Med Biol Eng Comput (2013) 51:657–664
DOI 10.1007/s11517-013-1035-8

ORIGINAL ARTICLE

Bayesian networks: a new method for the modeling of bibliographic knowledge

Application to fall risk assessment in geriatric patients

Laure Lalande · Laurent Bourguignon · Chloé Carlier · Michel Ducher

Received: 6 July 2012 / Accepted: 6 January 2013 / Published online: 20 January 2013

Abstract Falls in geriatry are associated with important morbidity, mortality and high healthcare costs. Because of the large number of variables related to the risk of falling, determining patients at risk is a difficult challenge. The aim of this work was to validate a tool to detect patients with high risk of fall using only bibliographic knowledge. Thirty articles corresponding to 160 studies were used to modelize fall risk. A retrospective case–control cohort including 288 patients (88 ± 7 years) and a prospective cohort including 106 patients (89 ± 6 years) from two geriatric hospitals were used to validate the performances of our model. We identified 26 variables associated with an increased risk of fall. These variables were split into illnesses, medications, and environment. The combination of the three associated scores gives a global fall score. The sensitivity and the specificity were 31.4, 81.6, 38.5, and 90 %, respectively, for the retrospective and the prospective cohort. The performances of the model are similar to results observed with already existing prediction tools using model adjustment to data from numerous cohort studies. This work demonstrates that knowledge from the literature can be synthesized with Bayesian networks.

Keywords Bayesian network · Fall risk · Geriatrics

L. Lalande · L. Bourguignon · C. Carlier · M. Ducher (✉)
Hospices Civils de Lyon, Groupement Hospitalier de Gériatrie, Service Pharmacie 40 Avenue de La Table de Pierre, 69340 Francheville, France
e-mail: michel.ducher@chu-lyon.fr

1 Introduction

About one-third of people aged over 65 years and living in the community fall at least once a year [1–3]. Fall risk increases with age (50 % people aged over 80 fall) [1, 2]. Falls are also more frequent among people institutionalized (nursing homes, hospitals) [4, 5]. Half of the people falling are recurrent fallers [1].

The consequences of falling in this population are various. Approximately 10–25 % of falls result in major injuries such as fractures, lacerations requiring sutures, head traumas, hematomas, etc [1, 6–8]. The most frequent fracture is hip fracture with potentially severe consequences: about 20 % of individuals with a hip fracture die within a year, and another 20 % move into some aged care institution for the first time [2]. Falls are thus associated with important morbidity, mortality and high healthcare costs related to the need for hospitalization and treatment [3]. Even if no physical injury occurs, falls can have a negative impact on daily life activities and quality of life as fallers develop a fear of falling which promotes inactivity. This can lead to loss of function, unnecessary dependency, social isolation and thus new falls or increased susceptibility to disease [4, 6, 9]. Classifying patients according to their fall risk level is the first step to organize appropriate prevention actions.

A small number of falls have a single cause, and in most cases they present a multi-factorial etiology [1, 3, 6]. They are the result of complex interactions between intrinsic and extrinsic factors [4]. Intrinsic factors are those related to the individual such as medical conditions known to be associated with an increased risk of falling and medications known to facilitate falls [1, 3, 6]. Extrinsic factors are those associated with environmental features [1, 6].

Because of the large number of variables related to the risk of falling, and because results vary from one study to

another [10], determining the patients at risk, especially when they do not have a fall history, is a difficult challenge for health care providers. Multifactorial fall risk assessment has already been developed but most existing tools have not been externally validated [11, 12], their development has relied on the retrospective reporting of falls [13, 14], some are too time consuming or equipment-dependent [15], and some others have been validated only in specific populations [14]. The aim of this work was to build a bibliographic-based tool that is able to identify older adults with high risk of falls; this tool would integrate numerous risk factors based on literature data, in order to obtain a fall risk assessment, giving robust results whatever the settings.

2 Methods

2.1 Literature search

A literature search was conducted with the Medline database (from 2000 to 2010) using the search terms falls, elderly, risk factors, medications, or diseases. Additional articles were identified by hand searching of bibliographic references. Abstracts of all articles identified in English or French by the search were reviewed; meta-analysis and studies which had determined odds ratio between falls and some risk factors were selected. We identified the most frequent factors implicated and then we looked for articles, reviews, and reports which focused either on medications or on medical conditions or on both. Altogether, data from approximately 160 studies were pooled and the variables identified were divided into three main categories: medications, diseases, and environment (living place, fall history).

2.2 Modeling

Bayesian networks belong to the family of graphical models. The network structure can be described as follows: each node in the graph represents a variable, while the edges between the nodes represent probabilistic dependencies among the corresponding variables.

Network is then defined by- an acyclic graph G,

$$G = G(V,\ E)$$

with V the set of n nodes of G, and E the set of edges of G,- a finite space of probabilities (p) noted (Ω, p),- variables linked to the node (edges) of graph which were defined on (Ω, p) as

$$p(V1,\ V2,\ \ldots ..Vn)\ = \Pi_{i=1\ldots n} p(Vi \mid C(Vi))$$

with $C(Vi)$ the set of variables related (parent of Vi) to Vi in the graph.

The specific interest of Bayesian networks is that they take into account knowledge from experts and also knowledge contained in data [16, 17].

In this work, we used a decision network also known as an "influence diagram" made of decision nodes and utility nodes. Decision nodes correspond to variables or events that will be predicted.

Netica® 2.05 software (Norsys Corporation, https://www.norsys.com) was used for modeling the fall risk.

The network was built as follows: the three categories of variables are represented by three utility nodes. Each variable is linked to a utility node, and the three utility nodes are directly associated with the decision variable (fall). A utility node is a node in the network whose expected value is to be maximized while searching for the best decision rule for each of the child nodes. A value taken by a variable X_j depends on the value taken by variable X_i. Node X_i can be referred to as "parent of X_j" and X_j referred to as "child of X_i" [18]. In our network, each variable had two possible issues (yes or no).

According to the strength of the association between a variable and the target variable (fall), an odd ratio for each variable was calculated from the data available in the articles. Those odds ratios enabled us to fill in the probabilistic tables. As much as possible, the odds ratio recorded from the literature was adjusted for age, sex, medical conditions, and other medications, to avoid redundancy and give an overestimated result. We chose factors which were clearly identified as increasing the risk of fall and we eliminated the variables for which the implication was still debated in the literature. The target variable (fall) was associated with a global fall score (GFS) whose value is proportional to the risk of falling. Once the network is built, a decision rule is found for the decision node.

2.3 Fall risk assessment

Once our network was elaborated, its ability to predict falls in elderly subjects was tested on two geriatric cohorts from two French geriatric hospitals: a retrospective case–control cohort and a prospective one followed during 3 months. Patients included in the retrospective case–control cohort were patients hospitalized in a geriatric unit during the year 2008. Cases were patients for whom a fall had been declared between January and June 2008. Controls were patients who had not fallen during this period and they were matched with the cases, given their gender, care unit and hospitalization date. For each patient of the two cohorts, anthropometric data (age, gender), and hospitalization information were collected. All the medical prescriptions were analyzed and the medications potentially implicated in falls were searched. For the prospective

cohort, at the inclusion, a GFS was calculated for each patient to predict a possible fall. Three months later, observed falls were compared with the network predictions. During the 3-month follow-up, medical prescriptions were checked in case of any medication change with special attention given to fall-inducing drugs. Two-hundred and eighty-eight patients were included in the retrospective cohort (144 cases and 144 controls) and 106 in the prospective cohort.

2.4 Performances of the network

2.4.1 Assessment of the beliefs of the model

Probabilistic tables are provided for each node, which express the probabilities of that node taking on each of its values. Table of probabilities showing the network knowledge is presented later in the article (Table 2).

2.4.2 Quantification of the linkage between nodes

The Kullback–Leibler distance or relative entropy is a non-symmetric measure of the difference between two variables P and Q with a probability distributions noted p and π, respectively. Specifically, the Kullback–Leibler divergence (l) of π from p is a measure of the global information lost when Q is used to approximate P.

$$l(p,\pi) = \sum_i piLn(\frac{pi}{\pi i})$$

The Kullback–Leibler distance is used to asses the degree of dependence between two variables of the network [19].

2.4.3 Evaluation of the predictive ability of our model

The ability of our network to predict falls was evaluated using ROC (Receiver Operating Characteristic) curves. An ROC curve graphically displays the relationship between sensitivity (y axis) and 1-specificity (x axis) and provides the opportunity to select the point that best represents the trade-off between the ability to detect the positives (sensitivity) against the failure to detect the negatives (specificity). The area under an ROC curve can be used as an overall estimate of its discriminating ability and sometimes is expressed as accuracy. For both cohorts, sensitivity and specificity for the best cut-off value, area under the ROC curve, positive predictive values (*PPV* proportion of those classified as high risk who fell), and negative predictive values (*NPV* proportion of those classified as low risk who did not fall) were calculated. We also calculated the Youden index and the total predictive accuracy. All analyses were performed using Medcalc software bvba (11.0.1, https://www.medcalc.be).

3 Results

3.1 Literature search

The analysis of 160 studies enabled us to identify 26 variables associated with an increased risk of falling (Table 1). Only predisposing factors were looked at, triggering factors such as slipping floors or inappropriate shoes were eliminated as they were not permanent elements.

The variables were divided into three categories:

- Illnesses: Parkinson's disease [6, 20], diabetes [6, 21], Alzheimer's disease or dementia [3, 6, 20, 22], gait or balance disorders [6, 7, 20], seizures [6], incontinence or urinary tract disorders [6], eye disorders (visual impairment) [6, 20], depression [4, 6, 9, 23], psychosis [6].
- Medications: cardiovascular drugs[2, 24] (β-blockers [1, 25, 26], antiarrhythmics [1, 5, 25], digoxin [1, 2, 5, 7], vasodilators [2, 5, 7, 8, 25], diuretics[1, 2, 5, 25, 26]), narcotic pain killers [1, 5, 6, 24–26], non-steroidal anti-inflammatory drugs (NSAI) [1, 5, 6, 25, 26], hypnotics [1, 6, 9, 24–28], antidepressants [1, 4–6, 16, 23, 25, 26, 28], anxiolytics [4, 5, 7, 8, 16, 24–26, 28],

Table 1 Odds ratio calculated from 160 studies from the literature

Variable	Odd ratio	Standard deviation	Number of studies
Diuretics	1.13	0.18	69
Vasodilators	1.49	0.60	10
Digoxin	1.46	0.22	37
Antiarrhythmics	1.73	0.80	31
Beta-blockers	1.03	0.14	52
Narcotic pain killers	1.01	0.38	54
NSAI	1.50	0.32	53
Hypnotics	1.40	0.20	84
Antidepressants	1.73	0.42	127
Anxiolytics	1.80	0.38	72
Neuroleptics	1.96	0.63	121
Parkinson's disease	3.03	1.70	2
Diabetes	1.18	0.07	1 (11,390 patients)
Seizures	2.22	0.13	1 (11,390 patients)
Incontinence	1.10	0.06	1 (11,390 patients)
Gait disorders	1.35	0.50	3
Visual impairment	1.57	0.45	3
Alzheimer's disease	2.05	1.09	4
Living place	1.30	0.34	5
Previous falls	2.10	0.40	6

Odds ratio obtained from the literature for each variable; they are expressed as mean and standard deviation. The number of studies used to determine the odds ratio for each variable is given

NSAI non-steroidal anti-inflammatory

neuroleptics [1, 3–6, 25, 26, 28], anti-parkinsonian drugs [5, 6, 24, 25], anti-diabetics [6, 7], anti-Alzheimer's disease [5, 6, 25], anticonvulsants [6, 7, 16, 25].
– Other: living place [2], previous falls [20].

The network is represented in Fig. 1. The threshold value of the decision rule is 167 for our network. The probability tables of the network are given in Table 2.

3.2 Predicting abilities of the network on the retrospective cohort

The characteristics of the retrospective cohort are given in Table 3.

On the retrospective cohort, the network showed 33.3 % sensitivity and 82.3 % specificity for the best cut-off value. The area under the ROC curve was 0.589 (Table 4). The network displays a 0.156 Youden index and a 58.1 % predictive accuracy.

3.3 Predicting abilities of the network on the prospective cohort

The characteristics of the prospective cohort are given in Table 3.

On the prospective cohort, the network showed 38.5 % sensitivity and 90 % specificity for the best cut-off value. The area under the ROC curve was 0.671. The maximized PPV and NPV of the network are 29 and 89 %, respectively (Table 4). The network displays a 0.285 Youden index and a 76.4 % predictive accuracy.

The amount of dependence between the different nodes quantified by the Kullback–Leibler coefficient is given in Table 5.

4 Discussion

People aged over 65 years are the fastest growing segment of the population. Costs and consequences resulting from falls are thus increasingly important.

The developed Bayesian network synthesizes data from the literature and results in a screening tool with good levels of reliability (90 % specificity). Concerning the development of our tool, numerous heterogeneous variables with no hypothesis on their distribution were available. Besides, bibliographic data do not give individual values. Given these initial conditions, Bayesian network was the most appropriate tool, and to our knowledge, this is the first time Bayesian networks are used to synthesize bibliographic data regarding elderly falls.

Recently, Bayesian networks have been used to develop diagnostic and prognostic tools. There is a growing interest in Bayesian networks in a variety of research fields for medical decision support: pancreatic cancer prediction [17], diagnosis of appendicitis [29], classification of mammographic finding in terms of benign or malignant [30], prediction of the outcome of pregnancies of unknown location [31], diagnosis of asthma exacerbations [32], survival estimation of patients with skeletal metastases [33], prediction of the risk of death in patients with sickle

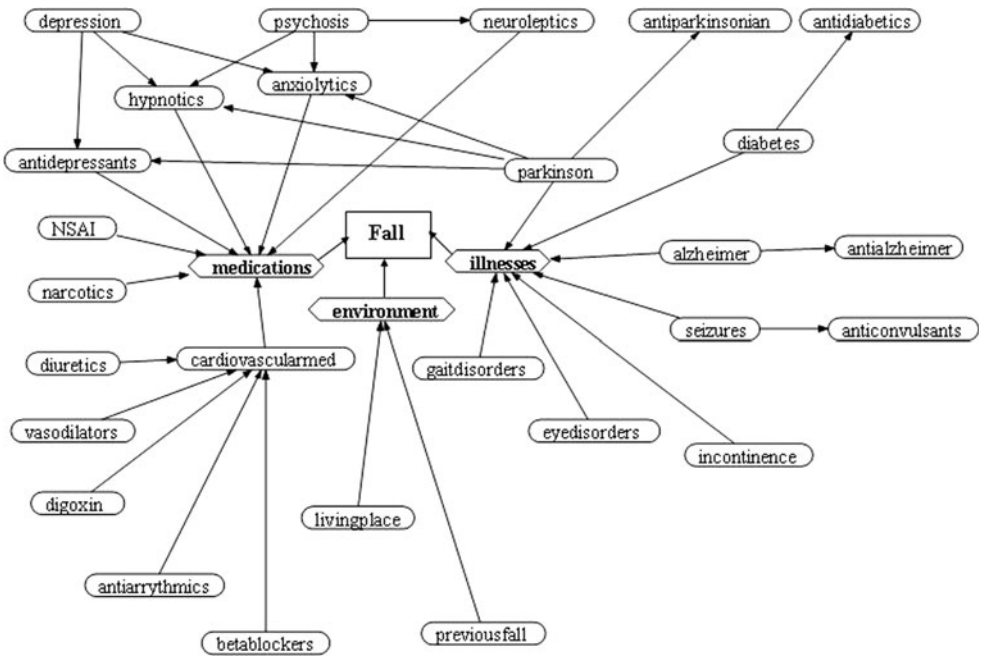

Fig. 1 Bayesian network for fall risk assessment. The decision node of the network is 'fall'. The three utility nodes are medications, diseases and environment. The *black bars* represent the probabilities' distribution obtained with the odds ratio from the literature

Table 2 Probability tables included in the network

	Yes	No
NSAI	0.06	0.94
Alzheimer	0.05	0.95
Anti-alzheimer	0.125	0.875
Anti-arythmics	0.12	0.88
Anticonvulsants	0.404	0.596
Antidepressants	0.416	0.584
Antidiabetics	0.082	0.918
Antiparkinsonian	0.163	0.837
Anxiolytics	0.426	0.574
Beta-blockers	0.2	0.8
Cardiovascular medications	0.138	0.862
Depression	0.15	0.85
Diabetes	0.05	0.95
Digoxin	0.14	0.86
Diuretics	0.3	0.7
Eye disorders	0.3	0.7
Gait disorders	0.04	0.96
Hypnotics	0.256	0.744
Incontinence	0.25	0.75
Narcotics	0.09	0.91
Neuroleptics	0.259	0.741
Parkinson	0.02	0.98
Previous fall	0.4	0.6
Psychosis	0.02	0.98
Seizures	0.01	0.99
Vasodilators	0.1	0.9
	Institution	Home
Living place	0.1	0.9

Probabilistic tables are provided for each node, which express the probabilities of that node taking on each of its values

cell disease [34], and role of overcrowding on bacterial transmission [35]. Most of the times, Bayesian networks were based on demographic, clinical, biological, or radiological parameters. Some studies compared different subsets of variables to select the best predicting ones [31]. Definition of risk variables was usually based on data [30–34], and rarely based on expert knowledge, literature [17], or a combination of these [29].

Table 4 Performance analysis of the network for both cohorts

	Retrospective cohort	Prospective cohort
Average fall score	215	238
Sensitivity (ROC)	33.3 %	38.5 %
Specificity (ROC)	82.3 %	90 %
AUC	0.589	0.671
p value (AUC)	0.0075	0.0045
PPV	–	29 %
NPV	–	89 %

ROC receiver operating characteristic, *AUC* area under curve, *PPV* positive predictive value, *NPV* negative predictive value

Some authors [36] have already used Bayesian networks to estimate the risk of falls. In this article, they compared the model obtained from expert knowledge and the model obtained from real data. But they only focused on specific variables: gait data. Moreover, these networks were built on a small sample of patients, and validation was only performed by re-sampling methods. Our network integrated different types of variables and was built using bibliographic data. Indeed, Bayesian networks based on bibliographic knowledge have proven their ability to outperform conventional predicting tools [17].

Many studies focused on the risk factors associated with falls. Even if some meta-analysis were carried out, most of the time, studies target a group of risk factors such as a family of medications or some specific illnesses [8, 21, 22]. The implication of medications is often hard to define as drug effects cannot always be distinguished from the underlying medical condition. Hence, this network integrates both medications and medical conditions. Fall prediction implies analyzing very heterogeneous variables (continuous, binomial, ranging). Bayesian networks were thus chosen because they can integrate a large quantity of heterogeneous data [19, 37]. Besides, even if no information is available for some variables, they can still give a result [38]. This is of major interest in clinical practice as information about a patient is often incomplete. Finally, our Bayesian network is easy to use, both in the number of items and their measurement, and is not time consuming. It is designed for use by clinical and non-clinical health care professionals with minimum training and is particularly suited to primary care.

Table 3 Cohort characteristics

		Age	Number of medications	Number of patients	Falls prevalence
Retrospective case–control cohort	Cases	88± 7 years	11 ± 4	144	–
	Controls	87± 7 years	12 ± 4	144	–
Prospective cohort		89 ± 6 years	10 ± 4	106	25 %

Age and number of medications are expressed as mean and standard deviation

Table 5 Dependence between nodes quantified by the Kullback–Leibler coefficient

Parent node	Child node	Kullback–Leibler
Previous fall	Environment	0.369746
Medications	Fall	0.222704
Antiarrhythmics	Cardiovascular drug	0.097808
Diabetes	Antidiabetics	0.094786
Illnesses	Fall	0.088555
Depression	Anxiolytics	0.075295
Depression	Antidepressants	0.060269
Digoxin	Cardiovascular drug	0.055677
Neuroleptics	Medications	0.053971
Anxiolytics	Medications	0.050235
Alzheimer	Antialzheimer	0.049471
Vasodilators	Cardiovascular drug	0.047754
Antidepressants	Medications	0.042543
Environment	Fall	0.039582
Depression	Hypnotics	0.038854
Eye disorders	Illnesses	0.030872
Alzheimer	Illnesses	0.029889
Parkinson	Anti parkinsonian	0.029356
Living place	Environment	0.016375
Parkinson	Illnesses	0.014095
Diuretics	Cardiovascular drug	0.013099
Psychosis	Neuroleptics	0.012555
Cardiovascular drug	Medications	0.011594
Hypnotics	Medications	0.011264
Psychosis	Hypnotics	0.008421
NSAI	Medications	0.005722
Psychosis	Anxiolytics	0.005444
Seizures	Illnesses	0.005160
Seizures	Anticonvulsants	0.004782
Parkinson	Antidepressants	0.004766
Gait disorders	Illnesses	0.002837
Parkinson	Hypnotics	0.002753
Parkinson	Anxiolytics	0.001968
Incontinence	Illnesses	0.000706
Diabetes	Illnesses	0.000692
Beta-blockers	Cardiovascular drug	0.000592
Narcotics	Medications	0.000007

Nevertheless, this tool presents some limits. First, medications were considered without taking into account the medication dose, the treatment duration or the number of medications belonging to the same family prescribed to the patient. Indeed, data available in the literature about these variables are quite rare and sometimes inexistent.

Furthermore, there is a limitation in the ability to predict falls from an overall score consisting of several risk factors because of the diversity pattern of fall causes among individuals [13]. Among active seniors, fall risk tends to be mostly related to mobility status, exposure to hazardous environments, and risk-taking behaviors [11]. These risk factors were not integrated to the network as they were occasional.

Several fall predicting tools have already been developed. A prediction tool should ideally have the following characteristics:[11, 39, 40] ease of completion, high adherence by staff, high inter-rater reliability, a transparent calculation of risk score based on the operational properties of the tool (and not arbitrarily assigned values), and prospective validation for predictive validity. To our knowledge, no such tool exists. Performances of existing tools have already been compared but their generalizability is limited because only a few have been tested in settings other than those in which they were originally developed such as the STRATIFY tool and the Morse Fall Scale [11, 39–43]. Some studies with an external validation were retrospective fitting of risk assessment applied to original data [13, 14], they did suggest useful predictive power but this was not confirmed by subsequent prospective validation. In addition, the external prospective validation tends to show that the tool may progressively be less effective in settings remote from the original cohort; [15, 39, 42] the heterogeneity of settings makes risk assessment tools not so effective when employed in settings or populations different from those used in the original study [40].

Different computational methods for disease diagnosis are currently used in practice such as logistic regression, decision tree, neural network, or expert-guided models. Bayesian networks have several advantages over these methods: they do not require a minimum sample size to perform the analysis and are theoretically suitable for small and incomplete data sets, they can combine different sources of knowledge, and they provide fast response once the model is compiled [44]. Applied to real data, Bayesian network have proven their ability to outperform logistic regression [29, 31], neural network [29], or expert knowledge [30, 36] in terms of diagnosis prediction. As Bayesian networks based on literature knowledge also have better performances than Bayesian networks based on data, we expect our network to provide more accurate results than any other tool for fall prediction.

The predicting ability of our network is roughly the same on both cohorts, though slightly better on the prospective cohort. The predictive validity of the already existing tools to predict falls is heterogeneous: sensitivities reported vary from 19.2 to 93.1 % and specificities from 22 to 96 % [11–15, 39, 41–43, 45]. Our network displays NPV of approximately 90 %; this result enables our network to be a powerful tool to focus monitoring on patients who are the most at risk.

Our network was initially developed from bibliographic data and then validated on two independent geriatric cohorts, that is to say, the information from these cohorts were not used to build the network. Both cohorts included geriatric hospitalized patients from two different settings. We expect our network predictions to be more effective on different populations than previously developed tools. In this manner, this tool could have a general use with good levels of reliability.

As a conclusion, this work proves that knowledge from the literature can be synthesized thanks to Bayesian networks. The obtained network can have clinical applications given its specificity. This tool could be used to focus monitoring and prevention actions on patients who are the most at risk. The robustness of our results demonstrates that it should be easier to generalize our tool for fall prediction in different settings.

Acknowledgments LL conducted the literature search, designed the network, performed the statistical analyses, and wrote the manuscript. LB helped with the analyses and the writing. CC supervised the data collection. MD had the idea for the study, supervised the study, co-supervised the analyses, and helped for the writing. All authors read and approved the final version of the manuscript.

Conflict of interest None.

References

1. Société française de gériatrie et gérontologie/HAS. Recommandations de bonnes pratiques professionnelles: evaluation et prise en charge des personnes âgées faisant des chutes répétées. April 2009. http://www.has-sante.fr/portail/jcms/c_793371/evaluation-et-prise-en-charge-des-personnes-agees-faisant-des-chutes-repetees. (Accessed 26 Jun 2012)
2. Cumming RG (1998) Epidemiology of medication-related falls and fractures in the elderly. Drugs Aging 12(1):43–53
3. Formiga F, Navarro M, Duaso E, Chivite D, Ruiz D, Perez-Castejon JM, Lopez-Soto A, Pujol R (2008) Factors associated with hip fracture-related falls among patients with a history of recurrent falling. Bone 43(5):941–944
4. Daal JO, Van Lieshout JJ (2005) Falls and medications in the elderly. Neth J Med 63(3):91–96
5. Walker PC, Alrawi A, Mitchell JF, Regal RE, Khanderia U (2005) Medication use as a risk factor for falls among hospitalized elderly patients. Am J Health Syst Pharm 62(23):2495–2499
6. Kelly KD, Pickett W, Yiannakoulias N, Rowe BH, Schopflocher DP, Svenson L, Voaklander DC (2003) Medication use and falls in community-dwelling older persons. Age Ageing 32(5):503–509
7. Koski K, Luukinen H, Laippala P, Kivelä SL (1996) Physiological factors and medications as predictors of injurious falls by elderly people: a prospective population-based study. Age Ageing 25(1):29–38
8. Pariente A, Dartigues JF, Benichou J, Letenneur L, Moore N, Fourrier-Réglat A (2008) Benzodiazepines and injurious falls in community dwelling elders. Drugs Aging 25(1):61–70
9. Fonad E, Wahlin TB, Winblad B, Emami A, Sandmark H (2008) Falls and fall risk among nursing home residents. J Clin Nurs 17(1):126–134
10. Baranzini F, Diurni M, Ceccon F, Poloni N, Cazzamalli S, Costantini C, Colli C, Greco L, Callegari C (2009) Fall-related injuries in a nursing home setting: is polypharmacy a risk factor? BMC Health Serv Res 9:228
11. Scott V, Votova K, Scanlan A, Close J (2007) Multifactorial and functional mobility assessment tools for fall risk among older adults in community, home-support, long-term and acute care settings. Age Ageing 36(2):130–139
12. Bongue B, Dupré C, Beauchet O, Rossat A, Fantino B, Colvez A (2011) A screening tool with five risk factors was developed for fall-risk prediction in community-dwelling elderly. J Clin Epidemiol 64(10):1152–1160
13. Demura S, Sato S, Shin S, Uchiyama M. (2011) Setting the criterion for fall risk screening for healthy community-dwelling elderly. Arch Gerontol Geriatr
14. Edmonson D, Robinson S, Hughes L (2011) Development of the Edmonson psychiatric fall risk assessment tool. J Psychosoc Nurs Ment Health Serv 49(2):29–36
15. Marschollek M, Rehwald A, Wolf KH, Gietzelt M, Nemitz G, zu Schwabedissen HM, Schulze M et al (2011) Sensors vs experts—a performance comparison of sensor-based fall risk assessment vs conventional assessment in a sample of geriatric patients. BMC Med Inform Decis Mak 11:48
16. Ensrud KE, Blackwell TL, Mangione CM, Bowman PJ, Whooley MA, Bauer DC, Schwartz AV, Hanlon JT, Nevitt MC, Study of Osteoporotic Fractures Research Group (2002) Central nervous system-active medications and risk for falls in older women. J Am Geriatr Soc 50(10):1629–1637
17. Zhao D, Weng D (2011) Combining Pubmed knowledge and EHR data to develop a weighted Bayesian network for pancreatic cancer prediction. J Biomed Inform 44(5):859–868
18. Ben-Gal I (2007) Bayesian networks. In: Ruggeri F, Faltin F, Kenett R (eds) Encyclopedia of Statistics in Quality and Reliability, Wiley, London
19. Minh N Do (2003) Approximation of Kullback–Leibler distance for dependence trees and Hidden Markov Model. IEEE signal process lett, pp 115–118
20. Ganz DA, Bao Y, Shekelle PG, Rubenstein LZ (2007) Will my patient fall? JAMA 297(1):77–86
21. Schwartz AV, Vittinghoff E, Sellmeyer DE, Feingold KR, de Rekeneire N, Strotmeyer ES, Shorr RI, Vinik AI, Odden MC, Park SW, Faulkner KA, Harris TB et al (2008) Diabetes-related complications, glycemic control, and falls in older adults. Diabetes Care 31(3):391–396
22. Allan LM, Ballard CG, Rowan EN, Kenny RA (2009) Incidence and prediction of falls in dementia: a prospective study in older people. PLoS ONE 4(5):e5521
23. Darowski A, Chambers SA, Chambers DJ (2009) Antidepressants and falls in the elderly. Drugs Aging 26(5):381–394
24. Tanaka M, Suemaru K, Ikegawa Y, Tabuchi N, Araki H (2008) Relationship between the risk of falling and drugs in an academic hospital. Yakugaku Zasshi 128(9):1355–1361
25. French DD, Campbell R, Spehar A, Cunningham F, Bulat T, Luther SL (2006) Drugs and falls in community-dwelling older people: a national veterans study. Clin Ther 28(4):619–630
26. Woolcott JC, Richardson KJ, Wiens MO, Patel B, Marin J, Khan KM, Marra CA et al (2009) Meta-analysis of the impact of 9 medication classes on falls in elderly persons. Arch Intern Med 169(21):1952–1960
27. Mets MAJ, Volkerts ER, Olivier B, Verster JC (2010) Effect of hypnotic drugs on body balance and standing steadiness. Sleep Med Rev 14(4):259–267

28. Vitry AI, Hoile AP, Gilbert AL, Esterman A, Luszcz MA (2010) The risk of falls and fractures associated with persistent use of psychotropic medications in elderly people. Arch Gerontol Geriatr 50(3):e1–e4
29. Sakai S, Kobayashi K, Nakamura J, Toyabe S, Akazawa K (2007) Accuracy in the diagnostic prediction of acute appendicitis based on the Bayesian network model methods. Inf Med 46:723–726
30. Burnside ES, Davis J, Chhatwal J, Alagoz O, Linstrom MJ, Geller BM et al (2009) Probabilistic computer model developed from clinical data in national mammography database format to classify mammographic findings. Radiology 251(3):663–672
31. Gevaert O, De Smet F, Kirk E, Van Calster B, Bourne T, Van Huffel S et al (2006) Predicting the outcome of pregnancies of unknown location: Bayesian networks with expert prior information compared to logistic regression. Hum Reprod 21(7):1824–1831
32. Sanders DL, Aronsky D (2006) Prospective evaluation of a Bayesian network for detecting asthma exacerbations in a pediatric emergency department. AMIA Symposium, p 1085
33. Forsberg JA, Eberhardt J, Boland PJ, Wedin R, Healey JH (2011) Estimating survival in patients with operable skeletal metastases: an application of a Bayesian belief network. PLoS ONE 6(5):e19956
34. Sebastiani P, Nolan VG, Baldwin CT, Abad-Grau MM, Wang L, Adewoye AH et al (2007) A network model to predict the risk of death in sickle cell disease. Blood 110(7):2727–2735
35. Waterhouse M, Morton A, Mengersen K, Cook D, Playford G (2011) Role of overcrowding in meticillin-resistant *Staphylococcus aureus* transmission: Bayesian network analysis for a single public hospital. J Hosp Infect 78:92–96
36. Cuaya G, Munoz-Melendez A, Nunez Carrera L, Morales EF, Quinones I, Perez AI, et al (2012) A dynamic Bayesian network for estimating the risk of falls from real gait data. Med Biol Eng Comput [Epub ahead of print]
37. Siegelmann HT, Holzman LE (2010) Neuronal integration of dynamic sources: Bayesian learning and Bayesian inference. Chaos 20(3):037112
38. Naïm P, Wuillemin PH, Leray P, Pourret O, Becker A (2007) In Eyrolles. Réseaux bayésiens. Algorithmes
39. Oliver D, Papaioannou A, Giangregorio L, Thabane L, Reizgys K, Foster G (2008) A systematic review and meta-analysis of studies using the STRATIFY tool for prediction of fall in hospital patients: how well does it work. Age Ageing 37(6):621–627
40. Oliver D, Daly F, Martin FC, McMurdo MET (2004) Risk factors and risk assessment tools for falls in hospital in-patients: a systematic review. Age Ageing 33(2):122–130
41. Schwendimann R, De Geest S, Milisen K (2006) Evaluation of the Morse Fall Scale in hospitalized patients. Age Ageing 35(3):311–313
42. Webster J, Courtney M, O'Rourke P, Marsh N, Gale C, Abbott B, McRae P, Mason K et al (2008) Should elderly patients be screened for their 'falls risk'? Validity of the STRATIFY falls screening tool and predictors of falls in a large acute hospital. Age Ageing 37(6):702–706
43. Milisen K, Staelens N, Schwendimann R, De Paepe L, Verhaeghe J, Braes T, Boonen S, Pelemans W, Kressig RW, Dejaeger E (2007) Fall prediction in inpatients by bedside nurses using the St Thomas's risk assessment tool in falling elderly inpatients (STRATIFY) instrument: a multicenter study. J Am Geriatr Soc 55(5):725–733
44. Uusitalo L (2007) Advantages and challenges of Bayesian networks in environmental modelling. Ecol Model 203:312–318
45. Muir SW, Berg K, Chesworth B, Klar N, Speechley M (2010) Application of a fall screening algorithm stratified fall risk but missed preventive opportunities in community-dwelling older adults: a prospective study. J Geriatr Phys Ther 33(4):165–172