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Association between personality profiles and motoric cognitive risk syndrome in community-dwelling older adults: a person-centered approach

Junwei Zhang[1], Lina Wang[1*], Chen Zhang[2], Xiaoyan Wang[2], Xue Sun[3], Chenyu Wang[1], Guanxiu Liu[1], Lulu Shi[1] and Bei Wu[4*]

Abstract

Background Motoric cognitive risk (MCR) syndrome is a predementia syndrome characterized by subjective cognitive complaints and slow gait in the absence of dementia and mobility disability. Although past research has suggested that personality traits could play a significant role in the onset and progression of MCR among older adults, the exact relationships between specific personality profiles and MCR remain unclear. This study aimed to examine the relationship between personality profiles and MCR among community-dwelling older adults.

Methods A cross-sectional study was conducted from March 2021 to January 2022. Personality traits, including openness, extraversion, agreeableness, conscientiousness and neuroticism, were measured using the 40-item brief version of the Chinese Big Five Inventory. The Latent profile analysis was used to identify personality profiles among these older adults who shared similar patterns of personality traits. The Lanza, Tan, and Bray's approach was employed to investigate the personality profile-specific differences in MCR prevalence. Furthermore, a stepwise multinomial logistic regression revealed unique population characteristics for different personality profiles.

Results A total of 538 eligible participants were included in this study. The mean age was 73.25 years (SD = 9.0) and 62.50% were females. This study identified four distinct personality profiles: the resilient, ordinary, reserved, and anti-resilient profiles. The resilient profile exhibited the lowest prevalence of MCR (mean = 6%, *SE* = 0.024), whereas the anti-resilient profile had the highest (mean = 20.3%, *SE* = 0.043). The prevalence of MCR differed among personality profiles (overall $\chi^2 = 14.599$, $p = 0.002$). Personality profile membership was characterized by different population characteristics. Notably, the anti-resilient profile was association with symptoms of depression (OR = 28.443, 95%CI = 11.095–72.912), while the reserved profile was linked with advanced age (OR = 1.031, 95%CI = 1.003–1.061). Overall, a low education level and poor sleep quality were the robust attribution factors.

*Correspondence:
Lina Wang
aring2000@163.com
Bei Wu
bei.wu@nyu.edu

Full list of author information is available at the end of the article

Conclusions This study revealed that personality profiles may assist in identifying older adults at greater risk of MCR. Increased awareness and management of personality profiles may contribute to the prevention of MCR.

Keywords Dementia, prevention and control, Motoric cognitive risk syndrome, Personality profiles, Latent profile analysis

Introduction

Dementia is becoming an increasingly global health concern due to the rapid rise in the number of older adults worldwide. Motoric cognitive risk (MCR) syndrome is a predementia syndrome characterized by subjective cognitive complaints (SCC) and slow gait (SG) in the absence of dementia and mobility disability [1]. MCR, a condition with a global prevalence of approximately 9.7% [1], amplifies the risk of cognitive impairment by approximately one-fold, is also associated with adverse health outcomes such as falls, recurrent hospitalization, and mortality [2, 3]. Therefore, identifying potential risk factors and developing novel screening and intervention strategies for MCR are crucial. Personality traits are relatively stable patterns of thoughts, feelings, and behaviors that distinguish individuals from each other [4]. The most extensively studied paradigm is the five-factor model (FFM), which encompasses openness, extraversion, agreeableness, conscientiousness and neuroticism [5]. These personality traits are reliable predictors of cognitive impairment and dementia [6]. Previous findings suggest that conscientiousness, openness, and extraversion are negatively associated with this risk of developing MCR, whereas neuroticism is positively associated with this risk [7–9]. Openness and extraversion may be linked to less cognitive decline and fewer psychosocial issues, such as depressive disorders [10], while higher conscientiousness is typically associated with better physical and mental health [9–11]. These factors contribute to a lower risk of MCR [2, 12]. Conversely, neuroticism is linked to higher levels of perceived stress and depressive disorders [10, 13], which in turn increase the risk of developing MCR [2, 12, 14]. Considering the potential role of personality traits in managing cognitive health within predementia syndromes, it is crucial to accurately delineate the specific association between personality traits and MCR. Such exploration could yield potential markers for MCR screening and prevention, thereby providing a scientific foundation for the development of personality-oriented MCR intervention measures.

In foundational studies that examine the association between personality traits and MCR, a predominant reliance on a variable-centered approach is observed [7–9]. This approach assumes homogeneity among research participants and tends to overlook potential interaction effects among personality traits at the individual level [5]. However, personality traits interact as a dynamic system that shapes an individual's personality rather than being isolated and can overlap in the real world [5, 15]. For instance, individuals high in neuroticism often exhibit low levels of other personality traits of the FFM; openness, extraversion, agreeableness, and conscientiousness usually show a positive correlation [16, 17]. This intersection reflects the multi-dimensional nature of personality traits. Furthermore, the interactions of personality traits increase the prediction of the outcome variable beyond the capabilities of a single-trait approach [18]. Given these shared response patterns, some researchers propose that broader personality categories could emerge. Latent profile analysis (LPA) is a statistical technique increasingly used in personality research to identify subgroups of individuals based on their responses to personality assessments [5, 19]. LPA emphasizes a person-centered approach, which focuses on understanding how traits cluster within individuals rather than how individuals vary on isolated traits [19]. It allows researchers to uncover hidden subgroups and classify individuals into distinct personality profiles that share similar personality trait patterns, which is valuable for capturing the complexity and holistic nature of personality. Additionally, the personality profiles identified by LPA exhibit heterogeneity and non-overlapping characteristics [20].

LPA has been widely used to identify distinct personality profiles within populations. Zhang et al. [21] applied LPA to the personality traits of FFM, revealing personality profiles such as ordinary, rigid, and reserved, which represent qualitatively and quantitatively different combinations of high and low scores across the traits. LPA has also been instrumental in studying how personality traits develop and change over time. A longitudinal study [22] has used LPA to track how individuals' personality profiles evolve, providing insights into the stability and dynamics of personality traits. Given the predictive role of personality traits in MCR, this study explored the latent personality profiles in the MCR population using LPA based on the FFM.

A systematic review of personality profiles based on the FFM, suggested that [5] three to four personality profile solutions are prevalent, with personality profiles of resilient (lowest neuroticism and highest other traits), undercontroller (low agreeableness and conscientiousness), overcontroller (high neuroticism, and low extraversion and openness), ordinary (intermediate scores on agreeableness, openness, and conscientiousness), and anti-resilient (highest neuroticism, and lowest other traits) emerging most frequently across these solutions.

Moreover, previous work indicated that the resilient profile frequently correlates with positive factors, whereas the anti-resilient profile correlates with negative factors [13, 15, 16]. Based on these findings, this study aimed to identify up to five distinct personality profiles described above among older adults. It proposes two hypotheses: (1) Individuals within the resilient profile are assumed to have a diminished risk of MCR, whereas those in the anti-resilient profile are likely to exhibit an increased risk. (2) Significant variations in population characteristics are anticipated across different personality profiles.

Methods

Study design and ethical considerations

A cross-sectional design was employed in this study to explore the personality profiles and examine the relationship between these profiles and MCR among the older adults in Huzhou city, Zhejiang Province, China, with data collected from March 2021 to January 2022. This study was reviewed and approved by the Institutional Review Boards of Huzhou Third Municipal Hospital (Ethical Approval Number: 2021 Ethics Review *No*.007) and conformed with the Declaration of Helsinki. All participants provided written informed consent after receiving a detailed explanation of the study objectives and procedures. This study complied with the STROBE Statement [23].

Participants

Community-dwelling adults aged ≥ 60 years were recruited from community senior centers and healthcare centers in 2 districts, which were randomly selected from 5 districts in Huzhou city, Zhejiang Province, China. Recruitment leaflets were distributed at community health centers and local senior centers. Additionally, local healthcare providers also assisted by making referrals to our study. Interested individuals were invited for an in-person interview to assess their eligibility by five trained staff. A trained neurologist-psychiatrist confirmed the diagnosis of MCR.

The inclusion criteria were as follows: (1) age ≥ 60 years old; (2) absence of severe visual or hearing impairments; (3) capability to understand and complete study-related questionnaires and physical assessments; and (4) voluntary participation with a signed informed consent form. The exclusion criteria were: (1) inability to walk independently, including use walking aids; (2) meeting the criteria for mild cognitive impairment or dementia; (3) presence of any serious physical illness, like acute myocardial infarction or heart failure or severe mental disorder, such as schizophrenia and bipolar disorder; (4) use of any cognitive enhancing medications within the past six months; and (5) Recent or upcoming medical procedures that could reduce mobility (e.g., hemodialysis, elective surgery). Participants were allowed, or required to withdraw from the study based on the following: development of a serious disease preventing continuation in the survey; request to be withdrawn from the survey. In the first round of eligibility assessments, a total of 703 potential participants were recruited with ability to walk independently. The second round of eligibility assessments included functional assessment of activities of daily, general cognitive function, medical health and medication history. A total of 538 eligible participants were included in this study.

Sample size Estimation

The sample size for this study was calculated using the epidemiological cross-sectional study formula [24]. To achieve a statistically robust estimation, the sample size calculation incorporated power estimation based on a 9.6% prevalence of MCR among older adults in China [25]. Using a 3% margin of error (d) and a 95% confidence interval ($Z = 1.96$), the required sample size was 371. Taking into account the invalid questionnaires (20%), the minimum sample size was set at 446.

Measures

Data collection was conducted in the community senior centers and healthcare centers, involving face-to-face interactions by five trained staff and a trained neurologist-psychiatrist.

Personality

Personality traits were evaluated by the staff using the Chinese Big Five Personality Inventory Brief Version. This version comprises 40 items and 5 dimensions, each dimension with 8 items rated on a 6-point scale, ranging from 1 (strongly disagree) to 6 (strongly agree), resulting in dimension scores between 8 and 48 [26]. Wang et al. demonstrated good internal consistency, with Cronbach's alpha coefficients ranging from 0.764 to 0.814 for the brief version [26], and the scale is a widely used tool for assessing personality traits within the Chinese population [27].

Motoric cognitive risk syndrome

A trained neurologist-psychiatrist conducted the MCR evaluation following previously reported criteria [1, 3], defining MCR as the co-occurrence of SCC and SG in older adults without dementia and mobility disability. SCC was assessed by asking participants [3]: "Do you feel you have more memory problems than most?". Those who responded "yes" were considered to have SCC. SG was quantified using precise measurements with a tape measure (measuring 4 m distance) and stopwatch. The average of two measurements was calculated and SG was defined as value ≤ 1.0 standard deviation (SD) below the

age- and gender-specific average gait speeds established among the study participants [1]. In this study cohort, SG was defined as follows: for males aged 60–74 years, < 0.8 m/s; aged ≥ 75 years, < 0.65 m/s; for females aged 60–74 years, < 0.78 m/s; and aged ≥ 75 years, < 0.62 m/s. Mobility disability was evaluated using the Lawton and Brody Activity of Daily Living scale, consisting of: (1) physical self-maintenance with six items (toileting, feeding, dressing, grooming, ambulation, and bathing) and (2) instrumental activities with eight items (using telephone, shopping, food preparation, housekeeping, laundry, transportation, medication management, and finances). A total ADL score ≥ 16 indicates dysfunction [28, 29]. Dementia diagnosis was confirmed by community physicians using the DSM-IV criteria and the mini-mental state examination (MMSE), in conjunction with chief complaints, family history, and past medical history of the older adults. Participants were deemed without dementia if achieving an MMSE score of at least 17 points (illiterate), 20 points (elementary school), or 24 points (secondary school or above) [30].

Population characteristics

Based on a comprehensive literature review and the objectives of this study, a set of covariates in the study were set, including age, sex, education level, monthly income, marital status, occupation, smoking history, alcohol consumption history, and body-mass index (BMI). Depression symptoms were assessed using the 15-item Geriatric Depression Scale (GDS-15), which demonstrates a sensitivity of 89% and a specificity of 77% for detecting depression symptoms with a cutoff score of 5, indicating its reliability for use in Community-dwelling older adults [31]. Physical activity was assessed with the Physical Activity Scale for the Elderly (PASE), which has a total score ranging from 0 to 500, with higher scores indicating greater levels of physical activity [32]. PASE has acceptable reliability (retest reliability was ICC = 0.79) [33]. Sleep quality over the preceding 30 days was measured using the Pittsburgh Sleep Quality Index(PSQI), with a score of ≤ 5 reflecting good sleep quality [34]. The Chinese version of PSQI demonstrated acceptable internal consistency, with Cronbach's α ranging from 0.82 to 0.83 in a cohort of Chinese adults [34].

Statistical analysis

Analyses involving the LPA and the Lanza, Tan, and Bray's(LTB) approach were conducted using Mplus 8.3 (Muthén & Muthén, 1998–2017), while all other analyses were performed using SPSS (IBM SPSS 23.0, SPSS, Inc.). Categorical variables were presented as frequencies and percentages, while continuous variables were expressed as a median with interquartile range (IQR). LPA was performed to identify personality profiles of older adults. Models ranging from 1 to 6 profiles were evaluated, using the following fit indices to determine the optimal number of personality profiles [20]: the Bayesian information criterion (BIC), the sample size adjusted Bayesian information criterion (aBIC), and the Akaike's information criterion (AIC). Low values of BIC, aBIC, and AIC indicate a better fit. Two likelihood ratio tests were used: the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR) and the bootstrap likelihood ratio test (BLRT). A $p < 0.05$ indicates that a model with a k-personality profile fits better than one with a k-1 personality profile. For classification accuracy, both entropy and average posterior probability were considered. Entropy values ranging from 0 to 1, with values over 0.80 being preferred [21]. An average posterior probability value of ≥ 0.80 indicates an excellent personality profile model [13, 20]. In addition, the LTB approach [35] was employed to specify MCR as distal outcome influenced by the personality profiles. Finally, a stepwise forward multinomial logistic regression was used to identify predictors of the personality profiles. All the statistical analyses used were two-tailed, and $p < 0.05$ was used to indicate statistical significance.

Results

Descriptive statistics

This study interviewed 538 participants. Of these, 18 were excluded due to missing or incomplete information, leaving a final sample of 520 older adults (Fig. 1). Participants ranged in age from 60 to 96 years, with a mean age of 73.25 ± 9.00 years; 62.50% were females, and the majority had an education level of middle school or below. The prevalence of MCR was 13.85%, as shown in Table 1.

Identification of the number of latent personality profiles

Standardized values of the five personality traits as continuous indicators were analyzed using LPA to extract the latent personality profiles. Six models were estimated, with the corresponding fit indices displayed in Table 2. As the number of profiles increased, the AIC, BIC, and aBIC values showed a downward trend. The VLMR and BLRT tests indicated that the four-profile model significantly outperformed the three-profile model. In contrast, the VLMR for the five-profile model was not significant, supporting the more parsimonious four-profile model. The entropy value of 0.835 and a high average posterior probability (0.865–0.978) for the four-profile model indicated its excellent classification accuracy. Additionally, the minimum profile proportion of 17.3% in the four-profile model met the acceptable standard (5%) [13, 16]. Hence, the four-profile was identified as the optimal solution based on the fit indices, profile size, and interpretability.

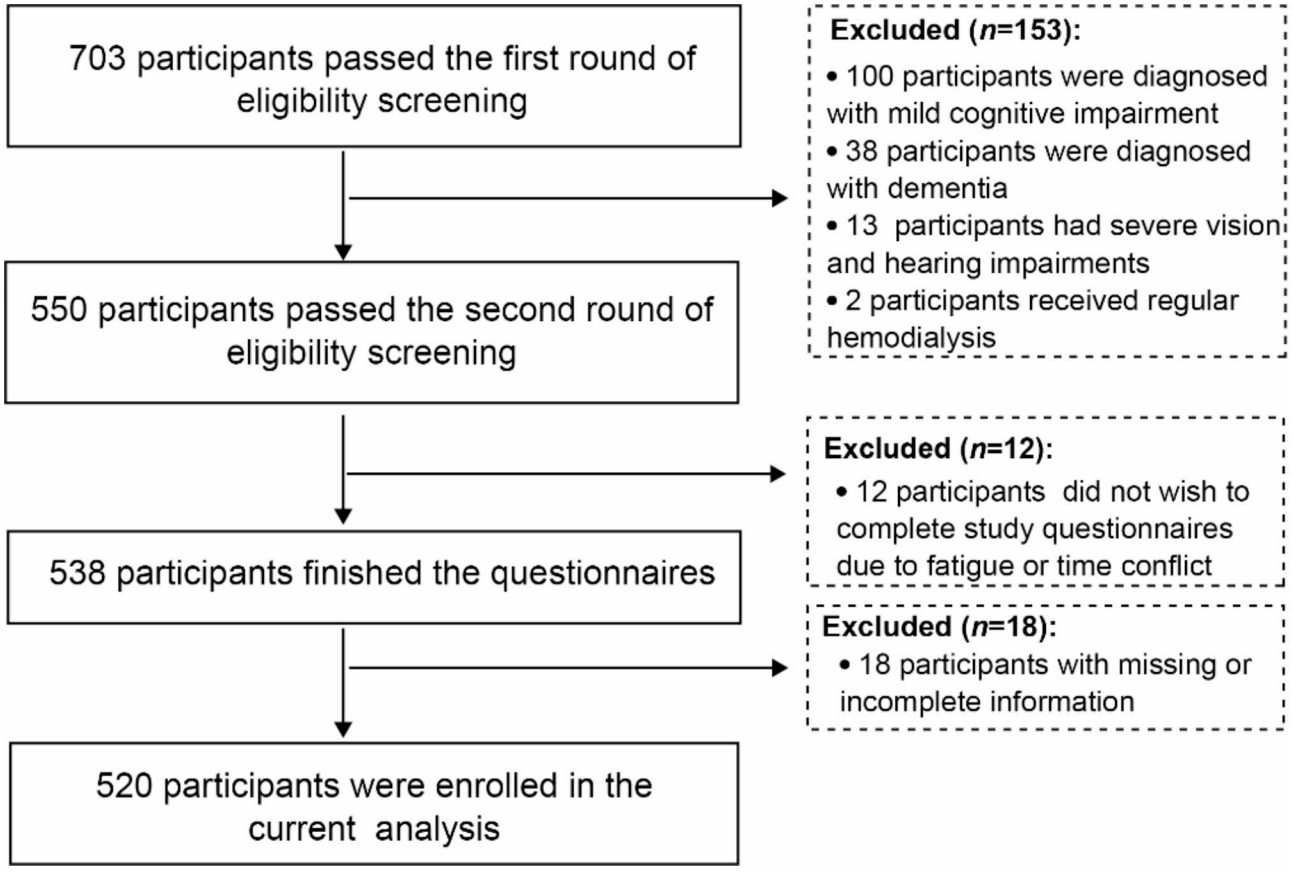

Fig. 1 Screening flowchart

The characteristics of the personality profiles

Heatmaps and profile plots were generated to illustrate the characteristics of the personality profiles and differences in personality traits within the four-profile solution, as depicted in Fig. 2. The heatmap (Fig. 2A) can more intuitively show the numerical variances across personality profiles in terms of personality traits, highlighting which traits contribute most to profile classification. Furthermore, the profile plots (Fig. 2B) help to assess the different composition patterns of personality traits within each personality profile. The personality profiles were labeled in accordance with the consensus naming based on a systematic review of personality profile research and insights from prior studies [5, 16, 36]. Profile 1 ($n = 129$, 24.8% of the participants) exhibited the lowest neuroticism and highest other personality traits, aligning with the resilient profile, also termed protective or well-adjusted [5]. Profile 2, the most prevalent ($n = 164$, 31.5% of the participants), displayed the relatively medium levels across all personality traits without any prominent traits, consistent with the ordinary profile, also known as moderate, common or average [5]. Profile 3 ($n = 137$, 26.4% of the participants) showed the lowest extraversion, a comparatively high conscientiousness, and lower levels of other personality traits, resembling the reserved profile or conservative [16, 36]. Profile 4 ($n = 90$, 17.3% of the participants) was marked by the highest neuroticism and low levels of other personality traits, fitting the anti-resilient profile, and was also described as vulnerable, rigid, and brittle [5].

The associations between personality profiles and MCR prevalence

The LTB approach was applied to explore the associations between personality profiles and MCR prevalence. Results suggested that a significant overall variance in MCR prevalence across personality profiles ($\chi^2 = 14.599$, $p = 0.002$), as detailed in Table 3. Pairwise comparisons showed that profile 1 had a lower probability of MCR prevalence compared to profile 3 and 4.

The unique associations between population characteristics and personality profiles membership

Forward stepwise selection was employed to conduct multinomial logistic regression, designating personality profiles as the dependent variable and age, sex, education level, monthly income, marital status, occupation, smoking history, alcohol consumption history, physical activity, sleep quality, BMI, and depression symptoms

Table 1 Participant characteristics ($n = 520$)

Variables	Frequency /Median	Percentage /IQR	Range
Age (years)	71.50	66–79	60–96
Sex			
Male	195	37.5	0–1
Female	325	62.5	0–1
Educational level			
Primary school and below	258	49.6	0–1
Middle school and above	262	50.4	0–1
Monthly income (Yuan)			
< 3000	231	44.4	0–1
≥ 3000	289	55.6	0–1
Marital status			
With spouse	427	82.1	0–1
No spouse	93	17.9	0–1
Occupation			
Non-manual labor	173	33.3	0–1
Manual labor	347	66.7	0–1
Smoking history			
No	442	85.0	0–1
Yes	78	15.0	0–1
Alcohol consumption history			
No	414	79.6	0–1
Yes	106	20.4	0–1
Sleep quality			
Poor	201	38.7	0–1
Good	319	61.3	0–1
BMI (kg/m^2)			
< 18.5	33	6.3	0–1
18.5–23.9	282	54.2	0–1
24-27.9	160	30.8	0–1
≥ 28	45	8.7	0–1
Depression symptoms			
No	430	82.7	0–1
Yes	90	17.3	0–1
MCR			
No	448	86.2	0–1
Yes	72	13.8	0–1
Physical activity (scores)	110.8	64.6-149.6	0-340.5
Personality traits (scores)			
Openness	16	8–25	8–48
Extraversion	30.5	18–39	8–48
Conscientiousness	40	33–46	10–48
Neuroticism	10	9–18	8–48
Agreeableness	41	36–45	8–48

Abbreviations: IQR: interquartile range; BMI: body mass index; MCR: motoric cognitive risk syndrome; Occupation category: non-manual labor (like civil servants, doctors, teachers, etc.) and manual labor (like peasants, construction worker, etc.)

as independent variables. The results were presented in Table 4, using the resilient profile as a reference due to its association with the most favorable outcomes for MCR prevention. The findings indicated that, compared with the resilient profile, participants with lower education levels and poorer sleep quality were more inclined to fall into the ordinary profile. Similarly, participants within the reserved profile tended to be older, have low education level, and suffer from poorer sleep quality compared to those in the resilient profile. Furthermore, participants with low education and poor sleep quality, depression symptoms, and no alcohol assumption history were at higher odds of being categorized within the anti-resilient profile.

Table 2 Fitness indicators of different latent profile models

Model	AIC	BIC	aBIC	Entropy	VLMR	BLRT	Class membership probability
1-profile	7393.476	7436.014	7404.272	—	—	—	1
2-profile	6758.282	6826.343	6775.555	0.978	$p<0.001$	$p<0.001$	0.823/0.177
3-profile	6572.977	6666.562	6596.729	0.881	$p<0.001$	$p<0.001$	0.175/0.558/0.267
4-profile	**6501.226**	**6620.333**	**6531.455**	**0.835**	$\boldsymbol{p=0.010}$	$\boldsymbol{p<0.001}$	**0.248/0.315/0.264/0.173**
5-profile	6433.412	6578.043	6470.119	0.838	$p=0.141$	$p<0.001$	0.252/0.283/0.148/0.081/0.237
6-profile	6383.540	6553.693	6426.724	0.847	$p=0.612$	$p<0.001$	0.029/0.146/0.296/0.079/0.225/0.225

Note: Data in bold denote the optimal solution. **Abbreviations**: BIC: Bayesian information criterion; aBIC: the sample size adjusted Bayesian information criterion; AIC: Akaike information criterion; VLMR: Vuong-Lo-Mendell-Rubin likelihood ratio test; BLRT: bootstrap likelihood ratio test

Discussion

Summary of the findings

Personality may play a crucial role in the development of MCR [7–9]. This study identified four distinct personality profiles constituted by the different combinations of personality traits, including the resilient, ordinary, reserved, and anti-resilient profiles. Hypothesis 1 was supported, indicating the differences in the prevalence of MCR among personality profiles, with the resilient profile exhibiting the lowest and the anti-resilient profile demonstrating the highest prevalence of MCR. Additionally, this study also revealed noticeable differences in population characteristics among the different personality profiles membership, supporting Hypothesis 2.

The personality profiles of community-dwelling older adults

This study complements prior variable-centered research investigating the relationship between personality traits and MCR. Four personality profiles among older adults were identified through LPA, aligning with the dominant solutions/models reported in the systematic review [5]. Notably, the resilient profile, ordinary profile, and anti-resilient profiles emerged as the most frequently-identified profiles within the four-profile solution by other research, correspond with the classic characteristics of these profiles [5]; the reserved profile is similar to the results found by previous studies [16, 21, 36], which reinforces the robustness of our results and provides a framework for comparing the predictors and outcomes of personality profiles across different studies.

The associations between personality profiles and MCR

The present study applied the advanced LTB approach [35] to examine the association between personality profiles and MCR prevalence in older adults. Consistent with the hypothesis, individuals in the resilient profile had the lowest prevalence of MCR. Several factors may elucidate this association. Firstly, lower levels neuroticism (the resilient profile) may diminish sensitivity to stress or challenging situations that evoke negative emotions, such as anxiety and depression [10, 37], which could impair cognitive function [38] and increase cognitive complaints [39]. Secondly, higher levels of openness, extraversion, conscientiousness, and agreeableness (the resilient profile) are likely to promote motivation and active engagement in physical [11] and social interactions [40], which are known to support cognitive and motor functions [41, 42]. Additionally, positive personality traits (marked by high openness, extraversion, conscientiousness, and agreeableness, or the resilient profile) might confer a protective effect against dementia, inflammation, and brain atrophy [6], whereas elevated neuroticism is associated with cardiovascular disease [43], all of which are potential mechanisms to MCR [2].

Conversely, individuals characterized by the anti-resilient profile appear to have a higher probability of MCR prevalence, potentially due to their tendencies towards high neuroticism and low openness, conscientiousness, extraversion, and agreeableness. The anti-resilient profile had a higher MCR prevalence than the resilient profile (20.3% vs. 6%, $p=0.004$). These results of this study are consistent with the outcomes observed in earlier studies utilizing a variable-centered method [7–9]. Therefore, individuals in the anti-resilient profile should be prioritized for MCR screening and intervention. Furthermore, the ordinary profile showed lower openness compared to the resilient profile, which was the principal distinguishing personality trait. Additionally, the prevalence of MCR was higher in the ordinary profile than the resilient profile, although this difference did not reach statistical significance (11.4% vs. 6%, $p=0.215$). Previous research has indicated that lower openness (the ordinary profile) is predominantly associated with memory function decline, a singular facet of overall cognitive function [44]. However, MCR involves a decline in comprehensive cognitive abilities, notably in areas beyond memory [35]. Therefore, this constraint warrants consideration in investigation of the association between openness and MCR.

Remarkably, while the reserved profile exhibited a low level of neuroticism comparable to that of the resilient profile, it also demonstrated lower levels of other personality traits. The reserved profile had a higher MCR prevalence than the resilient profile (19.7% vs. 6%, $p=0.002$). This suggests that low neuroticism alone may not be a sufficient protective factor against MCR; a combination

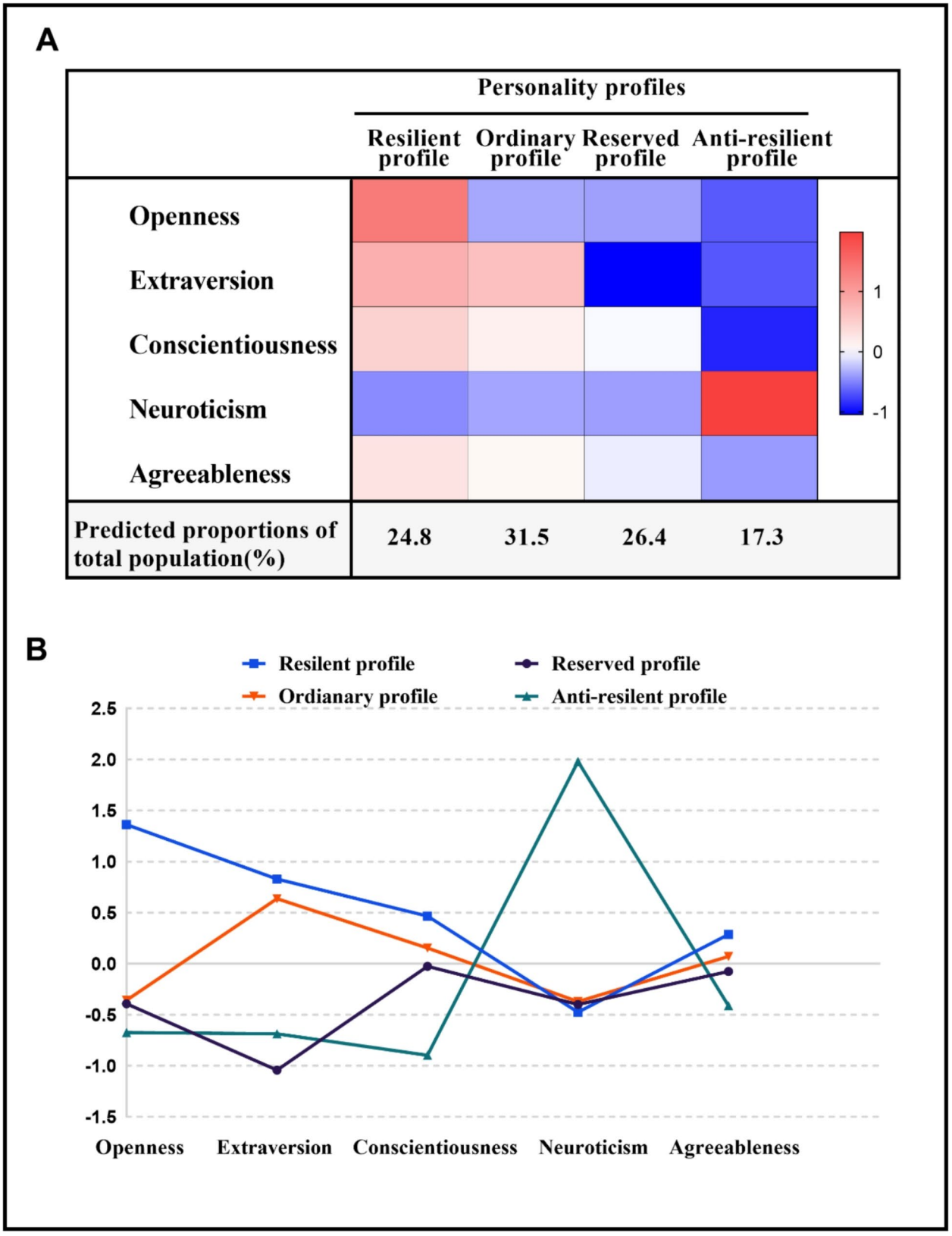

Fig. 2 Latent profile model: four-profile solution. Note: (**A**) Depiction of the results of the latent profile model, presenting the mean personality traits scores predicted for each profile. These scores were depicted on a gradient color scale ranging from blue (low) to red (high). (**B**) Illustration of the mean personality traits scores for individuals within each profile. Participants were allocated to profiles according to the predicted probability of profile memberships derived from the latent profile mode, with each exhibiting distinct personality feature patterns based on their personality profiles memberships

Table 3 Comparisons of mean MCR probability across personality profiles ($n = 520$)

Profile	MCR		Overall χ^2	*p*	Differences between profiles
	Mean	*SE*			
Profile 1 -- Resilient profile	0.060	0.024	14.599	0.002	Profile 1 < Profile 3,4
Profile 2 -- Ordinary profile	0.114	0.033			
Profile 3 -- Reserved profile	0.197	0.038			
Profile 4 -- Anti-resilient profile	0.203	0.043			

Abbreviations: MCR: motoric cognitive risk syndrome; *SE*: standard error

Table 4 Profiles membership correlates: Stepwise multinomial logistic regression analysis ($n = 520$)

Variable	Ordinary profile		Reserved profile		Anti-resilient profile	
	β(SE)	OR(95%CI)	β(SE)	OR(95%CI)	β(SE)	OR(95%CI)
Age	-0.020(0.014)	0.980(0.952,1.008)	**0.031(0.014)***	**1.031(1.003,1.061)***	-0.018(0.020)	0.982(0.943,1.022)
Education level (Ref: Middle school and above)						
Primary school and below	**0.547(0.246)***	**1.729(1.067,2.801)***	**0.538(0.257)***	**1.712(1.034,2.834)***	**0.829(0.358)***	**2.290(1.135,4.621)***
Alcohol consumption history (Ref: No)						
Yes	0.075(0.283)	1.078(0.619,1.877)	-0.303(0.308)	0.739(0.404,1.352)	**-1.305(0.507)***	**0.271(0.100,0.732)***
Depression symptoms (Ref: No)						
Yes	0.035(0.509)	1.036(0.382,2.809)	-0.076(0.529)	0.927(0.328,2.615)	**3.348(0.480)*****	**28.443(11.095,72.912)*****
sleep quality (Ref: Good)						
Poor	**0.846(0.275)****	**2.331(1.360,3.994)****	**0.888(0.284)****	**2.430(1.393,4.238)****	**1.411(0.369)*****	**4.099(1.988,8.454)*****

Note: Reference profile was the resilient profile ($N = 129$); Data in bold denote statistically significant results; *Indicate significant difference (*$p < 0.05$, **$p < 0.01$,***$p < 0.001$). **Abbreviations**: β: unstandardized beta value; *SE*: standard error; OR: odds ratio; CI: confidence interval

of other traits at moderate to high levels may also be requisite.

Additionally, the absence of difference in MCR prevalence (19.7% vs. 20.3%, $p = 0.910$) between the reserved profile (lower neuroticism) and anti-resilient profile (highest neuroticism) in the pairwise comparison lends which further supports the findings mentioned above. The results also suggest that relying on a single personality trait (e.g., low neuroticism) is insufficient for identify individuals at low risk of MCR. Instead, a comprehensive, person-centered method is necessary to examine personality profiles. For instance, individuals in the reserved profile, despite their low neuroticism, may still be associated with MCR prevalence due to moderate to low levels of other traits. Unexpectedly, individuals in the ordinary profile, who performed relatively lower neuroticism and higher levels of other personality traits compared to the reserved profile and anti-resilient profile, did not show difference in MCR prevalence (11.4% vs. 19.7% and 20.3%, $p = 0.138$ and 0.110). This may be attributable to the limited statistical power resulting from the small sample size of MCR cases ($n = 72$) in this study [45].

The personalized characteristics of personality profiles memberships

To establish effective targets based on personality profiles for the prevention and intervention in MCR, a stepwise multinomial logistic regression was performed to determine the predictor factors of personality profiles. The results suggest that depression symptoms strongly predict classification into the anti-resilient profile. This finding is consistent with previous person-centered studies [15] and supports variable-centered research [10] which indicates that a combination of high neuroticism and lower levels of other personality traits is more frequently observed in individuals with depression. The association might be attributable to the tendency of individuals with negative personality traits (marked by high neuroticism, and low other traits, or the anti-resilient profile) towards low and decreasing well-being and higher interpersonal aggression and anxiety [15, 46]. In addition, advanced age was a unique predictor of the reserved profile. This association might be related to the steady decline in openness, extraversion and conscientiousness (a lesser degree) with increasing age in older adults [47]. This study also discovered that good sleep quality and a high level of education were uniquely associated with the resilient profile (marked by lowest neuroticism and highest other traits), a finding that is consistent with the evidence from the study conducted by previous study [13], which also demonstrate that individuals within the resilient profile have better sleep quality. Moreover, previous variable-centered study has indicated that individuals with lower neuroticism and higher extraversion and conscientiousness were associated with better sleep quality [48]. This may be because they are less sensitive to stressors, which lessens the effects of depression and anxiety, thereby contributing to better sleep [13, 49]. For the level of

education, previous study [50] also found that individuals with the resilient profile exhibited high education levels, likely due to their low neuroticism and high other personality traits, which are correlated with active learning strategies [51] and academic performance [52]. This study also identified an association between the history of alcohol consumption and the resilient profile. Previous study [21] also observed the connection between resilient profiles and frequent heavy drinking. This finding may be due to the higher social interaction of individuals in the resilient profile, potentially increasing their exposure to social drinking circumstances [21]. However, The previous study [21] indicated that the reserved profile, marked by passive-dependent traits, had a correlation with frequent drinking. Earlier research has also found a significant link between the history of alcohol consumption and MCR [12]. Thus, further research is needed to explore if alcohol consumption is associated with the reserved profile and whether this association delineates a different relationship between the resilient profile and reserved profile with MCR prevalence. It is worth emphasizing that prior research has indicated that depression symptoms and advanced age may increase the risk of developing MCR, while high education level and good sleep quality seem to confer a protective effect [12, 53]. Hence, the relationship established in this study between personality profiles and these risk factors could shed light on the potential causality with MCR.

Study strengthens and implications

This study, using LPA, identified four distinct personality profiles and investigated the multilevel, multidimensional interrelations between personality traits and MCR. LPA can provide more detailed, personalized insights into variable interrelations, facilitating to develop more actionable and effective strategies tailored to the unique needs and preferences of diverse groups of individuals [54]. The findings of this study indicated that personality profiles may be important psychological factors in the occurrence of MCR, warranting heightened social and public attention, especially for those identified as high-risk personality profiles, like the reserved and anti-resilient profiles.

Some implications of our findings are as follows. Firstly, given the stability of personality traits in older adults, this study offers a framework for designing personalized intervention programs. For example, profile 1 in this study exhibited the lowest neuroticism and highest other personality traits, aligning with the resilient profile, also termed protective or well-adjusted [5], which is associated with a lower probability of MCR prevalence. By identifying specific personality profiles linked to MCR, this study provides a basis for developing targeted interventions that leverage these personality traits' advantages to improve cognitive resilience and prevent the progression to dementia. Secondly, this study elucidated the potential personality profiles within the MCR population and the associated influencing factors for each profile, which helps in refining preventative strategies. By identifying modifiable risk factors, including lower education level, depression symptoms, poor sleep quality, and alcohol consumption history, linked to specific personality profiles, healthcare providers can offer more effective, personalized care plans aimed at addressing external and situational factors to mitigate their impact on cognitive health, instead of attempting to alter inherent personality traits. The interventions may modulate psychological mechanisms related to MCR [2] (e.g., cognition [44], emotion [10], and behavior [11]) and facilitate the reduction of MCR prevalence. Finally, the findings suggest the importance of further exploring and validating personality trait-based interventions. Specifically, research should focus on how older adults with different personality profiles respond to various interventions to determine which are most effective in improving MCR and preventing dementia. Individuals with specific personality profiles might benefit more from interventions such as cognitive training, psychological support, or socialization activities. Additionally, research should investigate how these personality-based interventions can be seamlessly integrated into the daily care practices of older adults, ensuring that they continue to benefit from these interventions in their everyday lives.

Studies indicate that older adults receiving psychological education show improvements in managing stress and anxiety, which may mitigate negative personality traits and enhance overall cognitive functioning [55, 56]. Meanwhile, older adults participating in behavioral activation (BA) interventions report better life engagement and well-being. This suggests that BA could indirectly influence personality traits by altering behavior patterns and emotional responses [57, 58]. Such initiatives could increase an individual's awareness and understanding of the relationship between personality profiles and MCR. They could encourage measures to regulate the overexpression or underexpression of certain personality traits. Therefore, these interventions should be further developed and adjusted in future research to reduce the adverse effects of personality traits on MCR populations. In addition, a systematic review has shown that personality is plastic across the life course [59]. It is advisable to offer personality assessment and counseling services to assist individuals in understanding their personality profile and characteristics, establishing realistic goals and plans, satisfying their personalized psychological needs, and enhancing their mental health. These approaches could diminish the prevalence of MCR and ultimately contribute to dementia prevention.

In addition, the personality profiles in this study were identified based on the systematic review consensus [5], increasing the comparability with future studies examining the relationship between personality profiles and MCR.

Limitations and future research directions

This study presents certain limitations that serve as directions for future research. Initially, the use of cross-sectional survey data from Chinese community-dwelling older adults may not represent conditions in other countries, regions, or age groups. It also cannot determine the causal relationship or temporal order between personality profiles and MCR. In addition, the causal and mediating relationships between personality profiles and population characteristics require further validation through future cohort studies. Moreover, this study is limited to the five-factor personality model as the personality variable, which may not account for other personality frameworks (such as the HEXACO six-factor personality model). Meanwhile, there are potential variables, such as neuropsychiatric symptoms (NPS), which might influence the relationship between personality profiles and MCR. While this study measured depression and sleep quality, it lacked a systematic evaluation of NPS. Future research should include comprehensive assessments of NPS to understand their potential impact. Additionally, the assessment of personality traits and MCR in this study used self-report measures derived from questionnaires or scales, might not fully capture the precise or consistent levels of individual' s personality traits and occurrences of MCR, nor does it also completely mitigate the potential influence of confounding factors, such as social expectations, on the self-report outcomes. Future research could enhance the validity and generalization of these findings by incorporating larger, more diverse cohorts, to examining the potential variations in the association between personality profiles and MCR across different cultures or groups. In addition, further inquiry could integrate additional personality models or traits, along with psychological factors like cognitive function, emotion regulation, and coping strategies. This expansion could provide a more robust theoretical framework for MCR and a deeper understanding of the intricate relationship between personality profiles and MCR. Ultimately, to enhance the explanatory and predictive power of the relationship between personality profiles and MCR, future research should consider employing more diversified and in-depth statistical analysis methods, including causal inference techniques with longitudinal data and complex models like structural equation model, to explore causal relationship and potential mediating or moderating effects of other variables between personality profiles and MCR.

Conclusions

In conclusion, this study identified four personality profiles among the community-dwelling older adults using person-centered method, and comprehensively revealed the relationship between personality profiles and MCR through LTB approach. The reserved and anti-resilient profiles seem to had a higher probability of MCR prevalence, thereby complementing findings from previous variable-centered method researches. This study also detailed the unique population characteristics of each personality profile memberships, offering a theoretical foundation and experiential reference for future MCR prevention and treatment strategies based on these personality profiles.

Abbreviations

AIC	Akaike information criterion
aBIC	The sample size adjusted Bayesian Information Criterion
BIC	Bayesian information criterion
BLRT	Bootstrap likelihood ratio test
BMI	Body-mass index
CI	Confidence interval
FFM	Five-factor model
GDS	Geriatric Depression Scale
IQR	Interquartile range
LPA	Latent profile analysis
LTB	Lanza, Tan, and Bray's
MMSE	Mini-mental state examination
MCR	Motoric cognitive risk syndrome
OR	Odds ratio
PASE	Physical Activity Scale for the Elderly
PSQI	Pittsburgh Sleep Quality Index
SCC	Subjective cognitive complaints
SG	Slow gait
SE	Standard error
VLMR	Vuong-Lo-Mendell-Rubin likelihood ratio test

Supplementary Information

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Supplementary Material 1

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Author contributions

LNW contributed to the overall design of the research program, the manuscript revision and the financial support. BW contributed to conceptualization of study and manuscript revision. JWZ contributed to experimental design, data collection, data processing and paper writing; CZ and XYW contributed to participant recruitment; XS, CYW, GXL and LLS contributed to data collection and sorting.

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Data availability
Anonymized data will be shared by request from the corresponding authors on reasonable request.

Declarations

Ethics approval and consent to participate
This study was reviewed and approved by the Institutional Review Boards of Huzhou Third Municipal Hospital (Ethical Approval Number: 2021 Ethics Review No.007) and conformed with the Declaration of Helsinki. Informed consent was obtained from all participants.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Author details
[1]School of Medicine, Huzhou Key Laboratory of Precise Prevention and Control of Major Chronic Diseases, Huzhou University, Zhejiang, China
[2]Department of general medicine, Community health service center of Binhu Street, Zhejiang, China
[3]Department of Critical Care Medicine, Shandong Provincial Hospital Affiliated to Shandong First Medical University, Jinan, Shandong, China
[4]Rory Meyers College of Nursing, New York University, New York, USA

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