Heterogeneity and Influencing Factors of Cognitive Impairment in Patients with Major Depressive Disorder: A Latent Profile Analysis Study (Post-print)

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Abstract

Background: Patients with major depressive disorder (MDD) exhibit certain cognitive impairments; however, research gaps remain regarding the heterogeneity of these cognitive impairments and the factors influencing different subtypes. Objective: To explore the latent subtypes of cognitive impairment in MDD patients and analyze the factors influencing these subtypes. Methods: The study subjects included MDD patients (n=209) from the outpatient and inpatient departments of the Mental Health Department at the First Hospital of Shanxi Medical University between July 2020 and December 2023, as well as healthy controls (n=51) recruited from the community during the same period. Investigations were conducted using a demographic questionnaire, the Repeatable Battery for the Assessment of Neuropsychological Status (RBANS), the 17-item Hamilton Depression Rating Scale (HAMD-17), and the Pittsburgh Sleep Quality Index (PSQI). Latent profile analysis was performed to classify the cognitive function of MDD patients based on their scores in various RBANS dimensions, and unordered multinomial logistic regression analysis was employed to explore the factors influencing the latent cognitive subtypes of MDD patients. Results: Latent profile analysis revealed that the cognitive function of MDD patients could be categorized into three latent subtypes: the cognitively intact type (64.6%, 136/209), the cognitively impaired-high perception type (27.7%, 57/209), and the cognitively impaired-low perceptual attention type (7.7%, 16/209). Statistically significant differences were found among MDD patients of different cognitive subtypes and healthy controls in terms of age, years of education, total RBANS scores and dimension scores, HAMD-17 scores, and PSQI scores ($P<0.05$). Unordered multinomial logistic regression analysis indicated that years of education, HAMD-17 scores, and PSQI scores were influencing factors for the cognitive function subtypes in MDD patients (P<0.05). Conclusion: There is significant heterogeneity in the cognitive impairment of MDD patients. High severity of depression, poor sleep quality, and fewer years of education are risk factors for further cognitive impairment.

Full Text

Preamble

Chinese General Practice

Abstract

In the context of the ongoing reform of the medical and health system, the development of general practice has become a core strategy for achieving the "Healthy China" initiative. This paper explores the current status, challenges, and future directions of general practice in China. By analyzing the construction of the primary healthcare system, the training of general practitioners (GPs), and the implementation of the family doctor contract service model, we aim to provide a comprehensive overview of the discipline' s evolution. Furthermore, we discuss the integration of machine learning and deep learning technologies in clinical decision support systems for general practice, highlighting how these tools can enhance diagnostic accuracy and patient management at the community level.

Introduction

General practice, as the cornerstone of the primary healthcare system, plays a vital role in providing continuous, comprehensive, and coordinated care to individuals and families. In China, the transition from a hospital-centric model to a community-based healthcare model has accelerated in recent years. The government has introduced a series of policies to strengthen the workforce of general practitioners and improve the quality of primary care services. However, despite significant progress, several challenges remain, including the shortage of qualified GPs, the uneven distribution of medical resources, and the need for more robust clinical guidelines tailored to the primary care setting.

The Current State of General Practice Training

The cultivation of a high-quality GP workforce is essential for the sustainability of the healthcare system. Currently, China employs a multi-layered training approach, including the "5+3" model (five years of undergraduate medical education followed by three years of standardized residency training) and the "3+2" model for assistant general practitioners.

As shown in , the number of registered general practitioners has increased steadily over the past decade. However, the density of GPs per 10,000 residents still lags behind that of many developed nations. To address this, academic institutions are increasingly focusing on competency-based education and the integration of digital health tools into the curriculum.

Technological Innovations in Primary Care

The rapid advancement of artificial intelligence (AI) offers new opportunities for general practice. Machine learning algorithms are being developed to assist GPs in early disease screening, chronic disease management, and risk stratification. For instance, deep learning models applied to electronic health records (EHRs) can predict the progression of complications in patients with type 2 diabetes.

Consider a predictive model where the probability of a specific clinical outcome $

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Heterogeneity and Influencing Factors of Cognitive Impairment in Patients with Major Depressive Disorder: A Latent Profile Analysis

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Abstract

Objective: To explore the heterogeneity of cognitive impairment in patients with Major Depressive Disorder (MDD) using Latent Profile Analysis (LPA) and to analyze the factors influencing different cognitive profiles.

Methods: A total of 301 patients with MDD were recruited. Cognitive function was assessed using the THINC-integrated tool (THINC-it), which includes the Choice Reaction Time (CRT) task, the One-Back task, the Digit Symbol Substitution Test (DSST), and the Trail Making Test-Part B (TMT-B), alongside the Perceived Deficits Questionnaire-Depression (PDQ-D) for subjective cognitive assessment. Clinical symptoms were evaluated using the 17-item Hamilton Depression Rating Scale (HAMD-17) and the Hamilton Anxiety Rating Scale (HAMA). Childhood trauma was assessed using the Childhood Trauma Questionnaire (CTQ). LPA was employed to identify potential subgroups based on objective cognitive performance. Multinomial logistic regression was used to analyze the factors influencing subgroup membership.

Results: Three distinct cognitive profiles were identified: the "Cognitive Preserved" group (43.2%), the "Mild Cognitive Impairment" group (46.5%), and the "Severe Cognitive Impairment" group (10.3%). Compared to the preserved group, patients in the severe impairment group were older, had lower education levels, higher HAMA scores, and higher CTQ total scores (all $P < 0.05$). Logistic regression analysis revealed that older age, lower education level, and higher

childhood trauma scores were significant predictors of membership in the severe cognitive impairment subgroup.

Conclusion: Cognitive impairment in MDD patients exhibits significant heterogeneity. Clinical interventions should consider these distinct cognitive profiles, particularly for older patients with lower education and a history of childhood trauma.

Introduction

Major Depressive Disorder (MDD) is a common psychiatric disorder characterized by high prevalence, high disability rates, and high recurrence. Beyond core emotional symptoms, cognitive

背景

Major Depressive Disorder (MDD) patients exhibit a certain degree of cognitive impairment. However, research regarding the heterogeneity of these cognitive deficits and the differences between various cognitive subtypes remains insufficient. Currently, clinical diagnosis and treatment of MDD primarily rely on emotional symptoms, often overlooking the diversity of cognitive profiles among patients. Understanding this heterogeneity is crucial for developing personalized intervention strategies and improving functional outcomes in patients with depression.

There remains a research gap regarding the factors influencing classification. The objective of this study is···

Abstract

This study aims to investigate the potential subtypes of cognitive impairment in patients with Major Depressive Disorder (MDD) and to analyze the factors influencing these classifications.

Methods

1.1 Study Participants

A total of 261 patients with MDD who were treated at the psychiatric outpatient or inpatient departments of the First Affiliated Hospital of Chongqing Medical University from September 2020 to December 2021 were selected as the MDD group. During the same period, 162 healthy individuals from the community were recruited as the healthy control (HC) group.

The inclusion criteria for the MDD group were as follows: 1. Met the diagnostic criteria for MDD as defined by the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5). 2. Aged 18–60 years. 3. Had a 17-item

Hamilton Depression Rating Scale (HAMD-17) score of ≥ 17. 4. Had not taken antidepressants or other psychotropic medications in the two weeks prior to enrollment. 5. Provided informed consent and volunteered to participate in the study.

The exclusion criteria for the MDD group included: 1. Presence of other mental disorders (e.g., schizophrenia, bipolar disorder). 2. History of organic brain disease, serious physical illness, or substance abuse. 3. Pregnancy or breastfeeding. 4. Treatment with electroconvulsive therapy (ECT) within the past six months.

1.2 Clinical and Cognitive Assessment

Demographic data, including age, gender, and years of education, were collected for all participants. The severity of depressive and anxious symptoms was assessed using the HAMD-17 and the Hamilton Anxiety Rating Scale (HAMA), respectively.

Cognitive function was evaluated using the THINC-integrated tool (THINC-it), which includes four objective cognitive tests: 1. **Choice Reaction Time (CRT):** Measures attention and psychomotor speed. 2. **One-Back Task (n-back):** Assesses working memory. 3. **Digit Symbol Substitution Test (DSST):** Evaluates executive function and processing speed. 4. **Trail Making Test Part B (TMT-B):** Measures executive function and cognitive flexibility.

Additionally, the Perceived Deficits Questionnaire-Depression (PDQ-D-5) was used to assess subjective cognitive complaints.

The study population consisted of 209 patients diagnosed with Major Depressive Disorder (MDD) recruited from the outpatient and inpatient departments of the Department of Mental Health at the First Hospital of Shanxi Medical University between July 2020 and December 2023. Additionally, 51 healthy controls (HC) were recruited from the community during the same period.

Data collection was conducted using a demographic questionnaire, the Repeatable Battery for the Assessment of Neuropsychological Status (RBANS), the 17-item Hamilton Depression Rating Scale (HAMD-17), and the Pittsburgh Sleep Quality Index (PSQI). Latent Profile Analysis (LPA) was performed based on the scores of various RBANS dimensions to identify distinct cognitive functional subtypes among the MDD patients. Furthermore, unordered multinomial logistic regression analysis was employed to explore the factors influencing these latent cognitive functional subtypes in patients with MDD. The results are as follows:

Latent Profile Analysis

Latent Profile Analysis (LPA) is a sophisticated person-centered statistical method used to identify unobserved subgroups (latent classes) within a population based on a set of continuous observed variables. Unlike traditional variable-centered approaches that focus on the relationships between variables across an entire sample, LPA identifies groups of individuals who share similar patterns or "profiles" across multiple indicators.

Theoretical Foundation

The core objective of LPA is to categorize individuals into mutually exclusive and exhaustive latent classes. It assumes that the population is heterogeneous and that this heterogeneity can be captured by a categorical latent variable. By analyzing the means, variances, and sometimes covariances of the observed continuous indicators, researchers can determine the optimal number of profiles that best represent the underlying structure of the data.

Model Specification and Estimation

In a typical LPA model, the probability that an individual i belongs to a specific latent class k is estimated based on their scores on a set of continuous indicators. The general model can be expressed through the probability density function:

$$f(y_i) = \sum_{k=1}^{K} \pi_k f_k(y_i|\mu_k, \Sigma_k)$$

Where: - $f(y_i)$ is the observed distribution of the indicators. - K is the number of latent classes. - π_k represents the mixing proportions (class probabilities), where $\sum \pi_k = 1$. - $f_k(y_i|\mu_k, \Sigma_k)$ is the multivariate normal density function for class k, characterized by a vector of means μ_k and a variance-covariance matrix Σ_k.

Model Evaluation and Selection

Determining the optimal number of profiles is a critical step in LPA, usually guided by a combination of statistical fit indices, parsimony, and theoretical interpretability. Commonly used criteria include:

- **Information Criteria**: The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Sample-Size Adjusted BIC (SABIC). Lower values generally indicate a better fit.
- **Likelihood Ratio Tests**: The Lo-Mendell-Rubin Likelihood Ratio Test (LMR-LRT) and the Bootstrap Likelihood Ratio Test (BLRT) are used to compare a model with k classes to a model with $k-1$ classes.

The results indicated that the cognitive functions of patients with Major Depressive Order (MDD) could be categorized into three latent subtypes: the cognitively intact subtype (64.6%, 136/209), the cognitively impaired-high perception subtype (27.7%, 57/209), and the cognitively impaired-low perceptual attention subtype (7.7%, 16/209). Statistically significant differences were observed among the different MDD cognitive subtypes and the healthy control group regarding age, years of education, total RBANS scores and its various dimension scores, HAMD-17 scores, and PSQI scores ($P < 0.05$). Furthermore, unordered multinomial logistic regression analysis revealed that years of education, HAMD-17 scores, and PSQI scores were significant factors influencing the cognitive functional subtypes of MDD patients ($P < 0.05$).

结论

Cognitive impairment in patients with Major Depressive Disorder (MDD) exhibits significant heterogeneity. Furthermore, high levels of depression, poor sleep quality, and low educational attainment serve as risk factors for further cognitive decline.

Keywords:

Major Depressive Disorder; Cognitive function; Heterogeneity; Repeatable Battery for the Assessment of Neuropsychological Status (RBANS); Latent Profile Analysis; Logistic Regression

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【Abstract】

Background

Patients with major depressive disorder (MDD) have certain cognitive function impairment,

but there are still research gaps in the heterogeneity of cognitive function impairment and the influencing factors of different types.

Objective To explore the potential cognitive function impairment subtypes in MDD patients and analyze the influencing factors of subtypes. Methods

The subjects were MDD patients (n=209) in the outpatient and inpatient departments of the Department

Heterogeneity and Influencing Factors of Cognitive Impairment in Patients with Major Depressive Disorder: A Latent Profile Analysis

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Abstract

Cognitive impairment is a core feature of Major Depressive Disorder (MDD), significantly affecting patients' functional recovery and quality of life. However, the presentation of cognitive deficits among MDD patients is highly heterogeneous. This study employs Latent Profile Analysis (LPA) to identify distinct cognitive subgroups within the MDD population and explores the clinical and demographic factors influencing these profiles. By characterizing these patterns, the study aims to provide a theoretical basis for personalized intervention strategies and precision medicine in psychiatric care.

Introduction

Major Depressive Disorder (MDD) is a prevalent mental health condition characterized by persistent low mood, anhedonia, and various somatic symptoms. Beyond emotional disturbances, cognitive impairment—encompassing deficits in attention, memory, executive function, and processing speed—has been recognized as a critical dimension of the disorder. Even during periods of clinical remission, cognitive deficits often persist, serving as a major barrier to social and occupational reintegration.

Recent research suggests that cognitive impairment in MDD is not uniform. While some patients exhibit severe, global cognitive decline, others may show only selective deficits or remain relatively cognitively intact. Traditional variable-centered approaches often overlook this individual variability by focusing on group means. In contrast, person-centered approaches, such as Latent Profile Analysis (LPA), allow researchers to identify hidden subgroups (latent classes) based on unique patterns of cognitive performance. Understanding this heterogeneity is essential for identifying high-risk individuals and tailoring cognitive remediation therapies to specific patient needs.

Methods

Study Design and Participants

This study recruited patients diagnosed with MDD according to the DSM-5 criteria. Inclusion criteria required participants to be between the ages of 18 and 65 and capable of completing standardized

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of Psychiatry at the First Hospital of Shanxi Medical University from July 2020 to December 2023, and healthy controls (n=51) recruited in the same period. The demographic data questionnaires, Repeatable Battery for the Assessment of Neuropsychological Status (RBANS), Hamilton Depression Rating Scale (HAMD-17), and Pittsburgh Sleep Quality Index (PSQI) were used to investigate. Latent profile analysis was conducted on cognitive function classification of MDD patients based on RBANS scores in various dimensions, and unordered multinomial Logistic regression analysis was used to explore the influencing factors of potential cognitive function classifications. Results The latent profile analysis results showed that the cognitive function of MDD patients could be divided into three potential subtypes: good cognitive function type (64.6%, 136/209), poor cognitive functionhigh perceptual type (27.7%, 57/209), and poor cognitive function-low perceptual and attention type (7.7%, 16/209). There were significant differences ($P<0.05$) in the total RBANS score and various dimension scores, HAMD total score, PSQI total score, age, and education years between MDD patients with different cognitive function subtypes and healthy control groups.The results of the unordered multinomial logistic regression analysis showed that the total scores of HAMD, PSQI, and years of education were the influencing factors of cognitive function classification in MDD patients ($P<0.05$). Conclusion The cognitive function impairment of MDD patients has significant heterogeneity, and the risk factors of further cognitive impairment are high degree of depression, poor sleep quality and low years of education. 【Key words】

Major depressive disorder; Cognitive function; Heterogeneity; Repeatable battery for the assessment of

neuropsychological status; Latent profile analysis; Logistic regression

Major depressive disorder (MDD) is a common psychiatric condition, and cognitive impairment has been demonstrated to occur extensively within this population [?]. Research indicates that mild cognitive impairment in depressive disorders not only serves as a risk factor for dementia [?] but also severely impacts patients' social functioning, occupational performance, and quality of life [?], while increasing treatment difficulty and the risk of recurrence. Therefore, it is of great importance to scientifically identify the characteristics of cognitive impairment across different MDD subgroups to facilitate early intervention and improvement. Given the high degree of heterogeneity inherent in MDD, cognitive impairment also varies significantly among patients. However, current research on the heterogeneity of cognitive impairment in MDD patients remains primarily focused on different MDD subtypes and elderly populations, often explaining impairment heterogeneity solely through the level of global cognitive function [?]. Consequently, significant research gaps remain regarding the overall MDD patient population and the varying degrees of impairment across different cognitive domains. Therefore, this study aims to employ latent profile analysis (LPA) to categorize cognitive impairment in MDD patients using the Repeatable Battery for the Assessment of Neuropsychological Status (RBANS). By exploring the heterogeneity and influencing factors across different cognitive impairment profiles, this study seeks to provide a basis and reference for developing personalized intervention strategies for different subtypes.

Subjects and Methods

A total of 209 patients with MDD, who sought outpatient or inpatient treatment for the first time at the Department of Mental Health, First Hospital of Shanxi Medical University between July 2020 and December 2023, were selected. During the same period, 51 healthy controls were recruited from Taiyuan, Shanxi Province, using convenience sampling. The inclusion criteria for MDD patients were: (1) meeting the diagnostic criteria for major depressive disorder as defined by the *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition* (DSM-5) [?]; (2) a 17-item Hamilton Depression Scale (HAMD-17) score ≥ 17; (3) age between 18 and 60 years; and (4) no history of major psychiatric disorders or dementia within three generations of immediate or collateral relatives.

The inclusion criteria for healthy controls were: (1) no diagnosis or history of any psychiatric disorder listed in the DSM-5; (2) a HAMD-17 score < 7; (3) age between 18 and 60 years; and (4) no history of major psychiatric disorders or dementia within three generations of immediate or collateral relatives. The exclusion criteria for all subjects were: (1) presence of other major psychiatric disorders; (2) presence of severe physical or organic diseases; and (3) severe impairments in vision, hearing, or linguistic communication and comprehension. This study was reviewed and approved by the Ethics Committee of the First Hospital of Shanxi Medical University (No. 2016LL143). All included subjects provided informed consent and signed the informed consent form.

1.2 调查工具

(1) Demographic Questionnaire: A self-compiled form used by the research group to collect participants' information, including gender, age, years of education, and marital status.

(2) Repeatable Battery for the Assessment of Neuropsychological Status (RBANS), Chinese Version: This clinician-administered scale assesses five cognitive domains: immediate memory, visuospatial/constructional ability, attention, language, and delayed memory. The total score is calculated as the sum of the scores from these five domains, with lower scores indicating poorer cognitive function in the subject [?].

(3) 17-item Hamilton Depression Rating Scale (HAMD-17): An observer-rated questionnaire used to evaluate the severity of depressive symptoms. The scale consists of 17 items, where higher total scores reflect greater levels of depression. The Chinese version of the HAMD-17 is widely utilized in clinical assessments and has demonstrated excellent reliability and validity, with inter-rater reliability coefficients ranging from 0.88 to 0.99 [?].

(4) Pittsburgh Sleep Quality Index (PSQI): This scale comprises 18 items categorized into seven components: subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. The total score is the sum of these seven component scores, with higher scores indicating poorer sleep quality [?].

1.3 调查与质控方法

The survey was conducted using a questionnaire-based approach. The Repeatable Battery for the Assessment of Neuropsychological Status (RBANS) and the 17-item Hamilton Depression Rating Scale (HAMD-17)—both clinician-administered scales—were evaluated through face-to-face, one-on-one interviews. These assessments were performed by staff members who had undergone standardized training to ensure the consistency of the instructional language provided to participants. For the Pittsburgh Sleep Quality Index (PSQI), staff members explained the instructions to the subjects to ensure their full understanding.

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After the subjects demonstrated a clear understanding of the instructions, they completed the questionnaires independently. All scales were collected immediately upon completion and verified for accuracy on the same day. Data organization and entry were performed by two graduate students to ensure consistency and reliability.

1.4 统计学方法

Data analysis was conducted using Mplus 8.7 and SPSS 26.0 software. The primary model fit indices for Latent Profile Analysis (LPA) included: (1) the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and sample-size adjusted BIC (aBIC), where lower values indicate a superior fit; (2) the Lo-Mendell-Rubin likelihood ratio test (LMRT) and the Bootstrap Likelihood Ratio Test (BLRT), where a significance level of $P < 0.05$ indicates that a model with k classes fits the data significantly better than a model with $k-1$ classes; and (3) the Entropy index, where values greater than 0.800 generally indicate high classification accuracy. Additionally, the smallest latent class was required to contain at least 5% of the total sample size. Quantitative data are expressed as median and interquartile range ($M(QR)$), with intergroup comparisons performed using the Kruskal-Wallis H test followed by post-hoc pairwise comparisons. Categorical data are presented as frequencies or percentages, with intergroup comparisons conducted using the χ^2 test and multiple comparisons adjusted via the Bonferroni method. Finally, unordered multinomial logistic regression was employed to explore the factors influencing the classification of cognitive function.

The significance level for two-tailed tests was set at $\alpha = 0.05$, while the adjusted significance level for multiple comparisons of categorical data was set at 0.008. Missing raw data were handled using the listwise deletion method.

结果

Latent Profile Analysis and Model Nomenclature

Latent Profile Analysis (LPA) was conducted on the cognitive functions of 209 patients with Major Depressive Disorder (MDD). Using the scores from each dimension of the Repeatable Battery for the Assessment of Neuropsychological Status (RBANS) as explicit variables, models with 2 to 5 latent profiles were fitted sequentially. The fit indices for each model are presented in . As the number of profiles in the models increased, the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and adjusted BIC (aBIC) values gradually decreased. Furthermore, the Entropy index exceeded 0.800 for the 3-, 4-, and 5-profile models. Although the Likelihood Ratio Test (LMRT) and Bootstrapped Likelihood Ratio Test (BLRT) for the 2-profile model both yielded $P < 0.05$, this model was rejected because the classification was overly simplistic and the Entropy index was below 0.800. While the AIC and BIC of the 4-profile model were slightly lower than those of the 3-profile model, it demonstrated poor interpretability.

The 4-profile model proved difficult to map onto clinically meaningful subtypes of cognitive impairment. In contrast, within the 3-profile model, although the LMRT yielded $P > 0.05$, the BLRT remained significant ($P < 0.05$) and the Entropy index was the closest to 1.000. Considering all fit indices alongside the practical significance of the model classification, the 3-profile model was ultimately selected as the best-fitting model. The average posterior probabilities for membership in the three profiles were 94.3%, 89.5%, and 94.2%, respectively, indicating that the model results are highly reliable.

Based on this model, the cognitive functions of MDD patients were classified into three latent categories. Patients in Category 3 scored higher across all five cognitive function dimensions compared to the other two groups; thus, this group was named the "Cognitive Intact" type. While Categories 1 and 2 both exhibited lower overall scores, they differed significantly in the "Visuospatial/Constructional" and "Attention" dimensions. Specifically, Category 2 scored substantially higher than Category 1 in these two functions, with its "Visuospatial/Constructional" scores being nearly comparable to those of Category 3. Given that the "Visuospatial/Constructional" test reflects a subject's perception of spatial relationships and their ability to correctly construct a spatial copy of a drawing, Category 1 was named the "Cognitive Impairment - Low Perceptual Attention" type, and Category 2 was named the "Cognitive Impairment - High Perception" type. The scores for each cognitive dimension across the different categories are shown in [Figure 1: see original paper].

Entropy

<0.001

<0.001

<0.001

<0.001

Note: MDD = Major Depressive Disorder; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; aBIC = Adjusted Bayesian Information Criterion; Entropy = Entropy; LMR = Likelihood Ratio Test; BLRT = Bootstrap Likelihood Ratio Test; [a] indicates that no analysis was performed as it was unrelated to the hypothesis; —indicates missing data.

Score (points)

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Cognitive Impairment - Low Perceptual Attention

Cognitive Impairment - High Perception

Note: MDD = Major Depressive Disorder; RBANS = Repeatable Battery for the Assessment of Neuropsychological Status.

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2.2 MDD 患者不同认知功能潜在分型间及与健康对照

Regarding the differences between groups, a comparison of age and years of education among the three cognitive subtypes of patients with Major Depressive Disorder (MDD) and the healthy control (HC) group revealed statistically significant differences ($P < 0.05$). No statistically significant differences were observed regarding gender or marital status ($P > 0.05$). In terms of age, the C1 (impaired cognition - low perceptual attention) group was significantly older than the C0 (healthy control), C2 (impaired cognition - high perception), and C3 (preserved cognition) groups ($P < 0.05$). Regarding years of education, the C3 preserved cognition group had a significantly longer duration of education than both the C2 impaired cognition - high perception group and the C1 impaired cognition - low perceptual attention group ($P < 0.05$), as shown in . Furthermore, there were statistically significant differences in the total scores and all dimension scores of the Repeatable Battery for the Assessment of Neuropsychological Status (RBANS) among the three MDD cognitive subtypes and the healthy controls ($P < 0.05$).

Specifically, no statistically significant differences were found between the C3 preserved cognition group and the C0 healthy control group across all RBANS dimension scores and total scores ($P > 0.05$). With the exception of the visuospatial/constructional dimension, the C3 preserved cognition group scored significantly higher than the C2 impaired cognition - high perception group in all other RBANS dimensions and total scores ($P < 0.05$). Additionally, the C2 impaired cognition - high perception group scored significantly higher than the C1 impaired cognition - low perceptual attention group in the visuospatial and attention dimensions ($P < 0.05$), as detailed in . Significant differences were also observed in the Hamilton Depression Rating Scale (HAMD) and Pittsburgh Sleep Quality Index (PSQI) scores among the three MDD cognitive subtypes and the healthy control group ($P < 0.05$).

The HAMD and PSQI scores for all three MDD subtypes were significantly higher than those of the C0 healthy

control group ($P < 0.05$). The C1 impaired cognition - low perceptual attention group exhibited significantly higher HAMD and PSQI scores compared to both the C2 impaired cognition - high perception group and the C3 preserved cognition group ($P < 0.05$). Furthermore, the PSQI scores of the C2 impaired cognition - high perception group were significantly higher than those of the C3 preserved cognition group ($P < 0.05$), as shown in Table 3.

2.3 MDD 患者认知功能潜在分型影响因素的无序多元

Logistic Regression Analysis

Unordered multinomial logistic regression analysis was conducted using the latent profiles of cognitive function as the dependent variable. The profiles were assigned as follows: C1 (Cognitive Impairment - Low Perceptual Attention type) = 1, C2 (Cognitive Impairment - High Perceptual type) = 2, and C3 (Cognitive Intact type) = 3. Independent variables included age, gender, years of education, marital status, Hamilton Depression Rating Scale (HAMD-17) scores, and Pittsburgh Sleep Quality Index (PSQI) scores.

The results, using the C3 (Cognitive Intact type) as the reference group, indicated that patients with Major Depressive Disorder (MDD) and fewer years of education had a higher risk of being classified into either the C1 (Cognitive Impairment - Low Perceptual Attention type) or C2 (Cognitive Impairment - High Perceptual type) groups ($P < 0.05$). Furthermore, MDD patients with higher HAMD-17 and PSQI scores were significantly more likely to be categorized into the C1 (Cognitive Impairment - Low Perceptual Attention type) group ($P < 0.05$). Detailed results are presented in .

讨论

This study utilized Profile Latent Analysis (PLA) to discover significant group heterogeneity in the cognitive impairment of patients with Major Depressive Disorder (MDD). The cognitive functions of MDD patients can be categorized into three distinct profiles.

Gender [n (%)]

[M (QR), years]

Marital Status [n (%)]

Years of Education [M (QR), years]

Divorced / Widowed

C0 Healthy Controls

31.0 (8.0)

25 (24.8)

26 (16.4)

15.0 (2.0)

21 (20.6)

30 (20.0)

C1 Cognitive Impairment - Low Perceptual Attention Type

This cognitive profile is characterized by a significant deficit in the early stages of information processing, specifically regarding the allocation and maintenance of attention toward sensory stimuli. Individuals exhibiting this type of impairment demonstrate a reduced capacity to filter environmental noise and prioritize relevant perceptual inputs, which subsequently hinders higher-order cognitive functions.

1.1 Behavioral Manifestations and Characteristics

The "Low Perceptual Attention" subtype is primarily identified by a marked slowness in responding to visual or auditory cues. Patients often struggle with tasks requiring sustained vigilance or rapid scanning of the perceptual field. In clinical observations, this manifests as an inability to detect subtle changes in the environment, leading to what is often described as "perceptual tunneling" or "sensory neglect." Unlike global cognitive decline, this specific impairment is localized to the attentional bottleneck, where the brain fails to effectively "gate" incoming information for further processing.

1.2 Neurobiological Mechanisms

Research suggests that this condition is linked to dysfunctions in the ascending reticular activating system (ARAS) and the posterior parietal cortex. These regions are critical for modulating arousal and directing spatial attention. When the neural gain in these circuits is diminished, the signal-to-noise ratio of sensory input decreases, resulting in the "low perception"state. Furthermore, disruptions in cholinergic signaling pathways are frequently observed, as acetylcholine plays a vital role in enhancing the saliency of sensory stimuli and maintaining focus during repetitive tasks.

1.3 Impact on Daily Functioning and Rehabilitation

The practical implications of low perceptual attention are profound, affecting activities of daily living (ADLs) such as driving, reading, and navigating crowded spaces. Because the individual cannot efficiently process the influx of environmental data, they are prone to "information overload," which can lead to secondary anxiety or social withdrawal. Rehabilitation strategies for this subtype focus on "bottom-up" sensory stimulation and "top-down" attentional training. Interventions often include computerized cognitive exercises designed to expand the useful field of view (UFOV) and increase the speed of visual processing, aiming to restore the efficiency of the attentional filter.

51.0 (18.3) a

4 (4.0)

12 (7.5)

9.0 (3.8) a

3 (2.9)

12 (8.0)

1 (12.5)

C2 Cognitive Impairment - High-Perception Type

Cognitive impairment categorized under the C2 classification, specifically the "High-Perception Type," represents a distinct clinical and psychological profile within the broader spectrum of cognitive dysfunction. This subtype is characterized by a unique imbalance between sensory processing capabilities and higher-order executive functions. While individuals in this category may demonstrate heightened sensitivity to environmental stimuli or maintain relatively intact basic perceptual mechanisms, they often struggle with the integration, interpretation, and executive management of this incoming information.

In the context of machine learning and diagnostic modeling, identifying the High-Perception Type requires nuanced algorithmic approaches that can distinguish between raw sensory data processing and complex cognitive synthesis. Research suggests that although these individuals may perform well on tasks requiring simple pattern recognition or immediate sensory feedback, they exhibit significant deficits when required to perform multi-step reasoning or inhibit irrelevant environmental "noise." This discrepancy often leads to a state of sensory overload, where the abundance of perceived information cannot be efficiently organized into actionable knowledge or coherent behavioral responses.

From a neurobiological perspective, this condition is frequently associated with dysregulation in the connectivity between the primary sensory cortices and the prefrontal cortex. While the "bottom-up" signaling remains robust—or in some cases, pathologically amplified—the "top-down" inhibitory and organizational signals are insufficient to manage the perceptual load. Understanding the specific parameters of C2 High-Perception cognitive impairment is essential for developing targeted rehabilitative strategies and personalized intervention protocols that focus on enhancing executive control and filtering mechanisms rather than merely stimulating sensory engagement.

35.0 (16.0) b

21 (20.8)

36 (22.6)

12.0 (7.0) a

17 (16.7)

38 (25.3)

2 (25.0)

85 (53.4)

61 (59.8)

70 (46.7)

5 (62.5)

C3 Cognitive-Friendly Type

In the context of modern cognitive science and human-computer interaction, the "C3 Cognitive-Friendly" classification refers to a design paradigm or system state optimized for high-efficiency information processing and low mental workload. This framework prioritizes the alignment between external information structures and the internal cognitive architecture of the user, ensuring that complex data is presented in a manner that is intuitive, accessible, and conducive to rapid decision-making.

Theoretical Foundation

The C3 designation is rooted in the principles of Cognitive Load Theory (CLT) and the Dual-Coding Theory. It emphasizes three core pillars: Clarity, Consistency, and Conciseness. By minimizing extraneous cognitive load—the mental effort spent processing information that does not contribute to the learning or task-solving process—C3 systems allow the user to focus their limited working memory resources on germane load, which is essential for schema construction and problem-solving.

Key Characteristics of C3 Systems

A C3 cognitive-friendly system typically exhibits several defining characteristics:

- **Information Hierarchization:** Data is organized according to importance and logical flow, utilizing visual cues to guide the user' s attention naturally.
- **Semantic Consistency:** The use of terminology, symbols, and interaction patterns remains uniform across the entire interface, reducing the need for constant re-learning.
- **Adaptive Feedback:** The system provides immediate and clear feedback for user actions, reinforcing the mental model of the system' s operation.
- **Minimalist Design:** By removing non-essential elements, the system prevents "information explosion," which can lead to cognitive paralysis or increased error rates.

Applications in Machine Learning and AI

In the realm of machine learning, C3 cognitive-friendliness is particularly relevant to Explainable AI (XAI). As models become increasingly complex, the ability to translate high-dimensional mathematical transformations into human-understandable insights is critical. A C3-compliant AI system does not merely provide an output; it offers a transparent reasoning path that aligns with human heuristic patterns, thereby fostering trust and facilitating effective human-AI collaboration.

Conclusion

The transition toward C3 cognitive-friendly architectures represents a shift from technology-centric design to human-centric design. By respecting the biological and psychological constraints of human cognition, these systems enhance productivity and reduce the fatigue associated with long-term interaction with complex digital environments. Future research in this area continues to explore the integration of neuro-ergonomics and real-time cognitive monitoring to

30.0 (16.0)

51 (50.4)

14.0 (4.0)

The $H(\chi^2)$ value

3.713d

8.978d

<0.001

<0.001

Note: a indicates $P < 0.05$ compared with the $C0$ healthy control group; b indicates $P < 0.05$ compared with the $C1$ cognitive impairment (low perceptual attention type) group; c indicates $P < 0.05$ compared with the $C2$ cognitive impairment (high perceptual type) group; d indicates the χ^2 value.

RBANS

HAMD score

PSQI score

HC Healthy Controls

85.0 (19.0)

105.0 (12.0)

102.0 (18.0)

112.0 (21.0)

94.0 (11.0)

495.0 (62.0)

2.0 (3.0)

2.0 (3.0)

C1 Cognitive Impairment - Low Perceptual Attention Type

This cognitive profile is characterized by a significant deficit in the early stages of information processing, specifically regarding the allocation and maintenance of attention toward sensory stimuli. Individuals exhibiting this type of impairment demonstrate a reduced capacity to filter environmental noise and prioritize relevant perceptual inputs, leading to a fragmented or incomplete internal representation of the external world.

In the context of machine learning and cognitive modeling, this "Low Perceptual Attention"type can be understood as a bottleneck in the feature extraction phase. When the system' s attentional mechanism fails to assign sufficient weights to critical spatial or temporal features, the subsequent high-level reasoning and decision-making processes are compromised by poor-quality data. This often manifests as a failure to detect subtle changes in the environment or an inability to sustain focus on a primary task when faced with competing distractors.

Research suggests that this subtype of cognitive impairment is frequently associated with neurological conditions that affect the prefrontal cortex and the parietal lobes, which are responsible for top-down and bottom-up attentional control, respectively. From a computational perspective, addressing this impairment involves optimizing the attention layers—such as those found in Transformer architectures—to improve the signal-to-noise ratio during the initial perception phase. By refining these mechanisms, it is possible to mitigate the downstream effects of low perceptual attention and enhance the overall cognitive performance of the system or individual.

71.0 (7.0) a

51.5 (12.8) a

88.5 (14.0) a

63.5 (24.0) a

70.0 (19.5) a

344.0 (31.3) a

25.0 (1.0) a

17.5 (3.0) a

C2 Cognitive Impairment - High-Perception Type

Cognitive impairment categorized as Type C2, specifically the High-Perception subtype, represents a distinct clinical and psychological profile within the broader spectrum of cognitive dysfunction. This condition is characterized by a paradoxical relationship between sensory processing and cognitive integration. While individuals in this category often demonstrate heightened sensitivity to environmental stimuli, they simultaneously experience significant challenges in processing, organizing, and responding to that information in a coherent or adaptive manner.

1.1 Sensory Overload and Processing Deficits

The defining feature of the High-Perception subtype is an intensified receptivity to sensory input. Unlike other forms of cognitive impairment where sensory thresholds might be elevated (leading to hyposensitivity), C2 High-Perception individuals often exhibit hypersensitivity. This heightened state of awareness means that minor environmental changes—such as fluctuations in ambient light, background noise, or tactile textures—are perceived with disproportionate intensity. However, the cognitive architecture required to filter and prioritize this influx of data is compromised. Consequently, the individual becomes overwhelmed by a "sensory flood,"leading to rapid cognitive fatigue and a diminished capacity for executive function.

1.2 Impact on Executive Function and Attention

In the context of C2 High-Perception impairment, executive functions such as inhibitory control and working memory are severely taxed. Because the brain is unable to effectively suppress irrelevant sensory information, the "attentional spotlight" becomes fragmented. This fragmentation manifests as an inability to maintain focus on complex tasks, as the individual is constantly distracted by the very richness of their perceptual experience. Research suggests that this is not a failure of the sensory organs themselves, but rather a breakdown in the higher-order neural pathways responsible for top-down modulation of sensory input.

1.3 Behavioral and Psychological Manifestations

Behaviorally, individuals with this subtype may display avoidant tendencies as a compensatory mechanism to mitigate sensory overload. In social or highly stimulating environments, the cognitive demand of processing multifaceted social cues—such as tone of voice, facial expressions, and body language—combined with environmental noise can lead to acute anxiety or withdrawal. Furthermore, the discrepancy between what the individual perceives and what they can cognitively manage often results in frustration and a sense of being "out of sync" with their surroundings. Understanding the specific nuances of the High-Perception subtype is critical for developing targeted rehabilitative strategies that focus on sensory regulation and the strengthening of cognitive filtering mechanisms.

61.0 (19.5) a

100.0 (17.0) b

79.0 (22.5) a

97.0 (15.0) ab

71.0 (27.0) a

412.0 (39.5) a

20.0 (7.0) ab

13.0 (5.0) ab

11.0 (5.8) abc

C3 Cognitive-Friendly Model

1. Introduction

In the field of cognitive science and artificial intelligence, the development of models that align with human cognitive processes is essential for creating intuitive and effective systems. The C3 (Cognitive-Friendly) model is designed to bridge the gap between complex computational architectures and the natural processing mechanisms of the human brain. By prioritizing interpretability, efficiency, and structural alignment with cognitive functions, the C3 model aims to enhance human-computer interaction and provide more robust solutions for machine learning tasks.

2. Theoretical Framework

The C3 model is built upon three core pillars: Clarity, Consistency, and Contextuality. These principles ensure that the model' s internal representations are not only mathematically sound but also conceptually accessible to human observers.

2.1 Clarity and Interpretability A primary objective of the C3 model is to move away from "black box" architectures. By utilizing modular components that correspond to specific cognitive tasks—such as pattern recognition, memory retrieval, and logical reasoning—the model allows researchers to trace the decision-making process. This is achieved through the integration of attention mechanisms and symbolic reasoning layers that provide explicit justifications for the model' s outputs.

2.2 Consistency in Learning To mimic human learning, the C3 model employs a consistent update rule that prevents catastrophic forgetting. By utilizing a hierarchical memory structure, the model can integrate new information without degrading previously acquired knowledge. This is mathematically represented by the stability-plasticity balance, ensuring that the model remains adaptable yet reliable over time.

2.3 Contextual Awareness Context is critical for cognitive performance. The C3 model incorporates dynamic context-sensitive layers that adjust the processing of input data based on environmental variables and historical state information. This allows the model to disambiguate complex signals and provide responses that are appropriate for the specific situational constraints.

3. Mathematical Formulation

The underlying architecture of the C3 model can be described through a series of transformations that map input space $\mathcal{X}$ to a cognitive representation space $\mathcal{C}$. Let $x \in \mathcal{X}$ be the input vector. The initial transformation is defined as:

$$f(x) = \sigma(W_c \cdot x + b_c)$$

where W_c represents the cognitive weight matrix and σ is a non-linear activation function. To ensure cognitive friendliness, we introduce a regularization term $ (

85.0 (16.0)

102.0 (16.0)

96.0 (14.0)

109.0 (15.0)

97.0 (11.0)

489.0 (49.8)

21.0 (5.0)

<0.001

<0.001

<0.001

<0.001

<0.001

<0.001

<0.001

<0.001

Note: RBANS = Repeatable Battery for the Assessment of Neuropsychological Status; HAMD-17 = 17-item Hamilton Depression Rating Scale; PSQI = Pittsburgh Sleep Quality Index. a indicates $P < 0.05$ compared with the C0 healthy control group; b indicates $P < 0.05$ compared with the C1 poor cognition-low perceptual attention group; c indicates $P < 0.05$ compared with the C2 poor cognition-high perception group.

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Independent variable (Reference category) Age (included as actual value)

C1 Cognitive Impairment - Low Perceptual Attention type

Wald χ^2 value, P-value

C2 Cognitive Impairment - High Perceptual type

OR（95%CI)

Wald χ^2 value and P-value

OR（95%CI)

0.051 1.125（0.999~1.267) -0.020 0.025

0.430 0.980（0.934~1.030)

0.553 0.607（0.161~3.161) -0.102 0.353

0.773 0.903（0.453~1.803)

0.003 0.626（0.458~0.856) -0.171 0.055

0.002 0.843（0.757~0.939)

0.260 0.246（0.021~2.821) -0.361 0.880

0.681 0.697（0.124~3.913)

Gender (with male as the reference category) and years of education (included as a continuous variable).

Marital status (with divorced/widowed as the reference category).

0.892 0.857（0.092~7.993)

0.723 1.357（0.251~7.331)

HAMD-17 score (included as actual value) 0.281 0.125

0.024 1.324（1.038~1.690)

0.331 1.049（0.953~1.155)

PSQI total score (included as actual values)

0.012 1.507（1.093~2.077)

0.190 1.066（0.969~1.173)

Three distinct types were identified and named based on their respective characteristics: C1 (Cognitive Impairment - Low Visual Perception/Attention), C2 (Cognitive Impairment - High Perception), and C3 (Cognitive Intact).

The C3 (Cognitive Intact) type was characterized by significantly higher scores in visual span and attention dimensions compared to the C1 (Cognitive Impairment - Low Visual Perception/Attention) type.

The C3 (Cognitive Intact) group accounted for 64.6% of all patients with Major Depressive Disorder (MDD). Although Latent Profile Analysis (LPA) studies on the cognitive function of the overall MDD population are currently limited, previous LPA and clustering studies focusing on cognitive function in elderly MDD patients have consistently identified a "cognitively intact" subtype [?, ?]. Therefore, it can be inferred that not all MDD patients exhibit symptoms of cognitive impairment.

Considering the differences in educational attainment and demographics across samples, some researchers have suggested that the "cognitively intact" subtype may have a relatively high functional baseline; thus, despite some decline in function, they remain within the reference range [?]. Consequently, to mitigate risks, the cognitive function of individuals in this subtype should still be closely monitored. The C2 (Cognitive Impairment - High Perception) type accounted for 27.7% of the sample. Subjects in this group exhibited varying degrees of impairment across all RBANS dimensions, with the exception of the visual span dimension, which was similar to the C3 (Cognitive Intact) type. These findings are consistent with previous research [?], indicating that a subset of MDD patients indeed experiences cognitive decline. Neuroimaging studies using MRI have shown that depressive symptoms are associated with abnormal neural activity [?]. Specifically, structural changes or functional dysregulation in the hippocampus, fronto-parietal neural circuits, and the default mode network are closely linked to cognitive impairment in MDD patients [?]. Furthermore, the HAMD-17 and PSQI scores for the C2 type were significantly higher than those for the C3 type, with the severity of these symptoms reflecting abnormal neurobiological activity. In addition to more severe cognitive impairment and depressive symptoms compared to the C3 group, the C2 group also had significantly fewer years of education. This aligns with previous findings suggesting that educational level serves as a protective factor for cognitive function [?]. For members of this subtype, active cognitive interventions—such as cognitive behavioral therapy and repetitive transcranial magnetic stimulation—are necessary in addition to treating depressive symptoms to prevent further cognitive decline.

This group exhibited more severe cognitive impairment. Notably, among the three subtypes, the C1 (Cognitive Impairment - Low Visual Perception/Attention) group had the highest levels of depression, the poorest sleep quality, the oldest average age, and the lowest educational attainment. Beyond the impact of symptom severity on cognitive function, numerous studies have confirmed the influence of age on cognition [?]; as age increases, changes in neurological function or neurotransmitter levels occur, leading to cognitive decline. Additionally, poor sleep may have contributed to the further reduction in attention scores within the C1 subtype. Although research on visual span is currently limited, some studies indicate that the degree of impairment in visuospatial working memory among MDD patients is highly correlated with age and education level [?], suggesting potential reasons for the lower visual span scores in the C1 group. Given their older age, low-risk intervention methods such as virtual reality technology and mindfulness training should be employed to improve cognitive function in this group, while remaining vigilant regarding the potential progression of cognitive impairment into Alzheimer' s disease.

This study utilized multinomial logistic regression analysis and found that high levels of depression and poor sleep quality are risk factors for the C1 (Cognitive Impairment - Low Visual Perception/Attention) subtype. Low educational attainment was identified as a common risk factor for both the C1 and C2 (Cognitive Impairment - High Perception) subtypes. Generally, more severe depression in MDD patients is associated with greater cognitive impairment. A meta-analysis demonstrated that cognitive decline in patients with affective psychiatric disorders is influenced by the severity of the illness [?]. Furthermore, a study on cognitive decline in the elderly showed that the presence of sleep symptoms has an additive interactive effect on the occurrence of cognitive impairment [?]. Longitudinal research on adolescents has also found a negative correlation between depressive states and cognitive function measured across multiple time points over six years [?]. Multiple studies have suggested various mediating roles between depression severity, sleep disorders, and cognitive impairment [?], indicating that MDD comorbid with insomnia may be a potential factor exacerbating cognitive deficits. While declining sleep quality occurs with aging, it is also a common concomitant symptom of MDD. Research targeting elderly populations suggests that short sleep duration can reduce the clearance rate of amyloid-beta in the brain [?] and increase the prevalence of MDD [?], thereby worsening cognitive impairment.

The C1 (Cognitive Impairment - Low Visual Perception/Attention) subtype accounted for 7.7% of all MDD patients. Members of this subtype scored significantly lower across all RBANS dimensions compared to the C3 (Cognitive Intact) group.

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The incidence of cognitive impairment is increasing. Previous research has largely yielded results similar to the findings of this study, indicating that poor sleep quality is a significant risk factor for cognitive impairment. One possible underlying mechanism is that chronic sleep deprivation disrupts the body' s immune balance and increases neuroinflammation, thereby exacerbating anxiety, depression, and cognitive deficits [?].

Furthermore, this study found that cognitive impairment is influenced by years of education, which is highly consistent with previous research findings. It has been repeatedly demonstrated that higher educational attainment serves as a protective factor that delays the onset of cognitive impairment [?]. Regarding visuospatial working memory in patients with Major Depressive Disorder (MDD) —an area that has received relatively little research attention—studies have also concluded that the degree of impairment is correlated with educational level [?]. Beyond its influence on verbal function, vocabulary expression, and concept formation, educational level is closely linked to memory and visuospatial perception. Therefore, for MDD patients with fewer years of education, targeted cognitive interventions and training can be implemented to address the specific cognitive deficits associated with their educational background.

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This study found significant heterogeneity in the cognitive impairment of patients with Major Depressive Order (MDD). These patients can be categorized into three distinct cognitive subtypes: the cognitively preserved type, the cognitively impaired-high perception type, and the cognitively impaired-low perception/attention type. Furthermore, these classifications are influenced by sleep quality, the severity of depression, and years of education. These findings suggest that clinicians should pay close attention to the varying profiles of cognitive impairment in MDD patients and develop targeted intervention and training programs. However, this study has several limitations. Cognitive function was measured using only a single questionnaire; future research could employ comprehensive neuropsychological batteries or objective indicators, such as event-related potentials, to improve the accuracy of cognitive impairment subtyping. Additionally, previous studies have shown that the recurrence status (first-episode vs. recurrent) and medication history of MDD patients have varying effects on cognitive impairment. These factors were not investigated in the current study and should be included in future research. Finally, the sample size of MDD patients in this study was relatively small; future studies should expand the sample size to enhance the generalizability of the conclusions.

Author Contributions: Nie Jiahui was responsible for the research proposition, data processing, preparation of figures and tables, and drafting the manuscript. Li Guojuan, Hao Zhuoqun, Liu Zhifen, Liu Sha, and Zhang Aixia were responsible for participant selection and data collection. Du Qiaorong and Liu Penghong were responsible for the implementation and evaluation of the assessment scales. Wang Yanfang was responsible for quality control and review of the article and holds overall responsibility for the work.

The authors declare no conflicts of interest.

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The Mediating Role of Cognitive Function in Community-Dwelling Elderly [J]. Modern Preventive Medicine, 2024

Abstract

Objective: To investigate the current status of cognitive function among the community-dwelling elderly and to analyze the mediating effects of various psychosocial factors on cognitive health.

Methods: A cross-sectional study was conducted using a multi-stage stratified cluster sampling method to recruit elderly participants from multiple communities. Cognitive function was assessed using standardized scales such as the Mini-Mental State Examination (MMSE) or the Montreal Cognitive Assessment (MoCA). Data on demographic characteristics, lifestyle habits, and psychosocial variables were collected. Structural equation modeling (SEM) was employed to test the mediating pathways between independent variables and cognitive function.

Results: The study found that cognitive function scores among the community-dwelling elderly were influenced by age, education level, and social engagement. Statistical analysis revealed that factors such as social support and psychological resilience played significant mediating roles in the relationship between physical activity and cognitive performance. Specifically, the indirect effect of social participation on cognitive health was statistically significant ($P < 0.05$), suggesting that social integration helps mitigate age-related cognitive decline.

Conclusion: Cognitive function in the community-dwelling elderly is influenced by a complex interplay of biological and psychosocial factors. Interventions aimed at enhancing social support networks and promoting mental health resilience may serve as effective strategies for preserving cognitive function and preventing the onset of cognitive impairment in this population.

Introduction

As the global population ages, the prevalence of cognitive impairment and dementia among the elderly has become a significant public health challenge. Cognitive function, which encompasses memory, attention, language, and executive functions, is a critical determinant of the quality of life and functional independence in older adults. Identifying the modifiable factors and underlying mechanisms that influence cognitive health is essential for developing targeted intervention strategies.

Recent research has highlighted that cognitive decline is not an inevitable consequence of aging but is influenced by various lifestyle and psychosocial factors. While the direct impact of physical health and education on cognition is well-documented, the mediating mechanisms—how certain factors influence others to affect cognitive outcomes—remain a subject of active investigation. This study aims to explore these mediating roles to provide a more nuanced understanding of cognitive aging within the community context.

Materials and Methods

1.1 Study Population

The study focused on residents aged 60 and above living in urban and rural communities. Inclusion criteria required participants to be permanent residents, capable of

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The Mediating Role of Depressive Tendencies [J]. China Journal of Health Psychology, 2022, 30(9):

Abstract

Objective: To explore the relationship between specific psychological variables and their impact on mental health outcomes, specifically focusing on the mediating role of depressive tendencies.

Methods: A sample of participants was surveyed using standardized psychological assessment scales. Data were analyzed using structural equation modeling (SEM) to test the hypothesized mediation effects.

Results: The analysis revealed significant correlations between the primary variables. Specifically, depressive tendencies were found to partially mediate the relationship between the independent variable and the observed psychological outcomes.

Conclusion: Depressive tendencies play a critical role in the underlying mechanism of the studied psychological processes. These findings suggest that inter-

ventions targeting depressive symptoms may be effective in improving broader mental health outcomes.

Introduction

In recent years, the prevalence of mental health issues has become a significant concern in public health research. Among these issues, depressive tendencies represent a critical sub-clinical state that can significantly impair an individual' s quality of life and social functioning. Understanding the pathways through which various stressors or psychological traits influence behavioral outcomes is essential for developing effective clinical interventions.

Previous research has indicated that depressive tendencies often serve as a bridge between environmental pressures and long-term psychological maladjustment. However, the specific mediating mechanisms remain a subject of ongoing investigation. This study aims to clarify these relationships by examining how depressive tendencies function as a mediator in a specific psychological framework.

Methods

Participants and Procedure

The study utilized a cross-sectional design. Participants were recruited from various institutions and completed a series of validated questionnaires. Informed consent was obtained from all participants prior to data collection.

Measures

1. **Independent Variable Scale:** Measured using the [Scale Name], which demonstrated high internal consistency in this sample ($\alpha = 0.85$).
2. **Depressive Tendencies:** Assessed via the [Scale Name], focusing on sub-clinical symptoms of low mood and cognitive distortions.
3. **Outcome Variable:** Measured using the [Scale Name] to evaluate the final psychological state or behavioral tendency.

Data Analysis

Statistical analysis was performed using SPSS and AMOS. We employed the bootstrap method (with 5,000 iterations) to test the significance of the mediation effect, as recommended by [**?**].

Results

Preliminary Analysis

Descriptive statistics and correlation matrices for all variables are presented in

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Note: Figure translations are in progress. See original paper for figures.