To Adapt or Not to Adapt? Evidence on the Latent Adaptability Profiles of Young Adults

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Contents

Popular Abstract

The world is changing, and successful adaptation to novelty lies through openness, curiosity, confidence, and a growth mindset – in other words, adaptability. Nevertheless, how can we say if one is adaptable or not? Can it be explained by one's age, gender, or previous experience of adapting to change? Does the high level of adaptability associate with the performance on cognitive tests? This study aims to answer those questions by exploring young adults' profiles of adaptability by using several indications: perceived adaptability, openness to experience, openness to changing viewpoints, curiosity, and mindset and their link to various individual characteristics. Results demonstrated the presence of four distinct adaptability profiles; respondents in profiles differed in age, gender, immigration status, problem-solving self-concept and abstract reasoning. This study contributes knowledge on the nature of adaptability and demonstrates the key role of mindset in individuals' cognitive, behavioral, and affective adjustments to uncertainty and novelty.

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Abstract

Objective: Technological advancements, environmental changes, and the explosion of new knowledge demand individuals to constantly learn new things and adjust to novel situations quickly. Such adjustment requires a complex skill referred to as "adaptability". However, due to the complexity of the construct, one measure might not be an optimal representation of a person's adaptability. Therefore, this study explored young adults' profiles of adaptability by using several indications: perceived adaptability, openness to experience, openness to changing viewpoints, curiosity, and mindset. Specifically, the existence of unobserved adaptability profiles and their link to individual characteristics, such as age, gender, education, self-concept, and abstract reasoning, were explored. **Method**: Latent profile analysis was applied to analyze the data of a random sample of young adults (*N* = 1066; 18-35 years old) to identify groups of people with various levels of adaptability. Then, multinomial logistic regression was applied to estimate how individual characteristics predicted profile membership. Finally, the extent to which the adaptability profiles differed in cognitive ability was analyzed. **Results:** It was possible to identify four distinct adaptability profiles: "*very flexible*", "*rigid*", "*inconsistent*" and "*relatively flexible*". Growth and fixed mindsets had a crucial role in differentiating these profiles. Across the profiles, age, gender, immigration status, and problem-solving self-concept explained the probability of being assigned to a particular adaptability profile. Further analysis showed the difference in abstract reasoning levels between *"very flexible"*, *"relatively flexible"* and *"inconsistent"* profiles, implying that abstract reasoning is meaningfully related to adaptability. These findings contribute knowledge on the nature of adaptability and provide evidence for its antecedents and outcomes.

Keywords: adaptability, cognitive flexibility, latent profile analysis, problem-solving

Introduction

Technological changes, environmental pressure and evolving knowledge demand individuals to constantly learn new things and adjust to novel situations quickly. Such adjustment requires a complex skill studied by many researchers (Martin et al., 2012; Pulakos et al., 2000; Savickas, 1997), commonly named adaptability. Adaptability is believed to be a major determinant of an individual's success in dealing with changes (Ployhart & Bliese, 2006), learning new things (Green, 2012; Caroli & van Reenen, 2001), and declared to be an essential "21st-century skill" (OECD, 2013a).

VandenBos (2007, p. 19) defined adaptability as the "capacity to make appropriate responses to changing situations or the ability to modify or adjust an individual's behavior in meeting different circumstances or different people." Martin et al. (2013, p. 728) referred to adaptability as "appropriate cognitive, behavioral, and affective adjustments in the face of uncertainty and novelty." Finally, Mumford et al. (1994) defined adaptability as coping with a novel situation and acquiring new expertise and supposes its importance for creative problem-solving.

The existing research scope demonstrates the concept inconsistency. However, particular adaptability facets appear to be common across the research areas, which allows us to conceptualize adaptability as a compound trait or multidimensional construct that contributes to various outcomes in a situation of novelty and change. Successful adaptation is observed alongside openness, curiosity, willingness to acquire new knowledge, growth attitudes, and ability to cope with uncertainty (LePine et al., 2000; Pulakos et al., 2002; Stokes et al., 2010).

Due to the complexity of adaptability, assessing this concept requires a multidimensional measure, and no single instrument would capture it to the full extent. The present study aims to overcome this issue by using multiple adaptability indicators to understand the concept's nature and implying latent profile analysis. This method allowed identifying groups of people with similar adaptability patterns not observed upfront. Furthermore, individual background characteristics, such as age, gender, immigration status and self-concept were included to explain the profile membership of participants. In addition, the association between adaptability and abstract reasoning was explored.

The study contributes to the existing research with key insights into the nature of adaptability and possible determinants to predict adaptability patterns of young adults. In addition, defined indicators, consistent with some current research, can be used in future studies to understand adaptability within a specific educational or organizational context.

Theoretical Framework

Adaptability as a Complex Concept

Past research demonstrated a broad conceptualization of adaptability, defining it in terms of performance, training, cognitive flexibility, coping and resilience, and acquiring new knowledge (LePine et al., 2000; Martin & Rubin, 1995; Pulakos et al., 2002; Thoresen et al., 2004). Early studies conceptualized adaptability in terms of performance. Participants would be given a task with an unforeseen change, and adaptability was measured by demonstrated pre- and post-change performance (LePine et al., 2000). Then, Pulakos et al. (2000, 2002) developed and tested a taxonomy of adaptive job performance. According to them, adaptability is a complex phenomenon that compromises eight aspects: creative problem-solving, dealing with uncertainty, learning new tasks, handling stress and emergency, and demonstrating physical, cultural, and interpersonal adaptability. The further analysis supported indicated dimensions, and cognitive ability, personality and previous exposure to change and novelty predicted adaptability. However, it was unclear whether adaptability would exist distinct from the task context since this conceptualization did not result in a general adaptability factor.

To overcome this issue, Ployhart and Bliese (2006) presented the concept of individual adaptability, which compromised the described taxonomy of adaptive performance and introduced adaptability as a second-order construct with eight factors. Those factors represented adaptability in crises, culture, work stress, interpersonal, learning, physical, creativity, and uncertainty. According to this framework, adaptability is not a pure trait or skill but a composed characteristic that is unspecific to the task or situation, hence, influencing every type of performance. Savickas and Porfeli (2012, p. 749) adopted this perspective and defined adaptability as the "competency that allows solving unfamiliar, complex, and ill-defined problems.". By their interpretation, highly adaptable workers would be concerned about future tasks, take control over them, curiously explore possible opportunities and be confident about their competence to solve problems.

Particular traits were found to contribute to the successful adjustment to novel situations and may therefore be considered indicators of adaptability. For example, *openness to experience* relates to the greater performance in tasks that demand learning new approaches to solving them (Barrick & Mount, 1991), having an aspect of change (LePine et al., 2000), or requiring transition to a new role (Thoresen et al., 2004). It also contributes to successful career adaptation (Zacher, 2014, 2016) and coping with stress during organizational changes (Costa & McCrae, 1992; Judge et al., 1999). *Curiosity* is the other construct that contributes to dealing with uncertainty. Epistemic curiosity is the desire to motivate individuals to learn new ideas, eliminate information gaps, and solve intellectual problems (Litman, 2008). It influences the way people adapt to new tasks or situations (Dweck, 1986) and serves as an antecedent to adaptation in organizations (Harrison et al., 2011). *Creativity* and the lack of defensive rigidity contribute to adaptability (Mumford et al., 1993). When people move from familiar and well-defined problems to unfamiliar, ill-defined tasks, a creative approach, and growth attitude help maintain a high level of performance. *Growth and fixed mindsets* have gained attention in research (Dweck, 2012; Dweck & Yeager, 2019), and the growth mindset represents one's belief about the malleable, changing, and developing nature of traits and ability, while the fixed mindset shows the opposite idea about the fixed, rigid, and non-malleable nature of traits and ability. A growth mindset is essential for fostering adaptability since it 1) embodies the ability to adjust and regulate oneself in a novel situation (Lee & Jung, 2021; A. Martin et al., 2012; Zarrinabadi et al., 2021), 2) directly related with flexible thinking in learning (Tseng et al., 2020) and 3) lowers perceived cognitive load (Xu et al., 2020).

Martin et al. (2012, 2013) explored the concept of adaptability in the educational context and proposed a framework of adaptability with cognitive-behavioral and affective-emotional dimensions of adjustment to new, changing, uncertain circumstances, conditions, and situations. Research shows the importance of adaptability for educational outcomes as a predictor and mediator. For example, it is significant for fostering positive behavioral engagement such as persistence, planning, and task management and lowering negative behavioral engagement and self-handicapping for first-year university students (Collie et al., 2017), influencing the way students perceive changing nature of scientific knowledge (Scherer & Guttersrud, 2018). In addition, Zarrinabadi et al. (2021) demonstrate how adaptability mediates the relationship between mindset and self-concept, self-efficacy, and attitudes toward learning.

Although specific aspects of adaptability differ across theoretical conceptualizations, common adaptability features are consistent across research areas. In light of those differences, it appears to be possible to conceptualize adaptability as a compound trait, a multidimensional construct that arises in a situation of change and novelty. Successful adaptation to the new situation is observed alongside openness, curiosity, willingness to acquire new knowledge, belief in the malleable nature of traits, and ability to cope with uncertainty.

Individual Differences in Adaptability

Individual features relate to adaptability either by allowing individuals to apply strategies when dealing with a novel situation or by perceiving the uncertain situation as less stressful and may therefore explain variation between individuals (Ployhart & Bliese, 2006). Several studies demonstrated individual differences in adaptability, including demographic data and self-concepts as ancestors or predictors of adaptability.

Demographic Characteristics: Gender, Age, Education, and Immigration status

Researchers examined demographic characteristics, such as gender, age, education, and immigration status, as variables explaining variation in individual adaptability; yet, the results are controversial.

Age relates to adaptability by two means. First, it is believed that adaptability is mediated through knowledge and experience, which accumulate over the lifespan. Hence, older participants might demonstrate greater adaptability than younger ones (Zacher, 2014). Opposite to that, adaptability in older respondents might be lower than in young people if explained by declined openness and motivation to change (O’Connell et al., 2008). Results of the meta-analysis showed a low positive association between age and adaptability (Rudolph et al., 2017). A study conducted among university students in China shows higher levels of adaptability in male students (Hou et al., 2012), and similar results are present in middle-school students, with males demonstrating adaptive performance (Yu et al., 2019). However, other researchers do not support these *gender* differences (Hirschi, 2009; Rudolph et al., 2017; Tian & Fan, 2014).

The evidence on the relationship between *education* and adaptability is also controversial. Attaining higher levels of education might lead to a higher level of adaptability since it allows for resources and knowledge to master novel tasks (Zacher, 2014). Similar results were present among nurse students, where associate degree students demonstrate a higher adaptability level than baccalaureate students (Tian & Fan, 2014). However, the meta-analysis results did not show the association between education level and adaptability (Rudolph et al., 2017).

Association between *immigrant background* and adaptability might also be perceived in two manners. On the one hand, participants with an immigrant background have experience dealing with changes, which might contribute to future adaptation. For example, Martin et al. (2013) observed higher levels of adaptability among non-native English-speaking high school students in Australia. On the other hand, non-immigrant participants might meet fewer difficulties and possess greater resources for adjustment to uncertainty, as observed among local and immigrant students in Switzerland (Hirschi, 2009).

Although past research provides controversial evidence of the association between demographic characteristics and adaptability, it is important to account for their presence in modeling the relationship between adaptability, its ancestors, and outcomes (Martin et al., 2013).

Self-Belief Characteristic: Problem-Solving Self-Concept

Self-concept is defined as a “person’s self-perceptions that are formed through experience with and interpretations of one’s environment” (Shavelson et al., 1976, p. 411). It has emerged to be crucial for developing adaptability (Amarnani et al., 2018; Savickas, 1997). The mechanism behind this relationship is explained by the influence of an individual's confidence in being able to solve a novel task and face challenges in adaptation (Guan et al., 2014; van Vianen et al., 2012). However, even though the ability to solve complex and ill-defined problems is a dimension of adaptability, only a few studies explored the association between problem-solving self-concept and adaptability. Therefore, this issue should be addressed due to the connection between self-beliefs and adaptability.

Adaptability as Cognitive Flexibility

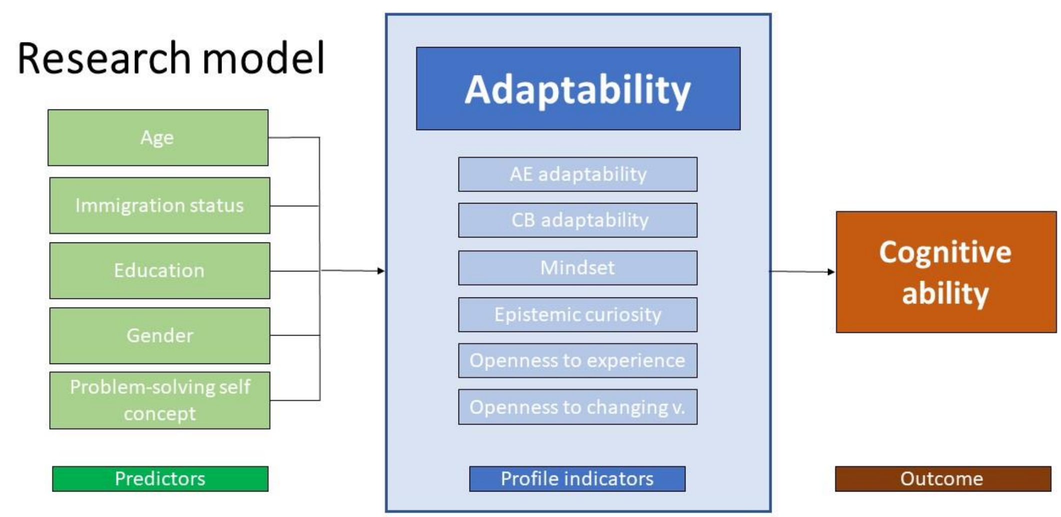
General intelligence, as a central construct in cognitive psychology, has gained much importance due to its high predictive validity for achievement and performance (Gottfredson, 2018), but does not explain variation in performance in the new, unexpected, or transitional environmental conditions (Cañas et al., 2003; Pulakos et al., 2002; Thoresen et al., 2004). Therefore, cognitive adaptation, or cognitive flexibility, is summoned to explain this variation. Cognitive flexibility is generally defined as recognizing a novel situation and updating cognitive response according to contextual demand (Martin & Rubin, 1995). However, the phenomena can be understood and measured in multiple ways. For example, some studies define cognitive flexibility as a trait that allows an individual to perceive change as an opportunity for further development and predict adaptive performance (Kobasa, 1979; Pulakos et al., 2006; Stasielowicz, 2020). Others explore it as a dynamic problem-solving task (Canas et al., 2003). Recent research anchors adaptability in the cognitive ability framework (Beckmann, 2014; Scherer, 2015) and considers it a property of cognition that requires the interaction of cognitive mechanisms such as attention shifting, conflict monitoring, and perception (Ionescu, 2012).

The Present Study

The present study is motivated by the lack of evidence on adaptability profiles that are based on a multidimensional conceptualization of adaptability. The literature review allowed us to distinguish shared features of adaptability in the adaptability system represented by self-beliefs (perceived adaptability), the willingness to engage in situations with some novelty (openness), and the motivation or drive to engage in novelty (curiosity). Consistent with the research tradition, all indicators have a novelty aspect, adaptive in nature, and are associated with tolerance of uncertainty. This set of indicators allows for identifying profiles, which are groups of respondents who share similar adaptability patterns. Additional variables, such as personal characteristics and cognitive flexibility, would predict membership in profiles (see Figure 1).

Figure 1

Research model identifying and describing adaptability profiles



Note. AE adaptability - Affective-emotional adaptability; CB - Cognitive-behavioral adaptability; Openness to changing v. - Openness to changing viewpoints.

The following research questions were formulated to reach the study goal of understanding the nature of adaptability:

1) Which adaptability profiles exist based on the selected measures?

2) To what extent is membership in the adaptability profiles predicted by individual characteristics (age, education, immigration status, self-concepts)?

3) To what extent do the adaptability profiles differ on the level of cognitive flexibility represented by the abstract reasoning test?

Methods

Sample and Procedure

The current study used ADAPT21 project data (Scherer & Niculescu, 2021). The data were collected in September 2021 via the Prolific assessment service (https://www.prolific.co/). The adaptability assessment package was administered to more than 1000 participants who were enrolled in universities and colleges and fluent in English or Norwegian (age range: 18-35 years). The sampling was partly randomized: Prolific randomly selected participants and invited them to participate among the persons fulfilling the below criteria. Since data collection and management proceed with anonymized data only, the current study is not subject to GDPR (General Data Protection Regulation) documentation (see Appendix I).

In total, N = 1,066 (50% women) participants completed the background questionnaire, and N = 958 (50% women) participants completed the cognitive assessment. The average age was 22 years (SD = 3.28, range = 17.00). About 86% of the respondents were students enrolled in tertiary education, with most respondents having obtained upper-secondary (45%) and bachelor's (31%) degrees. About 15% indicated that they lived in a country other than their birth country. 67% reported some experience with a job transition in the past six months.

Measures

The ADAPT21 project distributed a wide selection of scales to the respondent, and the used scales are presented in Appendix III.

Indicators of Adaptability

Perceived adaptability scale was developed and validated by Martin et al. (2013) and adapted by Scherer and Guttersrud (2018). It measures two dimensions of adaptability: cognitive-behavioral (6 items) and affective-emotional (4 items). Participants reported their belief in adjustment capability on a 6-point Likert scale ranging from 0 (*strongly disagree*) to 5 (*strongly agree*). The data showed a ceiling effect, such that the response options 0 and 1 were collapsed. The internal consistencies of the subscales were good (Cognitive-behavioral: Cronbach's $\alpha = 0.80$, Omega total $\omega_t = 0.86$; affective-emotional: Cronbach's $\alpha = 0.82$, Omega total $\omega_t = 0.84$).

Openness to experience was measured by adapting the Big Five Personality Trait Short Questionnaire (BFPTSQ) (Morizot, 2014). In the version used in the ADAPT21 project, double-barreled items were split into multiple items to improve the scale's psychometric properties. Respondents rated their self-perception as being open, inventive, original, and having new ideas by four items on a 6-point Likert scale ranging from 0 (*strongly disagree*) to 5 (*strongly agree*). To address a ceiling effect for this scale, response results from categories 0 and 1 were collapsed into one category. The internal consistencies of the scale resulted in good reliability, Cronbach's $\alpha = 0.83$ and Omega total $\omega_t = 0.86$.

Openness to changing viewpoints was assessed by an adaptation of the Comprehensive Intellectual Humility Scale (Krumrei-Mancuso & Rouse, 2016). Participants rated their willingness to challenge their knowledge and opinions by five items on a 6-point Likert scale ranging from 0 (*strongly disagree*) to 5 (*strongly agree*). Again, a ceiling effect was present, so response results from categories 0 and 1 were merged into one category. The internal consistencies of the scale were good, Cronbach's $\alpha = 0.84$ and Omega total $\omega_t = 0.86$.

Epistemic curiosity was measured by the scale adapted from Litman and Spiegelhalter (2003). D-type epistemic curiosity subscale was used in the study because the underlying construct represents a concern with reducing uncertainty and eliminating undesirable states of ignorance and is conceptualized as a need to know. The correctness, accuracy, and relevance of the desired information to a specific unknown are of utmost importance. Participants rated their willingness to challenge their knowledge and opinions by five items on a 6-point Likert scale ranging from 0 (*strongly disagree*) to 5 (*strongly agree*). The internal consistencies of the scale were good, Cronbach's $\alpha = 0.86$ and Omega total $\omega_t = 0.89$.

Growth and fixed mindset represent beliefs about the changing nature of skills and the capabilities to adapt (Dweck & Yeager, 2019). Growth and fixed mindset are measured by three items, each on a 6-point Likert scale ranging from 0 (*strongly disagree*) to 5 (*strongly agree*). The internal consistencies of the subscales were good (Fixed mindset: Cronbach's $\alpha = 0.91$, Omega total $\omega_t = 0.91$; Growth mindset: Cronbach's $\alpha = 0.84$, Omega total $\omega_t = 0.85$).

All the adaptability profile indicator scales were self-reports, which might possibly be affected by a common method bias (Podsakoff et al., 2003).

Predictors of Profile Membership

Demographic characteristics were obtained in the background questionnaire. Respondents were directly asked about their age (in years), gender, student status, and highest educational level. For the immigration status, participants answered the proxy question, “Are you currently residing in another country than your country of birth?” In addition, the item “Are you currently or have you recently (over the past six months) experienced a job transition?” was presented for the transition status. Both questions had “yes” or “no” response options.

Problem-solving self-concept was assessed by a scale similar to the one administered in the OECD PISA 2012 Student Questionnaire, Mathematics Self-Concept (OECD, 2013b). Specifically, the domain reference was changed from mathematics to problem-solving. Participants rated their confidence in solving problems by nine items on a 6-point Likert scale ranging from 0 (*strongly disagree*) to 5 (*strongly agree*). The internal consistencies of the scale were good, with Cronbach’s $\alpha = 0.87$ and Omega total $\omega_t = 0.90$.

Distal Outcome

Abstract reasoning was measured by the matrix reasoning item bank (MaRs-IB) test by Chierchia et al. (2019). Consistent with Ionescu (2012), this test compromises processing speed, conflict monitoring, and perception, which allows us to place it within a cognitive flexibility framework. Items of the test consist of an incomplete matrix of abstract shapes of various difficulties defined by design (one, two, or three unobserved abstract relations). Examples of items can be accessed in Appendix III. Participants’ performance in reasoning accuracy increased with age. The initial validation study suggested tests’ accuracy and sensitivity, but the authors recommend further psychometric validation. The current study uses 42 items, responses were coded binary, with 0 as incorrect and 1 as correct.

Methodological approach

Measurement of Latent Variables

The first step of the analysis was to fit and evaluate measurement models for adaptability indicators scales, problem-solving self-concept, and abstract reasoning measurement to explore psychometric properties and extract factor scores for further analysis. This method was successfully implemented by other researchers within the latent profile analysis approach (Marsh et al., 2009; Scherer, 2021) and has been identified to have several advantages. First, it allows for evaluating the psychometric properties of the scales and identifying items that do not accurately represent latent factors. This feature was vital for the current study since some scales were modified for the ADAPT21 project and needed additional evidence of construct validity. Second, it becomes possible to extract factor scores to each scale which makes it possible to control for the measurement error and account for the specific nature of the model in terms of latent factors correlations and residuals covariation (Morin & Marsh, 2015).

Robust maximum-likelihood (MLR) estimation was applied to account for possible violations of the multivariate normality assumption and obtain robust standard errors of all model parameters (Maydeu-Olivares, 2017). Model fit was evaluated with the goodness-of-fit indices with the root mean squared residual (SRMR) a cut-off value ≤ .08, root mean squared error of approximation (RMSEA) cut-off value ≤ .06, and supplementing Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI) ≥ 0.95 representing an acceptable fit (Hu & Bentler, 1999).

Adaptability indicators' scales – perceived adaptability, openness to experience, openness to changing viewpoints, growth and fixed mindset, and epistemic curiosity first were evaluated separately by fitting exploratory and confirmatory factor models, and the full multidimensional model was fit after identifying areas of local misfit and excluding item with factor loadings $\lambda_j \leq .40$. This approach allowed to handle missing data cases by utilizing full information maximum likelihood (FIML) as described in Enders and Bandalos (2001).

The abstract reasoning test's factor scores were estimated using composite-based structural equation modeling. The motivation for the model choice is the lack of structure clarity in the selected assessment. Confirmatory composite analysis (CCA) was developed by Theo K. Dijkstra and Jörg Henseler (Henseler et al., 2014). CCA is similar to CFA, but it compromises a composite reflective model with indicators forming the latent construct rather than a common factor reflective model such as in CFA. Therefore, the abstract reasoning concept was represented by an emergent variable, not a latent variable.

Model specification, identification, estimation, and assessment followed the procedure Henseler & Schuberth (2020) described. Fitting CCA allowed access to six emergent abstract reasoning variables, categorized by design (number and type of abstract relations). The second-order construct was estimated to represent the abstract reasoning ability factor score based on the emergent variables. An overall model fit test was supplied by ML estimation in the form of the chi-square (Jöreskog, 1967). Other fit indices are similar to those known from CFA and, described above, can be used for evaluating model fit (Schuberth et al., 2018).

This step of statistical analysis was conducted in R statistical software (see Appendix II) with the packages "lavaan" (Revelle, 2011) and "cSEM" (Rademaker, 2020).

Latent Profile Analysis

The second step considered latent profile analysis (LPA) to identify the latent profiles of participants' adaptability, using factor scores of *perceived adaptability* (cognitive-behavioral and affective-emotional), *openness to experience, openness to changing viewpoints, growth and fixed* *mindset and epistemic curiosity*. At the moment, no latent profile analysis was conducted on the selected adaptability measures.

LPA is a latent variable type of model that can identify categorical latent classes in the dataset based on continuous input variables (Lubke & Muthén, 2005; Nylund-Gibson & Choi, 2018). It is a person-centered approach, and the assumption behind the method is the presence of unobserved groups of respondents with similar adaptability patterns. Therefore, identified groups or profiles would be similar within the group but distinctive from the other groups (Masyn, 2013). The critical advantage of LPA compared to similar grouping analysis methods, such as cluster analysis, is the accuracy, flexibility, and possibility of extending the model by adding relevant covariates as predictors of profile membership or an outcome.

The crucial step in LPA is identifying the number of relevant profiles in the dataset and deciding the number of profiles to retain. First, estimating the one-profile model as the baseline model for the comparison is recommended. Then, the number of profiles (k) should increase by one by comparing a new fitted model with the previous (k-1) model. Next, various fit indices are used to evaluate model fit, such as the Bayesian information criterion (BIC), sample-size adjusted Bayesian information criterion (SABIC) and consistent Akaike information criterion (CAIC), with the lower value representing the better fit (Nylund-Gibson & Choi, 2018). Other fit criteria are the likelihood-based tests—the Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test (VLMR-LRT) and the bootstrapped likelihood ratio test (BLRT), where associated p values indicate whether adding a profile leads to a statistically significant improvement in model fit (Nylund et al., 2007). Then, it is crucial to consider the interpretability of the final model's number of profiles in how those profiles would be distinctive and explainable. Altogether, these criteria should be used to decide on the number of profiles in the data.

After landing on the final number of profiles, modifications of the model can be introduced, so means, variances, and covariance within the profiles would either vary, be restricted to be equal, or be fixed to zero. Models with different settings were compared using information criteria to choose the final latent profile model in the current study. This step of the analysis was conducted in Mplus version 7.3 (Muthén & Muthén, 1998) with the dataset with extracted factor scores by the package "MplusAutomation" (Hallquist & Wiley, 2018). In addition, to address the potential problem of local maxima, random starts and final stage optimizations were set as 800, 40 by following Morin et al. (2011).

Multinomial logistic regression on latent profiles

The final step of the analysis was extending the model by including predictors of the profile membership (demographics and problem-solving self-concept) and a variable of a distal outcome (abstract reasoning ability). Next, a multinomial logistic regression with one class as a reference was estimated. Finally, Cohen's *d* was estimated to obtain the standardized mean difference measure (Cohen, 1988). Again, the analysis was conducted in Mplus version 7.3 (Muthén & Muthén, 1998). For details, please refer to Appendix II.

Results

Descriptive Statistics, measurement models, and correlations

Before identifying latent profiles, the distribution of the variables of adaptability indicator scales was examined. Item-level descriptive statistics (Table S1, Appendix III) demonstrated that respondents tended to obtain maximum or near-maximum scores for the scales "perceived adaptability", "openness to experience", and "openness to changing viewpoints.". This indicated ceiling effects (Uttl, 2005). To address this issue, we collapsed scores for the first two response options so that the distribution would be closer to normality.

Then, a set of latent factor models for each scale was estimated and evaluated separately to indicate areas of local misfit and explore possible modifications to the model. Items with the lowest factor loadings were excluded from the analysis since they would not allow obtaining an accurate representation of latent factors. Factor loadings of the first indicators of the latent variables were fixed to 1 to identify the scales of the latent variables, and all exogenous latent variables were correlated by default. The CFA model with correlated factors describing the adaptability constructs showed good fit to the data, $\chi2$ (380) = 917.0, $p < .01$, CFI = 0.966, RMSEA = 0.031, SRMR = 0.038. For the predictor problem solving self-concept, we fit a single-factor CFA model which exhibited acceptable fit to the data, $\chi2$ (27) = 254.8, $p < .01$, CFI = 0.919, RMSEA = 0.090, SRMR = 0.052. The confirmatory composite model with six emergent variables was estimated and evaluated for the abstract reasoning test. It indicated acceptable fit, $\chi2$ (27) = 1309.0, $p < .01$, CFI = 0.908, RMSEA = 0.032, SRMR = 0.037. Emergent scores were used to specify the model with the second-order latent factor, which demonstrated acceptable fit with $\chi2$ (8) = 30.5, $p < .01$, CFI = 0.988, RMSEA = 0.056, SRMR = 0.022.

On the basis of these measurement models, the scores of adaptability scales, problem-solving self-concept and abstract reasoning were extracted. Table 1 shows descriptive statistics and factor score correlations. Fixed mindset was negatively and correlated with other variables among adaptability indicators measures. This correlation was significantly different from zero with p<.01 for the growth mindset (r = -.60 $p < .01$), cognitive-behavioral adaptability (r = -.08 $p<.01$), and openness to changing viewpoints (r = -.17 $p < .01$). Other variables were correlated positively. Problem-solving self-concept scores were positively and significantly associated with all adaptability variables, except for the fixed mindset, which was negatively associated with the problem-solving self-concept ($r = -.06$, $p < .05$). Abstract reasoning scores were negatively associated with all the adaptability variables, except for the openness to changing viewpoints, which was positively associated with abstract reasoning ($r = .09$, $p < .01$).

Table 1

Means, standard deviations, and correlations with confidence intervals of factor scores

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
Adaptability indicators										
1. ADAPTCB	0.00	0.59								
2. ADAPTAE	0.00	1.02	.47**							
3. OPENBF	0.00	0.78	.37**	.28**						
4. MINDSETF	0.00	1.05	-.08**	-.04	-.05					
5. MINDSETG	0.00	0.95	.27**	.23**	.26**	-.60**				
6. CURIOS	0.00	1.03	.33**	.18**	.25**	-.05	.23**			
7. OPENVP	0.00	0.54	.34**	.14**	.11**	-.17**	.18**	.17**		
Predictor										
8. PROBSC	0.00	0.70	.51**	.40**	.43**	-.06*	.25**	.44**	.23**	
Distal outcome										
9. ABSTR	0.00	0.50	-.02	-.06	-.11**	-.06	-.08*	-.08*	.09**	.00

Note. ADAPTCB – perceived cognitive-behavioral adaptability; ADAPTAE – perceived cognitive-behavioral adaptability; OPENBF – Openness to experience from Big Five scale; MINDSETF – fixed mindset; MINDSETG – growth mindset; OPENVP – Openness to changing viewpoints; PROBSC – problem-solving self-concept; ABSTR – abstract reasoning. * indicates $p < .05$. ** indicates $p < .01$.

Latent Profile Analysis

Number of Profiles

A series of LPA models with freely estimated means, variances set to be equal across profiles and covariances fixed to zero were estimated and evaluated to answer the first research question. Table 2 demonstrates the resultant information criteria, entropies, and the *p*-values of the likelihood-ratio tests. The absolute log-likelihood values and information criteria decreased with the increasing number of profiles, which favored adding the number of profiles. Regarding the decrease of the information criteria, the elbow plot showed a bend and suggested a profile solution with three or four profiles (see Figure 2).

Table 2

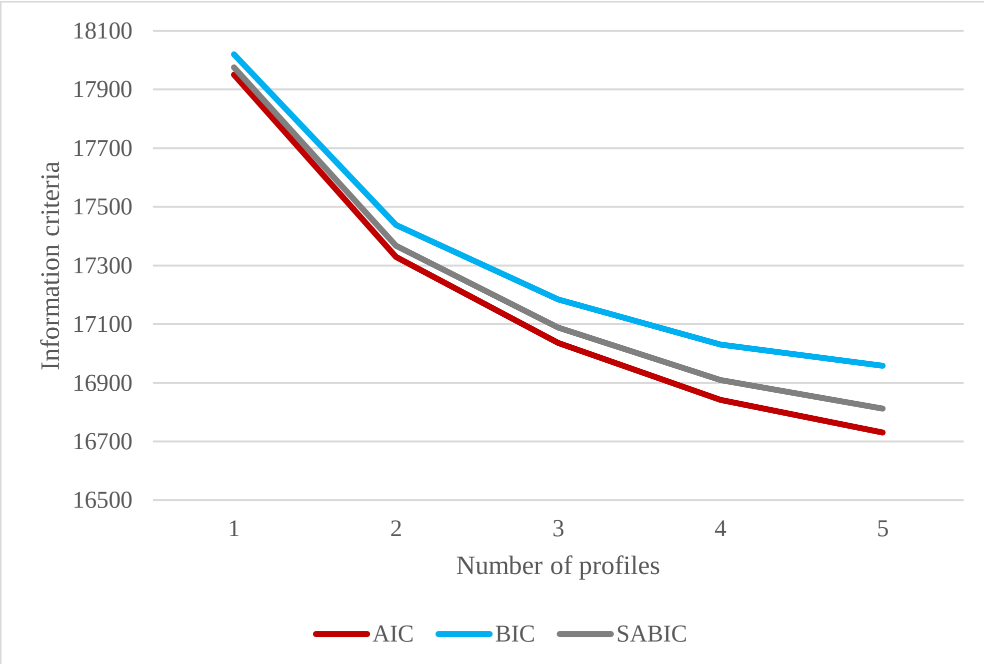
Fit Statistics and Classification Coefficients Adaptability Latent Class Analysis Models

K	*Log likelihood*	*AIC*	*BIC*	*SABIC*	*Entropy*	*Smallest class%*	*LMR p-value*
1	-8961.285	17950.570	18019.855	17975.389	-	-	-
2	-8642.455	17328.910	17437.786	17367.911	0.629	47%	<0.001
3	-8487.731	17035.462	17183.929	17088.645	0.687	24%	<0.001
4	-8383.040	16842.081	17030.139	16909.446	0.751	4%	<0.001
5	-8319.329	16730.658	16958.308	16812.205	0.758	4%	0.1040

Note. K - number of profiles; LL - log-likelihood; BIC - Bayesian information criterion; SABIC - sample-size adjusted BIC; LRT - Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test; p - p value. Entropy is included in the table but should not be used as a model selection statistic (Masyn, 2013)

Figure 2

Elbow plot of LPA fit indices



Note. Decrease of the information criteria. AIC - Akaike information criterion; BIC - Bayesian information criterion; SABIC - sample-size adjusted Bayesian information criterion.

In addition, adding five profiles compared to four profiles did not suggest any further significant improvement, as indicated by the Vuong-Lo-Mendell-Rubin adjusted likelihood-ratio test. To understand the best possible settings for data in terms of mean, variances, and covariances to be fixed or estimated freely, models of different combinations of those parameters were specified and evaluated. Fit indices demonstrated that the model with freely estimated means, variances fixed to be equal across profiles, and covariances to be fixed to zero would be the most optimal model (see Table 3). The final model demonstrated four profiles, with an entropy of .76 and 4% of a sample placed in the smallest profile.

Table 3

Fit Statistics and Classification Coefficients Adaptability Latent Class Analysis Models: Models with 4 profiles solution

Model	*Log likelihood*	*AIC*	*BIC*	*SABIC*	*Entropy*	*Smallest profile %*
M1	-8431.600	16939.2004	17127.25849	17006.56531	75%	4%
M2	-8345.411	16808.82135	17100.80628	16913.41424	73%	15%
M3	-8226.613	16571.22642	16863.21136	16675.81932	62%	7%
M6	-8009.023	16304.045	17011.73731	16557.54982	58%	15%

Note. Models: M1 – equal variances, covariances fixed to 0; M2 – freely estimated variances, covariances fixed to 0; M3 – equal variances, equal covariances; M6 – freely estimated variances and covariances. Means estimated freely for all models. LL - log-likelihood; BIC - Bayesian information criterion; SABIC - sample-size adjusted BIC; p - p value. Entropy is included in the table but should not be used as a model selection statistic (Masyn, 2013)

The entropy value did not meet the recommended cut-off criteria of 80% (Clark & Muthén, 2009), which indicates some overlap between profiles. However, Table 4**Error! Reference source not found.** demonstrates the probabilities of most likely profile membership by latent class modal assignment, and we see the distinct differentiation of one class from another. Therefore, considering fit indices and clarity in profile differentiation, the analysis with a four-profile model was conducted.

Table 4

Classification Probabilities: Four-Profiles model

Profiles	**Profile 1**	**Profile 2**	**Profile 3**	**Profile 4**
Profile 1	**0.85**	0.05	0.01	0.08
Profile 2	0.09	**0.85**	0.03	0.03
Profile 3	0.05	0.05	**0.90**	0.00
Profile 4	0.11	0.02	0.00	**0.87**

Note: Average Latent Class Probabilities for Most Likely Latent Profile Membership (Row) by Latent Profile (Column). In bold is the highest classification probability.

Description of Profiles

Table 5 demonstrates the four latent profiles with the means and standard deviations of the corresponding adaptability profile indicators. *Profile 3* compromised the largest group (*N* = 441, 42%), *profile 1* formed the second largest group (*N* = 354, 33%). Next was *profile 4* (*N* = 216, 20%) and *profile 2* had the smallest number of individuals (*N* = 47, 4%).

Table 5

Mean adaptability indicators scores for 4 profiles

	Profile 1 *N* = 354 (34%)		**Profile 2 *N* = 47 (4%)**		**Profile 3 *N* = 441 (42%)**		**Profile 4 *N* = 216 (20%)**	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
ADAPTCB	0.46	0.041	-1.011	0.124	-0.283	0.047	0.069	0.051
ADAPTAE	0.7	0.065	-1.042	0.15	-0.443	0.079	0.009	0.088
OPENBF	0.443	0.046	-1.109	0.237	-0.217	0.05	-0.014	0.077
MINDSETF	-0.39	0.078	0.988	0.177	-0.336	0.061	1.062	0.082
MINDSETG	0.688	0.055	-1.412	0.198	0.186	0.051	-1.14	0.104
CURIOS	0.55	0.072	-1.1	0.201	-0.296	0.061	-0.031	0.083
OPENVP	0.242	0.039	-0.367	0.103	-0.122	0.031	-0.054	0.049

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. ADAPTCB – perceived cognitive-behavioral adaptability; ADAPTAE – perceived cognitive-behavioral adaptability; OPENBF – Openness to experience from Big Five scale; MINDSETF – fixed mindset; MINDSETG – growth mindset; OPENVP – Openness to changing viewpoints.

Figure 3 graphically represents adaptability profiles, which can be described as follows:

Profile 1 (very flexible): Participants in this profile had high scores in perceived adaptability, openness, curiosity, high growth mindset, and low fixed mindset. They were reported to believe in the possibility of developing through life, did not accept the idea of fixed talent and intelligence, and perceived themselves as open and adaptable individuals.

Profile 2 (rigid): This profile was formed by respondents who scored relatively low in perceived adaptability, openness, and curiosity and scored high on the fixed mindset scale. These participants stated to believe that talent and intelligence are fixed. At the same time, they did not perceive themselves as adaptable, open, and flexible.

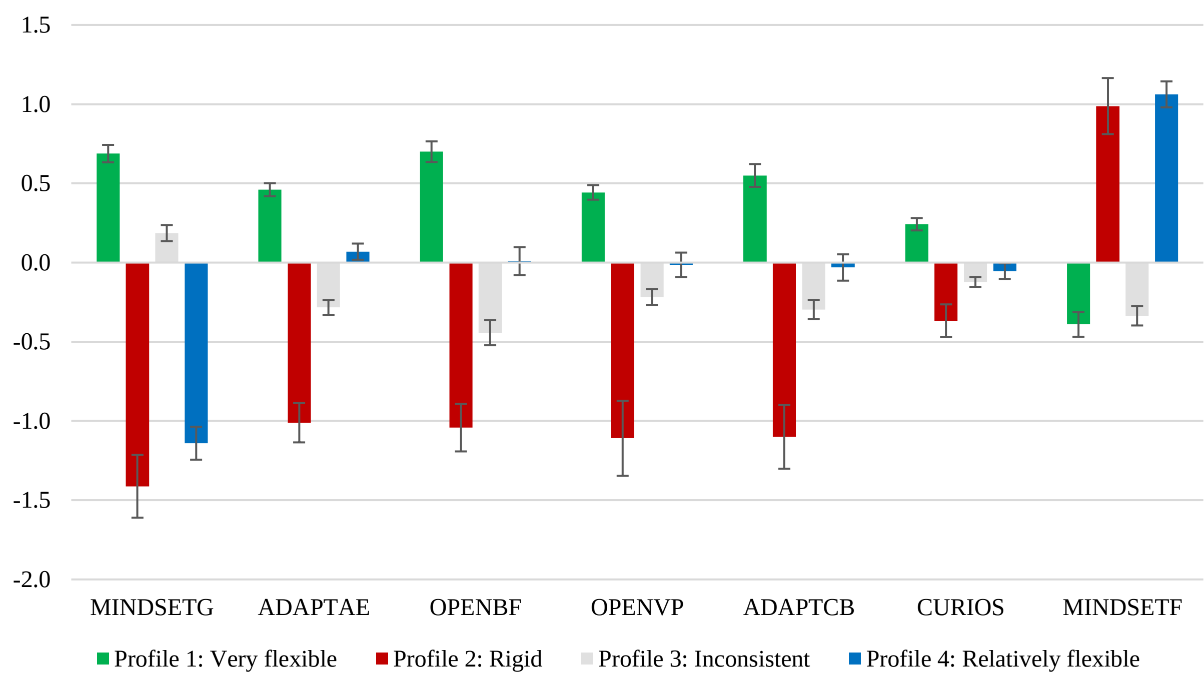
Profile 3 (inconsistent): This profile described individuals with inconsistent response patterns. They scored relatively low for perceived adaptability, openness, and curiosity but demonstrated a growth mindset. Respondents in this group reported that personal abilities can be developed and evolved through life but did not perceive themselves as ones who can adjust their thinking and emotions.

Profile 4 (relatively flexible): This profile described individuals with relatively high scores in perceived adaptability, openness, and curiosity but not having a growth mindset.

Overall, latent profile analysis demonstrated four homogeneous yet distinct profiles. We expanded the LPA model with explanatory variables to further understand how the profile membership can be explained and attributed.

Figure 3

Adaptability latent profile means



Note. ADAPTCB – perceived cognitive-behavioral adaptability; ADAPTAE – perceived cognitive-behavioral adaptability; OPENBF – Openness to experience from Big Five scale; MINDSETF – fixed mindset; MINDSETG – growth mindset; OPENVP – Openness to changing viewpoints.

Latent Profile Regression and Outcome Analysis

Predictors of Latent Profiles

Demographic variables and problem-solving self-concept were added to further understand the nature of adaptability profiles. Table 6 shows the latent profile regression results with unstandardized regression coefficients, standard errors, and odds ratios. The significant positive value indicates that the higher the score on the variable, the higher the probability of being a member of a particular profile compared to the reference profile.

Table 6

Results of the multinominal logistic regression predicting adaptability profile membership

	B	*SE*	*OR*	*p*
Profile 2 vs. 1: Rigid vs. very flexible				
EDUCAT	0.219	0.198	1.106	0.269
STUDENT	-0.292	0.633	-0.461	0.645
STUDENT2	-0.067	0.331	-0.203	0.839
TRANSIT	0.1	0.61	0.164	0.87
GENDER	-0.153	0.601	-0.255	0.798
AGE	-0.086	0.078	-1.096	0.273
IMMIGR	**-2.134**	**1.007**	**-2.118**	**0.034**
PROBSC	**-5.471**	**0.717**	**-7.632**	**0**
Profile 3 vs. 1: Inconsistent vs. very flexible				
EDUCAT	-0.034	0.094	-0.356	0.722
STUDENT	-0.244	0.383	-0.637	0.524
STUDENT2	0.01	0.204	0.048	0.962
TRANSIT	0.028	0.276	0.102	0.919
GENDER	0.254	0.279	0.907	0.364
AGE	**-0.119**	**0.047**	**-2.507**	**0.012**
IMMIGR	0.181	0.41	0.44	0.66
PROBSC	**-3.215**	**0.311**	**-10.341**	**0**
Profile 4 vs. 1: Relatively flexible vs. very flexible				
EDUCAT	-0.123	0.088	-1.4	0.162
STUDENT	-0.337	0.357	-0.942	0.346
STUDENT2	-0.146	0.191	-0.764	0.445
TRANSIT	-0.173	0.261	-0.665	0.506
GENDER	**-0.59**	**0.273**	**-2.157**	**0.031**
AGE	-0.024	0.041	-0.594	0.553
IMMIGR	0.456	0.335	1.363	0.173
PROBSC	**-1.476**	**0.393**	**-3.76**	**0**
Profile 3 vs. 2: Inconsistent vs. Rigid				
EDUCAT	-0.253	0.174	-1.448	0.148
STUDENT	0.047	0.519	0.091	0.927
STUDENT2	0.077	0.262	0.294	0.769
TRANSIT	-0.072	0.55	-0.131	0.896
GENDER	0.407	0.547	0.745	0.457
AGE	-0.033	0.07	-0.47	0.638
IMMIGR	**2.315**	**0.951**	**2.433**	**0.015**
PROBSC	**2.255**	**0.612**	**3.686**	**0**
Profile 4 vs. 2: Relatively flexible vs. Rigid				
EDUCAT	-0.342	0.201	-1.702	0.089

	B	*SE*	*OR*	*p*
STUDENT	-0.045	0.648	-0.07	0.945
STUDENT2	-0.079	0.345	-0.229	0.819
TRANSIT	-0.273	0.633	-0.432	0.666
GENDER	-0.436	0.64	-0.682	0.495
AGE	0.061	0.08	0.764	0.445
IMMIGR	**2.59**	**1.002**	**2.584**	**0.01**
PROBSC	**3.994**	**0.693**	**5.761**	**0**
Profile 4 vs. 3: Relatively flexible vs. Inconsistent				
EDUCAT	-0.09	0.096	-0.936	0.349
STUDENT	-0.092	0.356	-0.259	0.796
STUDENT2	-0.156	0.217	-0.72	0.471
TRANSIT	-0.202	0.285	-0.706	0.48
GENDER	**-0.843**	**0.299**	**-2.818**	**0.005**
AGE	**0.094**	**0.047**	**2.011**	**0.044**
IMMIGR	0.276	0.368	0.749	0.454
PROBSC	**1.739**	**0.417**	**4.168**	**0**

Note. EDUCAT – the highest educational level obtained; STUDENT – student status (0 = No, 1 = Yes); STUDENT2 – plans to become a student in the nearest future (No = 0, Yes = 1, Maybe = 2); TRANSIT – experiencing a job transition in the past 6 month (0 = No, 1 = Yes); GENDER – gender (0 = Female, 1 = Male); AGE – full age; IMMIGR – residing in the country other than birth (0 = No, 1 = Yes); PROBSC – problem-solving self-concept latent scores. In bold are associations significantly different from zero with p <.05

Across the profiles, student status, educational level, and experience of job transitions did not explain the profile membership. Instead, age, gender, immigration status, and problem-solving self-concept explained the probability of being assigned to a particular adaptability profile in comparison to other profiles as follows:

Profile 2 (rigid) vs. profile 1 (very flexible): Immigrants (B = -2.134, SE = 1.007, p < .05) and respondents with higher problem-solving self-concept scores (B = -5.471, SE = 0.717, p < .01) were less likely to be assigned to profile 2 compared to profile 1.

Profile 3 (inconsistent) vs. profile 1 (very flexible): Older respondents (B = -0.119, SE = 0.047, p < .05) and respondents with higher problem-solving self-concept scores (B = -3.215, SE = 0.311, p < .01) were less likely to be assigned to profile 3 compared to profile 1.

Profile 4 (relatively flexible) vs. profile 1 (very flexible): Females (B = -0.59, SE = 0.273, p < .05) and respondents with higher problem-solving self-concept scores (B = -1.476, SE = 0.393, p < .01) were more less to be assigned to profile 4 compared to profile 1.

In other words, respondents with an immigration background, older respondents, females and those with the higher problem-solving scores were more likely to be assigned to *profile 1 (very flexible)* as compared to the three other profiles.

Profile 3 (inconsistent) vs. profile 2 (rigid): Respondents with the immigration background (B = 2.315, SE = 0.951, p < .05) were more likely to be assigned to profile 3 as compared to profile 2. The same applied to the respondents with the higher problem-solving self-concept scores (B = 2.255, SE = 0.612, p < .01).

Profile 4 (relatively flexible) vs. profile 2 (rigid): Respondents with the immigration background (B = 2.59, SE = 1.002, p <.05) and those with the higher problem-solving scores (B = 3.994, SE = 0.693, p < .01) were more likely to be assigned to profile 4 as compared to profile 2.

In other words, respondents with an immigration background and those with higher problem-solving scores were less likely to be assigned to *profile 2 (rigid)*.

Profile 4 (relatively flexible) vs. profile 3 (inconsistent): Males (B = -0.843, SE = 0.299, p < .01) were less likely to be assigned to profile 4 compared to profile 3. Older respondents (B = 0.094, SE = 0.047, p < .05) and those with the higher problem-solving self-concept scores (B = 1.739, SE = 0.417, p < .01) were more likely they were to be assigned to profile 4 compared to profile 3.

Outcome Analysis

For the distal outcome of abstract reasoning, effects across profiles are inspected by estimating profile-specific mean and variance values for abstract reasoning scores and then conducting pairwise comparisons to determine whether the profiles would significantly differ. The inclusion of distal outcomes has not altered the nature of the groups. Table 7 demonstrates the mean abstract reasoning score differences between profiles.

Significant score differences were found between *profile 1* and *profile 3* (ΔM = -0.132, *SE* = 0.05, $p < .01$, Cohen's d = -0.209) with respondents in *profile 3* demonstrating the higher results; and between *profile 1* and *profile 4* (ΔM =-0.153, *SE* =0.061, $p < .05$, Cohen's d = -0.145) with respondents in *profile 4* having the higher scores in abstract reasoning. No other mean comparisons were significantly different from zero.

Table 7

Mean differences in abstract reasoning with respect to profiles

Difference between:	Estimate	S.E.	Est./S.E.	*p*-value	*Cohen's d*
Profile 1 and 2	0.036	0.097	0.374	0.708	0.0552
Profile 1 and 3	**-0.132**	**0.05**	**-2.655**	**0.008**	**-0.2091**
Profile 1 and 4	**-0.153**	**0.061**	**-2.495**	**0.013**	**-0.1447**
Profile 2 and 3	-0.168	0.098	-1.721	0.085	-0.2829
Profile 2 and 4	-0.189	0.108	-1.747	0.081	-0.3237
Profile 3 and 4	-0.021	0.055	-0.381	0.703	-0.2997

Note. Associations significantly different from zero with p <.05 are in bold.

Summary of Key Findings

Overall, the findings demonstrated four distinct adaptability profiles (*very flexible*, *rigid*, *inconsistent* and *relatively flexible*) among the respondents (RQ1). The membership in profiles was explained by *age*, *gender*, *immigration status*, and *problem-solving self-concept* (RQ2). In addition, *profiles 1* and *3* and *profiles 1* and *4* significantly differed in the abstract reasoning score (RQ3).

Discussion

Discussion

The study aimed to identify distinct adaptability profiles among ADAPT21 project participants. We specified key adaptability indicators and explored possible profile membership predictors like demographic characteristics and problem-solving self-concept. In addition, the relationship between adaptability and abstract reasoning as a measure of cognitive flexibility was studied.

Profiles of Adaptability (RQ1)

Our first research question was to identify adaptability profiles based on the following indicators: perceived adaptability, openness to experience, epistemic curiosity, openness to changing viewpoints, and mindset. To our best knowledge, no study was to identify latent profiles on given measures. The first thing to highlight is the existence of four distinct adaptability profiles. The participants in the sample were not uniform or homogeneous but rather varied in their adaptability levels and grouping with participants with similar adaptability profiles.

High adaptability, openness, and curiosity scores alongside the growth mindset indicated high adaptability. Conversely, low adaptability, openness, and curiosity scores alongside the fixed mindset indicated low adaptability. Hence, the analysis made four distinct groups of respondents with various adaptability patterns visible.

Profile 2 included respondents with a low adaptability response pattern. They did not report perceiving themselves to be able to adjust thinking and behavior, enjoying novelty, and would rather keep an opinion that was once established. These respondents demonstrated a fixed mindset and reported believing that one can learn new things but cannot change basic intelligence. *Profile 3* shared similar low adaptability patterns but had a growth mindset. While believing that intelligence can always be changed, they did not perceive themselves as capable of adjusting their thinking, behavior, and emotions.

As an opposite, *profile 1* included respondents with high adaptability scores. To interpret, these respondents would perceive themselves as being able to adjust thinking and expectations, reduce fear of failing, be creative, and be willing to revise their beliefs and opinions. In addition, they reported being curious about many different things and believed that one can change intelligence and learn new things. Lastly, *profile 4* consisted of respondents with slightly lower adaptability results and a fixed mindset.

The crucial finding of this analysis step was the vital importance of mindset for adaptability. Apparently, individuals perceive themselves as adaptable whether they, in general, believe in the malleable nature of personality and traits. Such an idea aligns well with Dweck's concept of mindset influencing several outcomes (Dweck, 2012; Dweck & Yeager, 2019). Furthermore, this confirms the importance of mindset in adjusting and regulating cognition, behavior and affect (Lee & Jung, 2021; A. Martin et al., 2012; Zarrinabadi et al., 2021).

However, further research would benefit our understanding of the role of the mindset in adaptability.

Predictors of Latent Profiles (RQ2)

The second research question was to understand whether age, gender, student status, experiencing a job transition, immigration status, and problem-solving self-concept would predict membership in adaptability profiles. Student status, educational level, and experience of job transitions did not significantly predict the probability of being assigned to a specific adaptability profile. However, age, gender, immigration status, and problem-solving self-concept explained the probability of being assigned to an adaptability profile.

Overall, respondents with an immigration background were more likely to be assigned to a profile with higher adaptability scores. One possible explanation for that is the successful experience of adaptation to a new country and culture that strengthened self-perceived adaptability. The other explanation is the reoccurring need to adapt to new conditions that activate adaptability traits such as openness and curiosity. This finding is, to some extent, consistent with Martin et al. (2013) observation of higher adaptability levels among non-native English-speaking high school students and controversial to Hirschi’s (2009) finding of non-immigrant participants having fewer resources for adjustment to uncertainty, observed among local and immigrant students in Switzerland.

Age was also a significant predictor of adaptability when evaluating the possibility of being assigned to *profile 3* compared to *profile 2* and *profile 4* compared to *profile 2*. In other words, the older respondents were more likely to be assigned to a profile with a higher adaptability pattern. This finding is consistent with the meta-analysis of career adaptability conducted by Rudolph et al. (2017). Perhaps, this association can be explained as hypothesized earlier by Zacher (2014): older participants might demonstrate greater adaptability if related to knowledge and experience accumulated during the lifespan.

Gender predicted probability to be assigned to *profile 4* compared to *3* and *profile 3* compared to *2*. In both cases, females were assigned to the profile with the higher adaptability scores, which was controversial in studies conducted in China (Hou et al., 2012; Yu et al., 2019), where male students demonstrated higher adaptability. However, the mechanism behind the association between gender and adaptability is unclear and perhaps, educational, career or cultural context could explain this association.

Problem-solving self-concept was a significant predictor for all profile comparisons. In general, respondents with a higher problem-solving self-concept were assigned to a profile with higher adaptability scores (e.g., *profile 3* vs. *profile 2*). Perhaps, an individual's confidence in being able to solve a novel task and face challenges influences successful adaptation. Therefore, variable-level research on this association the could provide additional insights.

Association between Profile Membership and Cognitive Ability (RQ3)

The third research question was whether profile membership would be associated with the abstract reasoning level. A significant difference was observed when comparing *profile 1* (very flexible) with *profile 3* (inconsistent); and *profile 1* (very flexible) with *profile 4* (relatively flexible). In both comparisons, respondents from the very flexible profile demonstrated had lower abstract reasoning scores. This finding is controversial to previous studies, where more adaptable, open and flexible respondents demonstrated higher scores on cognitive tasks (Kobasa, 1979; Lepine et al., 2000; Pulakos et al., 2006; Stasielowicz, 2020). Therefore, there is a need for additional evidence on discriminant and convergent validity studies to place the abstract reasoning measure by Chierchia et al. (2019) within the cognitive flexibility framework.

Limitations and Suggestions for Future Research

Several limitations of the present studies need to be noted. First, the study was based on a partially randomized sample, but it is limited in age (18-35 years respondents). Therefore, the generalizability of findings to other age groups should be studied. Furthermore, the sample was restricted to the respondents using Prolific service, which might lead to selection bias.

Second, the use of adaptability profile indicator scales as single-source self-reports may potentially be problematic due to common method bias (Podsakoff et al., 2003). Therefore, further validation of those scales with respective objective assessments or multiple sources (e.g., self-reports, reports by informants) is recommended.

Third, the cross-sectional data in this study limit the degree to which causal inferences on what determines profile membership can be drawn. Therefore, testing the predictor effects in longitudinal settings with causal designs will be beneficial to understanding how participants may transition between the profiles over time.

The current study discusses recommendations for further research. First, given the key role of mindset in discriminations of adaptability profiles, the need to explore the role of the mindset in adaptability is highlighted. Second, it would be beneficial to understand the psychometric properties of the abstract reasoning measure and collect evidence for validity so it can be applied in further studies as a cognitive flexibility measure.

Conclusion

To conclude, the current study identified four distinct adaptability profiles based on the selected measured and explored how demographic variables and self-concept predict profile membership. In addition, it demonstrated the relation of adaptability to abstract reasoning.

The generalizability of findings is limited to participants' age and the self-reported nature of adaptability profile indicators. Notwithstanding these limitations, the study has a few strengths. First, it provides the evidence for the selected measures of perceived adaptability, openness to changing viewpoints, mindset, openness to experience and epistemic curiosity as the adaptability measures and uncovers the unobserved groups of participants with the various levels of adaptability. Therefore, a given set of adaptability measures can be used in similar adaptability studies. Second, it highlights the power of mindset in how individuals perceive their adaptability. Third, it provides evidence for the antecedents and outcomes of adaptability profiles.

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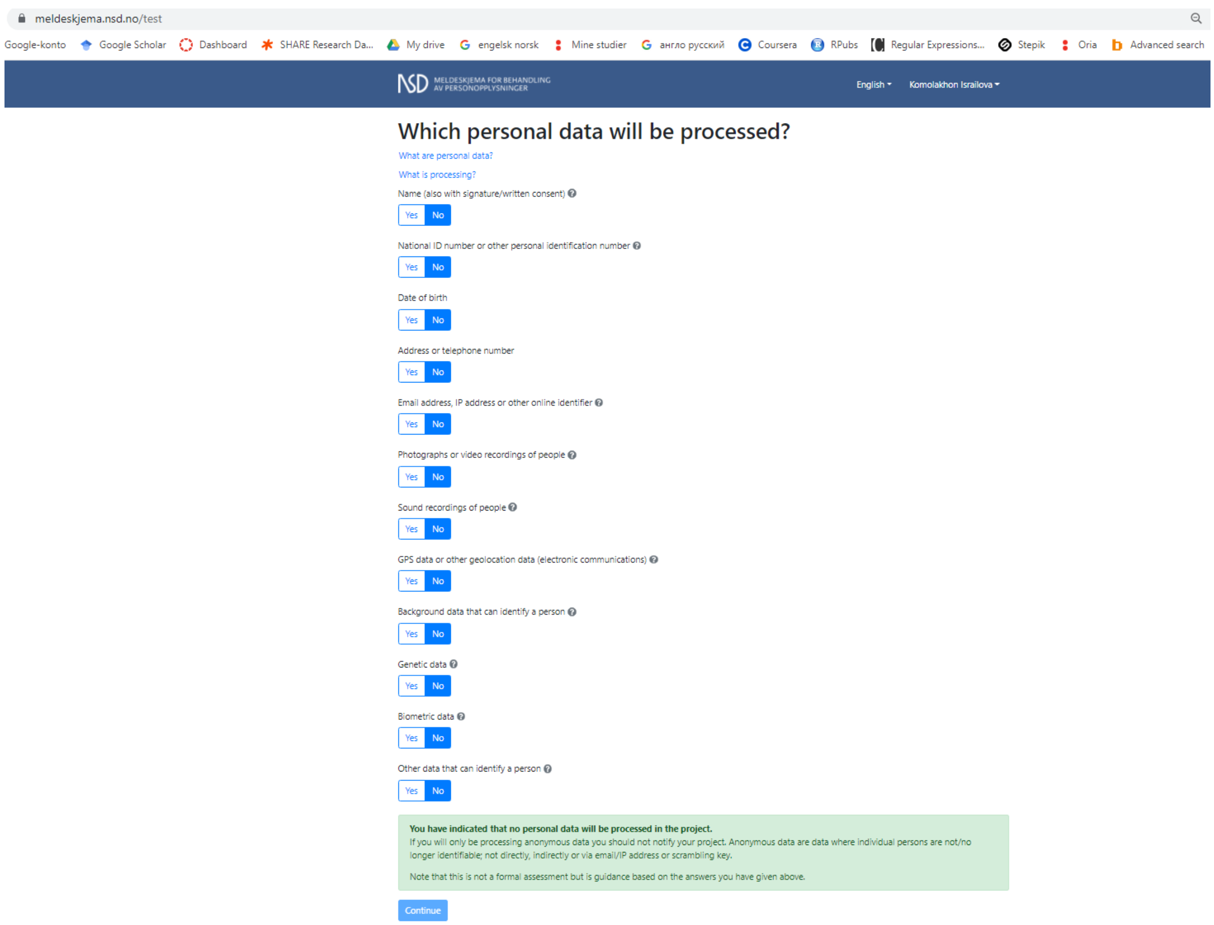
Appendix I: GDPR Documentation

The study was not subject to GDPR (General Data Protection Regulation) documentation since it proceeded only with anonymized data. No registration with NSD (Norwegian Centre for Research Data) was necessary.



Appendix II: Data Management and Analysis Code

R Script Analyses code

```
####PACKAGES####

library(readr) #read csv
library(questionr) #for NAs
library(corrplot) #for correlation plot
library(lavaan) #for measurement analysis
library(psych) #for measurement analysis
library(writexl) #for writing excel
library(semPlot) #for plots
library(mirt) #for IRT models
library(MplusAutomation) #for preparing data
library(tidyLPA) #profile estimation
library(poLCA) #profile estimation
library(mclust) #for latent profile analysis
library(dplyr) #for pipe
library(data.table) #for reshaping
library(ggplot2) #for plotting
library(tidyr) #for manipulations
library(cSEM) #for composite SEM

####LOAD DATA####
#read background data
data <- read_csv("Background_data.csv")
#read abstract reasoning data
cogdata <- read_csv("Abstract_reasoning_data.csv")
cogdata <- cogdata[-1]

#combine datasets though ID variable
ADAPT21_raw <- full_join(data, cogdata, by = "User.ID")

#select rows that contain only NAs
ind <- apply(ADAPT21_raw[2:147], 1, function(x) all(is.na(x)))
#delete them from the original dataset
ADAPT21_raw <- ADAPT21_raw[ !ind, ]

####PROFILES DATASET####
####prepare profiles the data####
#subset scales for extracting profiles
mydata <-
  ADAPT21_raw[,c("User.ID",
                 "BQ2.1.1","BQ2.1.2","BQ2.1.3","BQ2.1.4","BQ2.1.5","BQ2.1.6",
#cognitive-behavioral
                 "BQ2.1.7","BQ2.1.8","BQ2.1.9","BQ2.1.10","BQ2.1.11",
#affective-emotional adaptability
                 "BQ2.3.1","BQ2.3.2","BQ2.3.3","BQ2.3.4","BQ2.3.5","BQ2.3.6",
#openness to experience Big five

"BQ2.3.7","BQ2.3.8","BQ2.3.9","BQ2.3.10","BQ2.3.11","BQ2.3.12",
#openness to experience Big five
                 "BQ2.5.1","BQ2.5.2","BQ2.5.3",
#fixed mindset
```

```
                  "BQ2.5.4","BQ2.5.5","BQ2.5.6",
#growth mindset
                  "BQ2.6.1","BQ2.6.2","BQ2.6.3",
#I-type epistemic curiosity
                  "BQ2.6.4","BQ2.6.5","BQ2.6.6","BQ2.6.7","BQ2.6.8",
#D-type epistemic curiosity
                  "BQ2.9.1","BQ2.9.2","BQ2.9.3","BQ2.9.4","BQ2.9.5",
#openness changing viewpoins
                  "BQ3.1.1","BQ3.1.2","BQ3.1.3","BQ3.1.4","BQ3.1.5","BQ3.1.6"
#epistemological beliefs
  )]

str(mydata) #1,066 x 49

####explore dataset for profiles###
#descriptive
describe(mydata[, 2:49])
#frequency table
apply(mydata[, 2:49], 2, table, exclude = NULL)
#we observe that some scales show ceiling effect
#we combine first two categories to solve the issue
#categories 0 and 1 merged for the following scales:
#perceived adaptability #openness to experience #openness to changing
viepoints

mydata[c(2:12, 13:24, 39:43)] <-
  ifelse(mydata[c(2:12, 13:24, 39:43)] == 0, 0,
         ifelse(mydata[c(2:12, 13:24, 39:43)] == 1, 0,
                ifelse(mydata[c(2:12, 13:24, 39:43)] == 2, 1,
                       ifelse(mydata[c(2:12, 13:24, 39:43)] == 3, 2,
                              ifelse(mydata[c(2:12, 13:24, 39:43)] == 4, 3,
                                     ifelse(mydata[c(2:12, 13:24, 39:43)] ==
5, 4, NA
                                     ))))))

####FACTOR STRUCTURE PER SCALE####

####1. Perceived adaptability####
#exploratory analysis
#PCA
adapt_p <- 11  #number of measured variables
adapt_R <-
cor(mydata[,c("BQ2.1.1","BQ2.1.2","BQ2.1.3","BQ2.1.4","BQ2.1.5","BQ2.1.6",

"BQ2.1.7","BQ2.1.8","BQ2.1.9","BQ2.1.10","BQ2.1.11")][, 1:adapt_p], use =
"pairwise.complete.obs")
(adapt_PCA <- principal(r = adapt_R, nfactors = adapt_p, rotate = "none"))

#EFA
#Define the strategy for factor selection
(adapt_scree_parallel <- fa.parallel(x = adapt_R, n.obs = (1066 - 8), fm =
"pa"))
#efa with rotation that allows correlation between factors
(adapt_EFA<- fa(r = adapt_R, nfactor = 2, rotate = "promax", n.obs = (1066 -
8), fm = "pa"))

#CFA
```

```
#Model specification
adaptmodel1 <-'CognBehav =~ BQ2.1.1 + BQ2.1.2 + BQ2.1.3 + BQ2.1.4 +  BQ2.1.5
+ BQ2.1.6
               AffecEmot =~ BQ2.1.7 + BQ2.1.8 + BQ2.1.9 + BQ2.1.10 +
BQ2.1.11'
#Model estimation
adaptmodel1_fit <- cfa(adaptmodel1, data = mydata, estimator= "MLR")
#Summarize the results
summary(adaptmodel1_fit, standardized = TRUE, fit.measures = TRUE)

# Modification indices and EPC's
adaptmodel1_ind <- modificationindices(adaptmodel1_fit)
head(adaptmodel1_ind[order(adaptmodel1_ind$mi, decreasing=TRUE), ], 10)

#CFA
#Model specification with modifications
adaptmodel2 <-'
                  #Measurement model
                  CognBehav =~ BQ2.1.1 + BQ2.1.2 + BQ2.1.3 + BQ2.1.4 +
BQ2.1.5 + BQ2.1.6
                  AffecEmot =~ BQ2.1.7 + BQ2.1.8 + BQ2.1.9 + BQ2.1.10 +
BQ2.1.11
                  #Residual correlations
                  BQ2.1.7 ~~  BQ2.1.8 + BQ2.1.10
'
#Model estimation
adaptmodel2_fit <- cfa(adaptmodel2, data = mydata, estimator= "MLR")
#Summarize the results
summary(adaptmodel2_fit, standardized = TRUE, fit.measures = TRUE)
# Modification indices and EPC's
adaptmod2_ind <- modificationindices(adaptmodel2_fit)
head(adaptmod2_ind[order(adaptmod2_ind$mi, decreasing=TRUE), ], 10)

#model 3 - we drop item 10
adaptmodel3 <-'
                  #Measurement model
                  CognBehav =~ BQ2.1.1 + BQ2.1.2 + BQ2.1.3 + BQ2.1.4 +
BQ2.1.5 + BQ2.1.6
                  AffecEmot =~ BQ2.1.7 + BQ2.1.8 + BQ2.1.9 + BQ2.1.11
                  #Residual correlations
                  BQ2.1.7 ~~  BQ2.1.8
'
#Model estimation
adaptmodel3_fit <- cfa(adaptmodel3, data = mydata, estimator= "MLR")
#Summarize the results
summary(adaptmodel3_fit, standardized = TRUE, fit.measures = TRUE)

#reliability alpha
psych::alpha(mydata[,c("BQ2.1.1","BQ2.1.2","BQ2.1.3","BQ2.1.4","BQ2.1.5","BQ2
.1.6")]) #cog-behavioral
psych::alpha(mydata[,c("BQ2.1.7","BQ2.1.8","BQ2.1.9","BQ2.1.11")])
#affective-emotional
#omega
omega(mydata[,c("BQ2.1.1","BQ2.1.2","BQ2.1.3","BQ2.1.4","BQ2.1.5","BQ2.1.6")]
)
omega(mydata[,c("BQ2.1.7","BQ2.1.8","BQ2.1.9","BQ2.1.11")])
```

```
####2. Openness to experience Big five####
#exploratory analysis
#PCA
openBF_p <- 12  #number of measured variables
openBF_R <-
cor(mydata[,c("BQ2.3.1","BQ2.3.2","BQ2.3.3","BQ2.3.4","BQ2.3.5","BQ2.3.6",

"BQ2.3.7","BQ2.3.8","BQ2.3.9","BQ2.3.10","BQ2.3.11","BQ2.3.12")][,
1:openBF_p], use = "pairwise.complete.obs")
(openBF_PCA <- principal(r = openBF_R, nfactors = openBF_p, rotate = "none"))
#suggests 3 factor structure

#EFA
#Define the strategy for factor selection
(openBF_scree_parallel <- fa.parallel(x = openBF_R, n.obs = (1066 - 11), fm =
"pa"))
#efa with rotation that allows correlation between factors
(openBF_EFA <- fa(r = openBF_R, nfactor = 3, rotate = "none", n.obs = (1066 -
11), fm = "pa"))

#suggestion for items:
#factor 1 - items 1,3,4,5,7
#factor 2 - 11,7,8,12
#factor 3 - 2,6,9,10

#items 2,3,6,8,9 and 10 show ceiling effect
#items 3, 6, 8,11,12 don't seem to semantically represent the construct
#CFA showed that items 2,3,6,9,10 have low factor loadings
#CFA
#Model specification
openBFmodel1 <-'OpenBF =~ BQ2.3.1 + BQ2.3.2 + BQ2.3.3 + BQ2.3.4 + BQ2.3.5 +
BQ2.3.6 +
                BQ2.3.7 + BQ2.3.8 + BQ2.3.9 + BQ2.3.10 + BQ2.3.11 + BQ2.3.12'
#Model estimation
openBFmodel1_fit <- cfa(openBFmodel1, data = mydata, estimator= "MLR")
#Summarize the results
summary(openBFmodel1_fit, standardized = TRUE, fit.measures = TRUE)

#I suggest fitting a unidimensional model with items 1,4,5,7
#Model specification
openBFmodel2 <-'OpenBF =~ BQ2.3.1 + BQ2.3.4 + BQ2.3.5 + BQ2.3.7'
#Model estimation
openBFmodel2_fit <- cfa(openBFmodel2, data = mydata, estimator= "MLR")
#Summarize the results
summary(openBFmodel2_fit, standardized = TRUE, fit.measures = TRUE)
# Modification indices and EPC's
openBFmod_ind <- modificationindices(openBFmodel2_fit)
head(openBFmod_ind[order(openBFmod_ind$mi, decreasing=TRUE), ], 10)

#standardized Residual matrix
mean(residuals(openBFmodel2_fit, type="standardized")$cov) #high?
residuals(openBFmodel2_fit, type="standardized")$cov

#reliability alpha and omega
psych::alpha(mydata[,c("BQ2.3.1","BQ2.3.4","BQ2.3.5","BQ2.3.7")])
omega(mydata[,c("BQ2.3.1","BQ2.3.4","BQ2.3.5","BQ2.3.7")])
```

```
####3. Mindset####
#exploratory analysis
#PCA
mindset_p <- 6  #number of measured variables
mindset_R <- cor(mydata[,c("BQ2.5.1","BQ2.5.2","BQ2.5.3",
                           "BQ2.5.4","BQ2.5.5","BQ2.5.6")][, 1:mindset_p],
use = "pairwise.complete.obs")
(mindset_PCA <- principal(r = mindset_R, nfactors = mindset_p, rotate =
"none"))

#EFA
#Define the strategy for factor selection
(mindset_scree_parallel <- fa.parallel(x = mindset_R, n.obs = (1066 - 14), fm
= "pa"))
#efa with rotation that allows correlation between factors
(mindset_EFA<- fa(r = mindset_R, nfactor = 2, rotate = "promax", n.obs =
(1066 - 14), fm = "pa"))

#CFA
#Model specification
mindsetmodel1 <-'Fixed =~ BQ2.5.1 + BQ2.5.2 + BQ2.5.3
                Growth =~ BQ2.5.4 + BQ2.5.5 + BQ2.5.6'
#Model estimation
mindsetmodel1_fit <- cfa(mindsetmodel1, data = mydata, estimator= "MLR")

#Summarize the results
summary(mindsetmodel1_fit, standardized = TRUE, fit.measures = TRUE)

#reliability alpha
psych::alpha(mydata[,c("BQ2.5.1","BQ2.5.2","BQ2.5.3")]) #fixed
psych::alpha(mydata[,c("BQ2.5.4","BQ2.5.5","BQ2.5.6")]) #growth

omega(mydata[,c("BQ2.5.1","BQ2.5.2","BQ2.5.3")]) #fixed
omega(mydata[,c("BQ2.5.4","BQ2.5.5","BQ2.5.6")]) #growth
####4. Epistemic curiosity####
#we consider only one factor - D-type epistemic curiosity
#exploratory analysis
#PCA
curiosity_p <- 5  #number of measured variables
curiosity_R <- cor(mydata[,c("BQ2.6.4", "BQ2.6.5","BQ2.6.6",
"BQ2.6.7","BQ2.6.8")][, 1:curiosity_p], use = "pairwise.complete.obs")
(curiosity_PCA <- principal(r = curiosity_R, nfactors = curiosity_p, rotate =
"none"))

#EFA
#Define the strategy for factor selection
(curiosity_scree_parallel <- fa.parallel(x = curiosity_R, n.obs = (1066 -
16), fm = "pa"))
#efa with rotation that allows correlation between factors
(curiosity_EFA<- fa(r = curiosity_R, nfactor = 1, rotate = "promax", n.obs =
(1066 - 16), fm = "pa"))

#CFA
#Model specification
curiositymodel1 <-'curiosityDtype =~ BQ2.6.4 + BQ2.6.5 + BQ2.6.6 + BQ2.6.7 +
BQ2.6.8'
#Model estimation
```

```
curiositymodel1_fit <- cfa(curiositymodel1, data = mydata, estimator= "MLR")
#Summarize the results
summary(curiositymodel1_fit, standardized = TRUE, fit.measures = TRUE)

# Modification indices and EPC's
curiositymodel1_ind <- modificationindices(curiositymodel1_fit)
head(curiositymodel1_ind[order(curiositymodel1_ind$mi, decreasing=TRUE), ],
10)

#CFA
#Model specification
curiositymodel2 <-'
                  #Measurement model
                  CuriosityDtype =~ BQ2.6.4 + BQ2.6.5 + BQ2.6.6 + BQ2.6.7 +
BQ2.6.8
                  #Residual correlations
                  BQ2.6.7 ~~ BQ2.6.8
                  BQ2.6.4 ~~ BQ2.6.5
'
#Model estimation
curiositymodel2_fit <- cfa(curiositymodel2, data = mydata, estimator= "MLR")
#Summarize the results
summary(curiositymodel2_fit, standardized = TRUE, fit.measures = TRUE)

#reliability alpha and omega
psych::alpha(mydata[,c("BQ2.6.4", "BQ2.6.5","BQ2.6.6", "BQ2.6.7","BQ2.6.8")])
#curiosity
omega(mydata[,c("BQ2.6.4", "BQ2.6.5","BQ2.6.6", "BQ2.6.7","BQ2.6.8")])

####5. Openness to changing viewpoints####
#exploratory analysis
#PCA
openVP_p <- 5  #number of measured variables
openVP_R <- cor(mydata[,c("BQ2.9.1","BQ2.9.2","BQ2.9.3", "BQ2.9.4",
"BQ2.9.5")][, 1:openVP_p], use = "pairwise.complete.obs")
(openVP_PCA <- principal(r = openVP_R, nfactors = openVP_p, rotate = "none"))

#EFA
#Define the strategy for factor selection
(openVP_scree_parallel <- fa.parallel(x = openVP_R, n.obs = (1066 - 24), fm =
"pa"))
#efa with rotation that allows correlation between factors
(openVP_EFA <- fa(r = openVP_R, nfactor = 1, rotate = "none", n.obs = (1066 -
24), fm = "pa"))
#plot
fa.diagram(openVP_EFA, simple = FALSE)

#CFA
#Model specification
openVPmodel1 <-'OpennessVP =~ BQ2.9.1 + BQ2.9.2 + BQ2.9.3 + BQ2.9.4 +
BQ2.9.5'
#Model estimation
openVPmodel1_fit <- cfa(openVPmodel1, data = mydata, estimator= "MLR")

#Summarize the results
summary(openVPmodel1_fit, standardized = TRUE, fit.measures = TRUE)
```

```
# Modification indices and EPC's
openVPmodel1_ind <- modificationindices(openVPmodel1_fit)
head(openVPmodel1_ind[order(openVPmodel1_ind$mi, decreasing=TRUE), ], 10)

#CFA
#Model specification
openVPmodel2 <-'
                  #Measurement model
                  OpennessVP =~ BQ2.9.1 + BQ2.9.2 + BQ2.9.3 + BQ2.9.4 +
BQ2.9.5
                  #Residual correlations
                  BQ2.9.1 ~~ BQ2.9.2
'
#Model estimation
openVPmodel2_fit <- cfa(openVPmodel2, data = mydata, estimator= "MLR")
#Summarize the results
summary(openVPmodel2_fit, standardized = TRUE, fit.measures = TRUE)

#reliability alpha and omega
psych::alpha(mydata[,c("BQ2.9.1","BQ2.9.2","BQ2.9.3", "BQ2.9.4", "BQ2.9.5")])
#open
omega(mydata[,c("BQ2.9.1","BQ2.9.2","BQ2.9.3", "BQ2.9.4", "BQ2.9.5")])

####Final model####
#the final model account all modifications applied
#so we have the best possible representation of the latent constructs
#model - the final one
model1 <-'
                  #Measurement model
                  CognBehav  =~ BQ2.1.1 + BQ2.1.2 + BQ2.1.3 + BQ2.1.4 +
BQ2.1.5 + BQ2.1.6
                  AffecEmot  =~ BQ2.1.7 + BQ2.1.8 + BQ2.1.9 + BQ2.1.11
                  OpenBF     =~ BQ2.3.1 + BQ2.3.4 + BQ2.3.5 + BQ2.3.7
                  Fixed      =~ BQ2.5.1 + BQ2.5.2 + BQ2.5.3
                  Growth     =~ BQ2.5.4 + BQ2.5.5 + BQ2.5.6
                  CuriosityDtype =~ BQ2.6.4 + BQ2.6.5 + BQ2.6.6 + BQ2.6.7 +
BQ2.6.8
                  OpennessVP =~ BQ2.9.1 + BQ2.9.2 + BQ2.9.3 + BQ2.9.4 +
BQ2.9.5
                  #Residual correlations
                  BQ2.1.7 ~~  BQ2.1.8 #adaptability
                  BQ2.6.7 ~~ BQ2.6.8  #epistemic curiosity
                  BQ2.6.4 ~~ BQ2.6.5  #epistemic curiosity
                  BQ2.9.1 ~~ BQ2.9.2  #openness VP
'

#Model estimation
model1_fit <- cfa(model1, data = mydata, estimator= "MLR", missing = "FIML")
#FIML is used to solve the issue of missing data

#Summarize the results
summary(model1_fit, standardized = TRUE, fit.measures = TRUE)

#standardized Residual matrix
mean(residuals(model1_fit, type="standardized")$cov) #high?
residuals(model1_fit, type="standardized")$cov
```

```
#extract the factor scores
idx <- lavInspect(model1_fit, "case.idx")
fscores <- lavPredict(model1_fit, type = "lv", method = "ML")
## loop over factors
for (fs in colnames(fscores)) {
  mydata[idx, fs] <- fscores[ , fs]
}

#plot the model
fa.diagram(finalLambda.results, Phi=finalPhi.results, sort=FALSE,
errors=TRUE, digits=3)

####LATENT PROFILES####
#by tidyLPA

#fit and evaluate from 1 to 6 latent profiles
suppressMessages(mod_1c_v1 <-
                   estimate_profiles(
                     df = mydata[, c("CognBehav", "AffecEmot", "OpenBF",
"Fixed", "Growth", "CuriosityDtype", "OpennessVP")],
                     n_profiles = 1:6,
                     models = c(1,2,3,6)))

get_fit(mod_1c_v1)

####PREDICTORS####
#subset scales for profiles
predictors <-
  data[,c("User.ID",
          "BQ1.2.1","BQ1.2.2","BQ1.2.3",
          "BQ1.2'","BQ1.3", "BQ1.4", "BQ1.7",
          "BQ2.7.1","BQ2.7.2","BQ2.7.3",
          "BQ2.7.4","BQ2.7.5","BQ2.7.6",
          "BQ2.8.1","BQ2.8.2","BQ2.8.3",
          "BQ2.8.4","BQ2.8.5","BQ2.8.6",
          "BQ2.8.7","BQ2.8.8","BQ2.8.9"
  )]

#recode transition proxy
predictors$`BQ1.2'` <-
  ifelse(predictors$`BQ1.2'` == "0,1", 1, #yes
         ifelse(predictors$`BQ1.2'` == "1,0", 0, #no
                NA))

####Problem solving self concept####
#exploratory
#PCA
probSC_p <- 9  #number of measured variables
probSC_R <- cor(predictors[,c("BQ2.8.1","BQ2.8.2","BQ2.8.3",
                              "BQ2.8.4","BQ2.8.5","BQ2.8.6",
                              "BQ2.8.7","BQ2.8.8","BQ2.8.9")][, 1:probSC_p],
use = "pairwise.complete.obs")
(probSC_PCA <- principal(r = probSC_R, nfactors = probSC_p, rotate = "none"))

#EFA
#Define the strategy for factor selection
```

```
(probSC_scree_parallel <- fa.parallel(x = probSC_R, n.obs = (1066 - 22), fm =
"pa"))
#efa with rotation that allows correlation between factors
(probSC_EFA <- fa(r = probSC_R, nfactor = 1, rotate = "none", n.obs = (1066 -
22), fm = "pa"))
#plot
fa.diagram(probSC_EFA, simple = FALSE)


#CFA
#Model specification
probSCmodel1 <-'probSC =~ BQ2.8.1+BQ2.8.2+BQ2.8.3+
                          BQ2.8.4+BQ2.8.5+BQ2.8.6+
                          BQ2.8.7+BQ2.8.8+BQ2.8.9'
#Model estimation
probSCmodel1_fit <- cfa(probSCmodel1, data = predictors, estimator= "MLR")
#Summarize the results
summary(probSCmodel1_fit, standardized = TRUE, fit.measures = TRUE)

#modification indices
probSCmod_ind <- modificationindices(probSCmodel1_fit)
head(probSCmod_ind[order(probSCmod_ind$mi, decreasing=TRUE), ], 10)


#CFA
#Model specification
probSCmodel2 <-'probSC =~ BQ2.8.1+BQ2.8.2+BQ2.8.3+
                          BQ2.8.4+BQ2.8.5+BQ2.8.6+
                          BQ2.8.7+BQ2.8.8+BQ2.8.9
BQ2.8.6 ~~ BQ2.8.7 + BQ2.8.8 + BQ2.8.9
'
#Model estimation
probSCmodel2_fit <- cfa(probSCmodel2, data = predictors, estimator= "MLR")
#Summarize the results
summary(probSCmodel2_fit, standardized = TRUE, fit.measures = TRUE)

#reliability alpha and omega
psych::alpha(predictors[,c("BQ2.8.1","BQ2.8.2","BQ2.8.3",
                           "BQ2.8.4","BQ2.8.5","BQ2.8.6",
                           "BQ2.8.7","BQ2.8.8","BQ2.8.9")])

omega(predictors[,c("BQ2.8.1","BQ2.8.2","BQ2.8.3",
                    "BQ2.8.4","BQ2.8.5","BQ2.8.6",
                    "BQ2.8.7","BQ2.8.8","BQ2.8.9")])

#extract the factor scores
idx <- lavInspect(probSCmodel2_fit, "case.idx")
fscores <- lavPredict(probSCmodel2_fit, type = "lv", method = "ML")
## loop over factors
for (fs in colnames(fscores)) {
  predictors[idx, fs] <- fscores[ , fs]
}


####DISTAL OUTCOME####
#clean data because cSEM ddoesn't yet have tools to deal with missing data
mycogdata <- na.omit(cogdata)
```

```
#cSEM form the model with 6 emergent constructs
csmodel2 <-'
                  #Measurement part
                  OneRelation     <~ A1_1 + B2_1 + C3_1 + D4_1 + E5_1
                  TwoRelation     <~ D1E2 + A2B3 + A3C4 + A4D5 + B1C2 + B2D3
+
                                     B3E4 + C4D5 + C5E1
                  Logic           <~ X_5 + Y_5 + Z_5
                  ThreeRelation1  <~ A4B1D2 + B5C2D1 + B1C3E2 + A1B2D4 +
A2D1E5 +
                                     A3B4D1 + A3C5D2 + A3B1D4 + A3B2E5 +
B4C3D1
                  ThreeRelation2  <~ B4C2D5 + A2B5E3 + C5D4E1 + B2C3E4 +
A2D3E5 +
                                     A3B4C5_2 + A3B5D4_2 + A4B3E5_2 +
A4C5D3_2
                  ThreeRelation3 <~  A3C4E5_2 + A3D5E4_2 + B5C3D4_1 +
B5C4E3_1 +
                                     B3D4E5_1 + C3D5E4_1

                  # Structural model
                  OneRelation ~~ TwoRelation + Logic + ThreeRelation1 +
ThreeRelation2 + ThreeRelation3
                  TwoRelation ~~ Logic + ThreeRelation1 + ThreeRelation2 +
ThreeRelation3
                  Logic       ~~ ThreeRelation1 + ThreeRelation2 +
ThreeRelation3
                  ThreeRelation1 ~~ ThreeRelation2 + ThreeRelation3
                  ThreeRelation2 ~~ ThreeRelation3
                  '
#fit the model
csmodel2_fit <- csem(.data = mycogdata[,-1], .model =
csmodel2, .approach_weights = "MAXVAR", .resample_method = 'bootstrap')
#verify
verify(csmodel2_fit)
#fit statistics
assess(csmodel2_fit)
#summary
summarize(csmodel2_fit)
####extract cSEM scores####
csemdata <- getConstructScores(csmodel2_fit)
csemdata2 <- csemdata$Construct_scores
str(csemdata2)
csemdata2 <- as.data.frame(csemdata2)
#construct ID
mycogdata$ID <- seq.int(nrow(mycogdata))
#for the dataset with composite scores
csemdata2$ID <- seq.int(nrow(csemdata2))

#merge in one dataset
df_csem <- merge(mycogdata, csemdata2, by = "ID")
str(df_csem)

####Factor score of abstract reasoning####
#Explore factor scores
#correlation matrix
```

```
abstract_corr <- cor(csemdata2[,c("OneRelation", "TwoRelation", "Logic",
                                  "ThreeRelation1",
"ThreeRelation2" ,"ThreeRelation3")], use = "pairwise.complete.obs", method =
"pearson")
corrplot(abstract_corr)

#exploratory analysis
#PCA
(abstract_PCA <- principal(r = abstract_corr, nfactors = 6, rotate = "none"))

#model with 1 factor
(abstract_PCA2 <- principal(r = abstract_corr, nfactors = 1, rotate =
"none"))

#EFA
#Define the strategy for factor selection
(abstract_scree_parallel <- fa.parallel(x = abstract_corr, n.obs = 911, fm =
"pa"))

#efa with rotation that allows correlation between factors
(abstract_EFA<- fa(r = abstract_corr, nfactor = 1, rotate = "none", n.obs =
911, fm = "pa"))

#CFA
#Model specification
abstractmodel1 <-'#Measurement part
                  Ability =~ OneRelation + TwoRelation + Logic +
ThreeRelation1 + ThreeRelation2 + ThreeRelation3'
#Model estimation
abstractmodel1_fit <- cfa(abstractmodel1, data = csemdata2, estimator= "MLR")

#Summarize the results
summary(abstractmodel1_fit, standardized = TRUE, fit.measures = TRUE)

# Modification indices and EPC's
abstractmodel1_ind <- modificationindices(abstractmodel1_fit)
head(abstractmodel1_ind[order(abstractmodel1_ind$mi, decreasing=TRUE), ], 10)

#CFA
#Model specification
abstractmodel2 <-'#Measurement part
                  Ability =~ OneRelation + TwoRelation + Logic +
ThreeRelation1 + ThreeRelation2 + ThreeRelation3

                  #Covariation
                  OneRelation ~~    TwoRelation

'
#Model estimation
abstractmodel2_fit <- cfa(abstractmodel2, data = csemdata2, estimator= "MLR")

#Summarize the results
summary(abstractmodel2_fit, standardized = TRUE, fit.measures = TRUE)

#model comparison
anova(abstractmodel1_fit, abstractmodel2_fit)
```

```
#extract the factor scores
idx <- lavInspect(abstractmodel2_fit, "case.idx")
fscores <- lavPredict(abstractmodel2_fit, type = "lv", method = "ML")
## loop over factors
for (fs in colnames(fscores)) {
  df_csem[idx, fs] <- fscores[ , fs]
}


####FINAL DATASET####
#merge 3 datasets in one
ADAPT21 <- full_join(mydata, predictors, by = "User.ID")
ADAPT21 <- full_join(ADAPT21, df_csem, by = "User.ID")
ADAPT21 <- full_join(ADAPT21, mycogdata, by = "User.ID")

#the final data
ADAPT21_final <- ADAPT21[,c("User.ID",
                            "CognBehav", "AffecEmot", "OpenBF", "Fixed",
"Growth", "CuriosityDtype", "OpennessVP",
                            "BQ1.2.1", "BQ1.2.2", "BQ1.2.3", "BQ1.2'",
                            "BQ1.3", "BQ1.4", "BQ1.7", "probSC",
                            "Ability")]
#rename columns
colnames(ADAPT21_final) <- c("ID",
                             "ADAPTCB", "ADAPTAE", "OPENBF", "MINDSETF",
"MINDSETG", "CURIOS", "OPENVP",
                             "EDUC", "STUDENT", "STUDENT2", "TRANSIT",
                             "GENDER", "AGE", "IMMIGRATION",
                             "PROBSC",
                             "ABSTRACT")

#suspicious variable
ADAPT21_final$AGE
#2001 and 1997 inputs are probably birth age
#20 and 23 years

ADAPT21_final$AGE[ADAPT21_final$AGE == 2001] <- 20
ADAPT21_final$AGE[ADAPT21_final$AGE == 1997] <- 23

####SAVE DATA FOR MPLUS####
#prepareMplusData(ADAPT21_final, "ADAPT21.dat")
```

Mplus Analysis code

a) Mplus code for the LPA with four profiles

```
TITLE:     ADAPT 21 study
           Latent profile analysis
           4 classes model
DATA:      FILE IS "ADAPT21.dat";
           FORMAT IS FREE;
VARIABLE:  NAMES ARE
           ID ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG CURIOS
           OPENVP EDUCAT STUDENT STUDENT2 TRANSIT GENDER AGE
           IMMIGR PROBSC ABSTRACT;

           MISSING = .;
           ! Missing values are specified as .

           IDVARIABLE = ID;
           ! Student ID to appear in the output files

           USEVARIABLES ARE
           ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG    CURIOS
           OPENVP;
           !Variables to estimate latent profiles

           CLASSES = c(4);
           ! Number of classes to be extracted
ANALYSIS:  TYPE = MIXTURE;

           ESTIMATOR = MLR;
           ! The robust maximum likelihood estimation is
           chosen, it accounts for deviations from normality.

                STARTS = 800 40;
                STITERATIONS = 40;
                LRTBOOTSTRAP = 100;
                LRTSTARTS = 10 5 80 20;
                ! Settings for the analyses
                ! (Morin, Morizot, Boudrias, & Madore, 2011)

                PROCESSORS = 3;
                ! Choose a number of processors to be used
MODEL:     %OVERALL%

           %c#1%
           ! Latent profile 1
```

```
            [ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG CURIOS
            OPENVP];
            ! Request means of adaptability use variables in
            profile 1
            ! Notice that the variances of these variables are
            ! constrained to equality across profiles by
            default.

            %c#2%
            ! Latent profile 2
             [ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG CURIOS
            OPENVP];
            ! Request means of adaptability use variables in
            profile 2
            ! Notice that the variances of these variables are
            ! constrained to equality across profiles by
            default.

            %c#3%
            ! Latent profile 3
             [ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG CURIOS
            OPENVP];
            ! Request means of adaptability use variables in
            profile 3
            ! Notice that the variances of these variables are
            ! constrained to equality across profiles by
            default.

            %c#4%
            ! Latent profile 4
             [ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG CURIOS
            OPENVP];
            ! Request means of adaptability use variables in
            profile 4
            ! Notice that the variances of these variables are
            ! constrained to equality across profiles by
            default.
PLOT:       TYPE IS PLOT3;
                SERIES = ADAPTCB(1)
                         ADAPTAE(2)
                         OPENBF(3)
                         MINDSETF(4)
                         MINDSETG(5)
                         CURIOS(6)
                         OPENVP(7);
            ! Plot the latent profiles
OUTPUT:     SAMP; STAND; CINTERVAL;
```

```
            ! Sample statistics, standardized coefficients,
            and confidence intervals

            TECH1;
            ! provides parameter specification and ;
            ! starting values for all estimated parameters in
            the model;

            TECH7;
            !provides sample statistics for each class using
            raw data weighted by the estimated posterior
            probabilities for each class

            TECH11;
            ! LMR test;
            ! not for 1 class models;

            TECH14;
            ! BLRT;
            ! not for 1 class models;
SAVEDATA:   FILE IS LPA_4classes.txt;
            SAVE IS CPROBABILITIES;
            ! to call for the profile probability estimates;
```

b) Mplus code for the LPA with four profiles and covariates (predictors)

```
TITLE:      ADAPT 21 study
            Latent profile analysis
            4 classes model with predictors
DATA:       FILE IS "ADAPT21.dat";
            FORMAT IS FREE;
VARIABLE:   NAMES ARE
            ID ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG CURIOS
            OPENVP EDUCAT STUDENT STUDENT2 TRANSIT GENDER AGE
            IMMIGR PROBSC ABSTRACT;

            MISSING = .;
            ! Missing values are specified as .

            IDVARIABLE = ID;
            ! Student ID to appear in the output files

            USEVARIABLES ARE
```

```
            ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG CURIOS
            OPENVP EDUCAT STUDENT STUDENT2 TRANSIT GENDER AGE
            IMMIGR PROBSC;
            !Variables to used for analysis
            CLASSES = c(4);
            ! Number of classes to be extracted
ANALYSIS:   TYPE = MIXTURE;

            ESTIMATOR = MLR;
            ! The robust maximum likelihood estimation is
            chosen, it accounts for deviations from normality.

                 STARTS = 800 40;
                 STITERATIONS = 40;
                 LRTBOOTSTRAP = 100;
                 LRTSTARTS = 10 5 80 20;
                 ! Settings for the analyses
                 ! (Morin, Morizot, Boudrias, & Madore, 2011)

                 PROCESSORS = 3;
                 ! Choose a number of processors to be used
MODEL:      %OVERALL%

            c#1 ON EDUCAT STUDENT STUDENT2 TRANSIT GENDER AGE
            IMMIGR PROBSC;
            ! Multinomial logistic regression
            ! Use one profile as the reference

            c#2 ON EDUCAT STUDENT STUDENT2 TRANSIT GENDER AGE
            IMMIGR PROBSC;
            ! Multinomial logistic regression
            ! Use one profile as the reference

            c#3 ON EDUCAT STUDENT STUDENT2 TRANSIT GENDER AGE
            IMMIGR PROBSC;
            ! Multinomial logistic regression
            ! Use one profile as the reference

            %c#1%
            ! Latent profile 1
            [ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG CURIOS
            OPENVP];
            ! Request means of adaptability use variables in
            profile 1
            ! Notice that the variances of these variables are
            ! constrained to equality across profiles by
            default.
```

```
          %c#2%
          ! Latent profile 2
           [ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG CURIOS
          OPENVP];
          ! Request means of adaptability use variables in
          profile 2
          ! Notice that the variances of these variables are
          ! constrained to equality across profiles by
          default.

          %c#3%
          ! Latent profile 3
           [ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG CURIOS
          OPENVP];
          ! Request means of adaptability use variables in
          profile 3
          ! Notice that the variances of these variables are
          ! constrained to equality across profiles by
          default.

          %c#4%
          ! Latent profile 4
           [ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG CURIOS
          OPENVP];
          ! Request means of adaptability use variables in
          profile 4
          ! Notice that the variances of these variables are
          ! constrained to equality across profiles by
          default.
PLOT:     TYPE IS PLOT3;
              SERIES = ADAPTCB(1)
                       ADAPTAE(2)
                       OPENBF(3)
                       MINDSETF(4)
                       MINDSETG(5)
                       CURIOS(6)
                       OPENVP(7);
          ! Plot the latent profiles
OUTPUT:   SAMP; STAND; CINTERVAL;
          ! Sample statistics, standardized coefficients,
          and confidence intervals

          TECH1;
          ! provides parameter specification and ;
          ! starting values for all estimated parameters in
          the model;
```

```
            TECH7;
            !provides sample statistics for each class using
            raw data weighted by the estimated posterior
            probabilities for each class

            TECH11;
            ! LMR test;
            ! not for 1 class models;

            TECH14;
            ! BLRT;
            ! not for 1 class models;
SAVEDATA:   FILE IS LPA_4classes_pred.txt;
            SAVE IS CPROBABILITIES;
            ! to call for the profile probability estimates;
```

c) Mplus code for the LPA with four profiles and covariates and distal outcome

```
TITLE:        ADAPT 21 study
              Latent profile analysis
              4 classes model with predictors and distal
              outcome
DATA:         FILE IS "ADAPT21.dat";
              FORMAT IS FREE;
VARIABLE:     NAMES ARE
              ID ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG
              CURIOS OPENVP EDUCAT STUDENT STUDENT2 TRANSIT
              GENDER AGE IMMIGR PROBSC ABSTRACT;

              MISSING = .;
              ! Missing values are specified as .

              IDVARIABLE = ID;
              ! Student ID to appear in the output files

              USEVARIABLES ARE
              ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG CURIOS
              OPENVP EDUCAT STUDENT STUDENT2 TRANSIT GENDER
              AGE IMMIGR PROBSC ABSTRACT;
              !Variables used for the analysis

              CLASSES = c(4);
              ! Number of classes to be extracted
ANALYSIS:     TYPE = MIXTURE;
```

```
            ESTIMATOR = MLR;
            ! The robust maximum likelihood estimation is
            chosen, it accounts for deviations from
            normality.

                 STARTS = 800 40;
                 STITERATIONS = 40;
                 LRTBOOTSTRAP = 100;
                 LRTSTARTS = 10 5 80 20;
                 ! Settings for the analyses
                 ! (Morin, Morizot, Boudrias, & Madore,
            2011)

                 PROCESSORS = 3;
                 ! Choose a number of processors to be used
MODEL:      %OVERALL%

            c#1 ON EDUCAT STUDENT STUDENT2 TRANSIT GENDER
            AGE IMMIGR PROBSC;
            ! Multinomial logistic regression
            ! Use one profile as the reference

            c#2 ON EDUCAT STUDENT STUDENT2 TRANSIT GENDER
            AGE IMMIGR PROBSC;
            ! Multinomial logistic regression
            ! Use one profile as the reference

            c#3 ON EDUCAT STUDENT STUDENT2 TRANSIT GENDER
            AGE IMMIGR PROBSC;
            ! Multinomial logistic regression
            ! Use one profile as the reference

            %c#1%
            ! Latent profile 1
            [ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG CURIOS
            OPENVP];
            ! Request means of adaptability use variables in
            profile 1
            ! Notice that the variances of these variables
            are
            ! constrained to equality across profiles by
            default.

            [ABSTRACT](ab1)
            !Estimate abstract reasoning mean in profile 1
            !ABSTRACT is distal outcome here
```

```
                %c#2%
                ! Latent profile 2
                 [ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG
                CURIOS OPENVP];
                ! Request means of adaptability use variables in
                profile 2
                ! Notice that the variances of these variables
                are
                ! constrained to equality across profiles by
                default.

                [ABSTRACT](ab2)
                !Estimate abstract reasoning mean in profile 2
                !ABSTRACT is distal outcome here

                %c#3%
                ! Latent profile 3
                 [ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG
                CURIOS OPENVP];
                ! Request means of adaptability use variables in
                profile 3
                ! Notice that the variances of these variables
                are
                ! constrained to equality across profiles by
                default.

                [ABSTRACT](ab3)
                !Estimate abstract reasoning mean in profile 3
                !ABSTRACT is distal outome here

                %c#4%
                ! Latent profile 4
                 [ADAPTCB ADAPTAE OPENBF MINDSETF MINDSETG
                CURIOS OPENVP];
                ! Request means of adaptability use variables in
                profile 4
                ! Notice that the variances of these variables
                are
                ! constrained to equality across profiles by
                default.

                [ABSTRACT](ab4)
                !Estimate abstract reasoning mean in profile 4
                !ABSTRACT is distal outome here

MODEL
CONSTRAINT:     new(diff12 diff13 diff14 diff23 diff24 diff34);
```

```
              diff12 = ab1-ab2;
              diff13 = ab1-ab3;
              diff14 = ab1-ab4;
              diff23 = ab2-ab3;
              diff24 = ab2-ab4;
              diff34 = ab3-ab4;

              ! Estimate the mean difference in the ab score
              ! between all latent profiles.
              ! This will give us the effect of profile
              membership
              ! on the distal outcome
PLOT:         TYPE IS PLOT3;
                  SERIES = ADAPTCB(1)
                           ADAPTAE(2)
                           OPENBF(3)
                           MINDSETF(4)
                           MINDSETG(5)
                           CURIOS(6)
                           OPENVP(7);
              ! Plot the latent profiles
OUTPUT:       SAMP; STAND; CINTERVAL;
              ! Sample statistics, standardized coefficients,
              and confidence intervals

              TECH1;
              ! provides parameter specification and ;
              ! starting values for all estimated parameters
              in the model;

              TECH7;
              !provides sample statistics for each class using
              raw data weighted by the estimated posterior
              probabilities for each class

              TECH11;
              ! LMR test;
              ! not for 1 class models;

              TECH14;
              ! BLRT;
              ! not for 1 class models;
SAVEDATA:     FILE IS LPA_4classes_pred.txt;
              SAVE IS CPROBABILITIES;
              ! to call for the profile probability estimates;
```

Appendix III: Supplemental Material

Table S1

Item level descriptive statistics for adaptability scales

Item code	Mean	SD	Response categories						NA
			1	2	3	4	5	6	
	Perceived adaptability								
BQ 2.1.1	2.77	0.82	1	11	49	286	538	173	8
BQ 2.1.2	2.78	0.78	0	8	45	288	553	164	8
BQ 2.1.3	2.77	0.87	1	13	61	277	504	202	8
BQ 2.1.4	2.92	0.93	4	18	47	228	460	301	8
BQ 2.1.5	2.75	0.88	0	18	62	277	509	192	8
BQ 2.1.6	2.53	0.96	2	23	121	345	405	162	8
BQ 2.1.7	1.91	1.22	25	142	221	327	229	114	8
BQ 2.1.8	1.9	1.18	21	143	206	360	228	100	8
BQ 2.1.9	2.27	1.09	6	66	165	366	317	138	8
BQ 2.1.10	2.28	0.99	4	50	163	369	381	91	8
BQ 2.1.11	1.71	1.21	51	172	232	312	214	77	8
	Openness to experience								
BQ 2.3.1	2.41	1.12	9	60	138	323	341	184	11
BQ 2.3.2	3.17	0.9	4	13	28	163	393	454	11
BQ 2.3.3	2.19	1.04	13	54	176	409	294	109	11
BQ 2.3.4	2.59	1.18	11	52	128	269	310	285	11
BQ 2.3.5	2.52	1.06	8	36	128	317	371	195	11
BQ 2.3.6	2.92	1.04	4	23	75	227	354	372	11
BQ 2.3.7	2.34	1.14	15	63	158	322	318	179	11
BQ 2.3.8	2.59	1.25	16	71	118	250	286	314	11
BQ 2.3.9	2.82	1.12	12	37	87	221	342	356	11
BQ 2.3.10	3	0.97	4	22	45	204	412	368	11
BQ 2.3.11	2.22	1.31	36	111	161	270	262	215	11
BQ 2.3.12	1.94	1.3	46	142	216	276	226	149	11
		Mindset							
BQ 2.5.1	2.36	1.24	55	233	295	262	165	42	14
BQ 2.5.2	2.14	1.26	86	272	308	217	135	34	14
BQ 2.5.3	1.93	1.24	124	296	320	173	119	20	14
BQ 2.5.4	3.22	1.1	13	67	161	350	360	101	14
BQ 2.5.5	2.98	1.21	29	111	183	346	292	91	14
BQ 2.5.6	3.76	1.08	10	35	67	264	386	290	14
	Epistemic curiosity								
BQ 2.6.1	3.68	0.97	4	30	63	309	443	201	16
BQ 2.6.2	4.05	0.83	2	4	35	192	484	333	16
BQ 2.6.3	4.04	0.83	3	5	26	204	488	324	16

Item code	***Mean***	***SD***	***Response categories***						***NA***
			1	2	3	4	5	6	
BQ 2.6.4	3.21	1.25	19	83	190	304	271	183	16
BQ 2.6.5	3.21	1.1	15	57	166	388	307	117	16
BQ 2.6.6	3.13	1.18	16	89	195	316	315	119	16
BQ 2.6.7	3.32	1.19	18	68	148	308	341	167	16
BQ 2.6.8	3.26	1.09	11	59	157	368	332	123	16
Openness to changing viewpoints									
BQ 2.9.1	2.96	0.83	1	11	30	216	514	270	24
BQ 2.9.2	3.06	0.8	0	5	26	193	495	323	24
BQ 2.9.3	2.99	0.86	1	8	42	206	474	311	24
BQ 2.9.4	2.84	0.87	0	12	49	272	465	244	24
BQ 2.9.5	2.71	0.92	6	19	67	291	466	193	24

Note. The table presents the frequency of responses for adaptability indicator scales. We observe that some items have prevalent high responses. BQ = Background questionnaire, NA = Missing values (absolute frequency).

Scales used in dataset

Scales for the data are used from the ADAPT21 Background questionnaire and ADAPT21 Abstract reasoning assessment.

Perceived adaptability

The scale was adapted from Martin et al. (2013); items j and k were added from Scherer and Guttersrud (2018). For the latent factor analysis purposes item j was eliminated since it affected the model performance.

Thinking about yourself, to what extent do you agree or disagree with the following statements? In a new and unfamiliar situation, …							
		Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
(a)	I am able to think through a number of possible options to assist me.						
(b)	I am able to revise the way I think about the new situation.						
(c)	I am able to adjust my thinking or expectations.						
(d)	I am able to seek out new information, helpful people, or useful resources to effectively deal with the new situation.						
(e)	I am able to develop new strategies (e.g., a different way of asking questions or finding information).						

Thinking about yourself, to what extent do you agree or disagree with the following statements? In a new and unfamiliar situation, …	
(f)	I am able to change the way I do things.
(g)	I am able to reduce negative emotions.
(h)	I am able to minimize frustration or irritation so I can deal with it best.
(i)	I am able to draw on positive emotions.
(j)	I am able to draw on my expectations that I can certainly master challenges.
(k)	I am able to reduce my fear of failing.

Openness to experience

The scale was adapted from the Big Five Personality Trait Short Questionnaire (BFPTSQ) (Morizot, 2014). Originally reversed items were reversed to make them comparable to all other items. Double-barreled items were split to improve the psychometric properties of the scale. For estimating the latent factor scores items a, d, e, and g were selected since they were found to form a single unidimensional construct both statistically and semantically.

Thinking about yourself, to what extent do you agree or disagree with the following statements?
I see myself as someone who …

		Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
(a)	Is original often has new ideas						

Thinking about yourself, to what extent do you agree or disagree with the following statements? I see myself as someone who …	
(b)	Is curious about many different things.
(c)	Is ingenious., reflects a lot
(d)	Has lots of imagination.
(e)	(Is inventive, creative) Often has new ideas.
(f)	Reflects a lot.
(g)	Is inventive, Is creative.
(h)	Likes artistic or aesthetic experiences.
(i)	Is interested in different cultures, their customs, and values. reversed
(j)	Likes to reflect Tries to understand complex things.
(k)	Has (few) artistic interests. - reversed
(l)	Is sophisticated when it comes to art, music, or literature.

Openness to changing viewpoints

The scale was adapted from the *Comprehensive Intellectual Humility Scale* (Krumrei-Mancuso & Rouse, 2016).

To what extent do you agree or disagree with the following statements?

		Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
(a)	I have at times changed opinions						

To what extent do you agree or disagree with the following statements?	
	that were important to me, when someone showed me I was wrong.
(b)	I am willing to change my position on an important. issue in the face of good reasons.
(c)	I am open to revising my important beliefs in the face of new information.
(d)	I am willing to change my opinions on the basis of compelling reason.
(e)	I am willing to change my mind once it's made up about an important topic.

Epistemic curiosity

The scale was adapted from Litman and Spiegelhalter (2003). Items f-h measure interest-type (I-type) epistemic curiosity and items i-m measure deprivation-type (D-type) epistemic curiosity. D-type items were used for the analysis.

Thinking about yourself, to what extent do you agree or disagree with the following statements?

		Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
(a)	I enjoy learning about subjects that are unfamiliar to me I-type EC						

Thinking about yourself, to what extent do you agree or disagree with the following statements?	
(b)	I find it fascinating to learn new information
(c)	I enjoy exploring new ideas
(d)	I spend hours on a single problem because I can’t rest without answer.
(e)	I brood for a long time to solve a problem.
(f)	Conceptual problems keep me awake thinking.
(g)	I usually work harder if I can’t figure out a problem.
(h)	I work like a fiend at problems that I feel must be solved.

Mindset

Adapted form Yeager et al. (2016) and Dweck (Dweck, 2012).

Items a-c measure fixed mindset, and items d-f measure growth mindset.

Thinking about intelligence, to what extent do you agree or disagree with the following statements?

		Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
(a)	You can learn new things, but you can't really change your basic intelligence.						

Thinking about intelligence, to what extent do you agree or disagree with the following statements?	
(b)	Your intelligence is something about you that you can't change very much.
(c)	You have a certain amount of intelligence and you really can't do much to change it.
(d)	No matter how much intelligence you have, you can always change it quite a bit.
(e)	You can always substantially change how intelligent you are.
(f)	Learning new things can increase your underlying intelligence.

Problem solving self-concept

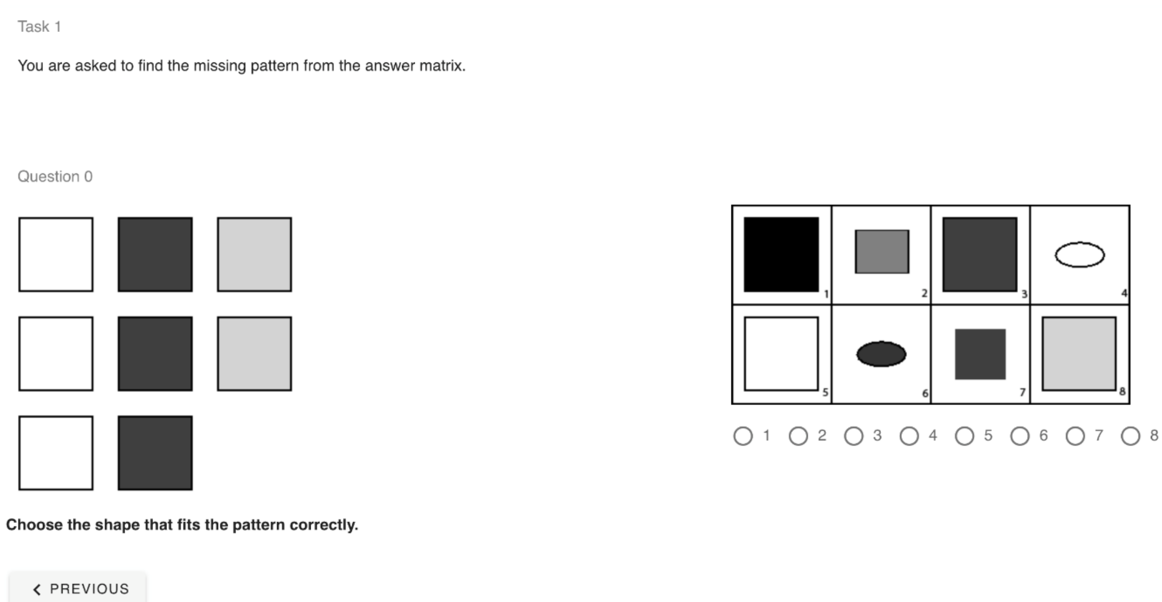
The compromises five positively formulated items. Adapted from the OECD PISA 2012 Student Questionnaire (Mathematics Self-Concept) (OECD, 2013b) and Mustafic et al. (2017). Items a-e are classical self-concept items. Items f-i are items closer to openness to problem solving. The scale represents unidimensional construct.

To what extent do you agree or disagree with the following statements?

		Strongly disagree	Disagree	Somewhat disagree	Somewhat agree	Agree	Strongly agree
(a)	I am good at solving problems.						
(b)	I am original in my ideas, thoughts,						

To what extent do you agree or disagree with the following statements?	
	and actions to solve problems.
(c)	I learn solving problems quickly.
(d)	I can solve even the most difficult problems.
(e)	Problem solving is easy for me.
(f)	I can handle a lot of information.
(g)	I am quick to understand things.
(h)	I seek explanations for things.
(i)	I can easily link facts together.

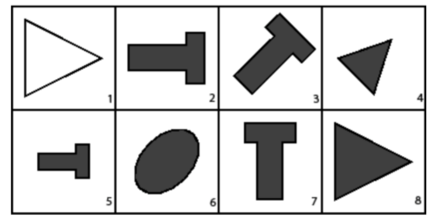
Abstract reasoning test examples



Task 7

You are asked to find the missing pattern from the answer matrix.

Question 0



○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8

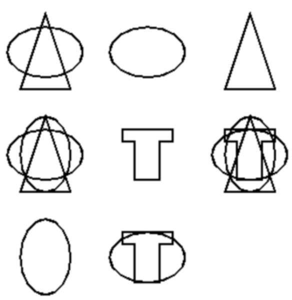
Choose the shape that fits the pattern correctly.

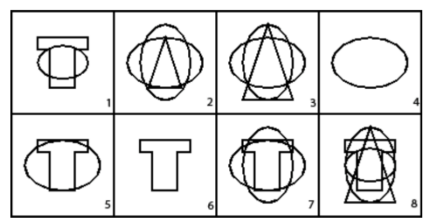
‹ PREVIOUS

Task 16

You are asked to find the missing pattern from the answer matrix.

Question 0





○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8

Choose the shape that fits the pattern correctly.

‹ PREVIOUS