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Psychometric Properties of Chinese Version of the Multiple Intelligence Scale (MIS) Among Older Adults: Rasch Analysis and Confirmatory Factor Analysis

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Abstract

The present study utilized advanced psychometric methods (i.e., Rasch analysis and confirmatory factor analysis [CFA]) to evaluate the factor structure of the Multiple Intelligence Scale (MIS) and its validity among Taiwanese older adults. Methods: A cross-sectional study design using convenience sampling was conducted among 200 community-dwelling participants aged 65 years or older. Results: The Rasch analyses showed that the MIS had good structure validity and unidimensionality. Among various CFA models testing the MIS factor structure, exploratory structural equation modelling performed the best given its parsimonious and excellent fit indices. Conclusions: The MIS can be used among older adults in a culturally-fair way for understanding their multiple intelligences. Using the MIS, healthcare providers could encourage older people to assess their own strengths and weaknesses of intelligence. The results suggest that more research on older adults' MI is needed to tailor bespoke therapeutic programs to individual needs in community settings.

Keywords

older adults, Rasch analysis, scale development, psychometric properties, Multiple Intelligence Scale

What this paper adds

- Current cognitive assessments are narrow and primarily assess academic intelligence, and there is little research examining the evaluation of multiple dimensions of intelligence among older adults.
- The results of the present study demonstrated that the Multiple Intelligence Scale (MIS) is an effective instrument for assessing MI among older adults and can distinguish the degree of difficulty between items.

Applications of study findings

- Analysis of the MIS psychometric profiles showed that older adults scored highest for intrapersonal and interpersonal intelligence and lowest for bodily-kinesthetic and naturalist intelligence.

- Exploratory structural equation modelling had the best model fit and showed that all items were embedded within their belonged domains, reflecting good construct validity and unidimensionality.

Introduction

The concept of intelligence can represent an individual's mental ability to solve problems, to think, and to make decisions. However, the definition is diverse. The two-factor theory of intelligence was first developed by Spearman in the early 19th century (Spearman, 1904), which emphasized the binary dimensions of intelligence, namely general and specific factors, to reflect an individual's intelligence in academic achievement. The general factor (g) was accordingly developed and divided into general fluid (G*f*) and crystallized (G*c*) intelligence based on the results of intelligence testing (Horn & Cattell, 1966). The g factor has been defined as the general mental ability to represent an individual's achievement or talents in academic and educational development. The fourth version of the Wechsler Adult Intelligence Scale (WAIS-IV) is widely known for combining comprehensive and verbal/non-verbal psychometric measurement to assess the g factor of intelligence, including G*f* and G*c*. The traditional intelligence test was designed to assess an individual's general intelligence, but it decreases with age, resulting in underestimated results among adults and older adults. The limitation of intelligence definition and measurements influenced the development of multidimensional approaches to intelligence, such as three-stratum models (Carroll, 1993) and the concept of multiple intelligence (Gardner, 1983, 1999, 2011). Emotional intelligence, and the development of such scales as the Wong and Law Emotional Intelligence Scale (Wong & Law, 2002), is a different concept in defining intelligence, but only comprises the emotional dimension of intelligence rather than a multidimensional approach.

This diversity reflects the developmental changes from binary to multiple domains of human intelligence. Individuals possess and represent their different intelligences while acquiring knowledge, solving problems, and demonstrating creativity in their cultural settings. Moreover, individuals show their strengths and weaknesses across multiple intelligence domains. The most well-known multiple intelligence (MI) approach is that of Gardner (1983, 1999), and it has been widely utilized in primary to advanced education to improve the learner's multiple capacities and achievement performances. Gardner (1999) defined MI as *"a biopsychological potential to process information that can be activated in a cultural setting to solve problems or create products that are of value in a culture"* (Shearer, 2012). Therefore, providing a culture-fair assessment for evaluating learners' performance and giving them an equal opportunity to perform well are essential concepts of MI (Cavas & Cavas, 2020; Morgan, 2021; Sharma, 2023).

MI includes linguistic, logical-mathematical, visual-spatial, bodily-kinesthetic, musical, interpersonal, intrapersonal, and naturalistic intelligence. Moreover, MI can be influenced by environmental factors and learning experiences. The three formal MIs (linguistic, logical-mathematical, and visual-spatial) have usually been considered as academic intelligence or cognitive-related intelligence (Castejon et al., 2010; Gardner, 1999; Visser et al., 2006; Waterhouse, 2023) as representing an individual's cognitive performance. Academic intelligence is considered as a predominant factor in assessing cognitive dysfunction or impairment. In the main, most cognitive assessments evaluate an individual's verbal/linguistic and logical/mathematical abilities, such as the Mini-Mental State Examination (MMSE) and the Montreal Cognitive Assessment (MoCA) (George et al., 2021; Guerrero-Berroa et al., 2009; Julayanont & Nasreddine, 2017). Although the MMSE and MoCA are commonly-used measures assessing cognitive function for older people, they only consider academic intelligence and do not assess older people's MI. Moreover, to the best of the present authors' knowledge, there are few MI studies that have been conducted among older adults.

Other than the three formal types of academic intelligence, there are other types of intelligence concerning older adults' daily lives. High performance in each intelligence is associated with high learning intention and effective performance in that domain. For example, bodily-kinesthetic intelligence represents the ability of physical fitness, and older adults have competence for engaging in physical activity from moderate to vigorous intensity for living healthily (Burzynska et al., 2020; Hamaya et al., 2024). Musical intelligence can be used to improve mental and cognitive health among older adults and is widely applied in the community and long-term care facilities (Raglio et al., 2024; Rogers & Metzler-Baddeley, 2024). Interpersonal and intrapersonal intelligence belong to the category of emotional intelligence, in which individuals need to understand their own and others' emotions around them to get along with. Both intelligences prompt self-directed learning, learning motivation, and communication effectiveness, which benefit older adults in active aging through their learning effectiveness (Jorfi et al., 2011; Lei et al., 2021; Okwuduba et al., 2021; Soleimani et al., 2020). According to Morris (2004), naturalistic intelligence, or ecological sensibility, is the capacity to observe, distinguish, and classify creatures in nature, including animals, plants, geology, and meteorology. A growing body of evidence-based interventional studies have shown the positive impacts of natural and forest intervention on physical, mental, and spiritual health among older adults (Catissi et al., 2024; Rajoo et al., 2020). In sum, other types of intelligence are essential for multiple types of development among older adults, and rethinking age and aging for them is essential.

The *UN [United Nations] Decade of Healthy Ageing* action plan advocated by the World Health Organization (WHO, 2020) mentions the importance of rethinking age and aging. The WHO (2020) first indicated that intrinsic capacity (IC) is the determinant of functional ability and a marker of healthy aging (Lopez-Ortiz et al., 2022; Yu et al., 2022). The concept of IC is defined as the combination of all an individual's physical and mental capacities, and most studies have used five dimensions to represent IC according to the development of Integrated Care for Older People (ICOPE) (i.e., locomotion, vitality, sensory, cognitive, and psychological). However, there is no gold standard assessment or clear criterion as a global measure (George et al., 2021; Lopez-Ortiz et al., 2022). This action plan advocates using diverse perspectives on cognitive aging, such as a holistic approach to MI assessment. Current cognitive assessments primarily assess academic intelligence, and there is little research examining the evaluation of multiple dimensions of intelligence among older adults. Lifelong learning and development in aging is of great importance. The development of MI can contribute to not only extending the theory of MI in the gerontology field but also helping communities enhance multiple dimensions of IC among older adults and delivering person-centered integrated primary health services to them according to their different MI spectrum patterns. Therefore, it seems insufficient to only value academic intelligence in improving IC. Subsequently, understanding older people's MIs may help advance the current practice in geriatric care.

Gardner (1998) first developed Project Spectrum with objective materials and activities for educators to evaluate children's performance in eight intelligences instead of utilizing traditional paper-and-pencil assessment. Regarding the original idea of MI assessment, Gardner's team showed that the assessment for MI should include the entire MI domains, distinguish the strengths and weaknesses, provide immediate feedback to learners, ensure validity in assessment, and identify the MI scoring range across domains (Davis et al., 2011; Morgan, 2021). However, the eight-domain MI assessment activities are complex and very long for educators to assess learners in practice (McMahon et al., 2004). Teele (1992, 1996) then developed the Teele Inventory of Multiple Intelligences (TIMI), which specifically assessed children's MI preference through several evaluations of teaching activities.

The Multiple Intelligence Developmental Assessment Scale (MIDAS; Shearer, 1999) is the best-known MI assessment for children and the general population in understanding how the learners value their own MI profile. Armstrong (2009) also developed an 80-item checklist of MI with eight MI dimensions specific to adults and in the classroom setting (Armstrong, 2009; Lii & Wong, 2010). Due to the differences in MI development in cultural settings, Tirri and Nokelainen (2011) developed the (five-point self-rating) Multiple Intelligences Profiling Questionnaire IX (MIPQ IX) to help both educators and learners know their strengths. This scale has been applied to the pre-adolescent, adolescent, and adult populations (Tirri & Nokelainen, 2008, 2011; Tirri et al., 2013). However, even though the current MI measurement instruments have examined other dimensions of MI, such as cultural intelligence (Earley, Ang, & Tan, 2006) and ethical sensitivity (Tirri & Nokelainen, 2011), their reliability and validity need further investigation, and eight or nine-and-a-half dimensions of intelligence still dominate the development of MI. Consequently, MI assessment for older adults remains unclear and (as yet) has no gold standard (Waterhouse, 2023).

In order to facilitate future studies incorporating MI into geriatric care programs, the first step is to develop a psychometrically robust measure assessing MI. Intelligence may represent different neural representations across cultural contexts (Davis et al., 2011; Waterhouse, 2023). The intelligence-fairness and cultural-fairness approach emphasizes equality toward the learners based on their different backgrounds and learning profiles. Many MI-oriented scholars have emphasized that intelligence should not be assessed through the lens of verbal, or any other, single ability (Gardner, 1999; Holden & Tanenbaum, 2023; Morgan, 2021; Sternberg, 2018; Visser et al., 2006). More importantly, academic intelligence predominates in Chinese culture. Therefore, paper-and-pencil tests influence all the tests in learning or working settings. This non-intelligence-fairness approach may hinder older adults from developing their IC throughout their lives. The Multiple Intelligence Scale (MIS; Chen, 2004; Hsieh, 2000) allows older adults to re-examine their mental ability and encourages them to engage in various social activities based on their advantages or weaknesses in intelligence.

The current cognitive assessments are narrow and primarily assess academic intelligence, and there is little research examining the evaluation of multiple dimensions of intelligence among older adults. Moreover, the present study applied two psychometric testing approaches (i.e., modern test theory and classical test theory) to provide different evidence regarding the Chinese MIS. The two different approaches can cross-validate if the Chinese MIS contains multiple intelligences. The use of modern test theory (i.e., the Rasch model used in the present study) contains the advantages of test and sample independence, an objective from ordinal-to-interval measurement, and distinguishes the difficulty between test and sample. Moreover, the measure unit (i.e., logit) is equivalent for both test and sample, which means the measures on (i) test and (ii) sample can be directly computed (Bond & Fox, 2013).

Classical test theory (CTT), which has been widely used in psychological measurement for decades, focuses on examining the relationship between observed scores and true scores, assuming that an individual's observed score comprises their true score plus measurement error. This fundamental approach helps evaluate scale reliability and construct validity through methods such as factor analysis. The main advantage of CTT in the present study was to identify the best fitting model in the Chinese MIS among competing models, thereby establishing factorial validity among older people.

Therefore, the present study aimed to validate the Chinese MIS among Taiwanese older adults. More specifically, an intelligence-fair or culturally-fair approach should be considered when developing cognitive assessments. MI assessment varies across different cultural contexts due to the diverse definitions of intelligence found in various countries.

Methods

Study design and participants

The study adopted a cross-sectional study design with a convenience sample of 203 community-dwelling individuals aged 65 years and older, recruited from five communities/senior centers in Kaohsiung City, Southern Taiwan, from August to November 2023. The characteristics of recruited communities are educational-based communities set by local government, non-profit organizations, or social welfare foundations. The recruited communities have support through abundant educational, social, and physical-oriented activities. In addition, they cooperate with the local government and receive financial support from them by conducting several ‘health promotion in aging’ programs. Kaohsiung residents aged above 65 years old can participate in the activities or courses affordably (and sometimes they are free of charge). Therefore, it was assumed that participants would be recruited come from various demographic backgrounds. The inclusion criteria were (i) being older-aged adults (≥ 65 years at the end of 2023), (ii) being able to read and write in Chinese, (3) being able to walk independently, and (4) having MMSE scores ≥ 18. Participants were excluded if they suffered from severe illness (e.g., cancer, chronic kidney disease, or spinal cord disease). Of the original 203 older adults, 200 met the inclusion criteria. The response rate was 100%.

Procedure

With the permission of the Kaohsiung government's social welfare unit, the present study liaised with social workers or leaders in the community/senior centers. After receiving their agreement to help recruit participants for the study, members of the research team administered the questionnaire to older adults directly. All participants provided written informed consent, and agreed to participate in the present study. The study was approved by the xxx (IRB ref: blinded for peer review).

Materials

The MIS (Chen, 2004; Hsieh, 2000) evolved from Armstrong's 80-item MI Inventory for students and adults (Armstrong, 1994, 2000, 2009; Gardner, 1999), was used to assess MI. In addition to Gardner, Armstrong was one of the first authors to develop MI theory into practice, including teaching strategy, activities, materials, and curriculum development. Armstrong's work has been well-developed along with Gardner's theory and bridged the gap between theory and practice. Consequently, the 80 items in the Chinese MIS were first developed to understand student intelligence traits among fifth- and sixth-grade elementary students (Hsieh, 2000). A total of 64 items of MIS remained after reliability and construct validity were confirmed, and it was further applied to high school students (Chen, 2004) and university students (Lii & Wong, 2010; Wong, 2013) in Taiwan. However, to date, it has never been administered to older adults.

The Chinese MIS has demonstrated excellent internal consistency for both elementary students (alpha = .97) and college students (alpha = .91) across the eight dimensions (Hsieh, 2000; Lii & Wong, 2010).

The MIS consists of 64 items, comprising eight domains of MI with eight items for each domain. The eight domains are linguistic, logical-mathematical, visual-spatial, bodily-kinesthetic, musical, interpersonal, intrapersonal, and naturalistic intelligence. Participants rate their agreement with MI's strengths or weaknesses in each domain. Items are rated using a five-point Likert scale from 1 (*strongly disagree*) to 5 (*strongly agree*), and the higher scores in each domain indicate higher intelligence in that domain. The MIS subscale score is calculated based on the sum of the eight items in each domain.

In addition, to assess the cognitive function of older adults, the 30-item MMSE was used to assess orientation, attention and calculation, message recording, short-term memory, language, and construction ability. The total score is 30, and participants with an MMSE score below 18 are defined as having severe cognitive impairment. This instrument has excellent internal consistency for community populations with a Cronbach's α coefficient of 0.91 (Folstein et al., 1975). The Cronbach's α in the present study was 0.71. Other demographic variables, such as sex, age, and educational background, were collected.

Data analysis strategy

The data analysis was conducted using a multi-step approach to examine the psychometric properties and factor structure of the MIS. Initially, descriptive statistics, including means and standard deviations, were calculated for each of the eight intelligences. A within-participants analysis of variance (ANOVA) was performed to compare the mean scores across the eight intelligences within the population of older adults. This approach was chosen because each participant provided scores for all eight intelligence types, creating a repeated measures design within the cross-sectional dataset. Post hoc analyses with Bonferroni correction were then conducted to identify specific differences between intelligence types.

Next, Rasch analyses were conducted to evaluate item validity for each subscale of the MIS separately. Prior to full analysis, two key assumptions of Rasch analysis were assessed: dimensionality of each subscale and monotonicity of response categories.

The dimensionality of each subscale was examined using eigenvalue ratios. A ratio of the first to the second eigenvalue greater than 4 was used as a criterion to indicate that a subscale assessed a single, coherent construct (Slocum-Gori & Zumbo, 2011). This analysis was performed separately for each of the eight intelligence subscales.

Monotonicity of item response categories was assessed using person-item maps, which visually represent the relationship between item difficulty and person ability on the same scale. These maps were generated for each subscale of the MIS. By examining the ordering of item thresholds in these maps, any violations of monotonicity can be identified, which is a key assumption of the Rasch model. This analysis helps ensure that for each item, higher response categories consistently correspond to higher levels of the assessed trait.

Item fit was determined by examining infit and outfit mean square (MnSq) statistics, with values between 0.5 and 1.5 considered acceptable (Jafari et al., 2012). Person reliability was also calculated to ensure that each subscale effectively differentiated between individuals with varying levels of the respective intelligence. This measure indicates the reproducibility of person ordering if the same sample of individuals were given a similar set of items assessing the same construct (Bond & Fox, 2021).

Confirmatory factor analysis (CFA) was additionally conducted to examine the factorial validity of the scale, specifically testing various factor structures. The tested models included: (1) a one-factor model, where all items load onto a single general factor; (2) an oblique eight-factor model, allowing correlations among factors; (3) a second-order factor model, with eight first-order factors loading onto one higher-order general factor; and (4) a bifactor model, where all items simultaneously load onto both a general factor and one of eight specific factors (representing eight different types of intelligence).

Figure 1 illustrates the first three structural models. The oblique eight-factor model represents eight distinct but correlated intelligence domains, while the second-order factor model posits that the relationships among these eight first-order factors can be explained by a higher-order general factor.

Figure 2 presents the bifactor model, which differs conceptually from the second-order model. Unlike the second-order model where the general factor influences items indirectly through first-order factors, the bifactor model specifies orthogonal relationships between the general and specific factors. This structure enables researchers to evaluate whether the scale primarily assesses a single construct while acknowledging multidimensionality through domain-specific factors.

Model fit was assessed using various indices, such as the comparative fit index (CFI), non-normed fit index (NNFI), standardized root mean square residual (SRMR), and root mean square error of approximation (RMSEA) with 90% confidence intervals. Exploratory structural equation modeling (ESEM) was also included in the model comparison to further investigate the factor structure of the scale. ESEM allows for cross-loadings of items on multiple factors, providing a more flexible and realistic representation of the data (represented in Figure 2). The ESEM model was compared to the CFA models using changes in fit indices (ΔCFI, ΔNNFI, and ΔRMSEA) to determine if it significantly improved model fit. The cutoff values for meaningful changes in fit indices were set at 0.015 for RMSEA and SRMR, and 0.01 for CFI and NNFI, as suggested by van Zyl and ten Klooster (2022).

Finally, composite reliability was computed to assess the convergent validity based on the factor loadings from the best-fitting model. Factor loadings greater than 0.50 were considered satisfactory, and composite reliability values above 0.60 were deemed acceptable (Hair et al., 2019).

Sample size justification

The study's sample size of 200 older adults meets the general rule of thumb for conducting structural equation modeling (SEM) (Jackson, 2003). This initial benchmark of 200 participants provides a foundational justification for the study’s sample size. In addition to meeting this general guideline, recent simulation studies in SEM methodology provide further support for the adequacy of the present study’s sample size under specific conditions. These studies offer more nuanced perspectives on sample size requirements, moving beyond simple numeric thresholds. More specifically, Gagné and Hancock (2006) demonstrated that when the number of indicators per factor is sufficient (e.g., seven), a sample size of 200 can yield convergence rates comparable to much larger samples. Wolf et al. (2013) found that as the number of indicators per factor increases from four to six or more, the minimum required sample size can decrease substantially, approaching or even dropping below 200, particularly when factor loadings exceed 0.60. Similarly, Moshagen and Musch (2014) reported negligible bias for factor loadings across sample sizes ranging from 200 to 1000 when there were five or more indicators per factor.

These findings suggest that the adequacy of sample size in SEM is more complex than previously thought and depends heavily on the characteristics of the measurement model. Factors such as the number of indicators per latent variable, the strength of factor loadings, and the overall model structure play crucial roles in determining the minimum required sample size. In light of these considerations, the MIS used in this study, which includes eight factors each with eight indicators, contributes to a required minimal sample size that is much lower than what traditional rules would suggest based on the ratio of sample size to number of variables (n/p) or the ratio of number of cases per model parameter (n/q). Indeed, recent simulation studies provide stronger evidence that the quality and number of indicators per factor are more important than simply considering absolute sample size values. This aligns with Jackson’s (2003) argument that the n/q should not be thought of in an absolute sense. Rather, the characteristics of the measurement model, such as those exhibited by the MIS scale, play a vital role in determining the adequacy of sample size for CFA.

Results

As aforementioned, 200 participants were recruited for the present study. The average age of participants was 71.57 years, ranging from 64 to 86 years. Approximately 76.50% of the participants were female (n = 153), and 88.50% had education higher than senior high school (n = 177). The means of MMSE scores were 28.28 (SD±1.60), while 3% of participants had an MMSE score ranging from 22 to 24 (n=6). Table 1 displays the participants' descriptive statistics for the eight multiple intelligences. The within-participants comparison showed significant differences across the eight types of intelligence in the sample ($F = 52.48$, $p < .001$, $\eta^2 = 0.21$).

The post hoc analysis with Bonferroni correction of *p*-values indicated that the highest scores were for intrapersonal intelligence, while the lowest scores were for bodily-kinesthetic intelligence and naturalist intelligence which were both significantly lower than other intelligences. Moreover, there were significantly positive correlations among these intelligences with magnitude at medium to high level. Among these correlations, the lowest were $r = 0.36$ (the association between linguistic and musical intelligence, as well as the association between logical-mathematical and musical intelligence), and the highest was $r = 0.61$ (the association between linguistic and logical-mathematical intelligence).

The assumptions of Rasch analysis were confirmed by assessing unidimensionality for each subscale and monotonically increasing item categories. More specifically, the eigenvalue ratios in each intelligence subscale were all greater than 4, confirming that each subscale assesses a single, coherent construct. Person-item maps (Figures S1-4) demonstrated that all item categories increased monotonically, indicating that higher response categories consistently corresponded to higher levels of the assessed trait. These maps show the distribution of person abilities and item difficulties on the same scale, where the alignment between them suggests that the items appropriately capture the range of abilities in the sample. The ordered thresholds observed in these maps confirmed that participants with higher ability levels were more likely to endorse higher response categories, supporting the proper functioning of the rating scale.

After confirming that the assumptions of Rasch analysis were met, the infit and outfit statistics for each item in their respective scales were conducted (Table 2). The results showed that nearly all items had satisfactory item validity, with infit and outfit values falling within the acceptable range of 0.5 to 1.5. This led to the retention of all items, except for Item 8 in the intrapersonal intelligence subscale (*"I write my reflections on significant life events in my diary"*) which was omitted from later analyses. The person reliability for each intelligence subscale was greater than 0.80 (see Table 2), indicating that each scale effectively differentiated between individuals with varying levels of the respective latent trait (i.e., specific intelligence type). These findings suggest that the person ordering based on their ability estimates was highly consistent and reproducible within each intelligence subscale.

After removing Item 8 of the intrapersonal intelligence scale, CFAs were conducted to test the factorial validity of the remaining items. Table 3 displays the model fit indices for distinct factor structures. Except for the one-factor structure, which adopts the strict assumption of a single underlying factor and does not meet the model fit criteria, all other factor structures demonstrated acceptable model fit.

The oblique eight-factor structure was further compared with the second-order factor structure. The results indicated that there was no substantial difference between the two structures in terms of model fit, as evidenced by the fact that the difference in fit indices did not exceed the threshold for a substantial improvement. Considering that the second-order factor structure is a more parsimonious model, requiring fewer parameters to be estimated (higher degree of freedom) compared to the oblique eight-factor structure where all inter-factor correlations need to be estimated separately, it could be considered to outperform the oblique eight-factor structure.

The ESEM approach yielded a substantial improvement in model fit, as evidenced by ΔCFI and ΔNNFI values greater than 0.01 and a ΔRMSEA value greater than 0.015. It is also noteworthy that the high correlations observed among the oblique eight factors (r ranging from 0.38 to 0.73, with most correlations higher than 0.50) were reduced to small to moderate correlations in the ESEM model (ranging from 0.10 to 0.28). An exception to this pattern was the association between the latent factors of musical intelligence and intrapersonal intelligence, which became non-significant in the ESEM model (from 0.38 in the oblique eight-factor model to non-significant in the ESEM model).

Finally, the bifactor structures, which include the bifactor CFA model and the bifactor ESEM model, did not significantly improve the model fit. The differences in fit indices between these bifactor models and their respective counterparts (the oblique eight-factor structure and the ESEM model) were not substantial. These findings suggest that the use of a bifactor structure is not necessary to represent the factor structure of the scale adequately.

Given that the ESEM presented the best factor structure, the factor loadings of each item were further assessed under this factor structure. The results showed that most of the item factor loadings were higher than 0.50, although some factor loadings were less than 0.30, which occurred in the logical-mathematical intelligence, bodily-kinesthetic, and naturalist intelligence subscales (see Table 4). Based on the factor loadings, the composite reliabilities were calculated to be 0.78 (linguistic intelligence), 0.79 (logical-mathematical intelligence), 0.64 (visual-spatial intelligence), 0.64 (bodily-kinesthetic intelligence), 0.81 (musical intelligence), 0.84 (interpersonal intelligence), 0.75 (intrapersonal intelligence), and 0.77 (naturalist intelligence), indicating acceptable to good convergent validity for each subscale.

Discussion

Exploring MI and its potential among older people is an important issue highlighted in the

WHO's Healthy Aging guidelines. However, to the best of the present authors' knowledge, none of the existing MI scales have been tested among older people or utilize Rasch analysis to determine the validity of individual items (Almeida et al., 2010; Bryan & Mayer, 2020; Castejon et al., 2010; Visser et al., 2006). The results of the present study demonstrated that the MIS is an effective instrument for assessing MI among older adults and can distinguish the degree of difficulty between items. Analysis of MI psychometric profiles showed that older adults scored highest for intrapersonal and interpersonal intelligence and lowest for bodily-kinesthetic and naturalist intelligence. Additionally, when considering the structure of the MIS, the ESEM was found to be a more parsimonious and showed that all items were embedded within their belonged domains, reflecting good construct validity and unidimensionality. All items demonstrated a good fit model and reliability except for Item 8 of intrapersonal intelligence

Intrapersonal intelligence and the deleted item

Only one item from the intrapersonal intelligence subscale was removed from MIS due to its poor item validity. There are a number of possible explanations. The 64-item MIS was designed to evaluate an individual's intelligence rather than their emotional feelings affected by MI ability. The removed item (*"I write my reflections on significant life events in my diary"*) evaluates the behavior with reflections through writing. However, the other seven items of intrapersonal intelligence rate individuals' inner traits, intention of behavior, and personality description. The MIS was designed to assess MI strengths and weaknesses rather than reflect their preferred behavior on emotions. In fact, MI studies imply that some sub-domains of MI, such as intrapersonal intelligence, are unlikely to be a general intelligence or represent a purely cognitive domain (Castejon et al., 2010; Visser et al., 2006).

The debate on whether MI theory belongs to a *g* factor or is a better conceptualization for evaluating multiple dimensions of intelligence is still an ongoing. Even if an individual's findings confirm that the MIS has good item discrimination and well-distinguished difficulty among older adults, the inconsistent past results in assessing MI or application to different populations remain a problem and need further investigation.

In addition, the removed item may comprise two dimensions of intelligence, namely linguistic and intrapersonal, which leads to poor validity. For example, older adults may remember their significant life events through different media rather than writing things in a diary. Because current item descriptions may be irrelevant to older adults, it may cause misunderstandings about the item and result in poor validity. Therefore, to improve the current MIS, future studies should revise the removed item through expert validation and add the new item back to the MIS for further validation.

Structure validity of the MIS among older adults

Considering the scale's structure, the findings showed that the ESEM presented the best factor structure among the six CFA models of the MIS. Previous MI studies with other MI measures (Almeida et al., 2010; Bryan & Mayer, 2020; Visser et al., 2006) have used exploratory factor analysis (EFA) or CFA to examine the relationships between specific MI domains and the *g* factor loadings. They concluded that only some MI domains are linked to purely cognitive abilities, while others are not. Moreover, the second or third-order factor analysis of intelligence should be considered when identifying intelligence based on *g* (Almeida et al., 2010; Bryan & Mayer, 2020; Lozano-Blasco et al., 2022; Visser et al., 2006).

The data in the aforementioned MI studies were analyzed using four different intelligence models through CFA. These studies rejected the previous assumption but supported the original definition in Gardner's model, which consists of six or seven first-order correlated factors (Castejon et al., 2010; Shearer & Karanian, 2017). Castejon et al.'s (2010) findings showed that the MI domains were positively correlated but theoretically independent. That is, all individuals have different MI strengths and weaknesses, and all MI domains exist (to a greater or lesser extent) in everyone's intelligence profile.

The present study explored Castejon et al.'s test model across eight domains and applied a new statistical methodology to confirm structural validity using ESEM. ESEM integrates the strengths of EFA, CFA, and SEM, and allows the cross-loadings not at zero between each subscale, and rationally estimates the correlations between factors (Asparouhov & Muthén, 2009; Marsh et al., 2009). Therefore, from the theoretical perspective, the present study using the ESEM confirmed that MI is multidimensional with eight first-order factors, and found that each domain of MI is necessary for various developments among older adults. The results address the knowledge gap that not only academic or cognitive intelligence is meaningful but that multiple intelligences are also meaningful and equally crucial for older adults. In addition, developing specific older adults' MI assessments, objectively evaluating assessment tools, and identifying MI profiles among older adults for lifelong learning need further investigation.

Regarding the diverse definitions of intelligence in different cultural contexts, specific MI assessment tools that are culturally-fair and age-fair are needed. Current MI studies have extended their population from young to middle adults, such as the MIDAS-C and MIPQ IX, with good reliability but acceptable validity. However, the reliability and validity of current MI assessment instruments need further consideration and examination specific to older adults. The present study's findings examining 200 older adults aged above 65 years with eight domains of MI demonstrated good overall fit validity in the ESEM. Similar to the ESEM structure in the present study, another Chinese MI measure (i.e., Chinese MIDAS) found an eight-factor structure (Wu, 2008, 2018) among preschool, teenagers, college students, and adults aged between 25 and 50 years old. Although the MIPQ IX was proposed a nine-factor structure among 195 adults with an age median of 26 years, it was recommended that the nine-factor structure should be revisited and revised (Tirri et al., 2013). In short, MI measures should be multidimensional and the present study's findings support the multidimensionality for MI measures.

MI across age groups

It is noteworthy that the present study's findings agreed with previous MI studies (Chen, 2004; Hsieh, 2000; Lii & Wong, 2010; Wu, 2018), which demonstrated that intrapersonal intelligence increases with age while bodily-kinesthetic intelligence decreases with age, with naturalist intelligence always being evaluated as the most disadvantaged weakness in Taiwanese cultural contexts but not found in other cultural settings, such as Finnish (Tirri & Nokelainen, 2008; Tirri et al., 2013). In the past, linguistic and interpersonal intelligence have been mentioned for its plasticity and growth with age in the student and young adult stage (Tirri & Nokelainen, 2008; Tirri et al., 2013). However, Taiwanese MI studies have shown that individuals ranging from 10 to 50 years old continuously rate their interpersonal intelligence as their best intelligence until around the age of 20 years, and their strongest intelligence then transfers from interpersonal to intrapersonal (Chen, 2004; Hsieh, 2000; Wu, 2018). In addition, naturalist intelligence has always been reported as the most disadvantageous form of intelligence across all life stages but gradually increases with age (Chen, 2004; Hsieh, 2000; Lii & Wong, 2010; Wu, 2018).

Limitations

The present study is one of the first to demonstrate the ESEM as the best-fit model for MI rather than bifactors and second-order models. Moreover, to the best of the authors' knowledge, the present MI study is the first to confirm the validity of MI structures through Rasch analysis among older adults. While the findings are well-validated, the study has some limitations that require further examination. First, only 200 study participants were recruited from Southern Taiwan, so the results may not be representative of the entire Taiwanese population or applicable to other Asian cultural contexts. Therefore, further MI studies using the MIS should be conducted in different community settings to confirm reproducibility. Second, the majority of study participants were female (76.50%), which differs from the study by Tirri et al. (2013), whose population contained mostly male participants. The differences in MI of each domain between genders should be explored, because gender differences in MI were not extensively examined in the present study. In fact, older female participants play a significant role in Taiwanese community/senior centers. Therefore, recruiting more older male participants to examine the differences among the entire older population is recommended. Third, one item of intrapersonal intelligence in MIS was removed due to poor validity in the study. However, for data integrity, re-examining the description of each item through expert validation and exploring MI structures specific to older adults in the future is recommended. Fourth, the use of self-report methods to assess MI among older adults may be challenging due to the possible problems in recalling their memories and past experiences, even among those participants without severe cognitive impairment.

Finally, the ESEM approach for future MIS research is suggested for older adults. However, it may be combined with other measurements to overcome the low loadings in bodily-kinesthetic intelligence (BKI) and visual-spatial intelligence (SI) dimensions. For example, partial results of senior fitness tests (SFTs) can be used to support BKI and assess general physical function, such as the step-in-place test (two minutes) or 8-foot up-and-go to assess aerobic and agility fitness. Alternatively, partial results of MMSE/MoCA could be used to support SI and assess the general concept of spatial construction, such as drawing a cube or an intersecting pentagon.

Conclusion

The heterogeneity in the aging process and MI development should be taken into consideration together for improving intrinsic capacity among older adults. Therefore, the present study extended MI theory to examine MI development, strengths, and weaknesses among older adults based on their responses to the MIS. The study's findings indicated that the MIS had good validity on items applied to older adults using Rasch analysis, and the ESEM was confirmed as the best model with good model fits. Globally, the results suggest that more research on older adults' MI is needed to tailor bespoke therapeutic programs to individual needs in community settings. Therefore, it is strongly recommended that health promotion/intervention service providers working in communities or long-term care facilities assess their older participants before conducting programs and confirm their possible learning abilities and motivations to support them living in healthy aging.

References

Almeida, L. S., Prieto, M. D., Ferreira, A. I., Bermejo, M. R., Ferrando, M., & Ferrándiz, C. (2010). Intelligence assessment: Gardner multiple intelligence theory as an alternative. *Learning and Individual Differences*, *20*(3), 225-230. doi:10.1016/j.lindif.2009.12.010

Armstrong, T. (2009). *Multiple intelligences in the classroom*. Association for Supervision and Curriculum Development.

Asparouhov, T., & Muthén, B. (2009). Exploratory structural equation modeling. *Structural Equation Modeling, 16*(3), 397-438. doi:10.1080/10705510903008204

Bond, T. G., & Fox, C. M. (2013). *Applying the Rasch model: Fundamental measurement in the human sciences* (2nd ed.). Psychology Press.

Bond, T. G., & Fox, C. M. (2021). *Applying the Rasch model: Fundamental measurement in the human sciences* (4th ed.). Routledge.

Burzynska, A. Z., Voss, M. W., Fanning, J., Salerno, E. A., Gothe, N. P., McAuley, E., & Kramer, A. F. (2020). Sensor-measured sedentariness and physical activity are differentially related to fluid and crystallized abilities in aging. *Psychology and Aging, 35*(8), 1154-1169. doi:10.1037/pag0000580

Bryan, V. M., & Mayer, J. D. (2020). A meta-analysis of the correlations among broad intelligences: Understanding their relations. *Intelligence*, *81*, 101469. doi:10.1016/j.intell.2020.101469

Carroll, J. B. (1993). *Human cognitive abilities. A survey of factor-analytic studies*. Cambridge

University Press.

Carson, J. G., & Longhini, A. (2002). Focusing on learning styles and strategies: A diary study in an immersion setting. *Language learning*, *52*(2), 401-438. doi:10.1111/0023-8333.00188

Castejon, J. L., Perez, A. M., & Gilar, R. (2010). Confirmatory factor analysis of Project Spectrum activities. A second-order g factor or multiple intelligences? *Intelligence*, *38*(5), 481-496. doi:10.1016/j.intell.2010.07.002

Catissi, G., Gouveia, G., Savieto, R. M., Silva, C. P. R., de Almeida, R. S., Borba, G. B., Rosario, K. A., & Leão, E. R. (2024). Nature-based interventions targeting elderly people's health and well-being: an evidence map. *International Journal of Environmental Research and Public Health, 21*(1), 112-131. doi:10.3390/ijerph21010112

Cavas, B., & Cavas, P. (2020). Multiple intelligences theory—Howard Gardner. *Science Education in Theory and Practice: An Introductory Guide to Learning Theory*, 405-418. doi:10.1007/978-3-030-43620-9_27

Chen, Si-Pei (2004). *The relationship between English proficiency and learning styles/ multiple intelligences: A case study of Fu-Hsing High School students*. Master's thesis. National Taiwan Normal University, Taiwan.

Davis, K., Christodoulou, J., Seider, S., & Gardner, H. (2011). *The theory of multiple intelligences.* In: Sternberg, R. J. & SB Kaufman, S. B. (Eds.), Cambridge Handbook of Intelligence (pp. 485-503). Cambridge University Press.

Earley, P.C., Ang, S. & Tan, J.S. (2006). *CQ: Developing cultural intelligence at work*. Stanford, CA: Stanford University Press.

Folstein, M. F., Folstein, S. E., & McHugh, P. R. (1975). "Mini-mental state". A practical method for grading the cognitive state of patients for the clinician. *Journal of Psychiatric Research, 12*(3), 189-198.

Gagne, P., & Hancock, G. R. (2006). Measurement model quality, sample size, and solution propriety in confirmatory factor models. *Multivariate Behavioral Research, 41*(1), 65–83. doi:10.1207/s15327906mbr4101_5

Gardner, H. (1983). *Frames of mind: The theory of multiple intelligences*. Basic Books.

Gardner, H. (1999). *The disciplined mind: What all students should understand*. Simon & Schuster.

Gardner, H. (2011). *Frames of mind: A theory of multiple intelligences*. Basic Books.

Gardner, H., Feldman, D. H., & Krechevsky, M. (1998). *Project Spectrum: Frameworks for Early Childhood Education*. Teachers College Press.

George, P. P., Lun, P., Ong, S. P., & Lim, W. S. (2021). A rapid review of the measurement of intrinsic capacity in older adults. *Journal of Nutrition, Health & Aging, 25*(6), 774-782. doi:10.1007/s12603-021-1622-6

George, P. P., Lun, P., Ong, S. P., & Lim, W. S. (2021). A rapid review of the measurement of intrinsic capacity in older adults. *Journal of Nutrition, Health & Aging, 25*, 774-782. doi:10.1007/s12603-021-1622-6

Guerrero-Berroa, E., Luo, X., Schmeidler, J., Rapp, M. A., Dahlman, K., Grossman, H. T., Haroutunian, V., & Beeri, M. S. (2009). The MMSE orientation for time domain is a strong predictor of subsequent cognitive decline in the elderly. *International Journal of Geriatric Psychiatry, 24*(12), 1429-1437. doi:10.1002/gps.2282

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hamaya, R., Shiroma, E. J., Moore, C. C., Buring, J. E., Evenson, K. R., & Lee, I. M. (2024). Time-vs step-based physical activity metrics for health. *JAMA Internal Medicine, 184*(7), 718-725. doi:10.1001/jamainternmed.2024.0892

Holden, L. R., & Tanenbaum, G. J. (2023). Modern assessments of intelligence must be fair and equitable. *Journal of Intelligence*, *11*(6), 126. doi:10.3390/jintelligence11060126

Horn, J. L., & Cattell, R. B. (1966). Refinement and test of the theory of fluid and crystallized general intelligences. *Journal of Educational Psychology, 57*, 253–270. doi:10.1037/h0023816

Hsieh, C. C. (2000). *The relationships between multiple intelligences, thinking styles, and critical-thinking abilities of the fifth-and sixth grade students*. Master's thesis. National Sun Yat-Sen University, Taiwan.

Jackson, D. L. (2003). Revisiting sample size and number of parameter estimates: Some support for the N:q hypothesis. *Structural Equation Modeling, 10*(1), 128–141. doi:10.1207/S15328007SEM1001_6

Jafari, P., Bagheri, Z., & Safe, M. (2012). Item and response-category functioning of the Persian version of the KIDSCREEN-27: Rasch partial credit model. *Health and Quality of Life Outcomes, 10*(1), 1-9. Doi:10.1186/1477-7525-10-127

Jorfi, H., Yaccob, H. F. B., Shah, I. M., & Jorfi, S. (2011). Emotional intelligence in teaching: The impact of intrapersonal and interpersonal (emotional intelligence's dimensions) on communication effectiveness and strategic information systems planning (SISP). *International Journal of Management and Administrative Sciences, 1*(1), 1-7.

Julayanont, P., & Nasreddine, Z. S. (2017). Montreal Cognitive Assessment (MoCA): Concept and clinical review. In A. J. Larner (Eds.), *Cognitive screening instruments: A practical approach* (pp, 139-195). Springer-Verlag Publishing. doi:10.1007/978-3-319-44775-9_7

Klimova, B. (2015). Diary writing as a tool for students' self-reflection and teacher's feedback in the course of academic writing. *Procedia-Social and Behavioral Sciences*, *197*, 549-553. doi:10.1016/j.sbspro.2015.07.189

Lei, D. Y., Cheng, J. H., Chen, C. M., Huang, K. P., & James Chou, C. (2021). Discussion of teaching with multiple intelligences to corporate employees' learning achievement and learning motivation. *Frontiers in Psychology, 12*, 770473. doi: 10.3389/fpsyg.2021.770473

Lii, S. Y. & Wong, S. Y. (2010). Using a multiple intelligences profile in the selection of a major discipline. *Journal of Humanities and Social Sciences, 6*(1), 13-30. doi:10.7118/JHSS.201006.0013

Lopez-Ortiz, S., Lista, S., Penin-Grandes, S., Pinto-Fraga, J., Valenzuela, P. L., Nistico, R., Emanuele, E., Lucia, A., & Santos-Lozano, A. (2022). Defining and assessing intrinsic capacity in older people: a systematic review and a proposed scoring system. *Ageing Research Reviews*, *79*, 101640. doi:10.1016/j.arr.2022.101640

Lozano-Blasco, R., Quílez-Robres, A., Usán, P., Salavera, C., & Casanovas-López, R. (2022). Types of intelligence and academic performance: A systematic review and meta-analysis. *Journal of Intelligence*, *10*(4), 123. doi:10.3390/jintelligence10040123

Marsh, H. W., Muthén, B., Asparouhov, T., Lüdtke, O., Robitzsch, A., Morin, A. J., & Trautwein, U. (2009). Exploratory structural equation modeling, integrating CFA and EFA: Application to students' evaluations of university teaching. *Structural Equation Modeling, 16*(3), 439–476. doi:10.1080/10705510903008220

McMahon, S. D., Rose, D. S., & Parks, M. (2004). Multiple intelligences and reading achievement: An examination of the Teele inventory of multiple intelligences. *Journal of Experimental Education*, *73*(1), 41-52. doi:10.3200/JEXE.71.1.41-52

Morris, M. (2004). The eighth one: Naturalistic intelligence. In J. L. Kincheloe (Ed.), *Multiple intelligences reconsidered*. Peter Lang.

Moshagen, M., & Musch, J. (2014). Sample size requirements of the robust weighted least squares estimator. *Methodology*, *10*(2), 60–70. doi:10.1027/1614-2241/a000068

Morgan, H. (2021). Howard Gardner's multiple intelligences theory and his ideas on promoting creativity. In F. Reisman (Ed.), *Celebrating giants and trailblazers: A-Z of who's who in creativity research and related fields* (pp.124-141). London, UK: KIE Publications.

Nückles, M., Roelle, J., Glogger-Frey, I., Waldeyer, J., & Renkl, A. (2020). The self-regulation-view in writing-to-learn: Using journal writing to optimize cognitive load in self-regulated learning. *Educational Psychology Review*, *32*(4), 1089-1126. doi:10.1007/s10648-020-

09541-1

Okwuduba, E. N., Nwosu, K. C., Okigbo, E. C., Samuel, N. N., & Achugbu, C. (2021). Impact of intrapersonal and interpersonal emotional intelligence and self-directed learning on academic performance among pre-university science students. *Heliyon, 7*(3), e06611. doi: 10.1016/j.heliyon.2021.e06611

Raglio, A., Figini, C., Bencivenni, A., Grossi, F., Boschetti, F., & Manera, M. R. (2024). Cognitive stimulation with music in older adults with cognitive impairment: A scoping review. *Brain Sciences*, *14*(8), 842. doi:10.3390/brainsci14080842

Rajoo, K. S., Karam, D. S., & Abdullah, M. Z. (2020). The physiological and psychosocial effects of forest therapy: A systematic review. *Urban Forestry & Urban Greening*, *54*, 126744. doi:10.1016/j.ufug.2020.126744

Rogers, F., & Metzler-Baddeley, C. (2024). The effects of musical instrument training on fluid intelligence and executive functions in healthy older adults: A systematic review and meta-analysis. *Brain and Cognition*, *175*, 106137. doi: 10.1016/j.bandc.2024.106137

Sharma, P. (2023). A review of semantic application of MI theory and effects for teacher training. *Journal of Enterprise and Business Intelligence*, *3*(4), 201-212. doi:10.53759/5181/JEBI202303020

Shearer, C. B. (1999). *Multiple Intelligences Developmental Assessment Scale*. Kent, OH: Multiple Intelligences Research and Consulting.

Shearer, C. B. (2012). An inter-rater reliability study of a self-assessment for the multiple intelligences. *International Journal of Psychological Studies*, *4*(3), 131-138. doi:10.5539/ijps.v4n3p131

Shearer, C. B., & Karanian, J. M. (2017). The neuroscience of intelligence: Empirical support for the theory of multiple intelligences? *Trends in Neuroscience and Education, 6*, 211-223. doi:10.1016/j.tine.2017.02.002

Slocum-Gori, S. L., & Zumbo, B. D. (2011). Assessing the unidimensionality of psychological scales: Using multiple criteria from factor analysis. *Social Indicators Research, 102*(3), 443-461. doi:10.1007/s11205-010-9682-8

Soleimani, M. A., Mohammadi, F., Mafi, M., & Zakani, A. (2020). The predictive role of social intelligence in successful aging in the elderly. *Asian Journal of Social Health and Behavior, 3*(4), 166-173. doi:10.4103/SHB.SHB_44_20

Spearman, C. (1904). 'General intelligence,' objectively determined and measured. *American Journal of Psychology, 15*(2), 201–293. doi:10.2307/1412107

Sternberg, R. J. (2018). Theories of intelligence. In S. I. Pfeiffer, E. Shaunessy-Dedrick, & M. Foley-Nicpon (Eds.), *APA handbook of giftedness and talent* (pp. 145–161). American Psychological Association. doi:10.1037/0000038-010

Teele, S. (1992). *Teele inventory of multiple intelligences*. Sue Teele and Associates.

Teele, S. (1996). Redesigning the educational system to enable all students to succeed. *NASSP Bulletin, 80*, 65-75. doi:10.1177/019263659608058311

Tirri, K., & Nokelainen, P. (2008). Identification of multiple intelligences with the Multiple Intelligence Profiling Questionnaire III. *Psychology Science, 50*(2), 206-221.

Tirri, K., & Nokelainen, P. (2011). *Measuring multiple intelligences and moral sensitivities in education*. Springer Science & Business Media.

Tirri, K., Nokelainen, P., & Komulainen, E. (2013). Multiple intelligences: Can they be measured? *Psychological Test and Assessment Modeling, 55*(4), 438-461.

van Zyl, C. J., & ten Klooster, P. M. (2022). Measurement invariance, cutoff values, and clinical utility of the KIDSCREEN-27 questionnaire: A Rasch analysis. *Quality of Life Research, 31*(3), 837-849. doi:10.1007/s11136-021-03054-2

Visser, B. A., Ashton, M. C., & Vernon, P. A. (2006). Beyond g: Putting multiple intelligences theory to the test. *Intelligence*, *34*(5), 487-502. doi:10.1016/j.intell.2006.02.004

Waterhouse, L. (2023). Why multiple intelligences theory is a neuromyth. *Frontiers in Psychology*, *14*, 1217288. Doi:10.3389/fpsyg.2023.1217288

Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample size requirements for structural equation models: An evaluation of power, bias, and solution propriety. *Educational and Psychological Measurement, 73*(6), 913-934. doi:10.1177/0013164413495237

Wong, C. S., & Law, K. S. (2002). Wong and Law Emotional Intelligence Scale. *The Leadership Quarterly*, *13*, 243-274. doi:10.1037/t07398-000

Wong, S. Y. (2013). Multiple intelligences, self-efficacy and learning intention among college students. *Journal of Humanities and Social Sciences*, 9 (2), 1-16.

World Health Organization (2020). *Decade of healthy ageing: Plan of action*. Retrieved June 18, 2024, from: https://reurl.cc/Y06qmn

Wu, W. T. (2008). *Guidebook of Chinese version of Multiple Intelligence Developmental Assessment Scale-C* (1st ed.). Psychological Publishing Company Limited.

Wu, W. T. (2018). *Guidebook of Chinese version of Multiple Intelligence Developmental Assessment Scale-C* (2nd ed.). Psychological Publishing Company Limited.

Yu, R., Leung, J., Leung, G., & Woo, J. (2022). Towards healthy ageing: using the concept of intrinsic capacity in frailty prevention. *Journal of Nutrition, Health and Aging*, 26(1), 30-36. doi:10.1007/s12603-021-1715-2

Table 1. Descriptive Statistics and Pearson Correlations Among the Eight Types of multiple Intelligences on the Multiple Intelligence Scale.

	M (SD)	1	2	3	4	5	6	7	8
1. Linguistic intelligence	27.05 (4.43)	1.00							
2. Logical-mathematical intelligence	26.63 (4.42)	0.61	1.00						
3. Visual-spatial intelligence	27.07 (3.93)	0.48	0.49	1.00					
4. Bodily-kinesthetic intelligence	25.62 (4.35)	0.45	0.43	0.60	1.00				
5. Musical intelligence	26.19 (5.26)	0.36	0.36	0.48	0.54	1.00			
6. Interpersonal intelligence	28.94 (5.34)	0.39	0.39	0.39	0.50	0.40	1.00		
7. Intrapersonal intelligence	30.52 (3.68)	0.48	0.38	0.44	0.46	0.37	0.60	1.00	
8. Naturalist intelligence	25.23 (5.19)	0.44	0.45	0.49	0.44	0.40	0.44	0.49	1.00

Note. all $p < .001$.

Table 2. Fit Statistics of Rasch analysis for items in the Multiple Intelligence Scale.

	Difficulty	Infit MnSq	Outfit MnSq
Linguistic intelligence *(Person reliability*: 0.86)			
1. I can quickly understand the main content when reading books	−0.76	0.96	0.95
2. Telling stories or jokes is easy for me	0.02	1.22	1.22
3. My writing or storytelling abilities are vital	0.62	1.02	1.01
4. I perform well in remembering names, places, dates,etc.	0.27	1.32	1.34
5. I can easily recognize the pronunciation of each word	−0.77	0.91	0.91
6. I am good at using metaphors or idioms	0.22	0.81	0.82
7. I can grasp the key points when speaking or writing	−0.43	0.75	0.74
8. I perform well in word games (such as crossword puzzles)	0.82	1.01	1.01
Logical-mathematical intelligence *(Person reliability*: 0.87)			
1. I can think about or read problems related to mathematics	0.40	1.09	1.09
2. My mental arithmetic skills are vital	0.34	1.02	1.03
3. I usually perform well in games that require calculation skills	0.18	0.93	0.94
4. I can categorize or grade things based on specific characteristics	−0.82	1.10	1.14
5. I find the content in math or science topics easy or straightforward	0.82	0.69	0.69
6. I can solve math problems in different ways	0.76	1.00	0.99
7. I can identify patterns and arrange them in a logical sequence	−0.57	1.18	1.18
8. I can analyze the causal relationships of things	−1.12	0.96	0.98
Visual-spatial intelligence *(Person reliability*: 0.78)			
1. Reading maps or charts is easier for me than reading text	0.21	1.22	1.23
2. When learning, I often form mental images to help myself remember or think	−0.32	1.08	1.07
3. In unfamiliar places, I can quickly find the right direction	0.31	1.17	1.18
4. I often use drawing to remember things or think about matters	0.79	1.07	1.07
5. I often notice beautiful or unique things around me	−1.12	0.84	0.83
6. I can describe three-dimensional spaces in detail, such as house structures or spatial arrangements	−0.13	0.96	0.95
7. I can quickly complete puzzles or maze games	0.54	0.84	0.85
8. I have strong abilities in recognizing colors and shapes	−0.28	0.81	0.85
Bodily-kinesthetic intelligence *(Person reliability*: 0.83)			
1. Sports activities like running or high jump are easy for me			
2. I can easily complete art or craft projects	0.63	1.06	1.06
3. I can use various movements to express the same thing or idea	0.44	1.35	1.35
4. I can easily imitate others' movements or manners	−0.42	0.78	0.79
5. I can quickly learn a new sport, such as playing basketball, dancing, or swimming	−0.11	0.94	0.95
6. I can quickly dance to the beat when I hear music	−0.01	0.93	0.92
7. I'm good at sports such as dancing, basketball, running, baseball, and volleyball.	−0.89	1.08	1.08
8. My movements are coordinated and graceful when dancing or doing gymnastics	0.36	0.98	0.99
Musical intelligence *(Person reliability*: 0.88)			
1. I often sing, whistle, or hum tunes	−0.40	1.02	1.02
2. I am good at playing a musical instrument	1.63	1.28	1.21
3. I can point out off-key or incorrect parts when listening to music	0.31	0.96	0.97
4. I can quickly distinguish the sounds of different instruments	0.01	0.92	0.94
5. Music quickly reminds me of certain situations and affects my mood	−1.13	1.22	1.25
6. I have a good sense of rhythm	−0.26	0.76	0.78
7. I can remember most of its melody after listening to a song	0.29	0.75	0.76
8. I actively seek out music or pay attention to music-related activities	−0.45	1.12	1.09
Interpersonal intelligence *(Person reliability*: 0.90)			
1. I have many good friends	−0.20	0.89	0.88
2. I often participate in group activities	−0.62	0.95	0.92
3. I take the initiative to care for others	−1.10	0.95	0.92
4. I am often elected as a leader or committee member	1.06	1.07	1.09
5. I frequently participate in group discussions	0.58	1.09	1.07

Table 2. (continued)

	Difficulty	Infit MnSq	Outfit MnSq
6. Friends often come to me for help	0.09	0.89	0.87
7. I can clearly understand others' views of me	0.10	0.89	0.88
8. In unfamiliar groups, I can quickly get along with everyone	0.09	1.21	1.22
Intrapersonal intelligence *(Person reliability:* 0.84)			
1. I clearly know my strengths and weaknesses	−0.33	0.71	0.68
2. I can engage in activities alone or learn by myself	−0.89	0.97	0.91
3. I work towards my goals without needing others' supervision	−0.25	0.88	0.90
4. I can accept others' criticisms and reflect on myself	−0.42	0.88	0.86
5. I can accurately express my feelings	−0.16	0.78	0.79
6. When facing setbacks, I can quickly regain calm	0.25	0.93	0.97
7. I can adjust my way of doing things	−0.11	0.74	0.77
8. I write my reflections on significant life events in my diary	1.90	1.90	2.14
Naturalist intelligence *(Person reliability:* 0.86)			
1. I have a lot of experience in collecting animal or plant specimens	0.99	1.13	1.13
2. I actively care for various small animals	0.33	1.17	1.18
3. I collect many unique stones and artifacts	0.55	1.05	1.05
4. I can quickly familiarize myself with the names and information of natural scenery, flora, and fauna	0.40	0.83	0.86
5. I often pay attention to and collect information about human development and relics	0.75	0.97	0.97
6. I read books related to nature to help myself understand the knowledge of the universe	0.44	0.80	0.81
7. I actively respond to environmental protection activities, such as garbage sorting or recycling	−1.74	1.13	1.20
8. I spend time everyday reading newspapers, watching TV news, or listening to the radio to learn about important daily events	−1.72	0.93	0.91

Values in gray shadows indicate that they were outside the acceptable range for INFIT and OUTFIT MnSq (0.5–1.5).

Table 3. Mode fit Across Different Factor Structures.

	χ^2 (*df*)	CFI	NNFI	SRMR	RMSEA (90% Confidence Interval)
One factor	5627.57 (1952)	0.947	0.945	0.098	0.071 (0.069–0.074)
Oblique eight factor	3167.33 (1862)	0.934	0.931	0.070	0.059 (0.054–0.064)
Second-order facor	3340.79 (1882)	0.927	0.924	0.075	0.062 (0.058–0.067)
Bifactor	2992.29 (1827)	0.941	0.937	0.069	0.057 (0.051–0.062)
ESEM	2062.46 (1477)	0.971	0.961	0.038	0.045 (0.035–0.054)
Bifactor ESEM	1904.61 (1422)	0.976	0.967	0.035	0.041 (0.030–0.052)

CFI = comparative fit index; NNFI = non-normed fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; ESEM = exploratory structural equation modeling.

Table 4. Factor Loadings Derived Under the ESEM Factor Structure.

	LI	LMI	SI	BKI	MUI	INPI	INRI	NI
LI								
1. I can quickly understand the main content when reading books	**0.61**	0.04	−0.03	−0.11	−0.02	0.03	−0.02	0.16
2. Telling stories or jokes is easy for me	**0.67**	0.02	0.08	−0.13	0.19	0.15	−0.12	0.03
3. My writing or storytelling abilities are vital	**0.56**	0.20	−0.09	0.12	0.04	0.16	0.08	0.05
4. I perform well in remembering names, places, dates,etc.	**0.31**	0.27	0.25	0.06	−0.11	0.06	−0.04	−0.05
5. I can easily recognize the pronunciation of each word	**0.58**	0.05	0.05	0.25	−0.03	−0.02	0.12	−0.09
6. I am good at using metaphors or idioms	**0.64**	0.06	−0.01	0.07	0.05	−0.11	0.13	0.12
7. I can grasp the key points when speaking or writing	**0.71**	−0.03	0.07	0.10	−0.02	0.01	0.02	0.07
8. I perform well in word games (such as crossword puzzles)	**0.30**	0.46	0.03	0.01	0.17	−0.02	0.10	0.09
LMI								
1. I can think about or read problems related to mathematics	0.02	**0.70**	0.04	0.02	−0.03	−0.06	−0.07	0.09
2. My mental arithmetic skills are vital	0.04	**0.64**	0.05	0.00	0.00	0.07	0.18	−0.03
3. I usually perform well in games that require calculation skills	0.08	**0.61**	0.01	0.06	0.06	0.19	0.12	−0.08
4. I can categorize or grade things based on specific characteristics	0.26	**0.26**	0.17	0.25	−0.11	−0.05	0.00	0.13
5. I find the content in math or science topics easy or straightforward	0.03	**0.79**	0.08	0.02	0.04	−0.01	−0.01	0.07
6. I can solve math problems in different ways	−0.01	**0.84**	−0.02	0.03	0.05	0.02	−0.03	0.09
7. I can identify patterns and arrange them in a logical sequence	0.17	**0.36**	0.06	0.14	0.05	0.07	0.03	0.10
8. I can analyze the causal relationships of things	0.36	**0.20**	0.12	0.30	0.02	−0.05	0.14	0.04
VSI								
1. Reading maps or charts is easier for me than reading text	0.18	−0.01	**0.34**	−0.04	0.05	0.03	−0.11	0.07
2. When learning, I often form mental images to help myself remember or think	0.03	0.08	**0.44**	0.34	−0.01	−0.10	−0.03	−0.08
3. In unfamiliar places, I can quickly find the right direction	0.10	0.18	**0.42**	0.00	0.15	0.10	−0.14	−0.02
4. I often use drawing to remember things or think about matters	−0.17	0.04	**0.64**	0.16	0.05	−0.07	−0.18	−0.02
5. I often notice beautiful or unique things around me	0.01	−0.11	**0.49**	0.05	0.05	0.07	0.28	0.13
6. I can describe three-dimensional spaces in detail, such as house structures or spatial arrangements	0.18	−0.02	**0.35**	0.00	0.20	0.03	0.15	0.08
7. I can quickly complete puzzles or maze games	0.00	0.30	**0.31**	0.01	0.07	0.13	−0.06	0.25
8. I have strong abilities in recognizing colors and shapes	0.06	0.03	**0.43**	0.12	0.07	0.03	0.23	0.12
BKI								
1. Sports activities like running or high jump are easy for me	0.03	−0.07	0.13	**0.46**	−0.03	0.25	−0.06	0.09
2. I can easily complete art or craft projects	−0.08	0.10	0.32	**0.07**	−0.03	0.22	0.05	0.14
3. I can use various movements to express the same thing or idea	0.12	0.16	0.13	**0.45**	−0.05	0.11	0.00	0.13
4. I can easily imitate others' movements or manners	0.21	−0.07	0.31	**0.26**	0.09	−0.03	0.14	0.06
5. I can quickly learn a new sport, such as playing basketball, dancing, or swimming	−0.06	0.05	0.15	**0.54**	0.05	0.01	0.09	0.10
6. I can quickly dance to the beat when I hear music	0.10	−0.19	0.17	**0.37**	0.39	0.09	−0.05	−0.01
7. I'm good at sports such as dancing, basketball, running, baseball, and volleyball.	0.00	0.01	−0.03	**0.68**	0.18	0.06	−0.05	0.04
8. My movements are coordinated and graceful when dancing or doing gymnastics	0.03	0.01	0.01	**0.55**	0.25	0.00	0.01	−0.07
MUI								
1. I often sing, whistle, or hum tunes	0.13	0.01	0.09	−0.02	**0.71**	−0.03	0.01	0.00
2. I am good at playing a musical instrument	−0.09	0.19	0.08	0.07	**0.42**	0.22	−0.29	0.17
3. I can point out off-key or incorrect parts when listening to music	0.04	−0.03	0.00	0.13	**0.70**	−0.06	0.09	0.00
4. I can quickly distinguish the sounds of different instruments	−0.15	0.07	0.00	0.27	**0.58**	−0.09	0.05	0.15
5. Music quickly reminds me of certain situations and affects my mood	0.14	−0.12	0.10	−0.04	**0.33**	0.10	0.06	0.21
6. I have a good sense of rhythm	0.09	0.14	0.08	0.09	**0.70**	0.04	−0.06	−0.06
7. I can remember most of its melody after listening to a song	−0.01	0.09	−0.01	0.14	**0.72**	0.05	0.08	0.03
8. I actively seek out music or pay attention to music-related activities	0.01	−0.06	0.07	−0.09	**0.56**	0.17	0.09	0.22

Table 4. (continued)

	LI	LMI	SI	BKI	MUI	INPI	INRI	NI
INPI								
1. I have many good friends	−0.01	0.12	0.18	−0.13	0.00	**0.74**	0.09	−0.01
2. I often participate in group activities	−0.01	0.04	0.04	0.08	−0.02	**0.67**	0.13	0.03
3. I take the initiative to care for others	0.06	−0.05	0.10	0.18	−0.01	**0.45**	0.32	0.01
4. I am often elected as a leader or committee member	0.07	0.06	−0.11	0.13	0.07	**0.78**	−0.12	0.12
5. I frequently participate in group discussions	0.05	0.03	−0.17	0.12	0.07	**0.68**	0.08	0.07
6. Friends often come to me for help	−0.01	0.00	0.07	0.17	−0.03	**0.65**	0.12	0.07
7. I can clearly understand others' views of me	0.10	−0.02	0.09	0.18	−0.04	**0.48**	0.30	−0.02
8. In unfamiliar groups, I can quickly get along with everyone	0.07	0.01	0.13	−0.09	0.18	**0.59**	0.02	0.11
INRI								
1. I clearly know my strengths and weaknesses	0.10	−0.01	−0.01	0.11	0.05	0.18	**0.59**	0.04
2. I can engage in activities alone or learn by myself	0.09	0.07	−0.11	0.00	0.14	0.09	**0.57**	0.14
3. I work towards my goals without needing others' supervision	0.15	0.05	0.06	0.11	−0.01	0.05	**0.50**	0.02
4. I can accept others' criticisms and reflect on myself	−0.13	0.06	0.14	0.18	−0.04	0.10	**0.57**	0.06
5. I can accurately express my feelings	0.08	0.01	0.24	−0.01	0.01	0.09	**0.47**	0.09
6. When facing setbacks, I can quickly regain calm	−0.07	0.14	0.10	−0.08	0.09	0.13	**0.58**	0.01
7. I can adjust my way of doing things	0.19	0.01	−0.08	0.03	0.09	0.04	**0.56**	0.07
NI								
1. I have a lot of experience in collecting animal or plant specimens	−0.08	0.04	−0.16	0.09	−0.02	0.19	0.14	**0.63**
2. I actively care for various small animals	−0.03	0.03	0.02	0.10	0.08	0.09	0.09	**0.50**
3. I collect many unique stones and artifacts	0.02	0.07	0.06	0.21	−0.10	0.00	0.13	**0.60**
4. I can quickly familiarize myself with the names and information of natural scenery, flora, and fauna	0.01	−0.05	−0.04	−0.03	0.10	−0.03	0.03	**0.76**
5. I opay attention to and collect information about human development and relics	0.13	0.08	0.20	−0.14	0.06	0.03	−0.11	**0.66**
6. I read books related to nature to help myself understand the knowledge of the universe	0.12	0.08	0.10	0.07	−0.01	−0.03	−0.08	**0.73**
7. I actively respond to environmental protection activities, such as garbage sorting or recycling	0.01	0.02	0.25	−0.02	−0.02	−0.07	0.41	**0.14**
8. I spend time everyday reading newspapers, watching TV news, or listening to the radio to learn about important daily events	0.11	0.08	0.35	−0.12	−0.05	−0.05	0.28	**0.24**

Note. The values in bold indicate the factor loadings that belong to their respective factors. LI—linguistic intelligence; LMI—logical-mathematical intelligence; VSI—visual-spatial intelligence; BKI—bodily-kinesthetic intelligence; MUI—musical intelligence; INPI—interpersonal intelligence; INRI—intrapersonal intelligence; NI—naturalist intelligence.