Acta Psychologica 255 (2025) 104957

Contents lists available at ScienceDirect

Acta Psychologica

journal homepage: www.elsevier.com/locate/actpsy

Personality profile analysis, personality-intelligence profile analysis, and the intergenerational transmission of both: Insights from Chinese evidence

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ARTICLE INFO

Keywords:
Personality profile
Personality-intelligence profile
Latent profile analysis
Intergenerational transmission

ABSTRACT

An individual-centered latent personality profile analysis represents a novel approach to personality research. Leveraging the China Family Panel Studies (CFPS) dataset, this study utilizes latent profile analysis to examine the Big Five personality traits. By integrating personality traits with cognitive abilities, a joint profile analysis of individual personality-intelligence is conducted. Three personality profiles and two personality-intelligence profiles are identified through latent profile analysis, and further subjected to exploratory factor analysis, revealing significant differences among various demographic groups. Intergenerational matching and testing of the samples reveal the presence of intergenerational transmission of these profiles. This study explores the personality profile landscape of Chinese residents and investigates the feasibility of joint profile analysis of personality-intelligence, offering a new avenue for studying the factors influencing intergenerational social and economic mobility.

1. Introduction

Since ancient times, countless philosophers, thinkers, and psychologists have attempted to capture the essential differences in behavior, thoughts, and emotional responses among individuals, leading to the emergence of the concept of personality. However, there has been ongoing debate regarding the content and structure of personality. The Five-Factor Model (FFT), established and developed by Allport and Odbert (1936), Cattell (1943), Norman (1967), Goldberg (1981), Costa and Mccrae (2010), and Digman (1990), has become one of the widely accepted theoretical frameworks in personality research. It is widely applied in industrial and organizational psychology, organizational behavior, human resource management, and labor economics.

Traditionally, the research approach in personality influence studies has been the “Variable-centered Approach”. This method isolates personality traits on different dimensions and measures them separately to describe differences between individuals, aiming to explore the impact of each single-dimensional personality trait on specific outcome variables. In empirical studies, personality variables on various dimensions are independently included in the empirical model, with limited effectiveness in examining the complex interactions of personality traits (Caspi et al., 2005). To address the limitations of the variable-centered approach, some scholars have introduced a structural philosophical approach[1] into psychological research and proposed the “Person-centered Approach”. It advocates viewing individual personality as a holistic entity or an organic combination of various personality traits, while fully considering the interactions among different dimensions of personality (Laursen & Hoff, 2006; Magnusson, 1999). By categorizing individuals into different personality profiles based on combinations of high and low personality traits (Donnellan & Robins, 2010), the approach explores how these combinations are associated with characteristics of different populations (Min & Su, 2020). The Person-centered approach offers at least three advantages: (1) it provides an efficient classification system, (2) it treats individuals as complete actors rather than isolated internal characteristics, and (3) it introduces new variables for personality research. Existing studies have found that personality profiles have particular explanatory power for individual behaviors such as social attitudes (Roth & Von Collani, 2007), psychological functioning (Merz & Roesch, 2011), mental health, happiness, and life events (Leikas & Salmela-Aro, 2014), psychological health of students (Merz & Roesch, 2011), youth drinking behavior (Zhang et al., 2015), vocational achievement (De Fruyt, 2002), and work-related stress and job

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[1] Structuralism, originating in the nineteenth century, is a methodological approach that considers social and cultural phenomena as being constructed by a series of internal structures and rules. These structures and rules are interconnected, interact with each other, and collectively shape human social behaviors and cultural expressions.

https://doi.org/10.1016/j.actpsy.2025.104957
Received 30 May 2024; Received in revised form 12 February 2025; Accepted 26 March 2025
Available online 1 April 2025

satisfaction (Van der Wal et al., 2016). In addition, Georg Henning et al. (2017) explored the impact of personality factors on individuals' changes in happiness before and after retirement, as well as their complex mechanisms of action (Henning et al., 2019). They found that personality factors modulated changes in individuals' happiness before and after retirement. Generally, individuals tend to experience a significant increase in happiness after retirement, while individuals exhibiting the "Under-controllers" personality profile showed a decrease in happiness. The dimension of Agreeableness played a key role, with high Agreeableness promoting increased post-retirement happiness. Rzeszutek and Gruszczyńska (2019) investigated the influence of personality profiles on the subjective well-being of HIV-infected individuals. Significant differences in subjective well-being were observed among different profiles, with individuals in the resilient profile exhibiting the highest levels of subjective well-being. Overcontrollers and undercontrollers had the second-highest levels of subjective well-being, while individuals in the average profile reported the lowest levels of subjective well-being. The "Person-centered Approach" has been widely applied not only in personality research but also in fields such as organizational behavior and educational psychology (Sun et al., 2023; Wittmers et al., 2024; Yang et al., 2024).

Based on various samples and different survey methods, existing personality profile studies have categorized samples into 2 to 5 profiles (Conte et al., 2017; Gerlach et al., 2018; Henning et al., 2017; Honkaniemi et al., 2013; Perera et al., 2018; Semeijn et al., 2020; Udayar et al., 2020; Van der Wal et al., 2016). However, certain personality profiles are named consistently across different studies, yet their exact connotations may vary. It is evident that the number and types of personality profiles differ across studies. Given the strong heterogeneity of personality profiles across various societies, eras, and demographics, conducting specific personality profile analyses for different groups becomes crucial. Nonetheless, the literature on personality profile analysis concerning Chinese samples remains underdeveloped and sparse (Chen et al., 2021; Tan, 2023).

As discussed above, the various dimensions of personality interact with each other and function structurally as an integrated whole within the individual, and therefore, personality should be viewed as an organic whole. A substantial body of empirical evidence has demonstrated that, while cognitive abilities and personality traits exhibit a considerable degree of independence, there are also intricate interconnections between them (Dougherty & Guillette, 2018). Jean Piaget (1958) applied structuralist ideas to psychological research, arguing that although the human psyche is composed of several components, it is not merely the simple sum of these components. Rather, these components are integrated according to specific processes and structures, thereby performing functions. Therefore, not only do the various dimensions of personality function as an integrated whole on the individual, but personality also interacts with other psychological elements in a structurally integrated manner.

Roberts (2006) proposed a new socioanalytic framework for personality psychology. This framework includes traits (Big Five personality traits), values/motives, abilities (Intelligence, language and spatial abilities, etc.), and narratives as the four units of analysis in personality psychology.[2] These four units of analysis influence each other and jointly shape the individual's identity and reputation, which in turn interact with the individual's cultural context, ultimately forming the individual's roles. Given the broad explanatory power of the Big Five personality profile, the question arises: does the structure formed by the Big Five personality traits and other psychological characteristics possess explanatory power? Personality and Intelligence, as important psychological traits of the individual, influence each other and work together to produce certain functions and effects, establishing a structural relationship. However, the authors of this paper have not found literature that analyzes the dimensions of personality and Intelligence as an integrated whole in profile analysis. This paper will combine personality and intelligence for latent profile analysis (personality-intelligence profile), which may provide a better strategy for individual identification. The personality-intelligence profile is an extension of the personality profile, rather than merely an inclusion of it. The personality-intelligence profiles utilize personality (levels of the Big Five personality traits) and cognitive abilities (results from literacy and mathematics tests) as variables, employing Latent Profile Analysis (LPA) to identify the combined patterns of the total sample across seven variables. These profiles, to some extent, depict the psychological structure of individuals in terms of personality and intelligence. Although the personality-intelligence profiles are composed of personality and cognitive abilities, they are not a simple summation of the levels of personality and intelligence, but rather integrate the two into an organic whole. Within this whole, the structural relationships within and between personality and intelligence have been identified to a certain extent. Personality and intelligence interact and function together within this structure. Therefore, the functionality and predictive power of this structure exceed the sum of the two as individual elements.

The issue of intergenerational transmission of socioeconomic status (SES) is central to social equity and justice. Compared to developed countries, developing nations exhibit a stronger tendency for intergenerational transmission, meaning that children from impoverished families in these countries face greater difficulties in improving their circumstances (Narayan et al., 2018). Therefore, investigating the mechanisms of intergenerational transmission in developing countries holds significant practical and theoretical importance. In the process of SES intergenerational transmission, personality and intelligence are critical factors that influence it. Both individual personality traits and intelligence are largely rooted in family background, thereby demonstrating a certain degree of intergenerational transmission. On the one hand, this is due to genetic inheritance from parents (Björklund et al., 2006; McGue et al., 1993; Deary et al., 2006), and on the other hand, it stems from the social context and developmental resources provided by family background (Conger & Donnellan, 2007; Roksa & Potter, 2011; Schweinhart et al., 2005).[3] Existing literature primarily examines the role of these psychological factors in the intergenerational transmission of SES from a "variable-centered approach." Although some studies have identified the influence of family and social structural factors on offspring behavior (Sun et al., 2023; Yang et al., 2024), few have explored the role of the structure of individual psychological characteristics in intergenerational transmission from a "person-centered approach." If personality and intelligence influence individuals in an organic and structured manner, and if the structure of these psychological factors exhibits intergenerational transmission, then personality profiles and personality-intelligence profiles may serve as potential factors in the intergenerational transmission of SES. In other words, the structure of parental psychological factors not only affects their own development but is also transmitted to their offspring, either innately or through environmental influences, significantly impacting the offspring's subsequent development. Ultimately, the transmission of internal psychological structures manifests as the intergenerational

[2] Unlike the trait-based approach that views the Big Five personality traits as a category of personality, Brent Roberts' concept of personality is more comprehensive. In his framework, the Big Five personality traits are regarded as a category of traits, serving as one of the units of analysis under the broader concept of personality.

[3] The aforementioned factors are all influences associated with family background, which does not imply that the determinants of personality traits and intelligence are necessarily linked to family background. In fact, there are numerous factors unrelated to family origin that shape the development of an individual's personality and intelligence. For instance, factors such as the era in which one lives, the social environment, personal self-selection, and random elements like luck play significant roles.

transmission of SES.[4] Addressing this theoretical gap, this paper attempts a preliminary exploration. Due to space limitations, this study first identifies personality profiles and personality-intelligence profiles in Chinese society using nationally representative large-sample data from the China Family Panel Studies (CFPS), providing potential explanatory variables for subsequent research. It then conducts multivariate regression analysis and finally tests their intergenerational transmission.

Given the aforementioned issues, this study utilizes data from the China Family Panel Studies (CFPS) to conduct latent profile analysis of personality traits and personality-intelligence profiles in Chinese samples, followed by multivariate factor analysis of the results to examine the intergenerational heritability of personality latent profiles and personality-intelligence profiles. The structure of this article is as follows: the Method section in Part 2, the Analysis Results in Part 3, and the Discussion and Conclusion in Part 4.

2. Method

2.1. Data

The data for this study were derived from the China Family Panel Studies (CFPS).[5] The CFPS is conducted by the Institute of Social Science Survey at Peking University and has received support from various institutions including the National Health Commission, National Bureau of Statistics, Shanghai University, Sun Yat-sen University, Lanzhou University, and the Institute for Social Research at the University of Michigan. This comprehensive survey tracks individual, family, and community-level information, providing an overview of social development in China. The project conducted surveys in 2010, 2012, 2014, 2016, and 2020. The questionnaire content encompasses personal data on education, occupation, and income; family information including member relationships, social interactions, living conditions, income and expenses, and asset status; and community-level data on infrastructure, population, transportation, resources, and medical services. The CFPS has become one of the most important and widely used survey datasets for studying contemporary politics, economics, culture, demographics, and social psychology in China.

The target sample size of CFPS consists of 16,000 households, covering the population of 25 provinces/cities/autonomous regions in China excluding Hong Kong, Macao, Taiwan, Xinjiang, Tibet, Qinghai, Inner Mongolia, Ningxia, and Hainan. The population in these 25 provinces/cities/autonomous regions accounts for approximately 95 % of the total national population (excluding Hong Kong, Macao, and Taiwan), making the CFPS sample nationally representative. CFPS employs a stratified sampling method with implicit stratification. Administrative divisions and socioeconomic levels serve as the primary stratification variables. CFPS provides respondents with a certain amount of compensation for their participation. To ensure maximal protection of respondents' rights, the CFPS project regularly submits ethics review applications to the "Biomedical Ethics Committee of Peking University" and conducts corresponding data collection activities only after obtaining ethical approval.[6]

This study utilized data from CFPS 2018. The CFPS 2018 individual questionnaire collected not only rich social demographic and behavioral information but also employed psychological scales to measure respondents' psychological factors, along with literacy and numeracy questionnaires to assess respondents' cognitive abilities. Large-scale datasets require high simplicity and accessibility, and literacy and numeracy questionnaires not only meet these criteria but also encompass both fluid intelligence and crystallized intelligence. Due to time and cost considerations, lengthy Big Five personality trait measurement scales are not suitable for large comprehensive surveys. Hence, survey data such as the Panel Study of Income Dynamics (PSID) in the United States, the Socio-Economic Panel Study (GSOEP) in Germany, and the British Household Panel Survey (BHPS) utilized the BFI-S short scale for personality trait measurement. CFPS 2018 adopted a similar approach by reducing the Big Five personality trait test scale to a brief form consisting of only 15 questions (including 4 reverse-scored questions). Each personality trait dimension was measured using three test questions, comprising both positively and negatively worded items. This study conducted reliability and validity tests on the Big Five personality questionnaire used.[7] The Cronbach's alpha coefficients for the conscientiousness, openness, agreeableness, extraversion, and emotional stability dimensions were 0.3884, 0.3206, 0.2728, 0.6039, and 0.3444, respectively. After removing reverse-scored items, the Cronbach's alpha coefficients increased to 0.4501, 0.5617, 0.5178, 0.6039, and 0.5206. The Kaiser-Meyer-Olkin (KMO) coefficients for conscientiousness, openness, agreeableness, extraversion, and emotional stability dimensions were 0.5602, 0.5009, 0.5053, 0.6381, and 0.5006, respectively. The results of reliability and validity tests for the BFI-S Big Five personality trait scale were not ideal. Several reasons contribute to this: Firstly, the Big Five model aims to encompass various aspects of human personality within its five dimensions, making the relationships between the secondary personality traits within each dimension relatively broad and loose. Secondly, the CFPS database is extensive and involves numerous samples, making it impractical to use long scales for personality trait assessment. Consequently, short scales were used, attempting to measure the five personality dimensions through 15 questions. This constraint led to each question assessing different aspects of personality without significant overlap. For example, in the conscientiousness dimension, the question QM201 (being diligent and careful) focuses on an individual's organization, while QM207 (often lazy) emphasizes self-discipline or perseverance. These distinctions are significant. Long scales can enhance reliability by including multiple very similar questions for each secondary trait, a luxury not afforded by short scales. Lastly, due to the substantial number of questions in the CFPS survey, the inclusion of reverse-scored items to enhance questionnaire quality tends to lower overall reliability and validity, as indicated in our analysis. The concept of "personality" is a rich and broad one. When conducting large-scale micro surveys and attempting to measure a rich and profound topic using a short scale, the internal consistency reliability represented by Cronbach's alpha is inevitably low. The concept of reliability is not equivalent to internal consistency; its meaning is broader. It should at least include test-retest reliability and inter-method reliability. Compared to internal consistency reliability, test-retest reliability, and inter-method reliability may perhaps be better measurement methods.

[4] Although personality, intelligence, and their structural relationships may hold promise in partially explaining the intergenerational transmission of SES, they are by no means the entirety or the decisive factors of the issue. This is because, first, due to the presence of other non-family-origin factors, personality, intelligence, and their structural relationships cannot be fully transmitted across generations. Second, given the existence of other influencing factors, personality, intelligence, and their structural relationships do not entirely determine an individual's socioeconomic achievements. Third, existing research has far from exhausted all the factors influencing individuals' psychological traits and social achievements, as random elements such as elusive personal free will and luck also play a role. Therefore, intergenerational mobility will always persist.

[5] The CFPS data used in this study were collected through a large-scale social survey organized jointly by several major academic institutions in China and were not collected by the authors themselves.

[6] The ethical review approval number for the CFPS project is standardized as IRB00001052-14010.

[7] The Cronbach's alpha coefficients calculated by Wu and Gu (2020) were reported as 0.42/0.33/0.34/0.61/0.32 and 0.45/0.56/0.52/0.61/0.52 (after removing reverse-scored items). While their findings show slight discrepancies compared to the results of this study, the differences in data processing methods remain unclear.

The CFPS did not conduct tests on the test-retest reliability and inter-method reliability of the BFI-S, and due to limitations in funding, time, and ethical approval, this study did not examine the test-retest reliability and inter-method reliability of the BFI-S scale in the CFPS data. However, Hahn et al. (2012) conducted a test on the test-retest reliability of the BFI-S results in GSOEP. The results indicated that the test-retest correlations for the BFI-S with a test-retest interval of 18 months were substantial and significant ($p < 0.01$), yielding 0.74 for Neuroticism, 0.80 for Extraversion, 0.72 for Openness, 0.57 for Agreeableness, and 0.67 for Conscientiousness. The mean stability coefficient of the BFI-S was 0.70.

Although the BFI-S short scale has its limitations, it has been utilized in various large-scale surveys, offering advantages that cannot be replaced by longer scales. Participants can complete the BFI-S test within minutes, demonstrating acceptable internal consistency, 18-month test-retest stability, convergent validity with longer scales, and discriminant validity. Most significantly, it allows access to large and diverse samples (Hahn et al., 2012). A substantial number of Chinese researchers, including the CFPS project leaders, trust and employ this questionnaire data for personality research. CFPS data remains a crucial survey material for studying the impact of personality factors on individual socioeconomic development within China (Han & Zhong, 2023; Li et al., 2024; Wu & Gu, 2020). Some studies suggest that reverse-scored items can reduce the reliability and validity of measurement outcomes, and removing four reverse-scored items can enhance the reliability and validity of the questionnaire. However, this study argues that since each dimension of the Big Five personality model encompasses numerous secondary personality traits, the correlational strength between each question is inherently weaker in the BFI-S scale to cover as many secondary personality traits as possible. Removing reverse-scored items would inevitably reduce the information content of the questionnaire. Sacrificing sample information on personality traits in the pursuit of questionnaire reliability and validity is deemed overly dogmatic and not cost-effective according to this study's perspective.

2.2. Measure

Latent Profile Analysis (LPA) is a clustering analysis method used to reveal the underlying structure and categories within data, known as profiles. In contrast to traditional clustering methods, LPA assumes that the data are determined by one or more latent categorical variables that are typically not directly observable. Through LPA, we can identify the latent profiles present in the data and investigate the characteristics and differences of these profiles across various variables. It extends the principles and steps of Latent Class Analysis (LCA) to continuous manifest variables, sharing similarities in statistical analysis principles (Lubke & Neale, 2006), and has been widely applied in studies of personality structure.

LPA estimates the correlations between observed indicators by setting latent categorical variables, thus maintaining local independence among the observed indicators. The basic assumption is that the probability distribution of various responses of the observed variables can be explained by a few mutually exclusive latent profile variables, with each profile having a specific tendency to select responses for the observed variables (Collins & Lanza, 2009). The computational principle is shown in Eq. 1, where I_k is the response vector for participant k, C is the assumed unique latent profile variable, T is the number of latent categories, $P(C = t)$is the probability of the participant belonging to the t-th latent profile, μ_t is the mean vector for each latent profile, and $\sum_t$ represents the covariance matrix of the latent profiles. Statistical analysis was conducted using Mplus 8.3 and STATA 17 software.

$$f(I_k) = \sum_{t=1}^{T} P(C = t) f\left(I_k|\mu_t, \sum\nolimits_t\right) \tag{1}$$

Latent Profile Analysis often relies on various fit indices to determine the optimal number of profiles, including (1) Akaike Information Criterion (AIC) (Akaike, 1987), (2) Bayesian Information Criterion (BIC) (Schwartz, 1978), (3) adjusted Bayesian Information Criterion (aBIC) (Enders & Tofighi, 2007), (4) Entropy index, (5) Bootstrapped Likelihood Ratio Test (BLRT) (McLachlan & Peel, 2000), and (6) LoMendell-Rubin adjusted likelihood ratio Test (LMRT) (Lo et al., 2001). Models with lower AIC, BIC, and aBIC values indicate a better fit. Entropy ranges from 0 to 1, with higher values indicating better fit. BLRT and LMRT compare the fit of the target model with a model with one fewer category. Significant results in BLRT and LMRT (e.g., $p < 0.05$) suggest that models with more categories fit better than those with fewer categories; a non-significant result indicates that the improvement in fit is not worth sacrificing parsimony by adding another category.

Some studies suggest (Nagin, 2005) that each profile should have an adequate number of individuals; otherwise, careful consideration should be given to whether the profile should be retained, with the smallest profile accounting for a minimum of 5 % of the total sample. Therefore, in addition to the six fit indices, this study also includes the Minimum Profile Share indicator— the proportion of the sample represented by the profile with the fewest individuals among all profiles. Additionally, each profile should exhibit clear distinctiveness, and when different profiles have similar theoretical interpretations, a more parsimonious profile model should be chosen (Howard et al., 2016). Therefore, this study not only examines various indices but also considers previous research conclusions, distinctiveness, and discriminative ability among profiles to determine the final number and type of profiles.

2.3. Variables

In this study, the entropy method was utilized to construct the five dimensions of the Big Five personality traits and two dimensions of intelligence. The specific synthesis process entailed converting reverse-scored questions into forward direction, combining and standardizing the relevant test scores. For clarity, questions concerning neuroticism were transformed into the emotional stability dimension (antiN). Secondly, employing the entropy method, the results of the Big Five personality model questionnaire were synthesized into five personality dimension variables—conscientiousness, extraversion, agreeableness, openness, and emotional stability (C, E, A, O, antiN). In the third step, the scores from the literacy and numeracy tests were standardized (Word & Math). The intergenerational transmission of personality profiles and personality-intelligence profiles necessitated matching parental and offspring sample information within the dataset. CFPS data were matched using codes for paternal and maternal samples, successfully aligning 10,449 samples. Specific variable descriptions are outlined in Table 1.

2.4. Descriptive statistics

The descriptive statistical results of the variables are presented in Tables 2-1, 2-2, and 2-3. As shown in Table 2-1, the sample size for the aggregated personality profile was 29,779, while the sample size for the aggregated personality-intelligence profile was 23,405. Conscientiousness (C) and Agreeableness (A) exhibited higher average values compared to the other three dimensions. Additionally, the mean scores for literacy (Word) were higher than those for mathematics (Math). It is important to note that differences between scores of various dimensions may stem from inherent disparities in personality and intelligence levels or could be a result of the questionnaire design itself. Therefore, discrepancies within the same profile on a specific dimension merit more attention than variations across different dimension scores. Table 2-2 illustrates that the correlations among the five dimensions of the Big Five personality traits are relatively low. This aligns with existing research findings, adhering to the inherent linguistic logic of the Big Five personality model and partially confirming the validity of the scale (Almlund et al., 2011). Furthermore, the correlations between

Table 1
Variable descriptions.

Attribute	Name	Abbr.	Description
Personality	Conscientiousness	C	Utilizing the entropy method, the corresponding questions in the scale are integrated into a single index, where a higher numerical value indicates a greater level of conscientiousness.
	Extraversion	E	Using the entropy method to integrate the corresponding questions in the scale into a single index, a higher numerical value indicates a higher level of extraversion.
	Agreeableness	A	Using the entropy method to integrate the corresponding questions in the scale into a single index, a higher numerical value indicates a higher level of agreeableness.
	Openness	O	Using the entropy method to integrate the corresponding questions in the scale into a single index, a higher numerical value indicates a higher level of openness.
	Emotional Stability	antiN	Using the entropy method to integrate the corresponding questions in the scale into a single index, a higher numerical value indicates a lower level of neuroticism and a higher level of emotional stability.
Intelligence	Literacy	Word	The standardized results of literacy test scores, with a higher numerical value indicating higher literacy skills.
	Math	Math	The standardized results of math test scores, with a higher numerical value indicating higher math skills.

Table 2-1
Descriptive statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
C	29,779	0.710	0.163	0	1
E	29,779	0.586	0.176	0	1
A	29,779	0.706	0.151	0	1
O	29,779	0.540	0.215	0	1
antiN	29,779	0.510	0.184	0	1
Word	23,405	0.550	0.311	0	1
Math	23,405	0.385	0.256	0	1

intelligence (Word, Math) and personality trait variables are also relatively low, with Openness (O) demonstrating the strongest association with intelligence. This partly validates the substantial independence between cognitive abilities (intelligence) and non-cognitive abilities (personality traits), with Openness showing the closest relationship with intelligence. This finding is consistent with previous research results (Judge et al., 2007). Within the intelligence factors, there exists a substantial correlation between literacy test scores and numeracy test scores. Despite their high correlation, from a neuroscientific perspective, they represent fundamentally different cognitive abilities. Thus, this study treats them as two distinct intelligence dimensions in latent profile analysis (Amalric & Dehaene, 2016). The distribution of covariates in the sample is outlined in Table 2-3, covering eight demographic characteristics including urban-rural status, gender, marital status, economic condition, educational background, occupation, geographical location, and birth era. The ratio of urban to rural residents and male-to-female samples is approximately 1:1. The majority of the sample comprises individuals with moderate education levels, married individuals, blue-collar workers, and those born during the construction era (1949–1978). Notably, due to a significant proportion of individuals with no income and income inequality, the sample income distribution skews rightward. The majority of the sample consists of low-income earners (below the income mean).

3. Results

3.1. Latent profile analysis of personality

In this study, latent profile analysis was initially conducted using personality variables (C, E, A, O, and antiN) obtained through the entropy method. The fit index results of the latent profile analysis are displayed in Table 3. As the number of profiles increases, the AIC, BIC, and aBIC decrease, with the rate of decrease gradually diminishing. When there are three profiles, the Entropy value reaches its maximum at

Table 2-3
Distribution of covariates in the sample.

Covariant	Category	Dummy variable	Sample size	Percentage
Household registration type	Countryside	City = 0	14,500	49.18
	Town	City = 1	14,982	50.82
Gender	Female	Gender = 0	14,946	50.19
	Male	Gender = 1	14,833	49.81
Education	Illiteracy/primary education	Lowedu = 1	12,303	41.31
	Secondary education	Midedu = 1	13,863	46.55
	Higher education	Highedu = 1	3613	12.13
Marital status	Unmarried	Marry = 0	6455	21.68
	Married	Marry = 1	23,324	78.32
Region	West	West = 1	8390	28.18
	North East	Eastnorth = 1	3927	13.19
	Eastern	East = 1	9767	32.8
	Central	Mid = 1	7694	25.84
Birth era	Pre-liberation	Liber = 1	3099	10.41
	Construction period	Bulid = 1	15,253	51.22
	Reform and opening up	Open = 1	11,427	38.37
Occupation	White collar	White = 1	4431	14.88
	Blue collar	Blue = 1	18,063	60.66
	Non-professionals or no professional record	Unem = 1	7285	24.46
Economic status	Low-income	Highinco = 0	23,192	77.88
	High income	Highinco = 1	6587	22.12

Note: Some covariates will be missing.

Table 2-2
Correlation between Big Five Personality and Intelligence.

	C	E	A	O	antiN	Word	Math
C	1						
E	0.1764	1					
A	0.3041	0.0673	1				
O	0.1849	0.2221	0.0972	1			
antiN	0.1014	0.1342	0.1058	−0.0172	1		
Word	−0.0791	−0.0243	0.0127	0.096	0.0852	1	
Math	−0.1296	−0.0453	−0.0273	0.1115	0.0695	0.7874	1

0.617; however, with five profiles, the LMRT is no longer significant, and the Min share approaches 0.05; BLRT remains significant across all profiles. The maximum value of Entropy is not considerably high, possibly due to the large sample size. Wang et al. (2017) found through Monte Carlo simulation that, under unchanged conditions, as sample size increases, the value of Entropy decreases. Considering the features of the aforementioned indices and based on subsequent regression analyses of latent class influences and differential testing results of intergenerational transmission of personality profiles, this study selects the 3-profile structure as the preferred outcome of latent profile analysis for the Big Five personality traits. Additionally, under the 3-profile scenario, the distinctiveness among each profile is notably evident.

As depicted in Fig. 1 and Table 4, within the three profiles, Class 1-I exhibits the highest mean values across all five personality dimensions, with a sample proportion of 15.36 %. This profile closely resembles the Resilient profile documented in existing literature (Van der Wal et al., 2016) and is considered one of the most socially desirable personality structures. Class 2-I has the highest sample proportion at 74.791 % and features mean values lower than Class 1-I but higher than Class 3-I across the five personality dimensions, placing it at an intermediate level. This class aligns with the Ordinary profile found in the mainstream population (Udayar et al., 2020) as observed in the current literature. Class 3-I, with a sample proportion of 9.849 %, exhibits generally lower mean values across all five personality dimensions compared to the first two profiles. Notably, Conscientiousness is particularly low in this class, while emotional stability (anti-Neuroticism) shows closer proximity to the Ordinary profile. This class closely resembles the Distressed profile identified in existing literature (Van der Wal et al., 2016) and is considered an unfavorable personality structure.

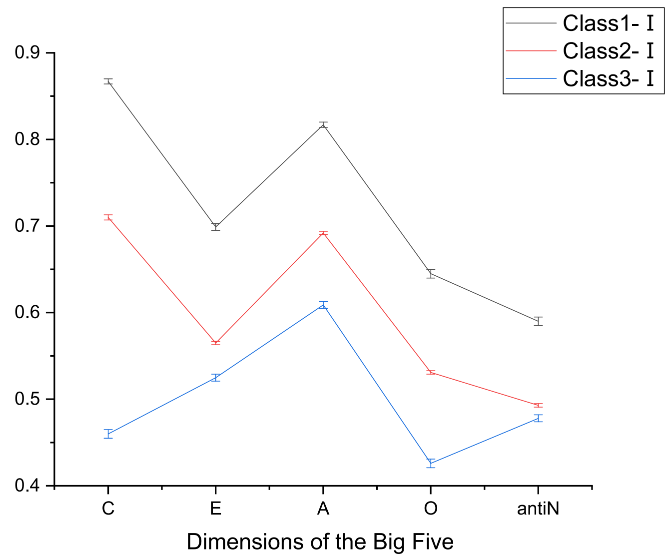

Fig. 1. Potential profiles of personality.

Table 4
Results of potential profiles of personality.

Profile	Class1-I	Class2-I	Class 3-I
C	0.867(0.003)	0.71(0.003)	0.46(0.005)
E	0.699(0.004)	0.565(0.002)	0.525(0.004)
A	0.817(0.003)	0.692(0.002)	0.609(0.004)
O	0.645(0.005)	0.531(0.002)	0.426(0.005)
antiN	0.59(0.005)	0.493(0.002)	0.478(0.004)
N(%)	4574(0.1536)	22,272(0.74791)	2933(0.09849)

3.2. *Latent profile analysis of personality-intelligence*

In this study, latent profile analysis was conducted on personality dimensions and intelligence variables (C, E, A, O, antiN, Word, and Math) to explore the personality-intelligence relationship. The fit index results of the latent profile analysis are presented in Table 5. As the number of profiles increases, the AIC, BIC, and aBIC decrease, with a sharp deceleration in the rate of decrease beyond the 3-profile mark. Entropy reaches its peak at 0.898 with 2 profiles; LMRT and BLRT display significance across all profiles, while Min share hits its minimum at 0.132 with 5 profiles. Upon examination, it is evident that different indicators show varying tendencies: AIC, BIC, and aBIC lean towards a 3-profile structure, Entropy favors a 2-profile structure, and LMRT along with BLRT inclines towards a 5-profile structure. However, after scrutinizing the various structures, it was observed that the 2-profile outcome exhibited distinct separability, whereas additional profiles tended to be overly similar and lacked distinctive characteristics. This complexity hindered interpretability across the profiles and diminished the significance of studying the population's personality-intelligence structure. Therefore, the study concludes that a 2-profile structure may present a more suitable outcome for latent profile analysis.

The 2-Profile Structure of Personality-Intelligence is illustrated in Fig. 2 and Table 6. Overall, when considering the seven dimensions, the gap in intelligence dimensions far exceeds that of the five personality dimensions. This disparity could be attributed to differences in measurement methods between intelligence and personality traits. Moreover, the variations in intelligence among different population groups may be greater than the differences in their personality aspects, as evidenced in the descriptive statistics in Table 2-1. Within the 2 profiles, Class 1-II constitutes 31.062 %, displaying higher intelligence (Word, Math), emotional stability (anti-Neuroticism), and openness, while conscientiousness and extraversion are relatively low. This profile is termed the "Low Conscientiousness-High Intelligence" profile. Class 2-II, representing 68.938 %, exhibits lower intelligence, emotional stability, and openness compared to the former profile, with extraversion and agreeableness holding steady, and a relatively higher level of conscientiousness. This profile is named the "High Conscientiousness-Distressed" profile. High intelligence often coexists with high emotional stability, openness, and low conscientiousness across the two profiles. This outcome aligns with the correlation results in Table 2-2 and is consistent with existing literature (DeYoung, 2011). The higher correlation between intelligence and openness may stem from shared psychological and biological underpinnings (DeYoung et al., 2009). Individuals with lower intelligence levels may exhibit greater conscientiousness as a compensatory mechanism. Less intelligent individuals may prioritize orderliness and structure, avoiding excessive use of intelligence in managing complex tasks. Similarly, they may exert greater effort in work and study to accomplish tasks that clever individuals handle with ease. Thus, enhancing one aspect can compensate for

Table 3
Indicator results of potential profile analysis of personality.

Profile	AIC	BIC	aBIC	Entropy	LMRT	BLRT	Share
1	−93,776.795	−93,693.779	−93,725.559				
2	−98,327.434	−98,194.609	−98,245.457	0.393	0.000	0.000	0.45757/0.54243
3	−100,201.734	−100,019.100	−100,089.015	0.617	0.000	0.000	0.74791/0.09849/0.15360
4	−101,490.072	−101,257.629	−101,346.612	0.585	0.000	0.000	0.08217/0.09520/0.65382/0.16881
5	−102,286.461	−102,004.208	−102,112.260	0.594	0.134	0.000	0.08969/0.61832/0.05155/0.11720/0.12324

Table 5
Indicator results of the potential profile analysis of personality-intelligence.

Profile	AIC	BIC	aBIC	Entropy	LMRT	BLRT	Share
1	−59,516.786	−59,403.936	−59,448.428				
2	−80,820.302	−80,642.967	−80,712.882	0.898	0.000	0.000	0.31062/0.68938
3	−92,732.621	−92,490.8	−92,586.139	0.888	0.000	0.000	0.26238/0.49964/0.23798
4	−96,770.138	−96,463.831	−96,584.594	0.864	0.000	0.000	0.40295/0.16556/0.20406/0.22743
5	−98,542.262	−98,542.262	−98,317.656	0.827	0.000	0.000	0.13172/0.21709/0.19158/0.27789/0.18171

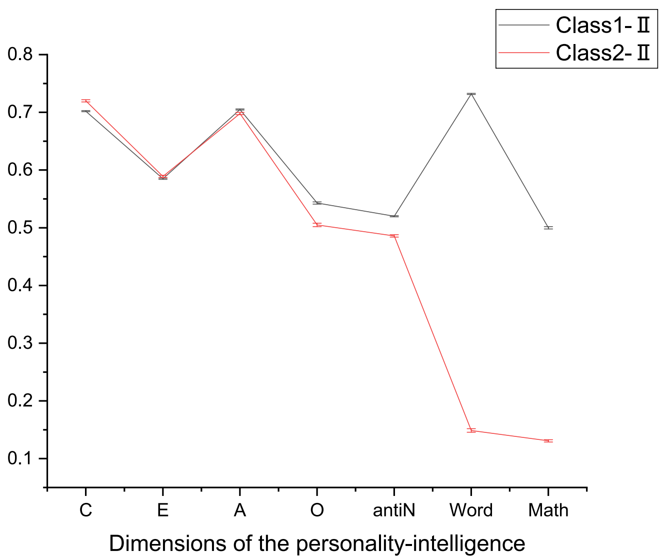

Fig. 2. Potential profiles of personality-intelligence.

Table 6
Results of potential profiles of personality-intelligence.

Profile	Class 1-II	Class 2-II
C	0.72(0.002)	0.702(0.001)
E	0.589(0.002)	0.585(0.001)
A	0.698(0.002)	0.705(0.001)
O	0.505(0.003)	0.543(0.002)
antiN	0.486(0.002)	0.52(0.001)
Word	0.149(0.003)	0.732(0.001)
Math	0.131(0.002)	0.5(0.002)
N(%)	7270(0.31062)	16,135(0.68938)

deficiencies in another (Chamorro-Premuzic & Furnham, 2005).

3.3. Multivariate regression analysis of personality profile and personality-intelligence profile

In this study, the robust three-step method R3STEP command in Mplus 8.3 software was utilized for multivariate logistic regression analysis with personality profile as the outcome variable and eight demographic characteristics as independent variables, including household registration type (with rural residents as the reference group), gender (with females as the reference group), marital status (with unmarried individuals as the reference group), economic status (with the low-income group as the reference group), educational level (with the uneducated and primary education level as reference groups), occupation type (with the unemployed and day laborers as the reference groups), geographical region (with the Western region as the reference group), and birth era (with individuals born before the establishment of the People's Republic of China in 1949 as the reference group) (Asparouhov & Muthén, 2012; Vermunt, 2010). The analysis results, as shown in Table 7, indicate that urban residents are more inclined to belong to the "Distressed profile"; compared to females, males are more likely to exhibit the "Resilient profile" and less likely to have the "Distressed profile"; married individuals are more likely to belong to the "Ordinary profile"; high-income individuals tend to exhibit the "Resilient profile" over low-income individuals; those with a secondary education level are less likely to be in the "Distressed profile," while individuals with higher education tend to belong to the "Ordinary profile"; white-collar professionals are less likely to have the "Distressed profile," whereas blue-collar workers tend to belong to the "Ordinary profile"; residents of Northeast China are more likely to fall into the "Distressed profile," while those in the Eastern and Central regions tend towards both the "Distressed profile" and "Ordinary profile"; individuals born between 1949 and 1979 are more inclined towards the "Ordinary profile," while those born after 1979 tend towards both the "Ordinary profile" and "Distressed profile." These differences may reflect both lifecycle patterns and variations in collective experiences among different generations.

Similarly, the study conducted multivariate logistic regression analysis on the personality-intelligence profile. The analysis results, as depicted in Table 8, indicate that urban residents, males, married individuals, high-income earners, higher education levels, Northeast region residents, white-collar professionals, and individuals born after the post-reform and opening up era (after 1979) are more likely to belong to the "Low Conscientiousness-High Intelligence" profile.

3.4. Intergenerational transmission of personality profile and personality-intelligence profile

In this study, the BCH command in Mplus 8.3 software was employed to investigate the intergenerational transmission of personality profiles from parents to their offspring, with the personality profile of parents as the independent variable and that of their children as the dependent variable, exploring the transmissive ability of personality profiles across generations (Bakk & Vermunt, 2016). The results, as shown in Table 9, reveal that the Resilient profile, Ordinary profile, and Distressed profile all exhibit intergenerational transmission. Specifically, parents categorized under the Resilient profile are more likely to nurture offspring with a Resilient profile; parents categorized under the Ordinary profile are more likely to raise offspring with an Ordinary profile; and parents categorized under the Distressed profile are more likely to have offspring with a Distressed profile. Furthermore, parents with an Ordinary profile are more likely to nurture offspring with a Distressed profile compared to parents with a Resilient profile.

Similarly, the study employed the personality-intelligence profile of the parental generation as the independent variable and that of the offspring generation as the dependent variable to explore the intergenerational transmission of personality-intelligence profiles. The results, presented in Table 10, demonstrate the intergenerational transmission of the "Low Conscientiousness-High Intelligence" profile and the "High Conscientiousness-Impoverished" profile. Parents with a "Low Conscientiousness-High Intelligence" profile are more likely to raise offspring with a similar profile, while parents with a "High Conscientiousness-Impoverished" profile are more likely to have offspring characterized by a "High Conscientiousness-Impoverished" profile.

Table 7
Logistic regression analyses of personality-potential profiles.

	Resilient vs ordinary		Distressed vs ordinary		Distressed vs resilient	
	Estimate (95%CI)	OR	Estimate (95%CI)	OR	Estimate (95%CI)	OR
City	−0.065 [−0.19044,0.06044]	0.937	0.082[−0.065,0.229]	1.086	0.147*[−0.01372,0.30772]	1.159
Gender	0.352***[0.23048,0.47352]	1.422	0.062[−0.08108,0.20508]	1.064	−0.29***[−0.4468,−0.1332]	0.748
Marry	−0.152*[−0.32252,0.01852]	0.859	−0.238***[−0.41636,−0.05964]	0.788	−0.0860[−0.28788,0.11588]	0.918
Highinco	0.16**[0.00908,0.31092]	1.174	−0.272***[−0.45036,−0.09364]	0.762	−0.432***[−0.62996,−0.23404]	0.649
Midedu	0.004[−0.13516,0.14316]	1.004	−0.266***[−0.43456,−0.09744]	0.767	−0.269***[−0.45128,−0.08672]	0.764
Highedu	−0.148 [−0.4028,0.1068]	0.862	−0.376***[−0.65824,−0.09376]	0.687	−0.2280[−0.54944,0.09344]	0.796
White	0.087 [−0.72248,0.89648]	1.091	−0.859**[−1.57048,−0.14752]	0.423	−0.947**[−1.79176,−0.10224]	0.388
Blue	−0.287 [−1.08472,0.51072]	0.751	−0.63*[−1.31992,0.05992]	0.532	−0.3440[−1.1672,0.4792]	0.709
Eastnorth	0.134 [−0.05024,0.31824]	1.143	0.523***[0.29172,0.75428]	1.687	0.389***[0.14596,0.63204]	1.476
East	−0.245***[−0.39788,−0.09212]	0.783	0.335***[0.14488,0.52512]	1.398	0.58***[0.3742,0.7858]	1.786
Mid	−0.247***[−0.4038,−0.0902]	0.781	0.243**[0.047,0.439]	1.275	0.49***[0.27832,0.70168]	1.632
Bulid	−0.443***[−0.65664,−0.22936]	0.642	−0.357**[−0.64316,−0.07084]	0.7	0.0860[−0.19428,0.36628]	1.09
Open	−1.321***[−1.5758,−1.0662]	0.267	0.234[−0.0698,0.5378]	1.263	1.554***[1.23844,1.86956]	4.732

Note: Using the profiles after vs as a reference group. *, * * and * * * are significant at the statistical levels of 10 %, 5 %, and 1 %, respectively. See Supplementary material for the full chart. Same as below.

Table 8
Logistic regression analyses of personality-intelligence latent profiles.

	High Conscientiousness-Impoverished vs Low Conscientiousness-High Intelligence	
	Estimate (95%CI)	OR
City	−0.425***[−0.52692,−0.32308]	0.654
Gender	−0.664***[−0.762,−0.566]	0.515
Marry	−0.23***[−0.38288,−0.07712]	0.795
Highinco	−0.693***[−0.86156,−0.52444]	0.5
Midedu	−2.704***[−2.83336,−2.57464]	0.067
Highedu	−20.07***[−20.07,−20.07]	0
White	−1.24***[−1.9162,−0.5638]	0.289
Blue	0.03 [−0.5972,0.6572]	1.03
Eastnorth	−1.111***[−1.27368,−0.94832]	0.329
East	−0.692***[−0.81744,−0.56656]	0.5
Mid	−0.563***[−0.68844,−0.43756]	0.57
Build	−0.352***[−0.50292,−0.20108]	0.703
Open	−1.61***[−1.80404,−1.41596]	0.2

Note: Using the "Low Conscientiousness-High Intelligence" profile as a reference group.

4. Discussion and conclusion

Based on the Chinese sample from the CFPS data, this study applied latent profile analysis to investigate the Big Five personality traits and personality-intelligence profiles of Chinese residents. The latent profile analysis of personality identified the Resilient profile, Ordinary profile, and Distressed profile. These profiles have been corroborated in existing literature (Van der Wal et al., 2016; Udayar et al., 2020). Tan (2023) obtained four personality profiles using the same data. Among these four profiles, Conscientiousness, Extraversion, Agreeableness, and Openness demonstrated clear associations. However, Emotional Stability displayed an unusual pattern—contrary to expectations, as other personality traits increased, Emotional Stability decreased. While this study lacks insight into the specifics of their data processing, the anomalous behavior of Emotional Stability is noteworthy. Some studies on personality profiles have utilized data collected independently, focusing on specific subgroups with relatively small sample sizes. Despite identifying unique profiles, these profiles are suggested to be considered sub-personality profiles specific to certain groups (Chen et al., 2021). The latent profile analysis of personality-intelligence revealed the "Low Conscientiousness-High Cognition" profile and the "High Conscientiousness-Impoverished" profile. This finding indicates that intelligence is more closely related to Openness and Emotional Stability, with the Low Intelligence profile exhibiting higher Conscientiousness. Differences in Extraversion and Agreeableness between the two profiles were minimal. This aligns with findings from existing literature (Ackerman, 1996; DeYoung, 2020; Moutafi et al., 2003, 2006). The results of the multivariate analysis indicated that eight covariates—household registration type, gender, marital status, economic status, educational level, occupation type, geographical region, and birth era—impact the distribution of personality profiles and personality-intelligence profiles. Intergenerational transmission testing revealed that both personality profiles and personality-intelligence profiles exhibit certain levels of intergenerational transmission. Similar to the influences on personality and intelligence factors, personality profiles and personality-intelligence profiles are also influenced by a series of demographic covariates and exhibit intergenerational transmission.

This study's incorporation of intelligence factors into personality profile research efforts provides some reference value for integrating other psychological traits into profile studies. In the realm of intergenerational mobility research, sociologists, economists, education scholars, and philosophers have discussed various factors influencing the intergenerational mobility of individuals in terms of occupation,

Table 10
Tests of intergenerational transmissibility differences (mean ± s) in personality-intelligence latent profiles.

		Parent			
	Profile	Class1-II	Class2-II	Overall Chi-Square	
Child	Class1-II	0.72 ± 0.008	0.68 ± 0.01	9.939***	1 > 2
	Class2-II	0.28 ± 0.008	0.32 ± 0.01	9.939***	2 > 1

Note: Class1-II is a Low Conscientiousness-High Intelligence profile and Class2-II is a High Conscientiousness-Impoverished profile.

Table 9
Tests of differences in intergenerational transmissibility of potential profiles of personality (mean ± s).

		Parent				
	Profile	Resilient (Class1-I)	Ordinary (Class2-I)	Distressed (Class3-I)	Overall Chi-Square	
Child	Resilient (Class1-I)	0.164 ± 0.011	0.095 ± 0.005	0.09 ± 0.014	31.328***	1 > 2,3
	Ordinary (Class2-I)	0.745 ± 0.013	0.778 ± 0.006	0.724 ± 0.021	6.709**	2 > 1,3
	Distressed (Class3-I)	0.091 ± 0.009	0.127 ± 0.005	0.186 ± 0.018	27.541***	3 > 2 > 1

income, education levels, and happiness. Personality and intelligence are considered crucial explanatory factors (Anger & Heineck, 2010; Heckman & Rubinstein, 2001). However, most empirical studies have primarily focused on studying variables individually rather than interpreting them as a cohesive unit, thereby overlooking the organic connections between different personality dimensions and intelligence dimensions. This study revealed a certain degree of intergenerational transmission within personality profiles and personality-intelligence profiles. This insight offers a pathway for considering that personality profiles and personality-intelligence profiles could potentially serve as explanatory factors for intergenerational mobility in socioeconomic status, presenting new variable selections for future studies on intergenerational mobility.

This study also provides the following management implications. From the perspective of human capital: Individuals must realize that completing a slightly complex task requires utilizing all abilities and mutual cooperation. Individuals should focus on the structure of their personality and abilities, and engage in self-education, rather than just focusing on a few dimensions; Traditionally, Chinese parents have tended to emphasize traits such as intelligence, diligence, responsibility, and agreeableness, neglecting other personality traits of their offspring. Chinese parents should consider the personality factors of their offspring more, and provide a more comprehensive and systematic education based on the talents and characteristics of the learners. They should also recognize that their profile characteristics will to some extent influence the features of their offspring, and they can optimize their ability structure through self-education as a positive example; In the process of building a management team and cultivating employee human capital, enterprises need to consider the factors of personality profile and personality-intelligence profile. How individuals with various profiles in a team can be matched and combined to achieve different corporate goals is a worthwhile issue to explore; This study finds that profiles have intergenerational transmission, and are related to socio-economic factors. This intergenerational transmission will to some extent lead to social inequality. For families with poorer profiles, the government should provide certain policy interventions to promote the improvement and development of the ability structure of minors (Cunha & Heckman, 2007). From a social selection perspective: in the recruitment and promotion process, companies can consider conducting personality tests for applicants, and combine them with educational background and intelligence factors to examine the compatibility of applicants' ability structure characteristics with the position; Traditionally, the Chinese education screening mechanism has been characterized by the "National College Entrance Examination" - this system emphasizes the intellectual factors of examinees. The reform of the Chinese education system can focus more on examining various personality traits of examinees to select individuals with good profiles. This will also urge examinees and parents to engage in self-education in a more balanced manner.

It is essential to acknowledge that this study is subject to certain limitations. Firstly, the internal consistency reliability of the data utilized in this study is relatively low, as elucidated in the Method section. It is hoped that future research will produce higher-quality survey data to address this shortcoming. Secondly, due to constraints in scope and research focus, this study did not delve into the mechanisms of intergenerational transmission in personality profiles and personality-intelligence profiles, nor did it address endogeneity and heterogeneity issues. Third, this study examines personality profiles and personality-intelligence profiles. Other psychological elements (such as narratives, values, and motivation) may still have structural effects, making it meaningful to investigate the profiles of these factors. Given these boundaries, future research will likely focus on systematically investigating the reasons for the formation and impact of profiles, uncovering the structural profiles of other psychological elements, and along with exploring the role of profile intergenerational transmission in individual intergenerational mobility in socioeconomic characteristics.

CRediT authorship contribution statement

Mingjun Wang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The author declares that there is no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

I sincerely thank Professor Guiwen Zhang (School of Economics, Liaoning University) and Associate Professor Yunfeng He (Liaoning Key Laboratory of Psychological Testing and Behavior Analysis) for their expert guidance and critical feedback. Their insights profoundly strengthened the theoretical framework and methodological rigor of this work. I also acknowledge the China Social Science Survey Center of Peking University for providing the survey data.

Data availability

Data will be made available on request.

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