzy composition in this example, we find in the minimum operation between the health status
and the relational matrix the values (0.75, 0.75, 0, 0, 0, 1), of which the maximum value is 1. So the possibility value of that patient having urge incontinence diagnosis is 1.

This procedure is applied to all the diagnoses considered, and at the end of the process, we find a matrix composed by all fuzzy possibility degrees for that patient in all the six possible diagnoses. The decision making was concluded with a defuzzification method that allowed the determination of the final diagnosis. In this case, the maximum value of the diagnostic possibility distribution was used. In the example illustrated in the figure, the maximum value was 1, and the urge UI was determined as the final diagnosis. Note that in this model approach, the conclusion of one or more final diagnoses is possible.

![Table 1](https://example.com/table1.png)

<p>| Table 1: Comparison Between the Diagnoses Determined by the Specialists and the Fuzzy Model |
|----------------------------------------|----------------------|------------------|</p>
<table>
<thead>
<tr>
<th>Diagnosis</th>
<th>Specialists</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stress</td>
<td>54</td>
<td>68</td>
</tr>
<tr>
<td>Urge</td>
<td>17</td>
<td>20</td>
</tr>
<tr>
<td>Retention</td>
<td>14</td>
<td>10</td>
</tr>
<tr>
<td>Total</td>
<td>12</td>
<td>9</td>
</tr>
<tr>
<td>Reflex</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Functional</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Urge + stress</td>
<td>97</td>
<td>80</td>
</tr>
<tr>
<td>Urge + total</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Urge + functional</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Urge + retention</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Stress + total</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Total + retention</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Reflex + retention</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Urge + stress + functional</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>195</td>
<td>195</td>
</tr>
</tbody>
</table>

The model described was used to determine the diagnosis of all 195 cases. The performance of the model was then evaluated by comparing the diagnoses obtained by using the model and those determined previously by the panel of three specialist nurses.

This research was approved by the research ethic committee of the institution.

![Table 2](https://example.com/table2.png)

| Table 2: Concordance of the Proposed Model With the Opinion of Specialist Nurses |
|----------------------------------------|----------------------|-------|
| Results                               | No.       | %     |
| Total concordance                     | 154       | 79.0  |
| Partial concordance: the model presented less diagnoses* | 23  | 11.8  |
| Partial concordance: the model presented more diagnoses* | 15  | 7.7   |
| Total discordance                     | 3         | 1.5   |
| Total                                 | 195       | 100.0 |

*As compared with the number of diagnoses determined by the specialists for a particular patient.

The comparison between the diagnoses determined by the fuzzy model and those made by the specialist nurses is shown in Table 1. In some cases, the model indicated one or two diagnoses other than the one determined by the specialists. However, more frequently, the model provided only one of the two diagnoses identified by the specialist nurses.

As shown in Table 2, the model was able to determine the diagnosis in total accordance with the panel of specialists in 79.0% of cases. In 11.8% of cases, the model determined fewer diagnoses than the specialists, and in 7.7% of cases, the model determined more diagnoses than the specialists. In 1.5% of cases, the model and the specialists determined different diagnoses. This research was approved by the research ethic committee of the institution.
The agreement between model and experts was excellent ($\kappa = 0.98, P < .0001$) or substantial ($\kappa = 0.69, P < .0001$), according to the interpretation table of $x^2$ index, when considering the overestimative accordance (accordance was considered when at least one diagnosis was equal) and the underestimative discordance (discordance was considered if at least one diagnosis was different), respectively.

**DISCUSSION**

Although the model had a simple structure, the diagnostic performance of the model in terms of agreement evaluation considering the opinion of the experts was very good. A model with a simple structure such as this can be easily converted into a simple and cheap computer program, usable even on handheld personal computers.

In three cases, the result seems to be contradictory as the model pointed out UI and retention together. However, in some circumstances, this can occur.

In the male population, benign prostatic hyperplasia can cause obstruction of the urinary flux and detrusor instability, that can cause urge incontinence. Even though this is uncommon in women, patients with chronic urinary retention can present incontinence. Another situation where UI and urinary retention can occur at the same time is in the presence of pelvic organ prolapse. Pelvic organ prolapse can occur in association with UI and, on occasion, may mask incontinence. Women with pelvic organ prolapse, depending on the severity, sometimes need to manually reduce the prolapsed organ to evacuate or urinate.

Individuals with urinary retention usually present frequent voids or dribbling when the pressure in the bladder rises because of the bladder filling beyond its normal capacity or because of coughing, straining, or exercising. This condition is known as overflow incontinence. As the case data were obtained mainly through anamnesis, overflow incontinence was perceived by a patient (woman) as a constant flow of urine, one of the major defining characteristics for total UI according to Carpenito. Therefore, a certain difficulty in reaching the differential diagnosis between these two conditions is to be expected.

Finally, if an individual with reflex UI has a lesion above the sacral micturition center, he/she could present incomplete emptying; therefore, a certain amount of retention would be expected. However, there are interventions recommended for urinary retention that must be avoided in the presence of reflex UI, for instance, the Credé maneuver, because this maneuver may damage the urethra or may induce vesicoureteral reflux if the external sphincter is contracted, leading to renal infection. In this case, obtaining more data to confirm the diagnosis is very essential, and the present model appears to be very useful, drawing attention to the two possibilities.

The diagnoses of urge UI and stress UI were frequently identified by experts and by the model, and these two diagnoses together have a great weight in this sample. The concomitance of these two diagnoses had been previously observed by other authors. Woodtli, on the basis of literature and on two clinical studies, had proposed the inclusion of the nursing diagnosis mixed incontinence for cases where there are joined symptoms of stress incontinence and urge incontinence, as used in medical literature. However, this has not yet been approved by NANDA.

Nursing diagnoses associated with alterations in urinary elimination require different interventions, and nurses who are not specialists need support to identify and to manage these diagnoses. One of the major obstacles toward effective incontinence management, for instance, is the false perception that incontinence is inevitable and irreversible. Early and accurate nursing diagnosis is the first step toward the management of incontinence, which is considered untreatable by many patients. Appropriate treatment, however, could improve the quality of life of patients and prevent the common sequelae associated with UI and those resulting from inadequate treatment strategies. Expert systems based on fuzzy logic could be helpful for the nurses to make a diagnostic decision regarding patients with alterations in urinary elimination.

Nurses concurrently assess patient need for nursing care in several domains of concern to nursing before deciding where the primary focus of nursing attention should be directed. The nursing diagnosis is considered complex and has a high risk for low accuracy because it is an interpretation of a human behavior. Frequently, nurses work with few indicators to affirm a diagnosis. Several times, the patient does not present all defining characteristics, and some of them can be common to different diagnoses, which also contributes to low accuracy. Fuzzy logic could contribute for diagnosis process, in any area of knowledge, because it offers theoretical bases that help transcend the conflicts between objectivity and subjectivity, respects gray zones (areas of uncertainty), and provides a contextual understanding of complex nursing phenomenon.

Fuzzy logic and its applications in nursing have been discussed by some authors. It could be useful in a variety of disciplines that are deeply related to human beings’ behaviors and intuition and when there are ambiguous concepts whose boundaries cannot be sharply defined. Nurses could learn about fuzzy logic and its applications on practice and research during undergraduate or graduate courses. However, deep knowledge in
this subject is commonly not required to use fuzzy applications.

CONCLUSION

The proposed model based on fuzzy relations is very simple and has quite a good performance. However, more tests with different populations and larger samples are recommended before this model can be used as a support system for clinical decision.

To evaluate the system and improve it, we are developing a software to be used by other nurses and in different institutions.

REFERENCES