Published in final edited form as:
Int J Med Inform. 2013 March ; 82(3): 201–208. doi:10.1016/j.ijmedinf.2012.05.012.

Fuzzy cognitive map in differential diagnosis of alterations in urinary elimination: A nursing approach

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Abstract

Purpose—To develop a decision support system to discriminate the diagnoses of alterations in urinary elimination, according to the nursing terminology of NANDA International (NANDA-I).

Methods—A fuzzy cognitive map (FCM) was structured considering six possible diagnoses: stress urinary incontinence, reflex urinary incontinence, urge urinary incontinence, functional urinary incontinence, total urinary incontinence and urinary retention; and 39 signals associated with them. The model was implemented in Microsoft Visual C++® Edition 2005 and applied in 195 real cases. Its performance was evaluated through the agreement test, comparing its results with the diagnoses determined by three experts (nurses). The sensitivity and specificity of the model were calculated considering the expert's opinion as a gold standard. In order to compute the Kappa's values we considered two situations, since more than one diagnosis was possible: the overestimation of the accordance in which the case was considered as concordant when at least one diagnoses was equal; and the underestimation of the accordance, in which the case was considered as discordant when at least one diagnosis was different.

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Conflicts of interest

There are no conflicts of interest.

Author's contributions

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

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Results—The overestimation of the accordance showed an excellent agreement (kappa = 0.92, $p < 0.0001$); and the underestimation provided a moderate agreement (kappa = 0.42, $p < 0.0001$). In general the FCM model showed high sensitivity and specificity, of 0.95 and 0.92, respectively, but provided a low specificity value in determining the diagnosis of urge urinary incontinence (0.43) and a low sensitivity value to total urinary incontinence (0.42).

Conclusions—The decision support system developed presented a good performance compared to other types of expert systems for differential diagnosis of alterations in urinary elimination. Since there are few similar studies in the literature, we are convinced of the importance of investing in this kind of modeling, both from the theoretical and from the health applied points of view.

Limitations—In spite of the good results, the FCM should be improved to identify the diagnoses of urge urinary incontinence and total urinary incontinence.

Keywords

Fuzzy logic; Urinary incontinence; Nursing diagnosis; Differential diagnosis

1. Introduction

Scientific and technological advances in medicine and health-care areas are notable, particularly in the last thirty years. However, the diagnostic process is still considered an art, being a complex task due to, among other things, the uncertainties present in this process. The relationship between a diagnosis and its symptoms is not always a bi-univocal correspondence, that is, different diagnoses share one or more symptoms, and the clinical observations are subject to errors and may be insufficient for a more precise diagnosis [1,2].

Urinary complaints are common in the general population. Urinary incontinence (UI), in particular, has high frequency especially among women, impairing daily activities, social interactions and self perception of health status [3].

However, one reason because the urinary alterations could be not diagnosed is the fact that health professionals often are not prepared to identify, treat or refer people with these problems. In addition, there are many identification uncertainties in the diagnosis of the different types of urinary incontinence as demonstrated in a study developed in the city of Campinas, Brazil, which aimed to investigate how physicians and nurses at primary care units investigate and manage the cases of female urinary incontinence and if they discriminate the different types of urinary incontinence. It was verified that, excluding the gynecologists, doctors and nurses rarely or never investigate if the woman has incontinence and when they do so, sometimes they do not know what to do or do not choose the more adequate conduct [4].

The differential diagnosis of disorders of the urinary elimination is sometimes difficult to be established for nurses who are not expert in the field and, for this reason, frequently they cannot indicate the more adequate treatment [4]. In the Netherlands, several national reports recommend involving nurse specialists to support general practitioners and to improve patient care [5]. Thus, it is possible that expert systems can play an important role as tools for decision support in the diagnosis of UI, and also improving the nursing care to these patients.

Due to the linguistic nature of urinary incontinence problem, and the vagueness and uncertainty of the concepts assessed, fuzzy sets theory presents advantageous characteristics to be used in such a classification task. Fuzzy sets theory was developed based on the concept of partially true values, ranging from 'completely true' to 'completely false', limits of the classical logic. Fuzzy systems, using fuzzy sets theory, have been applied with success in several health areas, such as: diagnostic systems [6,7,8], treatment of images [9], quality of life evaluation [10], epidemiology and public health [1,11,12].

Fuzzy cognitive map (FCM), a specific type of fuzzy systems, can be understood as the result of the synergy among fuzzy logic and neural network methodologies, for which the structure is implemented in a computational environment. In the FCM theory the systems are described by a symbolic representation (graphs) where concepts interact with each other through a dynamical process. This structure has been applied with success in the modeling and control of complex systems, which is the case of differential diagnosis systems [13]. The concepts modeled by FCM in differential diagnosis systems are diseases and symptoms, and the associations between them are described through the graphs' structures. Both qualitative and quantitative data can be represented in this kind of model [13].

Studying the applications of FCM in differential diagnoses in medicine [14] Souza et al. proposed a different dynamical process to perform the node's values updating. When the system is initialized with values that correspond to the patient's conditions, it is expected that the FCM will be able to find different steady-states – one for each patient. In this sense, Souza et al. [14] proposed to maintain fixed the values of the nodes related to patient's conditions.

The NANDA International (NANDA-I), a standardized nursing terminology, considers that urinary problems are nursing diagnoses, and in their taxonomy, version 2001–2002, present the following statements for nursing diagnoses [15]: impaired urinary elimination, stress urinary incontinence, reflex urinary incontinence, urge urinary incontinence, functional urinary incontinence, total urinary incontinence, risk for urge urinary incontinence, and urinary retention.

There are two types of expert systems previously published by the authors, that make the differential diagnosis of alterations in urinary elimination using NANDA-I nursing terminology [16,17,18]. The first system was based on classical rules and decision-tree structure (ALTURIN.SDD) [16,17], while the second was based on the fuzzy relations [18].

There are limitations of all above mentioned approaches. ALTURIN.SDD is limited by missing data, which happens when it is not possible to obtain all information from the patient or even to decide with absolute certainty if a signal or symptom is present or not [17]. On the other hand, in the fuzzy relation approach, the interaction between different signs or symptoms was not considered. Despite good global performance of this model, the lack of interaction of signs and symptoms may elevate or diminish the possibility of some diagnosis to occur. For example, by not considering the relationship between infravesical obstruction and detrusor instability, the model may indicate only one of the two expected diagnosis, which are urinary retention and urge urinary incontinence in men with benign prostatic hyperplasia [19,20].

In addition, there are other approaches in literature, including genetic algorithm [21], Boolean rules [22] and fuzzy logic [23]. However, they are devoted to medical practice and restricted to the three most common types of urinary incontinence, not taking into account nursing terminology.

In order to better explore the nursing diagnoses related to alterations in urinary elimination, we developed a decision support system using FCM with the diagnostic classification of NANDA-I.

2. Methods

In our study we developed a fuzzy cognitive map for the differential diagnosis of alterations in urinary elimination based on the dynamical structure proposed by Souza et al. [14] and on the modified proposal of Georgopoulos et al. [13]

First of all, it is important to determine the concepts that best describe the system, that is, the factors that are crucial for the modeling of the system [13]. For this, the NANDA-I taxonomy version 2001–2002 [15] was used, the same used to develop two other previous systems [16,17,18].

As the model should be able to make the differential diagnosis of real urinary problems [24], the nursing diagnosis of risk for urge urinary incontinence was not included in the analysis. Moreover, as the diagnosis of impaired urinary elimination is very unspecific and common to all cases of change in urinary elimination, it was also not included in the model. Thus, the FCM consider only six diagnoses: stress urinary incontinence, reflex urinary incontinence, urge urinary incontinence, functional urinary incontinence, total urinary incontinence and urinary retention.

To determine an actual nursing diagnosis, defining characteristics that include subjective and objective data, signs and symptoms must be present [24]. All the defining characteristics approved by the NANDA-I were used in the analysis. As suggested by [25], ‘decreased frequency’, that is decreased urinary 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/spasm’ 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, as it is common to all diagnoses including ‘urinary retention’ (the overflow incontinence of ‘urinary retention’). As a result, 39 defining characteristics were used in the fuzzy map. So the FCM included 45 concepts (39 defining characteristics and 6 diagnoses) (Table 1).

In general, FCM is elaborated using an expert or a group of experts that indicate which elements of the system influence other elements and for the corresponding concepts he/she determines the positive, negative or zero effect of one concept on the others [13]. In our study, it is a necessary condition that the experts dominate both urology and nursing diagnosis terminology, which is not common. So, this model was developed based on the expert knowledge of just one nurse that satisfied this condition. This expert established the interconnections and the fuzzy degree of association between concepts assigning values that could range between 0 and 1.

FCM consists of a set of nodes and edges that correspond to concepts and links between them (Fig. 1). Each concept (node) has a value that is a fuzzy number in the interval [0,1], which is updated through a dynamic process. These values represent a measure of the quantity of the concept (C) in the model. The degree of association (edge) are weights with values (ω_{ij}) in the interval [−1,1]. They represent the degree of the fuzzy relationship between the concept C_i and C_j. If this relationship is positive, then ω_{ij} is greater than zero; otherwise, ω_{ij} is negative.

Since the concepts and the interconnection values were defined, the FCM was prepared to shape the system. Its concepts had their initial values determined by the specialist and then the system was dynamically processed. For each step of simulation, the value of each term was determined by the influence of concepts interconnected weighted by their corresponding weights by Eq. (1):

$$A_i^{t+1}=f\left(\sum_{j=1,j\neq 1}^{n}\omega_{ji}A^t j\right), \quad (1)$$

where A_i^{t+1} is the value of the concept C_i at step $t+1$, A_j is the value of concept C_j at step t, ω_j is the value of the association between concepts C_j and C_i, and f is a transfer function, which ensures that the values of concepts remain in the interval [0,1] during the dynamic process. As proposed by Georgopoulos et al. [13], the logistic function was used like a transfer function, such as Eq. (2):

$$f(x)=\frac{1}{1+e^{-\lambda x}}. \quad (2)$$

Thus, the system was dynamically processed until obtaining a steady-state or a dynamical equilibrium. These cognitive maps could converge to a fixed point, which means that the values of concepts do not change with the updating, converge to a periodic cycle, which means that the values are periodically repeated, or a system presents a chaotic behavior [26].

The implementation of this FCM model was performed using the Microsoft Visual C++® Edition 2005. In addition to fix the values of the symptoms, after testing different scenarios, the best result was obtained with the competition scenario between diagnoses explained above.

Since the diagnoses in question were not exclusive, i.e. it is possible that the patient had more than one diagnosis, it was considered as the response of the model not only the diagnosis with the greatest value at the end of the simulation, as proposed by Souza et al. [14], but a range of values.

This research was approved by the Research Ethic Committee of the institution and all participants gave informed consent to the work.

3. Results

To evaluate the FCM performance, the model was applied to 195 cases of alterations in urinary elimination.

The initial tests with the model showed that the best results were obtained when considered as possible diagnoses those over a threshold of 12% of the highest value identified. Thus, all diagnoses with a value of at least 12% of the peak reached in the dynamic equilibrium were activated and applied to a given patient. Table 2 shows the values given by the expert to initialize the model.

The model was applied in 195 real cases and its performance was evaluated through out the agreement test, comparing its results with the diagnoses determined by three experts (nurses) in a previous study [17].

The sensitivity and specificity of the model were calculated considering the experts' opinion as a gold standard. In order to compute the Kappa's values we considered two situations, since more than one diagnosis was possible: the overestimation of the accordance in which the case was considered as concordant when at least one diagnosis was equal; and the underestimation of the accordance, in which the case was considered as discordant when at least one diagnosis was different.

Table 3 shows the diagnoses determined by experts and by the FCM. Compared to the experts, the FCM identified less 35 cases of stress urinary incontinence and less 11 cases of total urinary incontinence.

As shown in Table 4, the model was able to determine the diagnosis in total or partial agreement with the panel of experts in 94.9% of cases. In 10 cases (5.1%) the model had a diagnosis that differed completely from those determined by experts.

The agreement between the model and the experts was very good (kappa = 0.92, $p < 0.0001$) or moderate (kappa = 0.42, $p < 0.0001$), considering the overestimation and underestimation of the agreement, respectively.

Table 5 presents the calculation of sensitivity and specificity of the FCM in the determination of each of the diagnoses in study and in general. It is possible to note that although the sensitivity and specificity are high in general, the FCM provide a low specificity value in determining the diagnosis of urge urinary incontinence and a low sensitivity value to total urinary incontinence. Fig. 2 shows the receiver–operator curve (ROC) of the diagnoses urge urinary incontinence, stress urinary incontinence, total urinary incontinence and urinary retention, and the measurement of the area.

4. Discussion

The results obtained in this work were less accurate than those obtained by [18], which presented a very good agreement between model and experts (kappa = 0.98, $p < 0.0001$) or substantial (kappa = 0.69, $p < 0.0001$), when considering the overestimative accordance and the underestimative, respectively.

The sensitivity and specificity values of the fuzzy model based on fuzzy relationship structure were quite similar to FCM for all diagnoses (79% of sensitivity and 97% of specificity)[18]. However, the ALTURIN.SDD system presents better performance than FCM, since it had both sensitivity and specificity values exceeding 98% for all diagnoses [17].

There is no formal mechanism or a definition to guide the choice of the best model. Although the sensitivity and specificity values suggest that the performance of the FCM was worse than the ALTURIN.SDD system, it is important to consider some disadvantages of the ALTURIN.SDD that have been partly overcome in the new proposed model. One of the most relevant is the fact that the FCM is able to discriminate the diagnoses even when there are missing data or conflicting information [13]. This is not possible in the ALTURIN.SDD system, in which missing data can lead to inconclusive results. Another relevant aspect is that the system ALTURIN.SDD leads to the forced choice between the presence and absence of signs/symptoms (defining characteristics), characterizing a system based on the classical logic. In a counterpart, the FCM allows the uncertainty in the identification of the defining characteristics, which keeps closer to real situations.

In the majority of the cases the patient’s first information is linguistically obtained. In addition, different diagnoses can be confused with each other when the problem of health (or human response in the case of the nursing diagnoses) is in its initial state. Facing this, some models have proposed incorporating the duration of symptoms to the differential diagnosis [27]. However, the great difficulty to incorporate the temporal dimension of the defining characteristics of the nursing diagnoses is that there is little temporal knowledge, i.e., the literature is scarce on this subject.

Comparing the FCM model with the fuzzy system for differential diagnosis based on the composition of fuzzy relations [18] we found that both systems are similar from the sensitivity and specificity points of view. However, although the model based on fuzzy relations max–min presents a simpler mathematical structure when compared to FCM, it is not able to deal directly with the associations between signals/symptoms, which are present in the majority of medical or nursing diagnoses, that is, it does not represent all the degree of association between concepts like the FCM [13]. Moreover, the FCM is an area barely explored in its health applications, but in development, particularly regarding the role it can play in decision support systems.

A decision support system based on this model would be very useful for no specialist nurses, mainly if it includes clinical practice guidelines. But the information must be available at the point of care because providers hardly interrupt their activities to search literature [28] and, probably, to consult a system.

In this study the NANDA-I taxonomy version 2001–2002 [15] was used, comparing results with other expert systems. Although it is not the most up to date version, the current version does not include, for example, the mixed urinary incontinence, defined by the International Continence Society (ICS) as “the complaint of involuntary leakage associated with urgency and also with exertion, effort, sneezing or coughing” (p. 38) [29]. The very frequent concomitance of stress and urge urinary incontinence in our study (almost 50%), that is mixed urinary incontinence according the ICS, shows that is necessary to include this diagnosis on the NANDA-I taxonomy as recommended in literature for a long time [30]. Truly, terminology is an essential requirement for electronic health records but a comprehensive nursing terminology to be used in clinical practice is still a challenge [28].

Due to the good results obtained with this model, we are developing another system for decision support using the consensus terminology of the International Continence Society. We believe that a system based on that terminology could be useful not only for nurses but also for physicians and physiotherapists.

In addition, we developed a program geared to the user who is able to implement a fuzzy map, regardless of its application. This program is a first prototype for the future development of a specific system for differential diagnosis.

5. Conclusions

An FCM model was applied to 195 cases of urinary incontinence, following the NANDA-I classification categories. In spite of its good results compared to the fuzzy system for differential diagnosis based on the composition of fuzzy relations, the FCM should be improved to identify the diagnoses of urge urinary incontinence and total urinary incontinence.

A great advantage of FCM is that it is able to manipulate incomplete information, suggesting a diagnosis even when some data are unavailable and proposing differential diagnoses that could be better investigated. In addition, it can consider associations among several variables.

Finally, since there are few similar studies in the literature, we are convinced of the importance of investing in this kind of modeling, both from the theoretical and from the health applied points of view. The experience of this development can be applied in the creation of other expert systems, which can be used in teaching, research and assistance.

Acknowledgments

This work was supported by the National Council of Scientific and Technological Development – CNPq 476854/2004-0.

Dr. Marin was partially supported by grant NIH D43TW007015, BRIGHT and CNPq 301735/2009.

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Summary table

What was already known on the topic

- The urinary alterations are often no diagnosed and one reason is that health professionals are not prepared to identify, treat or refer people with these problems. In addition, there are many identification uncertainties in the diagnosis of the different types of urinary incontinence.
- Fuzzy sets theory has become a powerful tool for dealing with vagueness and uncertainty.
- Fuzzy cognitive map (FCM) can be understood as the result of the synergy among fuzzy logic and neural network methodologies, whose structure is implemented in a computational environment.
- The concepts modeled by FCM in differential diagnosis systems are diseases and symptoms, and the associations between them are described through the graphs structures. Both qualitative and quantitative data can be represented in this kind of model.

What this study added to our knowledge

- The model developed was able to manipulate incomplete information, suggesting a diagnosis even some data are unavailable.
- It proposed differential diagnoses that could be better investigated.
- This study confirms that is necessary to use fixed values for symptoms.
- Best results can be obtained when it is considered as possible diagnoses those that are on a range (up to 12% in this study) below the peak reached in the dynamic equilibrium.

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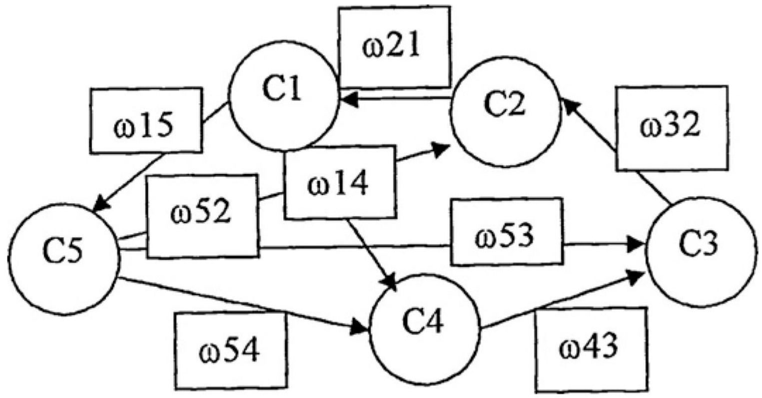

Fig. 1.
Graphical representation of a fuzzy cognitive map (FCM). It consists of a set of nodes and arcs that correspond to concepts (*C*) and links between them (*ω*)[13].

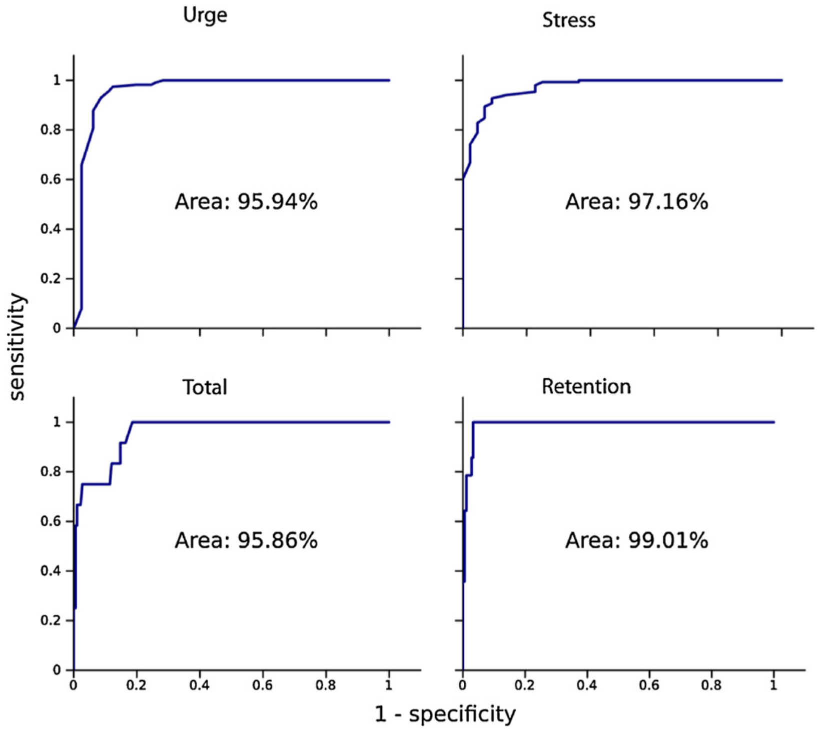

Fig. 2.

The receiver–operator curve (ROC) of the diagnoses urge urinary incontinence (urge), stress urinary incontinence (stress), total urinary incontinence (total) and urinary retention (retention), and the measurement of the area.

Table 1

The concepts used in the FCM: defining characteristics and diagnoses of NANDA – I, version 2001–2002 [15].

Nursing diagnosis (ND)	Defining characteristics (DC)
ND1 – urge urinary incontinence	DC1 – frequency (voiding more often than every 2 hours)
ND2 – stress urinary incontinence	DC2 – nocturia (more than 2 times a night)
ND3 – reflex urinary incontinence	DC3 – dysuria
ND4 – total urinary incontinence	DC4 – hesitancy
ND5 – functional urinary incontinence	DC5 – retention
ND6 – urinary retention	DC6 – urinary urgency
	DC7 – voiding in large amounts (>500 cm^3)
	DC8 – bladder contracture/spasm (symptom)
	DC9 – bladder contracture/spasm (observed by urodynamical testing)
	DC10 – voiding in small amounts (<100 cm^3)
	DC11 – inability to reach toilet in time
	DC12 – reported or observed dribbling with increased abdominal pressure
	DC13 – no sensation of urge to void
	DC14 – complete emptying with lesion above pontine micturition center
	DC15 – no sensation of bladder fullness
	DC16 – no sensation of voiding
	DC17 – incomplete emptying with lesion above sacral micturition center
	DC18 – sensations associated with full bladder such as sweating, restlessness, and abdominal discomfort
	DC19 – inability to voluntarily inhibit voiding
	DC20 – inability to voluntarily initiate voiding
	DC21 – predictable pattern of voiding
	DC22 – sensation of urgency without voluntary inhibition of bladder contraction
	DC23 – constant flow of urine at unpredictable times without uninhibited bladder contractions/spasm or distention
	DC24 – unsuccessful incontinence refractory treatments
	DC25 – lack of perineal or bladder filling awareness
	DC26 – unawareness of incontinence
	DC27 – amount of time required to reach toilet exceeds length of time between sensing the urge to void and uncontrolled voiding
	DC28 – loss of urine before reaching toilet
	DC29 – may only be incontinent in early morning
	DC30 – senses need to void
	DC31 – able to completely empty bladder
	DC32 – dribbling
	DC33 – bladder distention
	DC34 – small, frequent voiding
	DC35 – absence of urine output

Nursing diagnosis (ND)	**Defining characteristics (DC)**
	DC36 – sensation of bladder fullness
	DC37 – residual urine
	DC38 – overflow incontinence
	DC39 – decreased frequency

Table 2

Values given by the expert to the relationship between the defining characteristics DC and diagnoses of NANDA – I (see Table 1) before the training of the model.

	ND1	ND2	ND3	ND4	ND5	ND6
DC1	0.75	0.6	0	0.2	0	0.5
DC2	0.75	0.1	0	0.8	0.2	0
DC3	0.5	0	0	0	0	0.6
DC4	0.3	0	0	0	0	0.2
DC5	0.3	0	0.5	0	0	1
DC6	1	0.7	0	0	0	0
DC7	0.7	0	0.1	0	0	0
DC8	0.9	0	0.6	0	0	0
DC9	1	0	0.6	0	0	0
DC10	0.6	0.1	0.1	0.2	0	0.5
DC11	0.9	0	0	0	0.9	0
DC12	0	1	0	0	0	0.2
DC13	0	0	0.8	0	0	0
DC14	0	0	0.9	0	0	0
DC15	0.2	0	0.9	0	0	0
DC16	0	0	0.5	0	0	0.1
DC17	0.1	0	0.9	0	0	0.4
DC18	0	0	0.5	0	0	0.4
DC19	0.3	0.2	0.9	0	0.1	0
DC20	0.2	0	0.9	0	0	0.9
DC21	0	0	0.9	0	0	0
DC22	0.7	0	0.5	0	0	0
DC23	0	0.2	0	1	0	0.3
DC24	0.5	0.3	0	0.8	0	0
DC25	0.2	0	0.5	0.6	0	0
DC26	0	0	0	0.6	0	0
DC27	0.5	0	0	0	1	0
DC28	0.9	0	0	0	0.9	0

	ND1	ND2	ND3	ND4	ND5	ND6
DC29	0	0	0	0	0.7	0
DC30	0.8	0.9	0	0.1	0.7	0.1
DC31	0.7	0.9	0	0	0.7	0
DC32	0	0.2	0	0.2	0	0.9
DC33	0	0	0.2	0	0	0.9
DC34	0.1	0	0	0	0	0.7
DC35	0	0	0	0	0	0.7
DC36	0	0	0.1	0	0	0.7
DC37	0.1	0.1	0.2	0.1	0	0.7
DC38	0	0	0	0.1	0	0.9
DC39	0	0	0	0	0	0.8

Table 3

Diagnoses determined by experts and the fuzzy cognitive map.

Diagnosis	Experts	FCM
Stress	54	19
Urge	17	21
Retention	14	9
Total	12	1
Reflex	1	3
Functional	0	0
Urge + stress	97	116
Urge + functional	0	5
Urge + stress + functional	0	8
Urge + stress + retention	0	2
Urge + reflex + retention	0	1
Urge + total	0	3
Urge + retention	0	4
Stress + retention	0	1
Reflex + total	0	1
Reflex + retention	0	1
Total	195	195

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Table 4

Concordance of the proposed model with the opinion of experts (*n* = number of cases diagnosed).

Result	*n*	%
Total concordance	121	62.1
Partial concordance	64	32.8
Total discordance	10	5.1
Total	195	100.0

Table 5

Sensitivity and specificity of the fuzzy cognitive map in the determination of diagnoses related to alterations in urinary elimination.

Diagnosis	Sensitivity	Specificity
Urge	1	0.43
Stress	0.95	0.93
Reflex	1	0.97
Total	0.42	1
Retention	1	0.98
General	0.95	0.92