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Research article

Exploring relevant factors of cognitive impairment in the elderly Chinese population using Lasso regression and Bayesian networks

Qiao Chen [a,b], Tianyi Zhou [a], Cong Zhang [a], Xiaoni Zhong [a,*]

[a] College of Public Health, Chongqing Medical University, Chongqing, 400016, China
[b] Research Center for Medicine and Social Development, Chongqing Medical University, Chongqing, China

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ABSTRACT

Older adults are highly susceptible to developing cognitive impairment(CI). Various factors contribute to the prevalence of CI, but the potential relationships among these factors remain unclear. This study aims to explore the relevant factors associated with CI in Chinese older adults and analyze the potential relationships between CI and these factors.We analyzed the data on 6886 older adults aged≥60 from the China Health and Retirement Longitudinal Study (CHARLS) 2018. Lasso regression was initially used to screening variables. Bayesian Networks(BNs) were used to identify the correlates of CI and potential associations between factors. After screening with Lasso regression, 11 variables were finally included in the BNs. The BNs, by establishing a complex network relationship, revealed that age, education, and indoor air pollution were the direct correlates affecting the occurrence of CI in older adults. It also indicated that marital status indirectly influenced CI through age, and residence indirectly linked to CI through two pathways: indoor air pollution and education.Our findings underscore the effectiveness of BNs in unveiling the intricate network linkages among CI and its associated factors, holding promising applications. It can serve as a reference for public health departments to address the prevention of CI in the elderly.

1. Introduction

Cognitive impairment (CI) refers to an unstable neurological condition that lies between normal aging and dementia [1]. This condition has the potential to stabilize, improve, or progress to dementia [2]. Moreover, CI is closely linked to adverse health outcomes, such as poor quality of life, disability and mortality [3–5]. China is an ageing nation, with almost 200 million individuals aged 65 and older, comprising 13.50% of the overall population. It is estimated that by 2050, this number will rise to 380 million, encompassing 27.9% of the total population [6]. It is widely documented that cognitive functioning generally declines with older age [7–9]. According to relevant studies, it is projected that China will have 48.68 million individuals with CI by 2060, with over 360,000 new diagnoses each year [10]. Patients with CI face a significantly higher risk (5–20 times) of developing dementia when compared to individuals without CI [11]. Dementia is an irreversible condition, making it essential to identify and intervene during the crucial period of cognitive impairment. Several studies have demonstrated the effectiveness of lifestyle interventions and cognitive training in reducing or delaying the progression to dementia among high-risk individuals during this CI stage [12–14]. Consequently, identifying influencing factors and offering timely interventions are imperative to decrease the incidence of CI.

* Corresponding author.
E-mail address: zhongxiaoni@cqmu.edu.cn (X. Zhong).

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Previous studies have reported on various factors associated with CI, such as age, physical inactivity, diabetes, and social-economic status [15–19]. However, a common limitation of these studies is that they mainly utilized logistic regression based on independent conditions to investigate the prevalence of CI, and relied on odds ratios (ORs) to assess the strength of association. In reality, factors are often interdependent, and their relationships may exhibit a complex network structure. Bayesian networks (BNs) are a type of artificial intelligence method that does not rely on strict statistical assumptions [20]. The potential relationship between multiple factors is represented by constructing a directed acyclic graph, and the strength of the association is indicated by a conditional probability distribution table [21,22]. Furthermore, BNs can use the states (i.e., factors) of known nodes to infer the probability of unknown nodes (i.e., prevalence of CI or its absence), presenting a potentially more flexible approach for exploring the likelihood of CI prevalence in Chinese older adults.

Certainly, there are numerous factors related to CI, but it would be inappropriate to include all of them into BNs. The complexity and accuracy of the networks decrease as the number of factors increases. Hence, variable screening is of great necessity. *Lasso regression*, a linear regression method that utilizes L1 regularization, is frequently employed for variable feature selection, variable correlation analysis, and model simplification [23–25].

Therefore, our aim was to use Lasso regression as an initial filter for factors that strongly correlate with CI in older Chinese adults. Subsequently, we employed BNs to model the factors associated with CI and to investigate their potential relationships. The study may offer information and recommendations for the prevention and intervention of CI, thereby reducing the likelihood of future dementia development. Consequently, this study holds significant public health implications.

2. Materials and methods

2.1. Study design and data sources

This paper presents a cross-sectional study conducted using data from the China Health and Retirement Longitudinal Study (CHARLS) 2018 [26]. The data can be accessed through CHARLS's official website (https://charls.pku.edu.cn/en/). The CHARLS is a comprehensive national survey focused on examining the aging process among individuals aged 45 and above in the country. To ensure sample representativeness, CHARLS employed a stratified multi-stage probability-proportional-to-size (PPS) random sampling strategy, considering the per capita GDP of urban districts and rural counties. The baseline survey comprised 17,708 participants, encompassing 450 village committees and communities across 150 districts and counties in China. The 2018 follow-up survey for CHARLS utilized face-to-face computer-assisted personal interviews (CAPI) to gather information on the health and socioeconomic status of an aging population. The implementation of CAPI significantly enhanced our ability to identify and rectify errors made by the

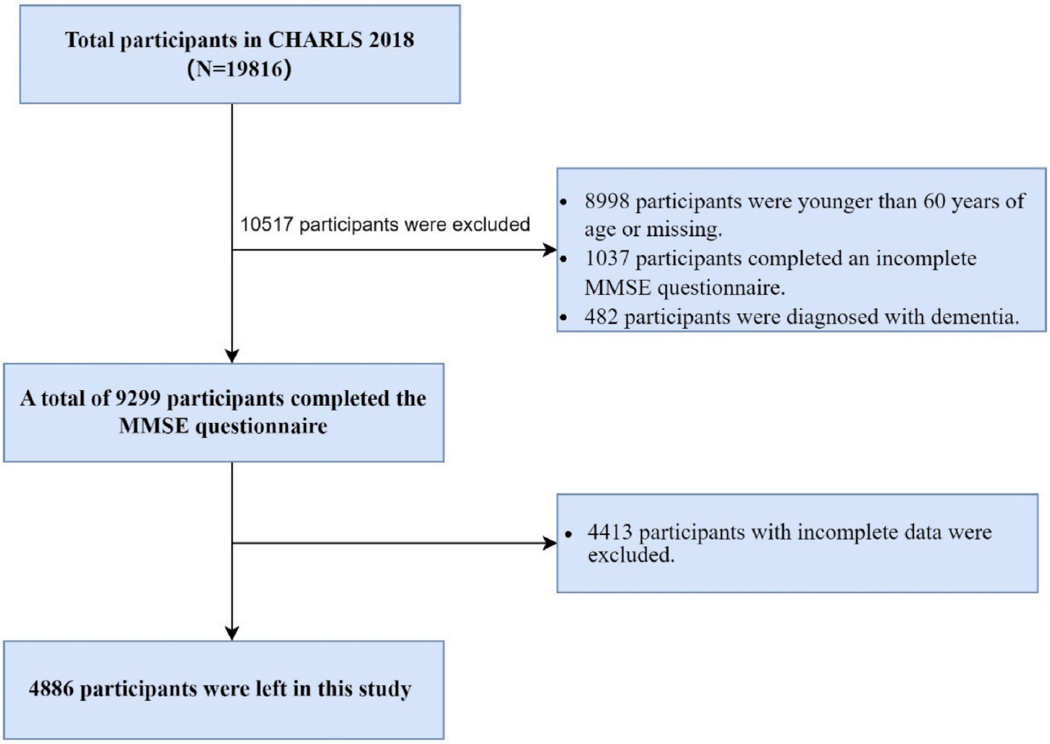

Fig. 1. Inclusion exclusion flowchart.

interviewers in the field, thereby ensuring the authenticity and validity of survey data. During the field work, CAPI immediately alerts the interviewer if there are any instances of sections being improperly skipped, incomplete, or if they appear to have taken insufficient time. Further details about CHARLS can be found elsewhere [27].

After reviewing the findings of prior studies and examining the research variables accessible in the CHARLS database, we selected a total of 24 variables for investigation. These variables are grouped into five dimensions: general demographics, physical health, daily life, healthcare, and satisfaction. For clarity, the corresponding level assignment for each research variable is illustrated in appendix Table S1.

2.2. Inclusion and exclusion criteria

The inclusion criteria of this study were (1) Participants aged ≥60 years; (2) Completing the complete Mini-Mental State Examination (MMSE). Exclusive criteria were: (1) Participants are diagnosed by dementia; (2) General data are missing and incomplete. The CHARLS 2018 survey included a total of 19,816 observations, after applying the inclusion and exclusion criteria, 4886 participants were included in this study (Fig. 1).

2.3. Measurement

2.3.1. Cognitive impairment (CI)

In this study, we utilized the MMSE scale to evaluate the CI of the participants. The MMSE scale's reliability and validity have been extensively assessed across diverse populations [28]. Recognizing the sensitivity of the MMSE scale to the educational level of participants [29]. we established CI criteria as MMSE scores <17 for illiterate subjects, <20 for those in primary school, and <24 for those with a middle high school or above. Participants with higher MMSE scale scores were categorized as having normal cognitive function.

2.3.2. Depression

In the present study, the Center for Epidemiologic Studies Depression Scale (CESD-10) was employed to evaluate the depression levels of the participants. The scale comprises 10 items, each rated on a four-point scale: "Mostly = 4″, "Sometimes = 3″, "Occasionally = 2″, and "Rarely = 1". Questions 5 and 8 were reverse scored. The range of depression scores is from 10 to 40, with higher scores indicating more greater severity of depression among older adults. Consistent with previous research, this study defined older adults with a scale score of >22 as having depression, while those with a score of ≤22 were considered as not having depression [30].

2.3.3. Indoor air pollution

The existence or absence of indoor air pollution mainly is primarily determined by the use of solid fuels. Building on prior research, this study categorizes the use of solid fuels, including coal, biomass charcoal, wood, or straw, as indicative of the presence of indoor air pollution. Conversely, the utilization of other clean fuels, such as natural gas or electricity, is considered the absence of indoor air pollution [31].

2.4. Bayesian networks

Bayesian networks (BNs) are a probability graph model that can show the degree of probability dependence between factors. BNs consist of a directed acyclic graph (DAG) and a conditional probability table (CPT) [20]. The DAG comprises nodes and directed edges, where each node represents a variable in the network. If variable X directs to variable Y, it indicates a direct probability dependency between X and Y. Moreover, if a new variable Z points to Y through X, it signifies an indirect probability dependence between Z and Y. The CPT provides a quantitative description of the strength of probability dependency. In BNs, the formula for calculating the joint probability distribution function of all nodes is as represented by equation (1).

$$\begin{aligned} P(x_1, x_2, ..., x_n) &= P(x_1)P(x_2|x_1)\cdots P(x_n|x_1, x_2, \cdots, x_{n-1}) \\ &= \prod\nolimits_1^n P(x_i|\pi(x_i)) \end{aligned} \tag{1}$$

$\pi(x_i)$ is the set of parent nodes of x_i, $\pi(x_i) \subseteq (x_1, x_2, \cdots, x_{i-1})$.When the value of $\pi(x_i)$ is known, x_i is conditionally independent of other variables in $(x_1, x_2, \cdots, x_{i-1})$.

2.5. Statistical analysis

Descriptive analysis was performed on the qualitative data using rates or composition ratios. Qualitative data were analyzed descriptively using rates or composition ratios. Data cleaning, matching, and categorizing were performed using SAS software (version 9.4; SAS Institute, Cary, NC, USA). The data cleaning process involved handling missing values, removing outliers, and classifying the levels of the research variables. Lasso regression was employed to screen for characteristic variables in the "glmnet" package of R software (version 4.3.1; https://www.rproject.org). Variables with non-zero coefficients in the lasso regression model were treated as network nodes of the BNs. The structure of BNs was created using the MMHC () function in the "bnlearn" package, and the Great Likelihood estimation was used for the parameter learning. Finally, the BNs and reasoning models were visualized using Netica software (version 6.0.9; Norsys Sofware Corp., Vancouver, BC, Canada).

3. Results

3.1. Characteristics of the study population

A total of 4886 study participants were included in this study. Of these, 2061 (42.1%) had CI, while 2825 (57.9%) did not. Out of the total participants, 2936 individuals (60.1%) were aged between 60 and 69 years; 1505 individuals (30.8%) were aged between 70 and 79 years; and 445 individuals (9.1%) were 80 years or older. The percentages of individuals with different education levels were as follows: illiteracy (26.6%), elementary school (46.3%), middle school (16.5%), and high school or above (10.6%). Moreover, 72.5% of the elderly participants lived in rural areas, and 35.5% of them were exposed to indoor air pollution in their homes. Among the elderly individuals with CI, 42.6%, 38.8%, 13.6%, and 5.0% were illiterate, elementary, middle, and high school or above, respectively. Further details can be found in Appendix Table S2.

3.2. Screening of variables associated with CI by lasso

A total of 24 relevant factors that could potentially impact CI were incorporated into the Lasso regression model. To determine the crucial parameter value ($\lambda = 0.01966134$) of the model, 10-fold cross-validation was employed. The variable screening process is elucidated in Figs. 2 and 3. Subsequently, the coefficients of factors that were not significantly associated with CI were reduced to 0 and eliminated. This yielded a final selection of 11 variables, as exhibited in Table 1. This approach aimed to identify factors strongly correlations with CI, consequently streamlining the structure of BNs.

3.3. Bayesian networks model of CI

Fig. 4 illustrates a BNs model consisting of with 12 nodes and 16 directed edges. The model's directed edges represent the probabilistic dependencies between the connected nodes, with the numbers representing the prior probabilities of each node. For example, the prior probability of CI was 42.1%, denoted as P(CI) = 0.421. The developed BNs revealed a complex network relationship between CI and various related factors in the Chinese elderly. Age, education level, and indoor air pollution were identified as three factors influencing cognitive impairment (CI). These factors acted as the parent nodes of CI, directly influencing its occurrence. Moreover, CI was a parent node of independent shopping, indicating a connection between the ability to shop independently and the presence or absence of CI. The BNs further unveiled indirect correlations, such as marital status with CI through age and residence with CI through two pathways: indoor air pollution and education level.

3.4. Conditional probabilistic reasoning of CI

A notable advantage of BNs lies in their ability to infer the probabilities of unknown nodes based on those of known nodes. Consequently, the developed BNs can be utilized to predict the risk of CI in independent elderly individuals. In the established BNs, age, educational level, and indoor air pollution were identified as the parent nodes of the CI (Fig. 4). For instance, if an individual is above 80 years old(Age≥80), the probability of experiencing CI is 57.4%, that is P(CI | Age≥80) = 0.574(Fig. 5). Furthermore, If he or she has used solid fuels like coal, biomass charcoal, wood, or straw for an extended period in the past, the probability of developing CI

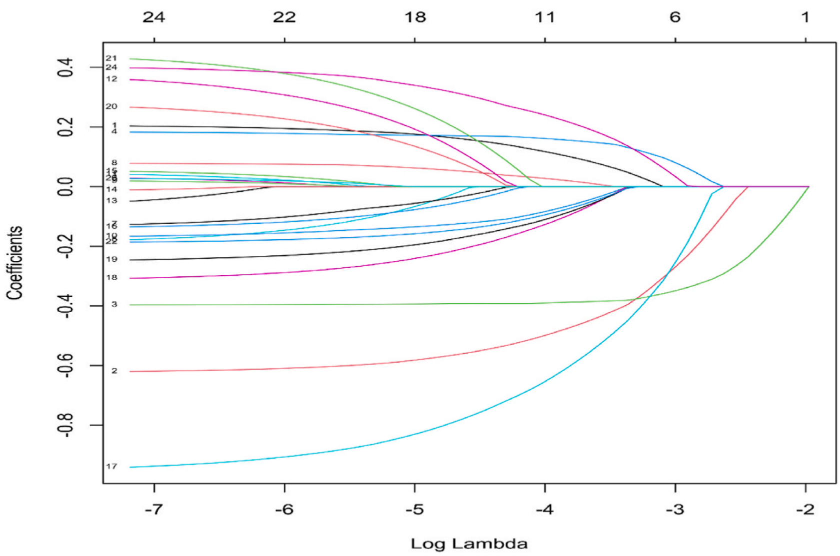

Fig. 2. Lasso coefficient solution path diagram.

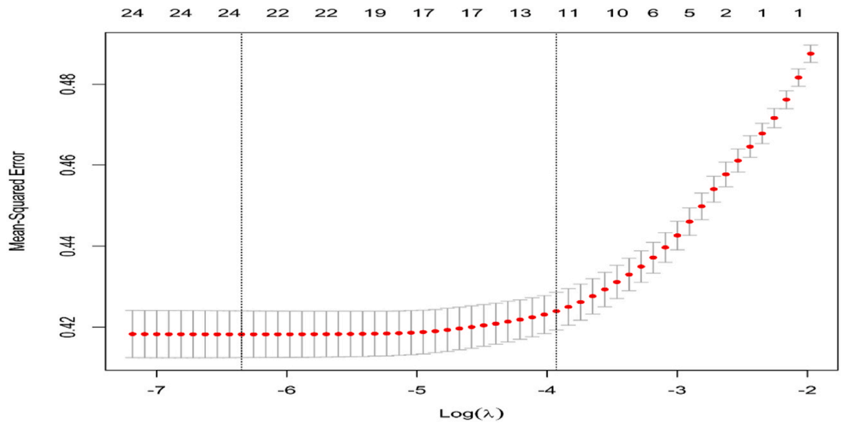

Fig. 3. Penalty coefficient λ-error diagram.

Table 1
Selected variables and their regression coefficients.

Variable	Coefficient	Variable	Coefficient
Age(x_1)	0.11164736	Shop independently(x_{17})	−0.63515953
Residence(x_2)	−0.48939254	Played Ma-jong(x_{18})	−0.11541769
Education level(x_3)	−0.38918838	Drinking(x_{19})	−0.10100419
Marital status(x_4)	0.15956759	Indoor air pollution(x_{21})	−0.08674442
Marital satisfaction(x_8)	0.02474950	Depression(x_{24})	0.23178432
Air quality satisfaction(x_{10})	−0.07623228		

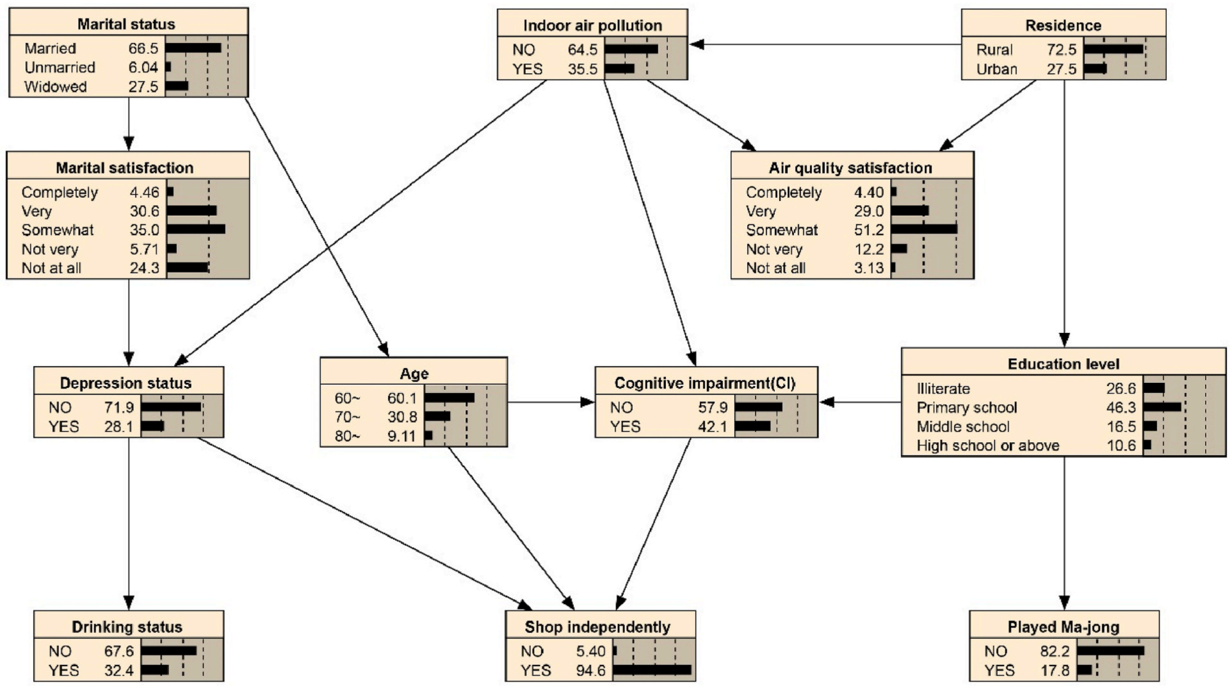

Fig. 4. CI Bayesian networks and prior probability using MMHC algorithm.

increases to 67.8%, that is P (CI | Age≥80, Indoor air pollution exist) = 0.678 (Fig. 6). Moreover, assuming that this elderly individual is also illiterate, the likelihood of developing CI becomes substantially higher at 79.8%, that is, P(CI | Age≥80, Indoor air pollution exist, Illiterate) = 0.798(Fig. 7). Similarly, the probability of an older adult experiencing difficulty shopping independently rises from

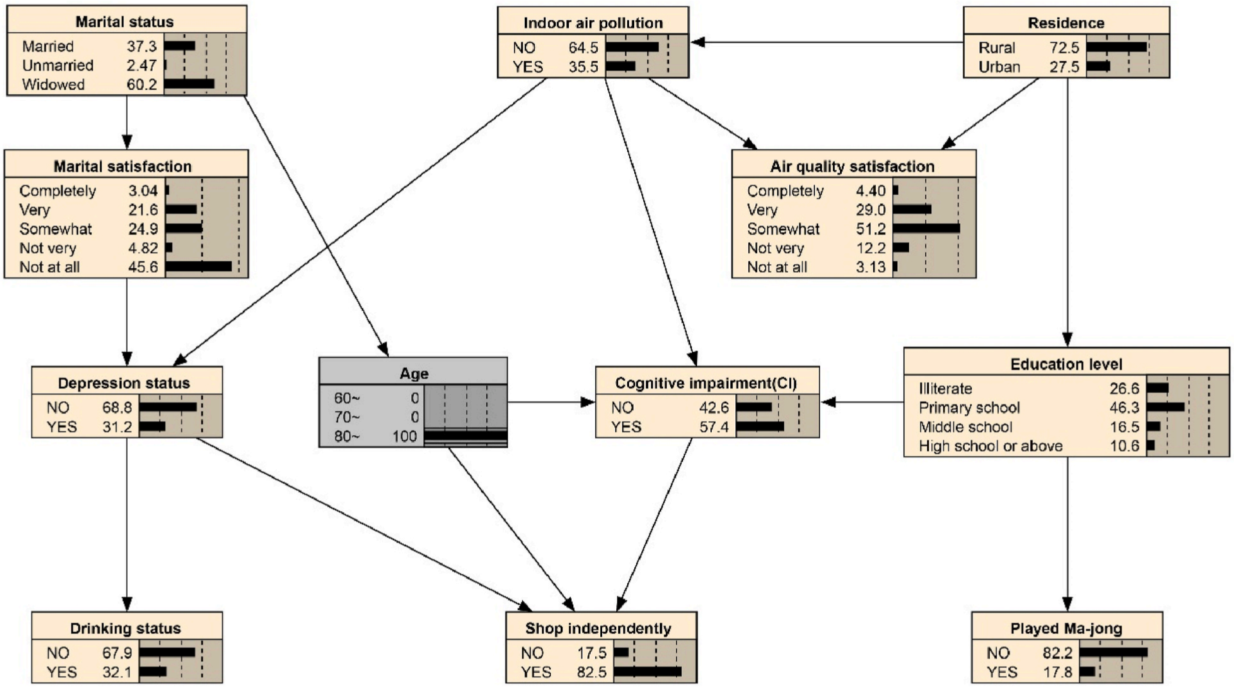

Fig. 5. Bayesian networks with known node probabilities I.

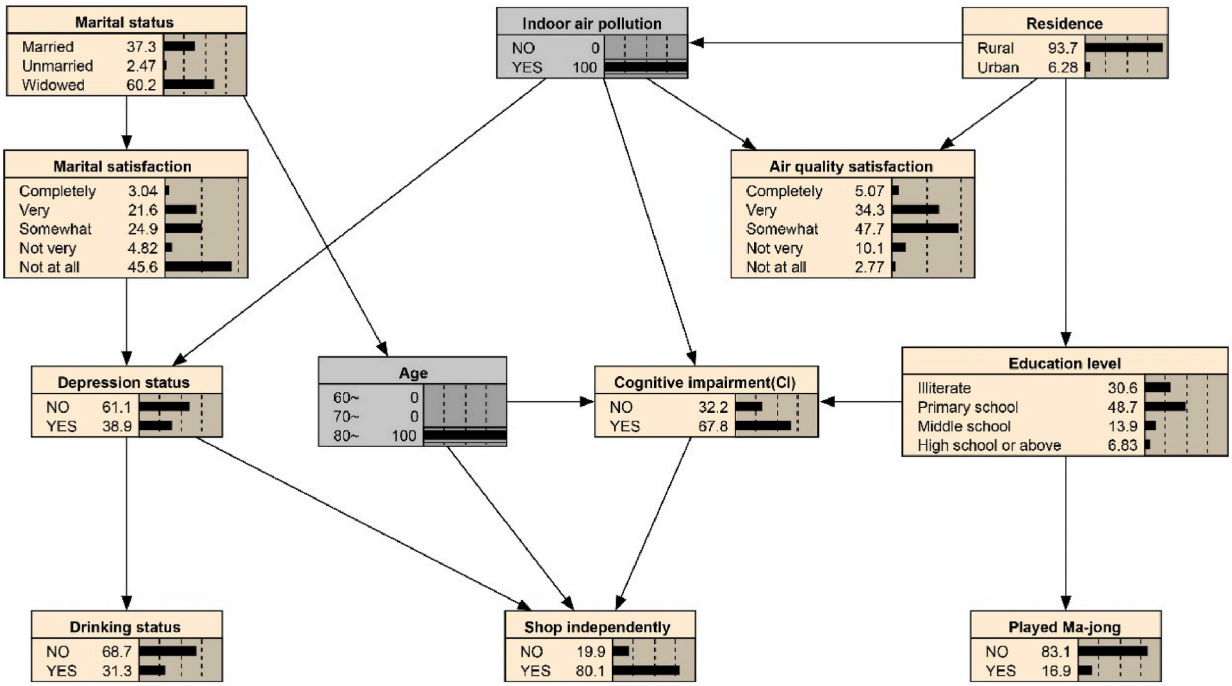

Fig. 6. Bayesian networks with known node probabilities II.

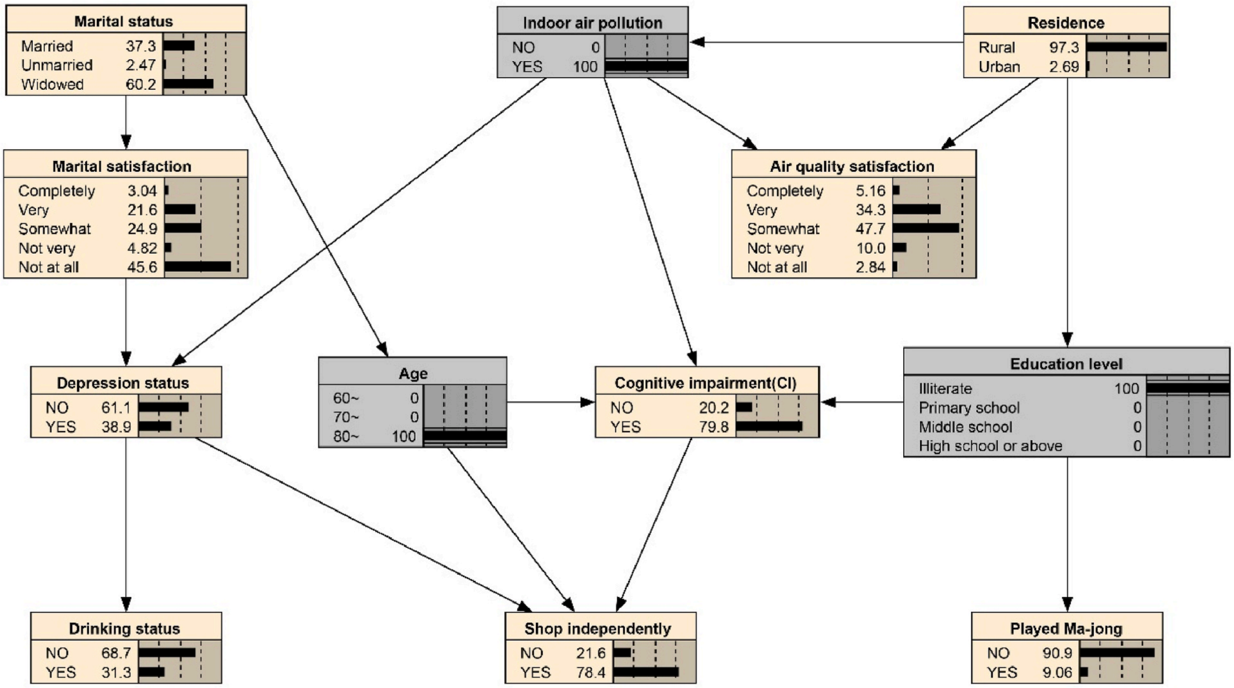

Fig. 7. Bayesian networks with known node probabilities III.

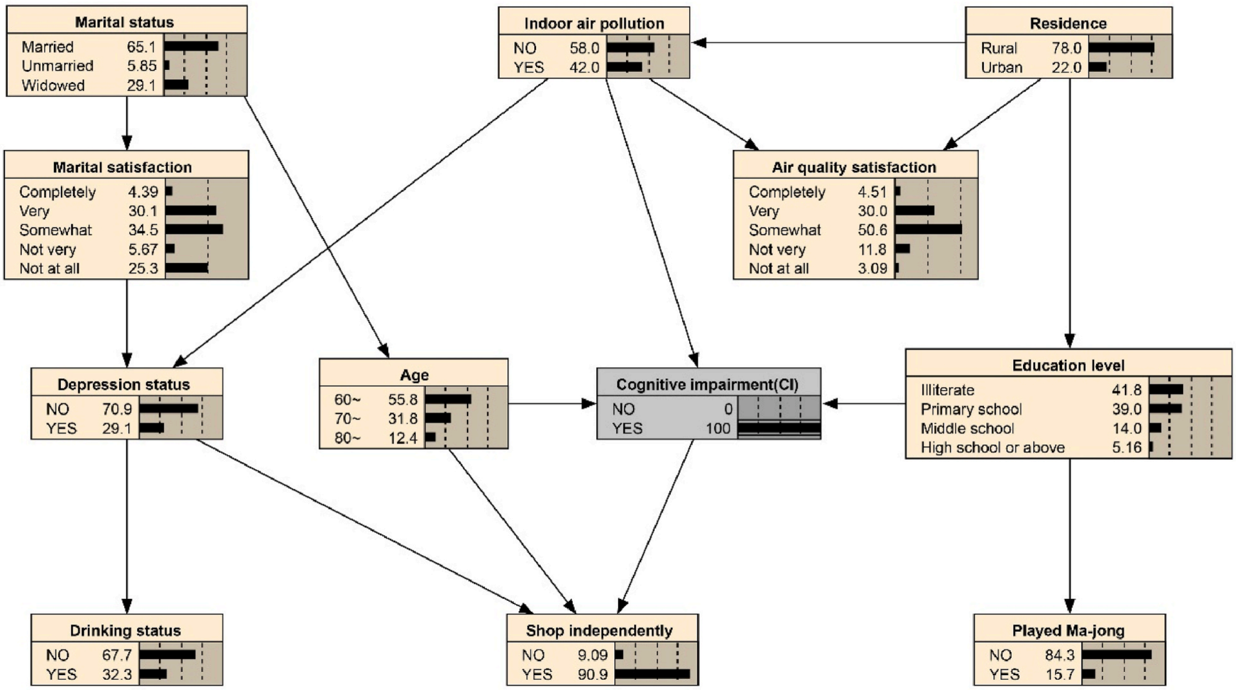

Fig. 8. Bayesian networks with known node probabilities IV.

5.4% to 9.09% if the person suffers from CI (Fig. 8).

4. Discussion

4.1. CI prevalence rate

The rising detection and prevalence rates of CI have made it an essential public health concern [10,32]. The findings of this study revealed that 42.1% of the elderly population aged 60 years or above experienced CI, surpassing the reported prevalence of CI among the elderly in Qingdao City, Shandong Province (20.11%) [33]. Additionally, it exceeded the international prevalence of CI reported in Italy (39.6%) [34]. These results indicate the importance of addressing the overall prevalence of among the elderly in China for relevant health authorities. Internationally reported indicate a range of prevalence rates for CI, varying from 20% to 41% [35–37]. The detection percentages of CI vary significantly across different studies, possibly because of variations in the assessment tools employed for measuring CI. Currently, assessment measurement tools for measuring CI include scales like MoCA, MMSE, and AD8 [38–40]. Notably, the MMSE scale is widely adopted, yet diverse criteria are applied to define CI scores. The majority of studies associate MMSE scale scores with education level to achieve a comprehensive diagnosis of CI [29,41,42].

4.2. Relevant factors

This study utilized BNs based on the MMHC algorithm to investigate the correlates of cognitive impairment (CI). This approach successfully identified both direct and indirect correlates of CI, while also enabling the estimation of the probability of CI prevalence. The findings of the BNs model indicated that age, education level, and indoor air pollution directly influenced the occurrence of CI among the elderly. Marital status had an indirect impact on CI through age, while residence was associated with CI through indoor air pollution and education. Furthermore, the BNs can describe the relationship between other factors, such as indoor air pollution, depression status, drinking and shop independently, as shown in Fig. 4. Additionally, the BNs could indicate the degree to which a specific risk factor raises the risk of developing CI. Figs. 5–7 illustrated the probabilistic relationship between CI and the three parent nodes: age, education level, and indoor air pollution. For instance, an individual who is illiterate, over 80 years old, and exposed to indoor air pollution is 79.8% more likely to develop CI ($P(CI \mid Age \geq 80, Illiterate, Indoor\ air\ pollution) = 0.798$).

Many national and international studies have confirmed that older individuals are more susceptible to CI compared to younger individuals, indicating a significant age difference in CI prevalence [43,44]. In our investigation, we elucidated that advanced age serves as a risk factor influencing the occurrence of CI, employing the conditional probabilistic reasoning process (Fig. 6). The aging process of the brain, accompanied by atrophy, declining hormone levels, and the overexpression of Tau protein, collectively contribute to the development of CI [45–47]. Therefore, regular health checkups for the elderly are necessary, particularly to monitor for the early signs of CI. Additionally, research findings have consistently shown that individuals with higher education levels or longer periods of education have a lower risk of developing CI as they age, while individuals with lower education levels are at higher risk [48,49]. This aligns with the findings of our current study, possibly attributable to the heightened cognitive engagement of better-educated seniors. Consequently, it is advisable to encourage the elderly to actively engage in lifelong learning and cognitive activities such as studying, reading newspapers, and playing mahjong. By Consciously strengthening memory and intelligence through these activities, the elderly can significantly reduce the risk of CI.

The impact of marital status on the occurrence of CI has consistently emerged as a focal point in prior research [50–52]. Unmarried or widowed individuals may encounter financial and emotional distress, directly influencing cognitive function [53]. Remarkably, this study reveals a novel perspective, demonstrating marital status indirectly influences CI through its association with age. This novel insight contributes to the existing body of knowledge in the field. Specifically, the findings suggest that unmarried and widowed individuals face heightened cognitive health disadvantages in late life. Therefore, it is crucial for relevant public health departments to enhance humanistic care for older adults and those who have lost a spouse.

The occurrence of CI in older individuals is also influenced by indoor air pollution, as supported by previous epidemiologic studies [54,55]. Older adults have been found to be highly are susceptible to the detrimental effects of indoor air pollution [56]. Aging may render individuals' brains more vulnerable to indoor air pollution or result in accumulated longer periods exposure, possibly contributing to the age-related differences in CI.

In general, older individuals residing in rural residences tend to have a lower level of education, use solid fuels more commonly, and are more likely to be exposed to indoor air pollution [57]. In this study, more than 80% of the elderly individuals living in rural areas had an education level below elementary school, with an illiteracy rate of 31.77%. Additionally, 45.88% of the individuals were exposed to indoor air pollution. On the contrary, the illiteracy rate among elderly individuals residing in urban areas was 13.11%, with an indoor air pollution rate was 8.12% (Tables S3–S4). These findings clearly demonstrate of the indirect influence of residence on CI through the two pathways: indoor air pollution and education level. On the contrary, older adults with higher levels of education are less likely to live in surroundings where air pollution exists [58]. It is possible that older individuals with greater education have a heightened awareness of health risks due to their extensive knowledge. Consequently, they may take preventive measures, such as installing air purifiers, to protect against the potential harm of indoor air pollution. This could explain the disparity in CI on education level.

This primary strength of this study resides in the utilization of BNs to effectively identify related factors associated with CI in elderly Chinese population. Furthermore, it reveals potential relationships between CI and its related factors. While traditional logistic regression, a model assuming independence of each related factor, can explore factors contributing to CI in older Chinese adults, it fails short in elucidating the specific the role a risk factor plays in the development of CI.

However, this study has some limitations. Firstly, it is a cross-sectional study, and the directed edges in the BNs graph only represent conditional dependencies between nodes, not causal relationships. To fully explore the deeper relationship between CI and its related factors, future longitudinal studies could employ dynamic BNs and multilevel temporal BNs. Secondly, while missing data may be inevitable in a large national study, excluding samples with incomplete information from our analyses may introduce selection bias. Thirdly, in addition to the variables included in this study, more comprehensive exploration of the factors associated with CI should include additional variables. In the future, we aim to further involve of laboratory indicators (e.g., complete blood count, blood electrolytes, blood glucose, etc.) and imaging indicators (e.g., head MRI, PET, SPET, etc.) to fully explore the correlates of CI.

5. Conclusions

Applying the BNs, we have identified age, education level, and indoor air pollution as direct correlates influencing the occurrence of CI in the elderly, Additionally, marital status and residence were found to be indirect correlates. BNs can effectively reveal the complex network connections between CI and its related factors. This finding can serve as a reference for public health departments aiming to target the prevention of CI in the elderly. Additionally, the conditional probabilistic reasoning of BNs enables the possibility of predicting the risk of CI, providing valuable assistance in clinical practice and potential applications.

Ethics approval

All respondents provided informed consent, and ethical approval for all CHARLS waves were granted by the Institutional Review Board (IRB) at Peking University. The IRB approval number for the biomarker collection was IRB00001052-11014 and the IRB approval number for the primary household survey was IRB00001052-11015.

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Data availability statement

This study analyzed publicly available datasets, which can be accessed at the following link: https://charls.pku.edu.cn/en/. The dataset is named the China Health and Retirement Longitudinal Study (CHARLS) 2018.

CRediT authorship contribution statement

Qiao Chen: Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tianyi Zhou:** Writing – original draft, Supervision, Data curation, Conceptualization. **Cong Zhang:** Writing – review & editing, Validation, Project administration, Conceptualization. **Xiaoni Zhong:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e27069.

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