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Bayesian Techniques in Predicting Frailty among Community-Dwelling Older Adults in the Netherlands

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ABSTRACT

Background Frailty is a syndrome that is defined as an accumulation of deficits in physical, psychological, and social domains. On a global scale, there is an urgent need to create frailty-ready healthcare systems due to the healthcare burden that frailty confers on systems and the increased risk of falls, healthcare utilization, disability, and premature mortality. Several studies have been conducted to develop prediction models for predicting frailty. Most studies used logistic regression as a technique to develop a prediction model. One area that has experienced significant growth is the application of Bayesian techniques, partly due to an increasing number of practitioners valuing the Bayesian paradigm as matching that of scientific discovery.

Objective We compared ten different Bayesian networks as proposed by ten experts in the field of frail elderly people to predict frailty with a choice from ten dichotomized determinants for frailty.

Methods We used the opinion of ten experts who could indicate, using an empty Bayesian network graph, the important predictors for frailty and the interactions between the different predictors. The candidate predictors were age, sex, marital status, ethnicity, education, income, lifestyle, multimorbidity, life events, and home living environment. The ten Bayesian network models were evaluated in terms of their ability to predict frailty. For the evaluation, we used the data of 479 participants that filled in the Tilburg Frailty indicator (TFI) questionnaire for assessing frailty among community-dwelling older people. The data set contained the aforementioned variables and the outcome "frail". The model fit of each model was measured using the Akaike information criterion (AIC) and the predictive performance of the models was measured using the area under the curve (AUC) of the receiver operator characteristic (ROC). The AUCs of the models were validated using bootstrapping with 100 repetitions. The relative importance of the predictors in the models was calculated using the permutation feature importance algorithm (PFI).

Results The ten Bayesian networks of the ten experts differed considerably regarding the predictors and the connections between the predictors and the outcome. However, all ten networks had corrected AUCs >0.700. Evaluating the importance of the predictors in each model, "diseases or chronic disorders" was the most important predictor in all models (10 times). The predictors "lifestyle" and "monthly income" were also often present in the models (both 6 times). One or more diseases or chronic disorders, an unhealthy lifestyle, and a monthly income below 1800 euro increased the likelihood of frailty.

Conclusions Although the ten experts all made different graphs, the predictive performance was always satisfying (AUCs >0.700). While it is true that the predictor importance varied all the time, the top three of the predictor importance consisted of "diseases or chronic disorders", "lifestyle" and "monthly income". All in all, asking for the opinion of experts in the field of frail elderly to predict frailty with Bayesian networks may be more rewarding than a data-driven forecast with Bayesian networks because they have expert knowledge regarding interactions between the different predictors.

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1. Introduction

Often characterized as one of the modern geriatric giants Won (2019), frailty is a syndrome Morley (2016); Ofori-Asenso et al. (2019) which is defined as an accumulation of deficits Rockwood and Mitnitski (2007) in physical, psychological, and social domains Gobbens et al. (2012b, 2010b). On a global scale, there is an urgent need to create frailty ready-healthcare systems Lim et al. (2017) due to the healthcare burden that frailty confers on systems and adverse outcomes among older people such as increased risk of falls Naharci and Tasci (2020), healthcare utilization Ensrud et al. (2018, 2020), disability Vermeulen et al. (2011), premature mortality Vermeiren et al. (2016), and decreased quality of life (QOL) Kojima et al. (2016). Over the past three decades, there has been a significant increase in literature focused on frailty; thus, what follows is a review of individual and systems-level modifiable and non-modifiable determinants of frailty across the life course representing populations in several continents (North America, Europe) Abeliansky et al. (2021); Aranda et al. (2011); Ensrud et al. (2018, 2020); Mian et al. (2021); Van Der Linden et al. (2018). In the review below, frailty measurement has been varied Fried et al. (2001); Gobbens et al. (2010b); Rockwood and Mitnitski (2007), however, contributes importantly to the literature because gaining a holistic understanding of life course predictors of frailty among heterogenous community-dwelling older adults and underserved communities is an upstream approach to identify viable interventions and develop responsive healthcare systems.

1.1. Individual level factors

1.1.1. Early adverse childhood events (ACEs) and the impact on frailty

Previous research has established that early adverse life events have a long-term impact on frailty Mian et al. (2021); Van Der Linden et al. (2018). Adverse childhood experiences (ACEs) which can include traumatic life events early in life such as maltreatment are predictive of frailty Mian et al. (2021); Van Der Linden et al. (2018). Several longitudinal studies based in Canada and Europe have found a relationship between ACEs and frailty Mian et al. (2021); Van Der Linden et al. (2018). In one Canadian-based, cross-sectional study of adults (N=27, 748) between 45–85 years of age, individuals who were exposed to ACEs had elevated levels of frailty Mian et al. (2021). Specific types of abuse (neglect and emotional abuse) were associated with the largest increases in frailty Mian et al. (2021). Further, a difference was found between men and women; in particular, stratified analyses found that women had higher frailty rates as compared to men Mian et al. (2021). Correspondingly, in a separate study utilizing data from the Survey of Health, Aging, and Retirement in Europe (SHARE), in a sample of women (N=13,283) and men (N=10,591) aged 50 and older, ACEs were associated with frailty at older age Van Der Linden et al. (2018).

1.1.2. The intersection between comorbidity, multimorbidity, disability on frailty

While chronic disease increases the likelihood of frailty, a seminal study established that frailty is not synonymous with comorbidity or disability Fried et al. (2001). Utilizing data from the Cardiovascular Health Study (N=5,317), among those who were frail, approximately 46.2% had a comorbid disease and 26.6% had frailty independent of disability or comorbidity with 5.7% of the sample impacted by disability and frailty Fried et al. (2001). Interestingly, less than a quarter (21.5%) presented with frailty, disability, and comorbidity Fried et al. (2001). There is a bidirectional relationship between frailty and multimorbidity; in fact, multimorbidity is a risk factor for developing frailty Majid et al. (2020). Further illustrating these findings, in a separate and more recent study using a longitudinal database among Canadian adults >65 years of age and older (N=1,643), data revealed that frailty was associated with disability, comorbidity, depression, and cognitive decline Mehrabi and Béland (2021). In summary, these findings highlight the importance of distinguishing frailty from disability and comorbidity; however, considering the association between these conditions.

1.1.3. The influence of age, gender, education, income, and ethnicity on frailty

The risk of frailty increases with chronological age Collard et al. (2012); Sanford et al. (2020); Van Der Linden et al. (2018); however, can be also found among younger community-dwelling populations, and underserved communities Loecker et al. (2021); Salem et al. (2013). As individuals age, they accumulate deficits (signs, symptoms, disease, etc.) over time Rockwood and Mitnitski (2007) which increases the likelihood of multimorbidity and adverse outcomes. Among community-dwelling older populations, gender is an important contributing factor to frailty as several studies have found that women are more likely to be frail as compared to men Collard et al. (2012); Cramm and Nieboer (2013). These findings can be due in part to a combination of biological, behavioral, and social factors Gordon and Hubbard (2020). Women tend to live longer as compared to age-matched men; however, are frailer Gordon and Hubbard (2020). Several studies have found that there are associations between some sociodemographic factors (e.g., lower education, lower income, and ethnicity) and increased risk of frailty Brigola et al. (2019); Majid et al. (2020); Van Assen et al. (2016). In an Amsterdam-based, longitudinal study that enrolled 47,768 individuals aged 65 years or older, findings revealed that lower education, lower income, and ethnicity were predictive of frailty Van Assen et al. (2016). In a separate review, authors contend that ethnic minority populations in economically developed countries demonstrate higher rates of frailty as compared to White indigenous older people Majid et al. (2020). Further, some authors charge that frailty risk can be mitigated by improvements in integration, citizenship status, and access to healthcare Majid et al. (2020).

1.1.4. The impact of supportive relationships and loneliness on frailty

As a social species, human beings Abeliansky et al. (2021) oftentimes have a different type of informal support which have the potential to aid aging in place and delay professional care and nursing home placement Bonsang (2009). While longitudinal evidence on types of relationships and frailty is limited, some authors have found that marital status may indeed be a protective factor against frailty Cramm and Nieboer (2013); Kojima et al. (2020). In a cross-sectional study of community-dwelling older adults (N=945) by Cramm and Nieboer (2013) Cramm et al. (2013), data revealed that older age was associated with higher frailty; however, marital status was associated with a lower likelihood of frailty. Protective factors against frailty included a strong sense of social cohesion and neighborhood belonging (p-value <0.05) Cramm et al. (2013). A systematic review found that married men had a lower frailty risk as compared to unmarried men Kojima et al. (2020). Tangentially, high levels of loneliness increase the risk of physical frailty; in a secondary data analysis among participants >60 years of age, among men, high social isolation increases frailty risk Gale et al. (2018). Corroborating these findings, in a separate study utilizing seven waves of data from the Health and Retirement study, data reveals that social vulnerability among elderly United States-based Americans increases frailty risk Abeliansky et al. (2021).

1.2. Structural level factors

1.2.1. Social determinants of health including neighborhood characteristics and their impact on frailty

Social determinants of health (SDH), defined as conditions in the places where people live, learn, work, and play Centers for Disease Control and Prevention and others (2018) may have a disproportionate impact on geriatric syndromes including frailty. For example, among underserved communities, such as people experiencing homelessness (PEH), frailty is often found in younger ages Brown et al. (2012); Salem et al. (2013). In a Boston-based study, 16.4% of PEH (N=247) between

50 to 69 years of age met the criteria for frailty Brown et al. (2012). Corroborating these findings, in a Los Angeles-based study, among middle-aged and older PEH at least >40 years of age (N=150), 54% met the frailty criteria utilizing the Frailty Index Salem et al. (2013). Predictors of frailty include age, female gender, healthcare utilization, low nutrition, and low resilience Salem et al. (2013). Several explanations are plausible for these findings; however, have multi-level implications. Contributing modifiable and nonmodifiable factors to early onset frailty can be found at the individual level (trauma), lifestyle choices (alcohol and drug use), and systems level (health care access, access to nutritious foods, safe places to exercise). Lifestyle choices such as alcohol use are predictive of frailty. In one cross-sectional, prospective cohort study of people living with HIV in New Orleans, data revealed that lifetime alcohol exposure was associated with frailty Maffei et al. (2020). While there is a body of research on neighborhoods and health, an emerging area of inquiry is the relationship between neighborhood characteristics on frailty Fritz et al. (2020). A scoping review found that neighborhood factors contributed both directly and indirectly to frailty Fritz et al. (2020). In a Rotterdam-based, cross-sectional study of community-dwelling adults >70 years of age, data revealed that having a strong sense of social cohesion and neighborhood belonging was protective against frailty Cramm and Nieboer (2013). In a study among older Mexican adults aged 75 years and older, data revealed that there was a neighborhood advantage "barrio" which was protective against frailty Aranda et al. (2011). Taken together, across several continents representing heterogeneous populations, the extant research has demonstrated that there are multi-level determinants of frailty; however, research to date is limited on the determinants of frailty among community-dwelling, older adults in the Netherlands.

1.3. Predicting frailty

Several studies have been conducted to develop prediction models for predicting frailty and mortality connected to frailty Gobbens et al. (2021); Gobbens and Van Der Ploeg (2021a, 2021b, 2022); Van Der Ploeg et al. (2022) and most studies used logistic regression as a technique to develop a prediction model. Modern techniques such as support vector machines, random forests, and neural networks have also been used to develop good prediction models for predicting frailty Van Der Ploeg et al. (2022). One area that has experienced significant growth is Bayesian techniques Lucas et al. (2004). The growing use of Bayesian techniques has taken place partly due to an increasing number of practitioners valuing the Bayesian paradigm as matching that of scientific discovery Lesaffre and Lawson (2012). This study used the opinion of experts who could indicate, using a Bayesian network graph, the important predictors of frailty and the interactions between the different predictors. Using our data, these Bayesian networks, based on expert opinion, were evaluated in terms of their ability to predict frailty.

2. Methods

2.1. Study population and data collection

In June 2008, the Tilburg frailty indicator (TFI) was sent to a sample of 1154 community-dwelling older people aged 75 years and older randomly drawn from the register of the municipality in Roosendaal, a town of 78,000 inhabitants in the Netherlands. Previous studies have demonstrated that the TFI is a valid and reliable questionnaire for assessing frailty among community-dwelling older people Dong et al. (2017); Gobbens et al. (2012a); Santiago et al. (2013); Uchmanowicz et al. (2016). A total of 484 participants completed the questionnaire (41.94% response rate) Gobbens et al. (2010b). As in a previous study, the data from five participants were left out of the analyses as they had too many missing values, leaving a data set of 479 participants Gobbens and Van Der Ploeg (2022). Part A of the TFI was used to collect data for the ten determinants of frailty: age, sex, marital status ethnicity, education, income, lifestyle, multimorbidity, life events, and home living environment. We used part B of the TFI to assess frailty. This part contains fifteen items referring to the physical (eight items), psychological (four items), and social (three items) domains of frailty Gobbens et al. (2010a). The score ranges from zero to fifteen; with higher scores indicating greater frailty. The cut-off point for distinguishing non-frail and frail older people is five Gobbens et al. (2010a). For the complete TFI questionnaire, see appendix Appendix A.

2.2. Measures

As outcome variable, we used the dichotomized frailty score (<5: non-frail, >=5: frail) and the ten dichotomized determinants of frailty as predictors.

2.3. Models

2.3.1. Expert opinion

We asked ten experts in the field of frail elderly to draw lines in a graph of an empty Bayesian network with the ten determinants of frailty and the outcome variable frailty. The lines symbolize the presumed relation between the ten determinants mutually and the relation of the ten determinants with frailty, based on their expert opinion and experience. The experts were highly experienced and had all conducted studies in the frailty domain and are particularly familiar with assessing frailty using the TFI. For the expert background, please refer to 6. In this way, we were able to gain insight into the relationships between the determinants and the outcome variable based on the opinion of experts in the field of frail elderly and to compare their expert opinions. With our data set, we used each expert graph to develop a Bayesian network model for the prediction of frailty.

2.3.2. Bayesian network

A Bayesian network is a mathematical construct that compactly represents a joint probability distribution among a set of variables. Bayesian networks are frequently employed for modeling domain knowledge in decision support systems, particularly in medicine Cao et al. (2020); Lucas et al. (2004). Learning Bayesian networks relates to variable selection for classification and has been used to design algorithms that optimally solve the problem under certain conditions Mani et al. (2005); Scutari (2009). In a Bayesian network, the probability for Y given $X_1,...,X_p$ is calculated as:

$$P(Y|X_1,\dots,X_p) = P(Y)^* \prod_{i=1}^{p} \frac{P(X_i|Y, X_{i+1},\dots,X_p)}{P(X_1,\dots,X_p)}$$

2.4. Analysis

For all analyses, we used R version 3.4.4 R Core Team (2018) and in particular the library "bnlearn". We used the function "cpquery" in the library "bnlearn" to calculate the probabilities with the Bayesian models Scutari (2009).

2.5. Statistics

We used counts and percentages to describe the predictors. The Chi-square test was used as a univariate technique to compare the predictors and the outcome variable. A p-value <0.05 was considered significant. The model fit of each model was measured using the Akaike information criterion (AIC) Akaike (1974). Small AICs indicate a better fit. The predictive performance of the models was measured using the area under the curve (AUC) of the receiver operator characteristic (ROC) Hastie et al. (2009); Steyerberg et al. (2019). AUCs towards 1 indicate better distinctive capability and AUCs >0.700 indicate good performance. The AUCs of the models were validated using bootstrapping with 100 repetitions Efron and Tibshirani (1994).

2.6. Relative importance of the predictor variables

The relative importance of the variables in the Bayesian network model was calculated using the permutation feature importance algorithm (PFI) Breiman (2001); Fisher et al. (2018) with 100 repetitions. We used the decrease in median apparent AUC as the measure for ranking the relative importance of the variables in the Bayesian network.

2.7. Bootstrap validation

We used the bootstrap validation procedure as proposed by Efron and Tibshirani Efron and Tibshirani (1994). Here, we briefly describe this procedure. First, a model was developed on the original data set, and the AUC of that model for the original data set was calculated (apparent AUC). Then, a sample with replacement was drawn from the original data set with a size equal to the size of the original data set. This sample was called the bootstrap sample. For this bootstrap sample, the model has developed again and the AUC for that bootstrap sample was calculated (AUC development). This model was then applied to the original data set and the AUC was calculated again (AUC validation). The difference between AUC development and AUC validation is defined as the optimism of the model. By subtracting this optimism from the apparent AUC, we obtained the corrected AUC. This process was repeated 100 times.

3. Results

3.1. Characteristics

Table 1 shows the number of valid values and the number and percentage of missing values for the variables in our data set.

Table 2 shows the frequencies and the percentages for the variables in our data set after deleting the subjects with at least one missing value. The resulting data set consisted of 373 records, instead of the 479 records in the original data set. Furthermore, the *p*-values are presented.

3.2. Performance

Table 3 shows the model fit for each model as measured by the AIC. The models “Expert8” and “Expert10” showed the best AICs (-3119 and -3101 respectively). Model “Expert1” showed the worst fit (AIC -2145).

Table 4 shows the AUCs of the various models and the results of the bootstrap validation. Model “Expert10” showed the highest apparent AUC (0.906) and also the highest optimism (0.128). The models “Expert2” and “Expert7” had the highest corrected AUCs (0.783 and 0.782 respectively).

3.3. Networks and variable importance

For all but one expert, whose graph contained a cycle, this section shows the graph of the Bayesian network based on their drawing followed by a graph that shows the importance of the variables in their Bayesian network.(Fig. 1)

Table 1
Valid- and missing values.

	Valid (n)	Missing (n)	Missing (%)
Frail	445	34	7.1
Gender	479	0	0.0
Age in years	467	12	2.5
Marital status	478	1	0.2
Country of birth	477	2	0.4
Highest education level	475	4	0.8
Monthly income in euro	438	41	8.6
Lifestyle	477	2	0.4
Diseases or chronic disorders	474	5	1.0
Life events	466	13	2.7
Satisfaction home living environment	475	4	0.8

Table 2
Frequencies predictors of frailty.

	Not frail		Frail		
	n	%	n	%	p-value
Gender					
male	109	53.7	60	35.3	0.001
female	94	46.3	110	64.7	
Age in years					
<80	112	55.2	75	44.1	0.043
≥80	91	44.8	95	55.9	
Marital status					
married or cohabiting	119	58.6	67	39.4	<0.001
other	84	41.4	103	60.6	
Country of birth					
the Netherlands	200	98.5	162	95.3	0.126
other	3	1.5	8	4.7	
Highest education level					
primary or secondary	170	83.7	146	85.9	0.669
higher	33	16.3	24	14.1	
Monthly income in euro					
1801 or more	75	36.9	34	20	0.001
less than 1800	128	63.1	136	80	
Lifestyle					
healthy	177	87.2	103	60.6	<0.001
unhealthy	26	12.8	67	39.4	
Diseases or chronic disorders					
none or one	143	70.4	48	28.2	<0.001
two or more	60	29.6	122	71.8	
Life events					
none	97	47.8	67	39.4	0.129
one or more	106	52.2	103	60.6	
Satisfaction home living environment					
satisfied	199	98	163	95.9	0.361
not satisfied	4	2	7	4.1	

Table 3
AIC models.

Experts	AIC
Expert1	− 2145
Expert2	− 2654
Expert3	− 2291
Expert4	− 2268
Expert5	− 2224
Expert6	− 2368
Expert7	− 2402
Expert8	− 3119
Expert9	− 2295
Expert10	− 3101

AIC=kaike’s information criterion

4. Discussion

Often characterized as one of the modern geriatric giants, frailty is a syndrome Morley (2016); Ofori-Asenso et al. (2019) which is defined as an accumulation of deficits Rockwood and Mitnitski (2007) belonging to physical, psychological, and social domains Gobbens et al. (2012b, 2010b). On a global scale, there is an urgent need to create frailty ready-healthcare systems Lim et al. (2017) due to the healthcare burden that frailty confers on systems and increased risk of falls Naharci and Tasci (2020), healthcare utilization Ensrud et al. (2018, 2020), disability Vermeulen et al. (2011), premature mortality Masel et al. (2009), and decreased QOL Kojima et al. (2016). In this study, we evaluated prediction models based on Bayesian networks created by experts in predicting frailty in the field of community-dwelling older people. For the

Table 4
Validation models.

Model		Development			Validation			Optimism			
	app	mean	2.5%	97.5%	mean	2.5%	97.5%	mean	2.5%	97.5%	cor
Expert1	0.796	0.810	0.776	0.847	0.761	0.727	0.786	0.049	0.006	0.092	0.747
Expert2	0.885	0.916	0.881	0.944	0.814	0.790	0.838	0.102	0.064	0.139	0.783
Expert3	0.863	0.891	0.854	0.927	0.791	0.765	0.817	0.101	0.064	0.139	0.762
Expert4	0.824	0.857	0.807	0.895	0.764	0.732	0.793	0.092	0.036	0.139	0.732
Expert5	0.817	0.852	0.813	0.889	0.777	0.751	0.800	0.075	0.034	0.118	0.742
Expert6	0.849	0.888	0.843	0.928	0.792	0.761	0.817	0.096	0.057	0.140	0.753
Expert7	0.894	0.914	0.887	0.940	0.803	0.779	0.822	0.111	0.078	0.146	0.782
Expert8	0.896	0.937	0.915	0.958	0.819	0.798	0.838	0.118	0.089	0.146	0.778
Expert9	0.812	0.854	0.808	0.896	0.777	0.743	0.804	0.077	0.036	0.118	0.735
Expert10	0.906	0.945	0.923	0.965	0.818	0.787	0.844	0.128	0.092	0.167	0.778

app=Apparent AUC cor=Corrected AUC

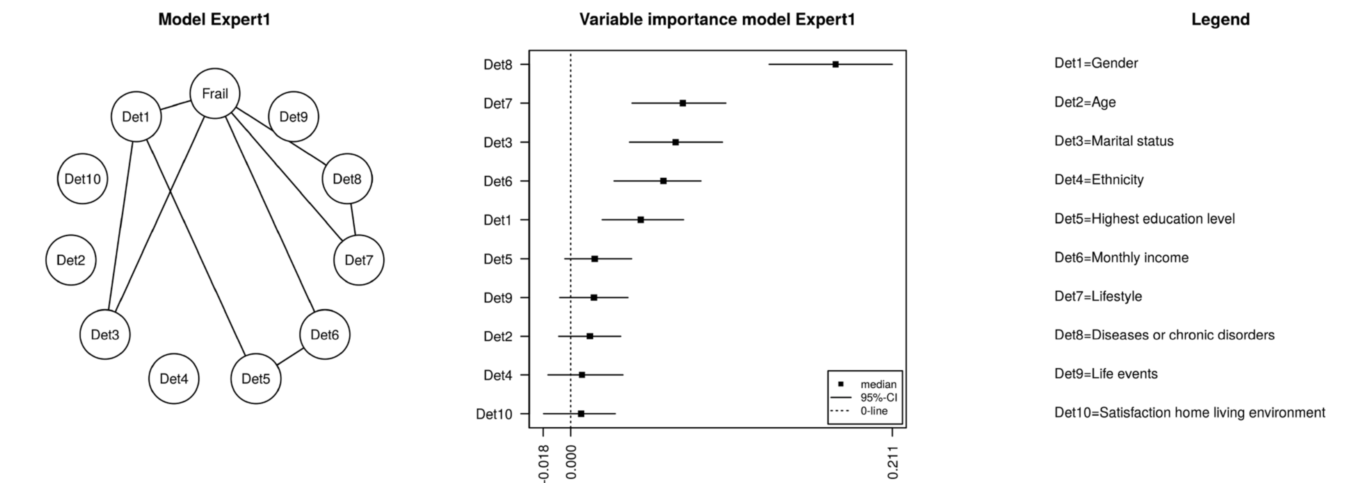

Fig. 1. Bayesian network and variable importance Expert1.

development of prediction models for frailty, we used a data set consisting of 479 participants who completed a questionnaire that contained determinants of frailty. The outcome variable was the frailty score assessed with the TFI (<5: non-frail, >=5: frail). The predictors were the ten determinants of frailty Gobbens et al. (2010a). The fit of the models was measured using Akaike's information criterion (AIC) Akaike (1974) and the performance of the models was evaluated using the area under the curve (AUC) of the receiver operator characteristic (ROC) Hastie et al. (2009); Steyerberg et al. (2019). The models were validated using bootstrapping with 100 repetitions Efron and Tibshirani (1994). The importance of the predictors in the models was based on permuted feature importance (PFI) with 100 repetitions Breiman (2001); Fisher et al. (2018).

4.1. Principal findings

The models that fitted best were the models "Expert8" and "Expert10" (AICs -3119 and -3101 respectively), probably because the underlying graphs of these models had a lot of connections between the nodes. Model "Expert10" showed the highest apparent AUC (0.906) and also the highest optimism (0.128). The models "Expert2" and "Expert7" had the highest corrected AUCs (0.783 and 0.782 respectively). For all models, the corrected AUCs were all >0.700, indicating that all models performed well in predicting frailty with the ten determinants. The importance of the predictors was measured using the PFI algorithm as described in 2.6. In each expert plot, we showed a graph with the predictor importance based on the median decrease in AUC with a 95% confidence interval. Evaluating the "top three" predictors in each model, predictor Det8 ("diseases or chronic disorders") was the most important predictor in all models (10 times). Predictors Det7 ("lifestyle") and Det6 ("monthly income") were also often present in the "top three" (both 6 times). The "top three" of the best performing model ("Expert2") consisted of Det8 ("diseases or chronic disorders"), Det6 ("monthly income") and Det7 ("lifestyle"), see Fig. 2.

4.2. Comparison to prior work

4.2.1. Medical perspective

Det8 of the TFI refers to multimorbidity. Multimorbidity is defined as the co-occurrence of several chronic diseases in the same person Marengoni et al. (2011). Multimorbidity and frailty are related but different concepts Cesari et al. (2017). A systematic review and meta-analysis showed that the prevalence of multimorbidity among frail individuals was high (72%). In addition, in pooled analyses, it was observed that multimorbidity was associated with frailty Vetrano et al. (2019). Previous studies also showed that Det7, an unhealthy lifestyle, mostly characterized by smoking, excessive alcohol use, low physical activity, and poor dietary habits, is associated with frailty Brinkman et al. (2018); Morley (2016); Woo et al. (2010). This also applies to a recent study among 45,336 Dutch community-dwelling individuals aged >= 65 years using the TFI as the measure of frailty Van Assen et al. (2022). The study by Van Assen et al. showed that lifestyle factors are not only associated with total frailty, but also with physical, psychological, and social frailty after controlling for sociodemographic characteristics of the participants Van Assen et al. (2022). Finally, Det6 is also a well-known determinant of frailty. A systematic review including nine studies revealed that financial issues were positively associated with frailty Hayajneh and Rababa (2021) and a meta-analysis aimed to estimate the pooled prevalence of frailty among community-dwelling elderly in low-income and middle-income countries showed that the

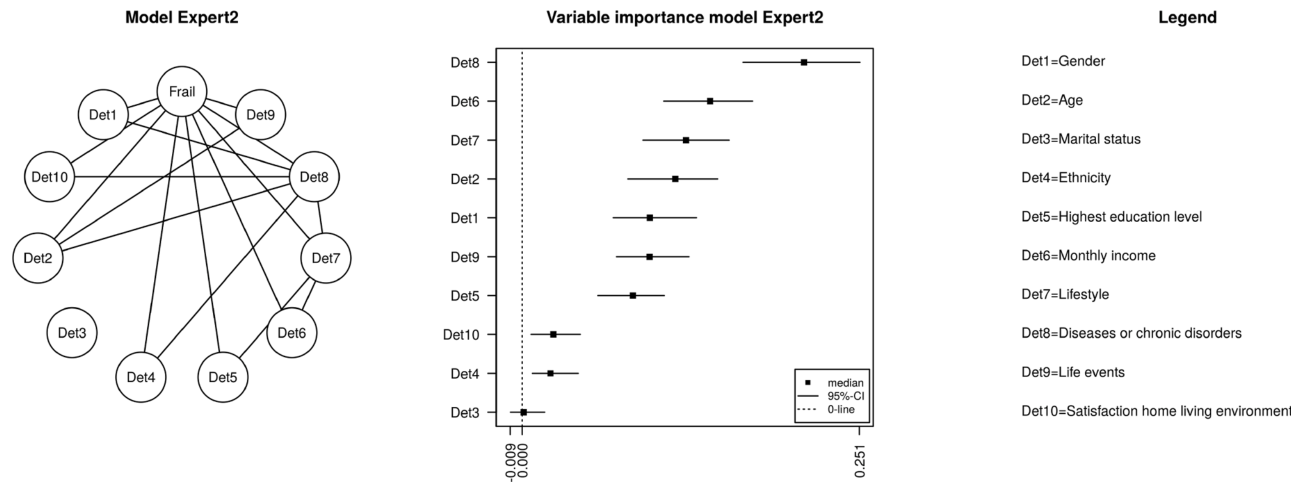

Fig. 2. Bayesian network and variable importance Expert2.

prevalence of frailty was higher compared to high-income countries Siriwardhana et al. (2018). Moreover, financial issues reduce the quality of life of older people Hayajneh and Rababa (2021). Therefore, it is important that healthcare and welfare professionals must pay attention to the financial problems that older people may have. (Figs. 3–10)

4.2.2. Modeling perspective

Bayesian modeling techniques, based on various algorithms, for the prediction of mortality in the domain of frail elderly, were compared to other modern modeling techniques such as support vector machines, random forests, and neural nets. The Bayesian models (hill-climbing and naive Bayes) performed slightly worse compared to the models generated by the aforementioned modeling techniques Van Der Ploeg et al. (2022). In 2018, Bayesian network classifiers were used for the construction of an inference engine for post-stroke outcomes Park et al. (2018). The Bayesian network classifiers were trained with a hill-climbing algorithm. The performance evaluation showed that the Bayesian networks, with different numbers of variables, performed well with AUCs >0.800. Amyotrophic lateral sclerosis (ALS) researchers used machine learning methods to predict the genetic architecture of ALS Karaboga et al. (2021). In this study, they took advantage of Bayesian networks and machine learning methods to predict ALS patients with blood plasma protein levels and independent personal features. The Bayesian network showed the best result (AUC 0.970) with gender and age as effective variables for ALS. In 2016, De Waal et al. presented lessons learned from a case study in rhino poaching predictive modeling De Waal et al. (2016). They stated that the structure and parameters of a Bayesian network can be determined by learning observed data or by eliciting expert knowledge during the design process. However, structures most often contain latent variables when following an expert-driven approach (participatory modeling) to determine causal links between variables. They also stated that experts understand abstract concepts that can be modeled in the network, but for which data is impossible to find. A Bayesian network fully trained with observed data leaves little room for reasoning about stakeholder knowledge and perspectives De Waal et al. (2016). The latter is exactly why we asked experts to draw their graphs showing the relationships between the predictors and the outcome.

4.3. Limitations

Several limitations of this study should be addressed. First, our sample consisted exclusively of people independently living in the municipality of Roosendaal. Therefore, the generalizability of the findings can be questioned. Second, the TFI is a frailty instrument using self-reported data, so frailty is subjectively assessed. However, the construct validity of the TFI has been determined in detail using objective measurements Gobbens et al. (2010b). Third, frailty was measured with the TFI, a self-reported questionnaire. The use of another frailty measure, such as the phenotype of frailty by Fried et al. Fried et al. (2001), would have led to different results. Fourth, we focused on the outcome "frail". However, with the Bayesian networks, it is also

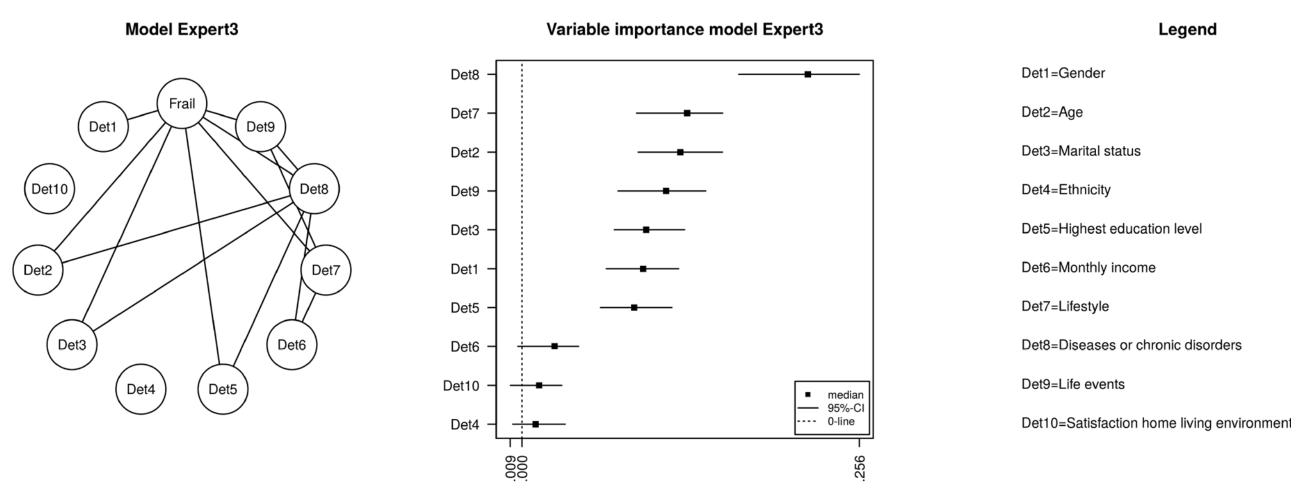

Fig. 3. Bayesian network and variable importance Expert3.

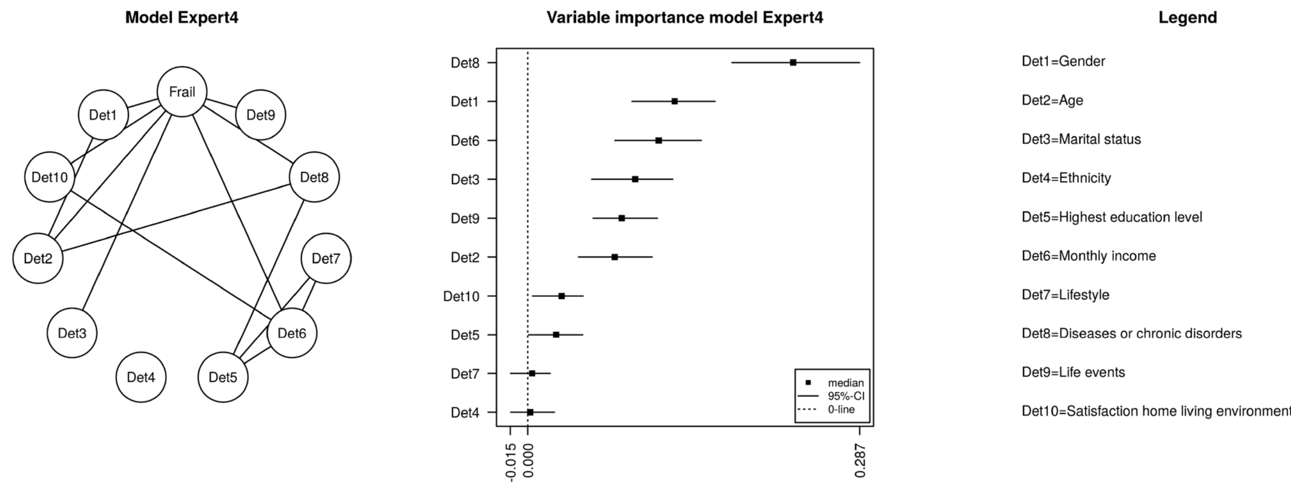

Fig. 4. Bayesian network and variable importance Expert4.

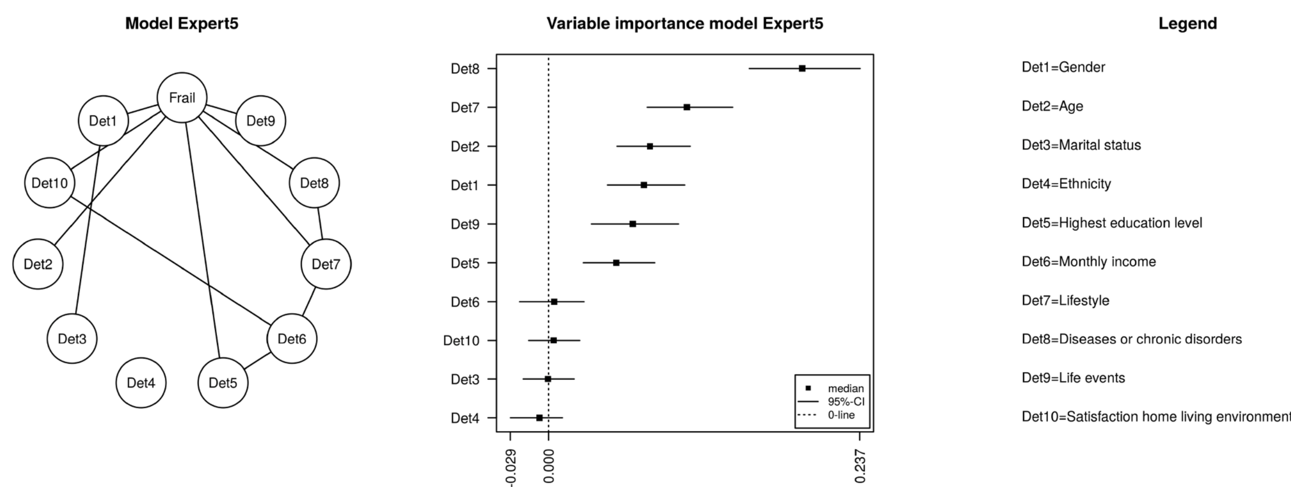

Fig. 5. Bayesian network and variable importance Expert5.

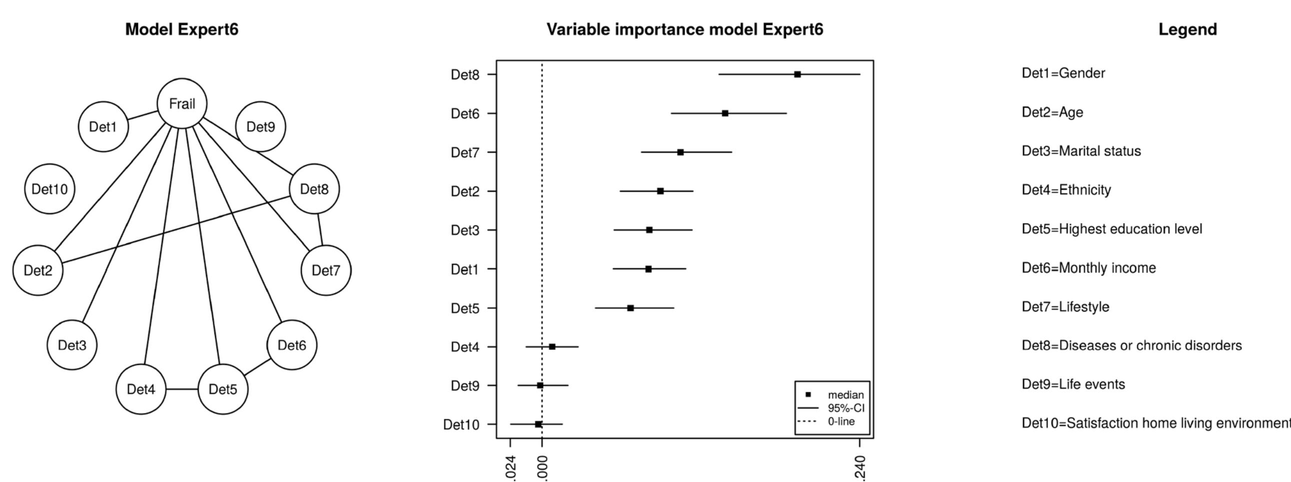

Fig. 6. Bayesian network and variable importance Expert6.

possible to make predictions for other outcome variables with other conditional variables ("diseases or chronic disorders" given "frail" for example), so we did not examine the full potential of the Bayesian networks. Fifth, the low response rate can be considered as a potential limitation that may impact the study results. The non-respondents could potentially represent a higher score on the TFI, which may have caused an underrepresentation of severely frail older people. However, another study among Dutch older people Metzelthin et al. (2010) (mean age 77.2

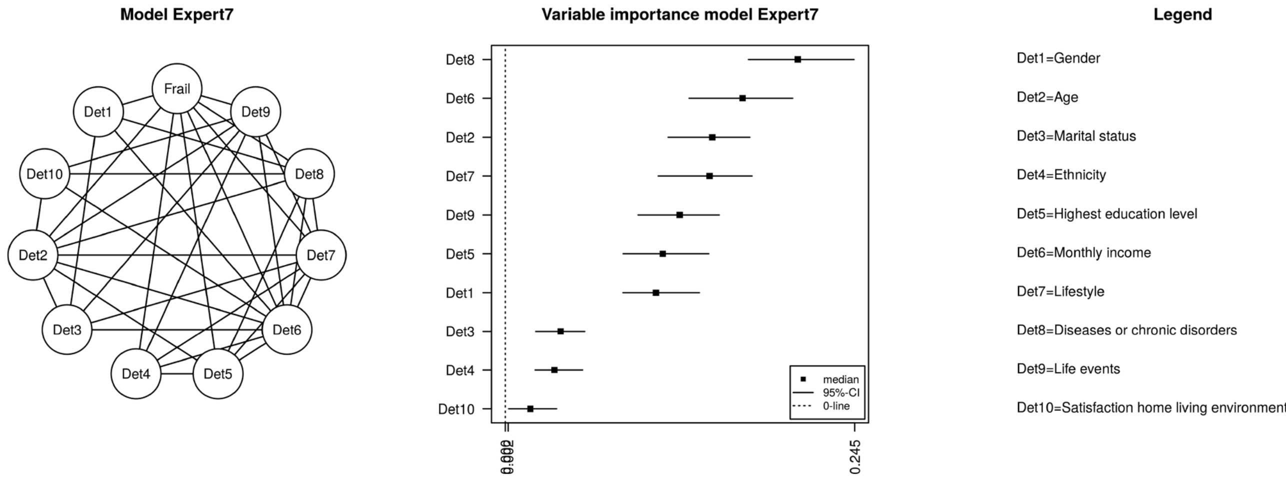

Fig. 7. Bayesian network and variable importance Expert7.

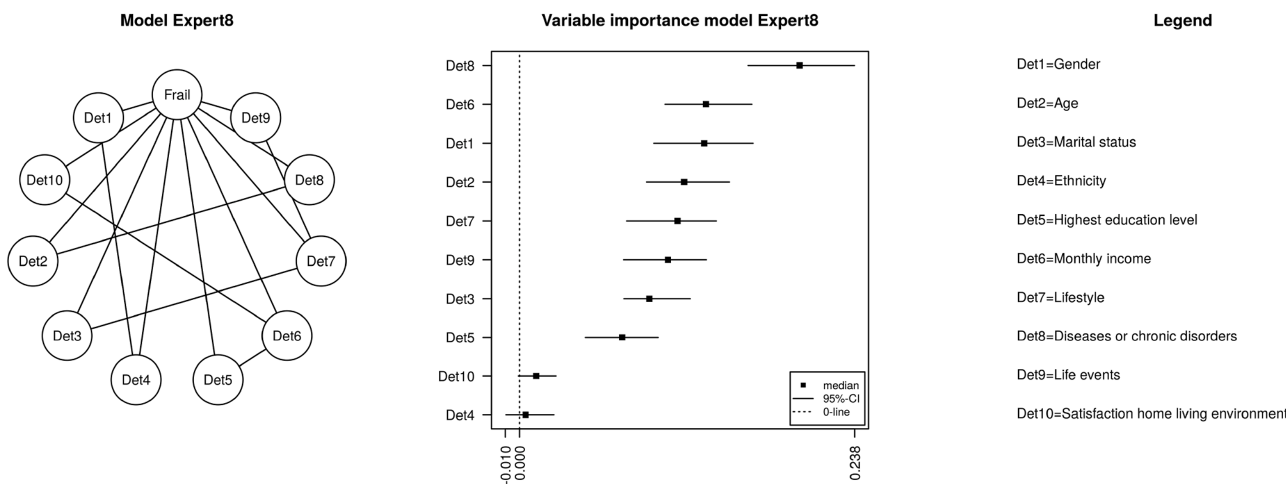

Fig. 8. Bayesian network and variable importance Expert8.

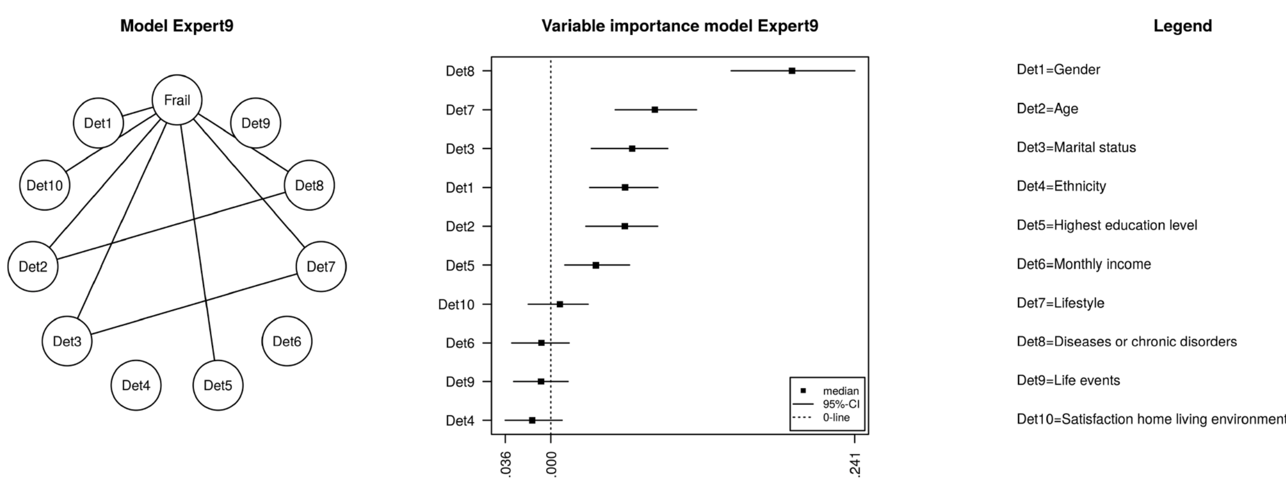

Fig. 9. Bayesian network and variable importance Expert9.

years, sd 5.5) with a higher response rate (77%) found that the prevalence of frailty using the TFI was 40.2% compared to 47.1% in our study (mean age 80.3, sd 3.8).

4.4. Conclusions

Although the ten experts all made a different graph, the predictive performance was always satisfying (AUCs >0.700). While it is true that the predictor importance varied all the time, the top three of the pre-

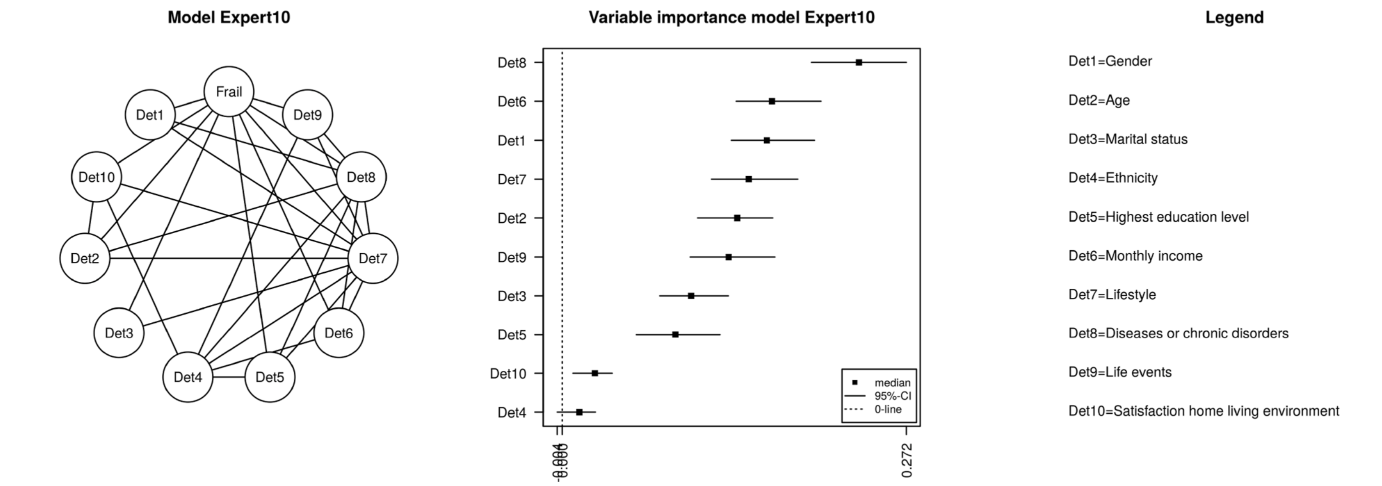

Fig. 10. Bayesian network and variable importance Expert10.

dictor importance consisted of "diseases or chronic disorders", "lifestyle" and "monthly income". Taken together, asking for the opinion of experts in the field of frail elderly to predict frailty with Bayesian networks may be more rewarding than a data-driven forecast with Bayesian networks because they have expert knowledge regarding interactions between the different predictors.

5. Declarations

5.1. Ethics approval and consent to participate

All procedures performed in studies involving human participants followed the ethical standards of the institute and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. For the present study, medical ethics approval was not necessary because treatments or interventions were not offered or withheld from respondents. Moreover, the integrity of respondents was not encroached upon because of participating in this study, which is the main criterion in medical-ethical procedures in the Netherlands Central Committee on Research Involving Human Subjects (2016). Informed consent related to detailing the study and maintaining confidentiality was observed.

5.2. Consent for publication

Not applicable.

5.3. Availability of data and materials

The dataset used and analyzed during the current study is available from the corresponding author upon reasonable request.

5.4. Funding

The authors received no specific funding for this work.

5.5. Authors contributions

Tjeerd van der Ploeg, Benissa E. Salem, and Robbert J. J. Gobbens wrote the main manuscript text and Tjeerd van der Ploeg prepared all figures, all tables and performed all analyses. Tjeerd van der Ploeg, Benissa E. Salem, and Robbert J. J. Gobbens reviewed the manuscript.

Declaration of Competing Interest

The authors declare that they have no competing interests.

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Appendix A. Tilburg Frailty Indicator (TFI) questionnaire

Tilburg Frailty Indicator (TFI)*

Gobbens RJJ, van Assen MALM, Luijkx KG, Wijnen-Sponselee MTh, Schols JMGA. The Tilburg Frailty Indicator: psychometric properties. J Am Med Dir Assoc 2010; 11(5):344-355.

Part A Determinants of frailty

1. Which sex are you?	0 male	0 female
2. What is your age?	.... years	
3. What is your marital status?	0 married/living with partner 0 unmarried 0 separated/divorced 0 widow/widower	
4. In which country were you born?	0 The Netherlands 0 Former Dutch East Indies 0 Suriname 0 Netherlands Antilles 0 Turkey 0 Morocco 0 Other, namely...............	
5. What is the highest level of education you have completed?	0 none or primary education 0 secondary education 0 higher professional or university education	
6. Which category indicates your net monthly household income?	0 €600 or less 0 €601 - €900 0 €901 - €1200 0 €1201 - €1500 0 €1501 - €1800 0 €1801 - €2100 0 €2101 or more	
7. Overall, how healthy would you say your lifestyle is?	0 healthy 0 not healthy, not unhealthy 0 unhealthy	
8. Do you have two or more diseases and/or chronic disorders?	0 yes	0 no
9. Have you experienced one or more of the following events during the past year?		
- the death of a loved one	0 yes	0 no
- a serious illness yourself	0 yes	0 no
- a serious illness in a loved one	0 yes	0 no
- a divorce or ending of an important intimate relationship	0 yes	0 no
- a traffic accident	0 yes	0 no
- a crime	0 yes	0 no
10. Are you satisfied with your home living environment?	0 yes	0 no

Part B Components of frailty

B1	**Physical components**			
11.	Do you feel physically healthy?	0 yes		0 no
12.	Have you lost a lot of weight recently without wishing to do so? *('a lot' is: 6 kg or more during the last six months, or 3 kg or more during the last month)*	0 yes		0 no

Do you experience problems in your daily life due to:

13.	..........difficulty in walking?	0 yes		0 no
14.	..........difficulty maintaining your balance?	0 yes		0 no
15.	..........poor hearing?	0 yes		0 no
16.	..........poor vision?	0 yes		0 no
17.	..........lack of strength in your hands?	0 yes		0 no
18.	..........physical tiredness?	0 yes		0 no
B2	**Psychological components**			
19.	Do you have problems with your memory?	0 yes	0 sometimes	0 no
20.	Have you felt down during the last month?	0 yes	0 sometimes	0 no
21.	Have you felt nervous or anxious during the last month?	0 yes	0 sometimes	0 no
22.	Are you able to cope with problems well?	0 yes		0 no
B3	**Social components**			
23.	Do you live alone?	0 yes		0 no
24.	Do you sometimes miss having people around you?	0 yes	0 sometimes	0 no
25.	Do you receive enough support from other people?	0 yes		0 no

[*] The TFI was translated into English using the method of back-translation.

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