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Abstract

The aim of this study is to investigate interrelationships between overexcitability and learning patterns, from the perspective of personality development according to Dabrowski's theory of positive disintegration. To this end, Bayesian structural equation modeling (BSEM) is applied which allows for the simultaneous inclusion in the measurement model of all, approximate zero cross-loadings and residual covariances based on zero-mean, small-variance priors, and represents substantive theory better. Our BSEM analysis with a sample of 516 students in higher education yields positive results regarding the validity of the model, in contrast to a frequentist approach to validation, and reveals that overexcitability – the degree and nature of which is characteristic of the potential for advanced personality development, according to Dabrowski's theory – is substantially related to the way in which information is processed, as well as to the regulation strategies that are used for this purpose and to study motivation. Overexcitability is able to explain variations in learning patterns to varying degrees, ranging from weakly (3.3% for reproduction-directed learning for the female group) to rather strongly (46.1% for meaning-directed learning for males), with intellectual overexcitability representing the strongest indicator of deep learning. This study further argues for the relevance of including emotion dynamics – taking into account their multilevelness – in the study of the learning process.

Keywords: Bayesian structural equation modeling; overexcitabilities; Dabrowski's theory of positive disintegration; learning patterns; confirmatory factor analysis with covariates; Mplus

Introduction

Approaches to learning and personality

One of the central purposes of higher education is to stimulate deep learning (Entwistle, 1997). In an investigation of qualitative differences in the processes and strategies of learning, as well as in the outcomes regarding what is understood and remembered among groups of Swedish university students, Marton and Säljö (1976) draw a distinction between surface-level and deep-level processing of information. Entwistle (1997) argues that the surface/deep dichotomy describes important differences in the ways in which students learn. A deep approach, in which the objective is to understand, is characterized by the construction of meaning by relating concepts, by connecting new information and prior knowledge, by exploring underlying patterns and principles, and by gathering evidence and formulating conclusions that allow careful and critical argumentation. In contrast, a surface approach is characterized by a focus on memorization, with the intention to reproduce knowledge.

Various questionnaires have been developed to test these two levels of information processing in students. Examples include the Approaches to Studying Inventory (ASI) (Entwistle & Ramsden, 1983), the Study Process Questionnaire (SPQ) (Biggs, 1987), and the Inventory of Learning Styles (ILS) (Vermunt, 1994).

Many empirical studies have investigated the impact of personality on academic achievement and the extent to which approaches to learning can constitute an additional explanatory factor. Scholars have also examined the possibility that learning approaches are situated within the broader concept of personality. A large part of the research on the extent and nature of associations between personality and learning approaches draws upon the Neuroticism–Extraversion–Openness Five-Factor Inventory (NEO-FFI) (Costa & McCrae, 1992) to measure personality according to five factors (i.e., neuroticism, extraversion, openness, conscientiousness, and agreeableness). In addition, the SPQ is used to gauge learning strategy and motive (with three possible outcomes at the aggregate level: the deep, surface, or achieving approach to learning – the latter reflects a strategic approach and is related to achievement motivation). The results of studies based on these instruments are relatively consistent, indicating a weak to moderate relationship between personality traits and learning approaches. A moderately positive relationship between the personality trait openness – as characterized by active imagination, aesthetic sensitivity, attentiveness to inner feelings, preference for variety, and intellectual curiosity (Costa & McCrae, 1992) – and the deep learning approach has been demonstrated in several studies (Chamorro-Premuzic & Furnham, 2009; Chamorro-Premuzic, Furnham, & Lewis, 2007; Furnham, Christopher, Garwood, & Martin, 2007; Zhang, 2003). These studies also report a negative correlation between openness and the surface learning approach. A positive association of conscientiousness with the achieving (von Stumm & Furnham, 2012) and deep approaches to learning appears to be a relatively general empirical finding, as is the positive relationship between the personality trait neuroticism and the surface learning approach (Chamorro-Premuzic et al., 2007; Furnham et al., 2007; Zhang, 2003). No clear relationship has been established for the personality factor agreeableness, and extraversion has been shown to have a positive relationship with the deep and achieving approaches to learning (Chamorro-Premuzic & Furnham, 2009).

The relationship between personality and learning has also been investigated using other questionnaire instruments. The results of these studies also provide evidence of positive associations between openness and the deep learning approach and between neuroticism and the surface approach. In addition, conscientiousness and extraversion are related to the deep and strategic approaches (Diseth, 2003; Duff, Boyle, Dunleavy, & Ferguson, 2004).

In general, the personality trait of openness exhibits the strongest association with the way in which learning is approached (Chamorro-Premuzic & Furnham, 2009), and a learning pattern is likely to be the result of interplay between personality attributes and dynamic contextual influences (Entwistle & McCune, 2004; Vermunt & Vermetten, 2004).

As noted by Entwistle and McCune (2004), inventories of learning and studying (whether earlier or more recent) pay little or no attention to the factor of emotion. However, empirical research indicates that emotions are substantially related to learning approach, students' motivation, self-regulation, and academic achievement (Pekrun, Goetz, Titz, & Perry, 2002). Positive activating emotions (e.g., hope, pride, and enjoyment, including excitement) seem to induce learning strategies such as "elaboration, organization, critical evaluation, and metacognitive monitoring" (Pekrun, Goetz, Titz, et al., 2002, p. 97), and may strengthen motivation and self-regulation (Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011). Negative activating emotions (e.g., anxiety, anger, and shame), on the other hand, appear to lead to the use of rehearsal strategies, and may reduce intrinsic motivation and induce reliance on external regulation (Pekrun, Goetz, Titz, et al., 2002).

Authentic learning and personality

Dabrowski's Theory of Positive Disintegration

Kazimierz Dabrowski (1902-1980), a Polish psychiatrist and psychologist, emphasizes the importance of "authentic education," which involves being aware of and understanding the developmental potential of a child and the role that this potential plays in the development of a truly human individual. Authentic education encourages children to transcend mediocrity and to develop their own personal hierarchies of values and aims, which they are then taught to realize (Rankel, 2008).

According to Dabrowski (1964/1967; Mendaglio, 2008), personality is achieved through a process of positive disintegration, which begins with the disintegration of a primitive mental organization aimed at meeting biological needs and conforming to societal norms.

Reintegration subsequently takes place at a higher level of human functioning, as characterized by autonomy, authenticity, and empathy.

Achieving the highest level of human development – or enacting the personality ideal – depends on the developmental potential of an individual, which is determined by the individual's level of innate heightened excitability (overexcitability) and the presence of specific talents, abilities and autonomous inner forces that cultivate growth (dynamisms).

Dabrowski distinguishes five levels of development, which are not sequential, age-related, or universal. The first level (Primary Integration) is characterized by egocentrism, conformity, automatic functioning, a prevalence of external over internal conflict, and a low level of self-awareness. It is present in high levels in the average person and, according to Dabrowski, it reflects a low level of mental health. The second level (Unilevel Disintegration) is a transitional phase between integration and disintegration, and it is an initial indication of development. The process of disintegration is initiated by deep external and internal conflicts (through the awareness of a discrepancy between how life ought to be and how it is), which cause intense negative emotions. Individuals endowed with sufficient developmental potential are able to achieve further disintegration and advanced development. In this process, dissolving dynamisms (e.g., ambivalence and ambitendency and, subsequently, disquietude with oneself, feelings of inferiority towards oneself, discontentment with oneself, and feelings of shame and guilt) cause a feeling of dissatisfaction with oneself and with society, and weaken and ultimately destroy primary integration. Subsequently, developmental dynamisms (e.g., self-awareness, self-control, subject-object attitude, syntony, identification, empathy, self-education, and autopsychotherapy) reduce the distress by moving toward an ideal and creating a new mental structure. Higher-level emotions are experienced, thus leading to the creation of a hierarchy of values drawing on both universal and individual values. Attaining the third level of development (Spontaneous Multilevel Disintegration) depends largely on the presence of a high level of overexcitability and a special developmental dynamism ("Third Factor Dynamism"), which gives rise to self-determinism, in which the individual is directed by an inner voice and personal values that reflect a high moral level. Dissolving and developmental dynamisms ultimately constitute an internal mental environment (Inner Psychic Milieu) that is self-directed and free of conflict. The fourth level of development (Organized Multilevel Disintegration) is thus characterized by the conscious self-organization of the course of development. Higher values are pursued, and a strong sense of responsibility towards oneself and others is developed. In the fifth level of development (Secondary Integration), personality is achieved. The individual experiences inner peace, being driven by a personality ideal based on a personal hierarchy of values. Inner conflict is no longer experienced, and empathy, autonomy, and authenticity are fully developed. Only a few people achieve the highest level of human development (Dabrowski, 1964-1967; Mendaglio, 2008).

Overexcitabilities

According to Dabrowski, the developmental potential of an individual depends in part on the extent and nature of psychic intensity. Dabrowski uses the term "overexcitability" to refer to an above average responsiveness to stimuli, due to heightened sensitivity of the central nervous system, which generates a different, more intense, and more multi-faceted experience of internal and external reality (Dabrowski, 1964-1967; Mendaglio, 2008).

Dabrowski distinguishes five forms of overexcitability. Psychomotor overexcitability is characterized by intense physical activity, work addiction, nervous habits, rapid speech, impulsiveness, competitiveness, and an urge to action. Sensual overexcitability involves enhanced receptivity of the senses, aesthetic appreciation, sensuality, and pleasure in being the center of attention. Imaginational overexcitability is characterized by a capacity to visualize events very well, as well as by ingenuity, fantasy, a need for novelty and variety, and poetic and dramatic perception. Intellectual overexcitability is characterized by an intensified activity of the mind, as well as by asking penetrating questions, reflective thought, problem solving, searching for truth and understanding, conceptual and intuitive integration, and an interest in abstraction and theory. Emotional overexcitability involves an intense connectedness with others, as well as the ability to experience things deeply, strong affective and somatic expressions, sensitivity in relationships, responsiveness to others, and well-differentiated feelings toward self (Daniels & Piechowski, 2009; Silverman, 2008). Dabrowski considers the last three forms of overexcitability essential to advanced human development (Mendaglio, 2008).

Empirical research has shown that emotional, intellectual, and imaginational overexcitability are important indicators of personality development (Falk & Miller, 2009; Miller, Silverman, & Falk, 1994), and that gifted individuals can be distinguished according to these three forms of overexcitability (Piechowski, Silverman, & Falk, 1985).

Aim of this study

The aim of this study is to investigate interrelationships between overexcitability, as measured by the Overexcitability Questionnaire-Two (OEQ-II) (Falk, Lind, Miller, Piechowski, & Silverman, 1999), and learning patterns, as gauged by the Learning and Motivational Questionnaire (LEMO) (Donche, Van Petegem, Van de Mosselaer, & Vermunt, 2010), from the perspective of personality development according to Dabrowski's theory of positive disintegration, and using Bayesian structural equation modeling (BSEM) with informative, small-variance priors (Muthén & Asparouhov, 2012). All of the above-mentioned studies that investigated interrelationships between personality and approaches to learning made use of maximum likelihood estimation in their structural equation model. However, none of these studies generated good model fit, as measured by the chi-square statistic. The results of validation studies indicate that most learning questionnaire instruments exhibit slight cross-loadings and measure several supplementary minor learning approach factors. On the one hand, freeing all cross-loadings and residual covariances leads to a non-identified model (Muthén & Asparouhov, 2012); on the other hand, modifying the model using modification indices in a frequentist analysis may capitalize on chance (MacCallum, Roznowski, & Necowitz, 1992), with a large risk of model misspecification (Muthén & Asparouhov, 2013). Using Bayesian analysis as a pragmatic approach, we hypothesize that the BSEM model will generate a good fit to the data because it may take into account the existence of trivial cross-loadings in the confirmatory factor analysis (CFA) model and many minor correlated residuals among the factor indicators. The BSEM technique allows for the simultaneous inclusion in the model of all, approximate zero cross-loadings and residual covariances based on zero-mean, small-variance priors, and consequently represents substantive theory better (Muthén & Asparouhov, 2012).

Some level of conceptual congruence between the Big Five personality factors and the five forms of overexcitability can be assumed. The NEO-FFI defines the five personality factors according to a set of facets (Costa & McCrae, 1992). The openness factor is related to intellectual overexcitability through the facet of ideas, to imaginational overexcitability through the facet of fantasy, to emotional overexcitability through the facets of feelings and values, to psychomotor overexcitability through the facet of actions, and to sensual overexcitability through the facet of aesthetics (Gallagher, 2013; Vuyk, Krieshok, & Kerr, 2016). In light of these relationships and in light of the empirical finding that openness is related to deep learning, we primarily hypothesize a positive relationship between overexcitability and meaning-directed learning, which corresponds to the deep approach as measured by the SPQ (Vermunt & Minnaert, 2003). Moreover, some correspondence can be presupposed between the attainment of higher levels of multilevel disintegration, as presented in Dabrowski's theory, and some characteristics of the deep learning approach (e.g., self-regulation, autonomous motivation, and critical processing), along with the adoption of mastery goals which are characterized by a focus on learning and understanding, heightened task enjoyment, and "a focus on self-improvement using self-referenced standards" (Vrugt & Oort, 2008, p. 125). The use of mastery-approach goals has been linked to deep learning, self-regulation, intrinsic motivation, and self-determination (Elliot, 1999; Liem, Lau, & Nie, 2008; Vrugt & Oort, 2008). In Dabrowski's theory, the phase of organized multilevel disintegration is characterized by the conscious self-organization of the course of development and by the emergence of autonomy, authenticity, self-education, autopsychotherapy, and the third factor dynamism, which gives rise to self-determinism. Convictions and standpoints are examined critically and rejected if they are of insufficient value. A personal hierarchy of values is consciously constructed and used as a reference against which to assess various behaviors and relationships with others. Attaining multilevel disintegration depends largely on the presence of a high level of overexcitability (Dabrowski, 1964-1967; Mendaglio, 2008).

However, the five forms of overexcitability are not equally important with respect to the developmental process (Mendaglio, 2012). Dabrowski considers emotional, intellectual and imaginational overexcitability essential to advanced personality development (Dabrowski, 1972; Mendaglio, 2008-2012). Positive developmental potential is comprised of all of the five overexcitabilities, although emotional, intellectual and imaginational overexcitability aid the transformation of the lower forms of overexcitability, i.e., psychomotor and sensual overexcitability (Mendaglio, 2012). However, a recent psychometric study indicated that the construct of psychomotor overexcitability, as captured by the OEQ-II, behaves differently to intellectual, imaginational, emotional, and sensual overexcitability, and that only the latter forms of overexcitability load substantially on a superordinate general construct of positive developmental potential (De Bondt & Van Petegem, 2015). Therefore, we further propose a positive relationship between positive developmental potential – which represents the interaction between intellectual, imaginational, emotional, and sensual overexcitability – and meaning-directed learning.

According to Dabrowski's theory, intelligence is of secondary influence on personality development – in contrast to emotions (Mendaglio, 2008). However, if combined with a high level of overexcitability and a strong autonomous drive to achieve individuality, intelligence could function as a catalyst if used in the service of the developmental process. Therefore, we additionally hypothesize a moderating effect of intellectual ability on the influence of overexcitability on the learning approach.

All analyses were carried out using the Mplus software program (Version 7.4; Muthén & Muthén, 1998-2015).

Material and Methods

Participants

The OEQ-II was added to a study conducted in Flanders investigating the influence of learning patterns on academic performance and the successful transition from secondary to higher education. The instrument was added to a fifth survey, which was conducted in the first semester of the academic year in which the respondents were in the second consecutive year of a program of higher education (most were in the second year of their studies). In all, 516 students (318 women: 61.6%; 198 men: 38.4%) completed the three measures discussed below. Of these respondents (M = 19.54 years; SD = 0.67), 356 (69%) had completed general secondary education before entering higher education, while 26% had followed technical secondary education, 4% had followed vocational secondary education, and 1% had followed secondary education in the arts.

Measures

Overexcitabilities

Falk et al. (1999) developed a self-report questionnaire to measure the degree and nature of overexcitability. The OEQ-II was initially used in giftedness research in the United States, but there is an increasing tendency in empirical research worldwide to use the instrument as a supplementary measure of dispositional traits. The OEQ-II consists of 50 items, equally representing intellectual overexcitability (e.g., "I love to solve problems and develop new concepts"), imaginational overexcitability (e.g., "Things that I picture in my mind are so vivid that they seem real to me"), emotional overexcitability (e.g., "I am deeply concerned about others"), psychomotor overexcitability (e.g., "If an activity is physically exhausting, I find it satisfying"), and sensual overexcitability (e.g., "I love to listen to the sounds of nature"). The items are scored along a five-point Likert scale with response options ranging from "Not at all like me" to "Very much like me." The OEQ-II demonstrates good factorial validity (De Bondt & Van Petegem, 2015; Van den Broeck, Hofmans, Cooremans, & Staels, 2014). The instrument was translated into Dutch, using back-translation, by the first author of this article, and it was tested on several young adults, in order to ensure the comprehensibility and proper interpretation of the items. In this study, as represented in Table 1, the Cronbach's alphas all exceed 80%, thus indicating good reliability, as well as consistency with the results of previous studies.

(Table 1)

Because of significant interrelationships between gender and the extent and nature of overexcitability (Bouchet & Falk, 2001; De Bondt & Van Petegem, 2015; Van den Broeck et al., 2014; Wirthwein, Becker, Loehr, & Rost, 2011), statistical analyses will be performed for the different gender groups separately.

Learning patterns

The LEMO is composed of the Inventory of Learning Styles-Short Version (ILS-SV) (Donche & Van Petegem, 2008), and an abbreviated version of the Academic Self-Regulation Questionnaire (SRQ-A) (Ryan & Connell, 1989) and the Academic Motivation Scale (AMS) (Vallerand et al., 1992).

The ILS-SV is a shortened version of the ILS developed by Vermunt (1994). It aims to differentiate respondents according to the cognitive processing strategies and metacognitive regulation strategies that they apply in their studies. Processing strategies are determined according to the extent to which individuals relate and structure information (e.g., “I compare conclusions from different teaching modules with each other”), engage in critical processing (e.g., “I try to understand the interpretations of experts in a critical way”), analyze (e.g., “I study each course book chapter point by point and look into each piece separately”), memorize (e.g., “I learn definitions by heart and as literally as possible”), and engage in concrete processing (e.g., “I pay particular attention to those parts of the course that have practical utility”). Each of these five scales consists of four items that are scored along a five-point Likert scale that reflects the degree of personal applicability of each proposed strategy according to response options ranging from “I never or hardly ever do this” to “I (almost) always do this.” The degree of self-regulation (e.g., “I use other sources to complement study materials,” four items), external regulation (e.g., “I study according to the instructions given in the course material,” six items), and lack of regulation (e.g., “I confirm that I find it difficult to establish whether or not I have sufficiently mastered the course material,” four items) provide insight into the regulation strategies that respondents use in learning. The items included are scored in a manner similar to that used for the processing strategies.

Study motivation is measured by the SRQ-A, which differentiates between an experienced desire to study (e.g., “I am motivated to study because I experience pleasure while learning new things," six items) and an experienced duty to study (e.g., "I am motivated to study because I am supposed to do this," six items), and the AMS, which generates a score for the extent of experienced amotivation (e.g., "I once had good reasons for going to college, however, now I wonder whether I should," three items). The items are scored according to their correspondence to personal motives based on a five-point Likert scale, with response options ranging from "Does not correspond at all" to "Corresponds exactly."

The scales for relating and structuring, critical processing, self-regulation, and autonomous motivation provide insight into the extent to which respondents adopt the meaning-directed learning pattern. The scales for analyzing, memorizing, external regulation, and controlled motivation characterize the reproduction-directed learning pattern. The undirected learning pattern is characterized by amotivation and a lack of regulation. A high degree of concrete processing characterizes the application-directed learning pattern.

In the present data set, all Cronbach's alphas for the LEMO factors were higher than 63% indicating a more or less acceptable level of internal consistency (see Table 1).

Intellectual ability

Intellectual ability is measured by the Prüfsystem für Schul- und Bildungsberatung Test 3 (PSB-3) (Horn, 1969). The PSB-3 is a non-verbal intelligence test with a 5-minute time limit, which measures reasoning capacity and is composed of 40 items, each consisting of 8 symbols from which one should select the incorrect figure. In this study, the Cronbach's alpha reliability coefficient exceeds 80% ($\alpha = .828$), thus indicating good internal consistency, as well as consistency with the results of previous studies.

Analyses

Before performing a Bayesian analysis of the multiple indicators, multiple causes (MIMIC) model, as represented in Figure 1, a maximum likelihood analysis was carried out for comparison purposes. Using maximum likelihood estimation, a CFA model with covariates was tested with the five overexcitability indicators, positive developmental potential (which represents the interaction between intellectual, imaginational, emotional, and sensual overexcitability), and intellectual ability as observed exogenous variables, with all of the learning pattern indicators as observed endogenous variables, and with meaning-directed, reproduction-directed, undirected, and application-directed learning as unobserved endogenous variables. Since this study should be regarded as exploratory, all learning pattern factors were regressed on all of the covariates in the MIMIC model.

(Figure 1)

Subsequently, a Bayesian analysis of the MIMIC model was performed with zero-mean and small-variance priors[1] for cross-loadings and residual covariances in the measurement model. Target loadings with non-informative priors – i.e., normally distributed priors with a mean of zero and infinite variance – and cross-loadings with strong informative priors – i.e., normally distributed priors with a mean of zero and a variance of 0.01, yielding 95% small cross-loading bounds of ±0.20 (Muthén & Asparouhov, 2012) – were utilized in this model. An inverse-Wishart prior distribution $IW(0, df)$ with df = 17 was applied for the correlated residuals, corresponding to prior zero-means and variances of 0.01 (MacKinnon, 2008). In

[1] Drawing on Bayes theorem, the formula for the posterior distribution $P(\theta|z)$ of the unknown parameter θ given the observed data z can be expressed as:

$$P(\theta|z) = \frac{P(\theta,z)}{P(z)} = \frac{P(z|\theta)\,P(\theta)}{P(z)}$$

where $P(\theta)$ stands for the prior distribution of the parameter, reflecting substantive theory or the researcher's prior beliefs, and $P(z|\theta)$ is referred to as the distribution of the data given the parameter, which represents the likelihood (Kaplan & Depaoli, 2012; Kruschke, Aguinis, & Joo, 2012; Levy, 2011; Zyphur & Oswald, 2015). Omitting the marginal distribution of the data $P(z)$ in the formula, reveals the proportionality of the unnormalized posterior distribution to the product of the likelihood and the prior distribution (Kaplan & Depaoli, 2012; Levy, 2011). The uncertainty regarding the population parameter value, as indicated by the variance of its prior probability distribution, is influenced by the observed sampling data, yielding a revised estimate of the parameter, as reflected in its posterior probability distribution (Kaplan & Depaoli, 2012).

this BSEM analysis, every tenth iteration was used – in order to reduce autocorrelation between successive posterior draws – with a total of 100,000 iterations and one MCMC[2] chain to describe the posterior distribution.

Model fit assessment

The following fit measures were used as a means of evaluating the quality of the frequentist MIMIC model: the chi-square statistic, comparative fit index (CFI; Bentler, 1990), and root mean square error of approximation (RMSEA; Steiger, 1990). A non-significant chi-square value, CFI values close to 1 (Hu & Bentler, 1995), and a value of the RMSEA of 0.05 or less (Browne & Cudeck, 1989) indicate a close fit of the model.

For the BSEM model, fit assessment was carried out using Posterior Predictive Checking in which – as implemented in Mplus – the likelihood-ratio chi-square statistic for the observed data is compared to the chi-square based on synthetic data obtained by means of draws of parameter values from the posterior distribution (Asparouhov & Muthén, 2010; Muthén & Muthén, 1998-2015; Scheines, Hoijtink, & Boomsma, 1999). The simulated data should approximately match the observed data if the model fits the data (Kaplan & Depaoli, 2012). The Posterior Predictive *p*-value (PP*p*) measures the proportion of the chi-square values of the replicated data that exceeds that of the observed data. A low PP*p* (< 0.05) indicates poor model fit. On the contrary, a PP*p* of 0.50, as well as a 95% confidence interval (CI) for the difference in the chi-square statistic for the observed and simulated data that contains zero positioned close to the middle of the interval, are both indicative of excellent model fit

[2] Bayesian estimation makes use of Markov chain Monte Carlo (MCMC) algorithms to iteratively draw random samples from the posterior distribution of the model parameters (Muthén & Muthén, 1998-2015). The software program Mplus uses the Gibbs algorithm (Geman & Geman, 1984) to execute MCMC sampling. MCMC convergence of posterior parameters, which indicates that a sufficient number of samples has been drawn from the posterior distribution to accurately estimate the posterior parameter values (Arbuckle, 2016), is evaluated via the potential scale reduction (PSR) convergence criterion (Gelman et al., 2014; Gelman & Rubin, 1992). When a single MCMC chain is used, the PSR compares variation within and between the third and fourth quarters of the iterations. A PSR value of 1.000 represents perfect convergence (Kaplan & Depaoli, 2012; Muthén & Muthén, 1998-2015).

(Muthén & Asparouhov, 2012). Results of simulation studies show the PP*p* to demonstrate sufficient power to reveal important model misspecifications (Muthén & Asparouhov, 2012).

Results

Descriptive statistics

Descriptive summary statistics for the overexcitability and learning pattern indicators are reported per gender group in Table 1. The overexcitability mean outcomes are consistent with all other studies using the OEQ-II, in which the two highest scores have been for emotional, intellectual, or psychomotor overexcitability (Falk & Miller, 2009). Also of note are the relatively high mean scores for the scales measuring autonomous motivation, relating and structuring, external regulation and concrete processing, as well as the low average results for amotivation, all of which could be expected, given the higher intellectual profile of the respondents (cf. results for intellectual ability).

Maximum likelihood CFA with covariates

Table 2 shows the chi-square statistic, CFI, and RMSEA for the evaluation of the frequentist MIMIC model. Highly significant chi-square statistics, RMSEA values of more than 0.05, and CFI values of less than .90 all indicate that both female and male models fit the data poorly.

(Table 2)

BSEM with informative, small-variance priors for cross-loadings and residual covariances in the measurement model

Subsequently, a Bayesian analysis was performed using zero-mean and small-variance priors for cross-loadings and residual covariances in the measurement model. The 95% CIs for the difference between the observed and the replicated chi-square values cover zero and the PP*p*s are 0.165 and 0.175 for the female and male group, respectively, both indicating satisfactory model fit. Good MCMC convergence was established for the two models. However, the covariates of intellectual ability and positive developmental potential had no substantive effect on any of the learning patterns and, consequently, these variables were dropped from the Bayesian MIMIC model. As represented in Table 2, omitting all non-significant[3] structural parameters yields good model fit for both the female (PPp = 0.157, Δ observed and replicated χ^2 95% CI [-24.650, 72.266]) and male groups (PPp = 0.147, Δ observed and replicated χ^2 95% CI [-22.991, 73.444]). Good MCMC convergence was found for the two models. Thus, the results of both BSEM models can be reliably interpreted. The hypothesized factor loading pattern for the LEMO was fully recovered, with substantial target loadings and only one non-trivial cross-loading (i.e., the loading of analyzing on the meaning-directed learning factor for the male group), as displayed in Table 3 (in Mplus, the reported estimates are the medians of their posterior distributions). Eight (i.e., 15%) minor residual covariances were found to be significant at the 5% level, for both groups. Excluding these residual correlations may lead to the poor fit of the frequentist models (Cole, Ciesla, & Steiger, 2007).

(Table 3)

In Bayesian analysis, the deviance information criterion (DIC) can be used for the purpose of comparing different models, where the model with the lowest DIC value is preferably selected (Spiegelhalter, Best, Carlin, & van der Linde, 2002). The DIC values generated by the full model and the more parsimonious model were 14349.204 and 13294.546 for the female group, and 8891.444 and 8213.141 for the male group, respectively. Thus, the models that only included substantive structural parameters produced the smallest DIC values.

[3] In Bayesian parameter estimation, the term "significant" is used by the authors to indicate that the 95% Bayesian credibility interval of a particular parameter did not cover zero. The Bayesian credibility interval can be retrieved directly from the percentiles of the posterior probability distribution of the model parameters. Using the posterior distribution percentiles, it is possible to determine directly the probability that a population parameter value is situated within a specific interval. If the posterior probability interval of a particular parameter does not contain zero, the null (condition) can be rejected as implausible, and as a consequence, the parameter is considered significant (which is indicated by a one-tailed Bayesian p-value below .05). A hypothesis testing perspective was also used in assessing model fit (Levy, 2011).

Table 4 presents the estimation results of the Bayesian MIMIC model for the structural parameters for both gender groups. As hypothesized, intellectual overexcitability is strongly indicative of the meaning-directed learning pattern for both females (β = .596, p < .001) and males (β = .547, p < .001). Moreover, it predicts the absence of the undirected learning pattern for both the female (β = -.282, p < .01) and male groups (β = -.402, p < .001), and it is a supplementary indicator of application-directed learning (β = .371, p < .001 for females, and β = .472, p < .001 for males). Imaginational overexcitability is indicative of the meaning-directed learning pattern but only for the female group, and the results from the Bayesian model reveal a negative relationship (β = -.199, p < .001). Moreover, imaginational overexcitability is an indicator of the undirected learning pattern (β = .348, p < .001 for females, and β = .275, p < .001 for males). Likewise, in contrast to what was hypothesized, emotional overexcitability is indicative of the reproduction-directed learning pattern (β = .181, p < .01 for females, and β = .456, p < .001 for males) and even of the undirected learning pattern for the male group (β = .274, p < .001). As expected, psychomotor overexcitability predicts the meaning-directed learning pattern but only for the male group, and the results reveal a negative relationship (β = -.143, p < .01). It is also indicative of the application-directed learning pattern for the female group (β = .209, p < .001). As hypothesized, sensual overexcitability is indicative of the meaning-directed learning pattern (β = .120, p < .05 for females, and β = .191, p < .01 for males).

(Table 4)

We can conclude that intellectual, imaginational (negative parameter), and sensual overexcitability account for 37.2% of the variance in meaning-directed learning for the female group. For the male group, 46.1% of the variance in meaning-directed learning can be explained by intellectual, psychomotor (negative parameter), and sensual overexcitability. In addition, emotional overexcitability accounts for 3.3% and 20.8% of the variance within reproduction-directed learning for the female and male group, respectively. Intellectual (negative parameter), imaginational, and emotional overexcitability (the latter only with respect to males) explain 13.7% and 25.4% of the variance within undirected learning for the female and male group, respectively. Intellectual and psychomotor overexcitability (the latter only with respect to the female group) account for 21.1% and 22.3% of the variance within application-directed learning for females and males, respectively.

Discussion

The aim of this study was to investigate interrelationships between overexcitability, as measured by the OEQ-II, and learning patterns, as gauged by the LEMO, from the perspective of personality development, according to Dabrowski's theory of positive disintegration. To this end, the new concept of BSEM, as presented by Muthén and Asparouhov (2012), was applied with informative, small-variance priors for cross-loadings and residual covariances in the measurement model. The analysis yielded positive results regarding the validity of the model, in contrast to the maximum likelihood MIMIC models which could not generate a satisfactory model fit, due to the existence of many minor cross-loadings and residual covariances.

Empirical research on the relationship between personality and approaches to learning draws heavily on the Big Five model in order to determine the most prominent characteristics of personality. This study approaches personality with indicators of overexcitability, the relative presence of which is characteristic of the potential for advanced personality development according to Dabrowski's theory. The results of both MIMIC models indicate that overexcitability is definitely related to the manner in which learning is approached, ranging from weakly (3.3% for reproduction-directed learning for the female group) to rather strongly (46.1% for meaning-directed learning for males). As hypothesized, intellectual overexcitability is a strong indicator of meaning-directed learning. Analogous to the negative relationship between openness and surface learning, intellectual overexcitability also predicts the absence of the undirected learning pattern. Intellectual overexcitability is also indicative of the application-directed learning pattern. These results are consistent with the findings of the study by von Stumm and Furnham (2012), which establish that the Big Five personality traits have weak explanatory power with regard to approaches to learning, although their results show that Typical Intellectual Engagement is strongly indicative of the deep learning approach. A certain level of conceptual correspondence can be presupposed. Intellectual overexcitability is also characterized by a high level of curiosity, wide-ranging and deep interests, and "a voracious appetite and capacity for intellectual effort and stimulation" (Daniels & Meckstroth, 2009, p. 43). Furthermore, as expected, sensual overexcitability is substantially related to the meaning-directed learning pattern.

However, contrary to what was hypothesized, emotional, imaginational, and psychomotor overexcitability are not indicative of deep learning. Emotional overexcitability is instead related to surface learning, as it is the only explanatory factor for reproduction-directed learning in both gender groups and even indicative of undirected learning with regard to the male group. The positive relationship between emotional overexcitability and the surface approach to learning is not completely unintelligible given that emotional overexcitability is related to the neuroticism factor of the Big Five model through the facets of anxiety, depression, self-consciousness, and vulnerability. Furthermore, results of qualitative and quantitative research on associations between emotions and learning indicate that hopelessness correlates negatively with motivational variables and positively with the external regulation of learning, and anxiety is positively associated with extrinsic avoidance motivation and external regulation (Pekrun, Goetz, Frenzel, et al., 2011; Pekrun, Goetz, Titz, et al., 2002). Moreover, positive associations between anxiety and the use of rehearsal strategies were found in some studies (Pekrun, Goetz, Titz, et al., 2002). According to Dabrowski, however, emotional overexcitability represents “the most important aspect of human development. It is a significant, logical component of developing a person’s potential” (Daniels & Meckstroth, 2009, p. 51). However, “emotions are multilevel in nature, as characterized by concrete or increasingly abstract referents” (Mendaglio, 2008, p. 19). Multilevelness or a hierarchical organization of human development is the hallmark of Dabrowski’s personality theory. Although the OEQ-II does not define the five overexcitability factors according to a set of hierarchically structured facets, a multilevel perspective can clearly be distinguished. Regarding the emotional overexcitability factor, the item “I am deeply concerned about others” is situated on a higher, more humane, and even more abstract level in the process of human development in comparison with the item “I can feel a mixture of different emotions all at once.” Organizing the OEQ-II as a hierarchical factor model could more accurately indicate the relationships between facets of overexcitability and aspects of the learning approach and, simultaneously, between the level of personality development and some positioning in the surface/deep learning dichotomy given a certain learning environment.

According to our results, imaginational overexcitability explains the undirected learning pattern, and this applies to males as well as females. Moreover, imaginational overexcitability is negatively associated with the meaning-directed learning pattern regarding the female group. However, most of the items representing imaginational overexcitability, as measured by the OEQ-II, are substantially content-related to the facet of fantasy in the openness factor of the NEO-FFI. Apparently, varying levels of relatedness to the deep learning approach applies to the different facets of the openness factor. In this context, Chamorro-Premuzic and Furnham (2009) argue that future research should explore the relationship between sub-facets of openness and approaches to learning in greater depth, including individual differences other than the Big Five personality factors (e.g., emotional intelligence) that are likely to be associated with learning. Despite the positive association with undirected learning, imaginational overexcitability is an indicator of giftedness (Piechowski, 1979; Piechowski et al., 1985), and imagination leads to discovery and invention (Daniels & Meckstroth, 2009). Therefore, it is important to consider aspects of creativity and intuition in the study of learning processes and to include them in an optimal student learning inventory. One of the items of the OEQ-II representing imaginational overexcitability reads: “When I get bored, I begin to daydream.” In this context, Pekrun, Goetz, Titz, et al. (2002) state that “emotions such as relaxation or boredom imply physiological as well as cognitive deactivation, thus leading to reduced attention and more shallow, superficial processing of information” (p. 97). Moreover, boredom seems to be negatively related to deep learning related criteria such as intrinsic motivation, self-regulation, and the adoption of flexible learning strategies (Pekrun, Goetz, Frenzel, et al., 2011).

According to Dabrowski, an individual’s developmental potential is comprised of all of the five overexcitabilities, specific talents and abilities, and a strong autonomous drive to achieve individuality (Dabrowski, 1964-1972; Mendaglio, 2008-2012). However, given the divergent results for the overexcitabilities discussed above, it is statistically logical that no substantive relationship was found between the interaction term “positive developmental potential” and the meaning-directed learning pattern. Thus, the third hypothesis was not confirmed. Organizing the OEQ-II according to a set of hierarchically structured facets would give better insight into associations between higher levels of personality development and aspects of more advanced learning approaches. Furthermore, intellectual ability is not indicative of meaning-directed learning. This result corresponds to previous studies that mentioned no substantive relationships between intelligence and approaches to learning (Diseth, 2002; Furnham, Monsen, & Ahmetoglu, 2009; von Stumm & Furnham, 2012), in contrast to a study by Chamorro-Premuzic and Furnham (2008), which indicates a weak to moderate positive relationship between intelligence and the deep learning approach.

Nevertheless, our results clearly demonstrate that overexcitability affects learning patterns, but that other factors also play a significant role. Dabrowski emphasizes the importance of a supportive environment for facilitating personality development in the case of moderate developmental potential (Mendaglio, 2008). Pekrun, Goetz, Titz, et al. (2002) also emphasize the importance of a nurturing educational environment and its reciprocal linkages with emotions and learning effects. In Dabrowski's concept of authentic education, the importance of awareness among educators of multilevelness in the course of human development is emphasized in particular. Educational systems should support the development of a personal hierarchy of values – based on universal, objective moral values – and the pursuit of "the highest level of human functioning, which is characterized by several dynamisms such as self-awareness, self-control, autonomy, authenticity, and great empathy" (Rankel, 2008, p. 96). Education should aim to accomplish the transition from an unconscious or uncritical assumption of biological and societal norms to the development of a conscious, high value-based self-determinism. "Differentiation, humanization, and creativity" (Rankel, 2008, p. 86) should be given particular attention in an evolutionary progressive education system.

With regard to the limitations of this study, we have to note that although the BSEM approach to factorial validation better represents substantive theory and avoids the need for a long series of model modifications with a substantial risk of misspecification, it is an innovative method that requires further research. In particular, the susceptibility of the PP*p* to specific model features, the number of variables, variable distributions, and model misspecification needs to be investigated in more detail (Muthén & Asparouhov, 2012). Nevertheless, the Bayesian approach to statistics has many advantages over the frequentist approach. Bayesian analysis makes it possible to incorporate prior knowledge – with different degrees of uncertainty, as indicated by the variance of the prior distribution – into parameter estimation, and is well suited for testing complex, non-linear models with non-normal distributions, regardless of sample size (Kruschke et al., 2012).

A second limitation of this study is the use of two self-report instruments to determine overexcitability and learning patterns. A more complete grasp of these latent constructs would require additional in-depth research on its neurobiological foundations. In line with the literature discussed, this study represents a cross-sectional analysis. Longitudinal research could provide insight into the degree and nature of causality between overexcitability and learning. Bidirectional causation between overexcitability and learning, with a moderating effect of aspects of the learning environment, may be presupposed. An inspiring learning context with room for elaboration, a critical attitude, self-determination, and personal growth will most likely strengthen the intellectual intensity and intrinsic motivation of the students. By contrast, highly regulated and somewhat authoritarian learning environments that emphasize reproduction of knowledge, may rather extrinsically motivate students, lead to a more superficial learning approach, and possibly provoke fear, to which people endowed with higher levels of emotional overexcitability may react more strongly. In contrast, focusing on humanization and moral evolution in educational systems may empower emotional intensity and may ultimately lead to progression in human evolution. Furthermore, a stimulating learning environment that provides space for intuition, imagination, creativity, and invention may sharpen the imaginational intensity of pupils and prevent boredom. Though, we should keep in mind that, according to Dabrowski, the quality of the social environment is of secondary importance in the case of strong – or very weak – developmental potential (Mendaglio, 2008).

A third limitation is the sole use of a nomothetic approach to analyze interrelationships between the features of developmental potential and learning approaches, without including an idiographic perspective which could reveal each individual uniqueness.

Despite its limitations, this study contributes to the existing research on the extent and nature of associations between personality and learning by considering personality traits from the perspective of developmental potential. Overexcitabilities are definitely related to learning approaches and – if combined and under the condition of a strong presence of the third factor – seem to be driving forces in the course of personality development (Falk & Miller, 2009; Lysy & Piechowski, 1983; Miller et al., 1994). Future studies should examine ways of creating a differentiated and facilitating learning environment with regard to personality, ability, and emotion dynamics, taking into account their multilevelness, which could lead to high-quality learning and the optimal realization of an individual's developmental potential.

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Table 1. Descriptive statistics for females and males and Cronbach's alphas.

		Females				Males			
	α	Mean	*SD*	Skewness	Kurtosis	Mean	*SD*	Skewness	Kurtosis
Intellectual overexcitability	.800	3.450	0.581	-0.035	0.102	3.540	0.538	0.161	-0.128
Imaginational overexcitability	.838	2.809	0.779	0.220	-0.195	2.708	0.663	0.148	-0.245
Emotional overexcitability	.820	3.737	0.571	-0.245	-0.153	3.162	0.617	-0.097	0.148
Sensual overexcitability	.863	3.295	0.736	-0.147	-0.175	3.112	0.691	0.041	0.054
Psychomotor overexcitability	.861	3.233	0.714	0.105	-0.217	3.380	0.700	-0.253	-0.094
Relating and structuring	.719	3.710	0.635	-0.626	0.826	3.601	0.610	-0.340	-0.237
Critical processing	.736	3.410	0.735	-0.454	0.160	3.497	0.681	-0.377	0.747
Self-regulation	.695	2.981	0.744	-0.019	-0.199	2.878	0.814	0.232	-0.326
Autonomous motivation	.840	3.785	0.661	-0.438	0.371	3.590	0.748	-0.419	0.164
Analyzing	.691	3.483	0.690	-0.244	0.307	3.322	0.741	-0.173	-0.421
Memorizing	.737	3.573	0.769	-0.415	0.127	3.143	0.788	-0.331	-0.151
External regulation	.639	3.769	0.524	-0.648	2.473	3.532	0.568	0.031	-0.327
Controlled motivation	.797	2.830	0.862	-0.242	-0.477	2.740	0.781	-0.021	-0.355
Lack of regulation	.759	2.619	0.818	0.186	-0.536	2.562	0.769	0.231	-0.296
Amotivation	.877	1.400	0.680	2.018	4.069	1.638	0.861	1.463	1.534
Concrete processing	.654	3.524	0.647	-0.268	0.306	3.556	0.650	0.063	-0.352
Intellectual ability	.828	31.310	4.157	-0.501	0.198	31.200	4.172	-0.656	0.378

Table 2. Maximum likelihood and Bayesian MIMIC model testing results for females (n = 318) and males (n = 198).

Model	χ^2	***df***	***p*-value**	**RMSEA**	**CFI**	**PP *p***	**95% CI**
Females							
ML-MIMIC	336.524	88	0.000	0.094	0.765		
BSEM-MIMIC						0.157	-24.650-72.266
Males							
ML-MIMIC	225.043	88	0.000	0.089	0.824		
BSEM-MIMIC						0.147	-22.991-73.444

Note: MIMIC = multiple indicators, multiple causes; *df* = degrees of freedom; RMSEA = root mean square error of approximation; CFI = comparative fit index; PP *p* = posterior predictive probability; CI = confidence interval; ML = maximum likelihood; BSEM = Bayesian structural equation modeling.

Table 3. Bayesian MIMIC model estimation results for the measurement parameters for females (n = 318) and males (n = 198) using small-variance priors for cross-loadings and residual covariances.

Factor Loadings	**Females**				**Males**			
	MDL	**RDL**	**UDL**	**ADL**	**MDL**	**RDL**	**UDL**	**ADL**
Relating and structuring	**0.775***	0.038	-0.038	0.047	**0.824***	-0.005	-0.078	-0.003
Critical processing	**0.903***	-0.031	0.020	-0.015	**0.833***	-0.003	-0.003	0.005
Self-regulation	**0.524***	0.012	0.104	0.052	**0.687***	0.011	0.082	-0.009
Autonomous motivation	**0.609***	0.004	-0.070	0.029	**0.800***	0.004	-0.026	-0.006
Analyzing	0.086	**0.703***	-0.083	-0.053	0.153*	**0.457***	-0.065	0.093
Memorizing	-0.043	**0.700***	0.038	-0.042	-0.023	**0.759***	0.065	-0.026
External regulation	-0.006	**0.612***	-0.079	-0.030	-0.096	**0.621***	-0.025	0.003
Controlled motivation	-0.007	**0.495***	0.161	0.091	-0.125	**0.690***	0.053	-0.098
Lack of regulation	0.014	0.022	**0.890***	0.058	0.036	0.012	**0.819***	0.060
Amotivation	-0.027	-0.017	**0.644***	-0.030	-0.073	-0.014	**0.743***	-0.063
Concrete processing	-0.001	-0.012	0.059	**0.941***	-0.012	0.004	0.017	**0.929***
Factor Correlations	**Females**				**Males**			
	MDL	RDL	UDL	ADL	MDL	RDL	UDL	ADL
MDL	1.000				1.000			
RDL	0.134	1.000			0.248*	1.000		
UDL	-0.218	0.162	1.000		-0.223	0.036	1.000	
ADL	-0.326*	0.035	-0.114	1.000	0.339*	0.203	-0.110	1.000

Note: MDL = meaning-directed learning; RDL = reproduction-directed learning; UDL = undirected learning; ADL = application-directed learning. The standardized coefficients in bold represent factor loadings that are the largest for each factor indicator.

* Significance at the 5% level in the sense that the 95% Bayesian credibility interval does not cover zero.

Table 4. Bayesian MIMIC model estimation results for the structural parameters for females (n = 318) and males (n = 198).

Parameter				95% Credibility Interval	
	Estimate	Posterior *SD*	One-tailed *p*	Lower 2.5%	Upper 2.5%
Females					
Meaning-directed learning regressed on					
Intellectual overexcitability	0.596	0.046	0.000	0.500	0.681
Imaginational overexcitability	-0.199	0.058	0.000	-0.314	-0.085
Sensual overexcitability	0.120	0.053	0.012	0.016	0.224
Reproduction-directed learning regressed on					
Emotional overexcitability	0.181	0.065	0.005	0.049	0.303
Undirected learning regressed on					
Intellectual overexcitability	-0.282	0.076	0.001	-0.423	-0.125
Imaginational overexcitability	0.348	0.060	0.000	0.225	0.458
Application-directed learning regressed on					
Intellectual overexcitability	0.371	0.063	0.000	0.240	0.485
Psychomotor overexcitability	0.209	0.054	0.000	0.103	0.315
Males					
Meaning-directed learning regressed on					
Intellectual overexcitability	0.547	0.056	0.000	0.432	0.650
Psychomotor overexcitability	-0.143	0.055	0.004	-0.251	-0.036
Sensual overexcitability	0.191	0.061	0.001	0.072	0.311
Reproduction-directed learning regressed on					
Emotional overexcitability	0.456	0.063	0.000	0.324	0.570
Undirected learning regressed on					
Intellectual overexcitability	-0.402	0.087	0.000	-0.561	-0.220
Imaginational overexcitability	0.275	0.076	0.000	0.123	0.421
Emotional overexcitability	0.274	0.077	0.000	0.119	0.423
Application-directed learning regressed on					
Intellectual overexcitability	0.472	0.074	0.000	0.312	0.601

Note: MIMIC = multiple indicators, multiple causes.

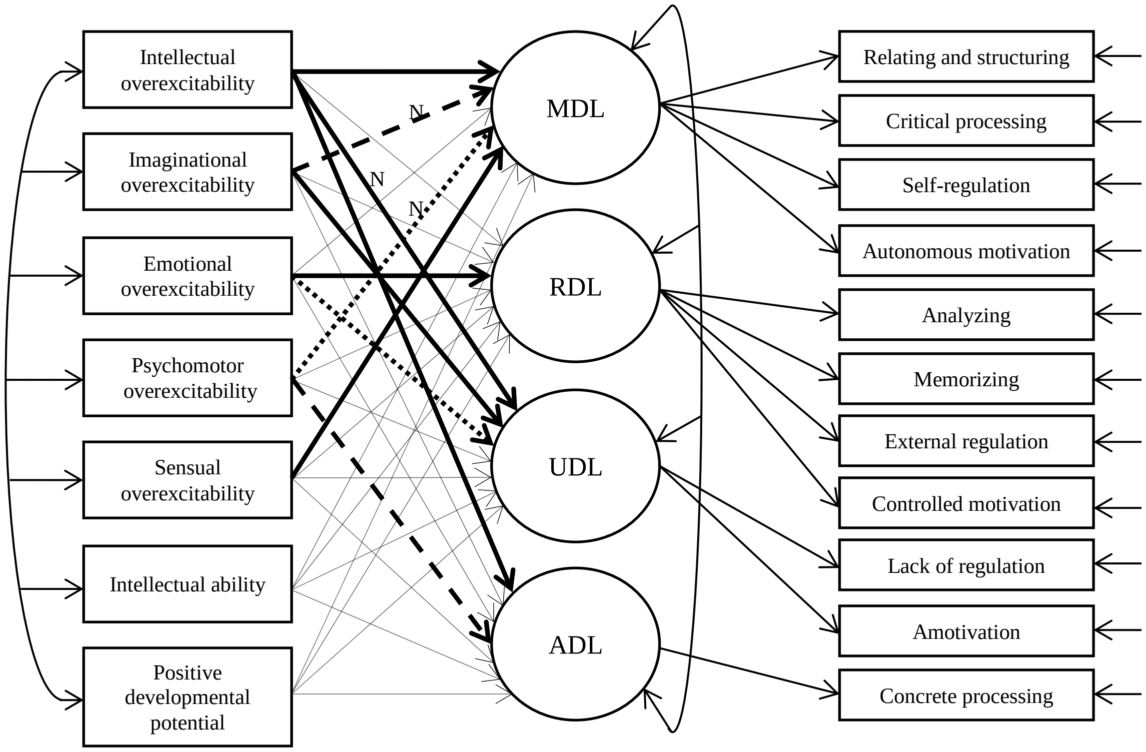

FIGURE 1. Multiple indicators, multiple causes model for females and males.

Note: MDL = meaning-directed learning; RDL = reproduction-directed learning; UDL = undirected learning; ADL = application-directed learning. Note: The bold lines represent significant – in the sense that the 95% Bayesian credibility interval does not cover zero – relationships for both female and male Bayesian models with zero-mean, small-variance priors for cross-loadings and residual covariances. The dashed lines represent non-trivial relationships with regard to the female group, while the dotted lines correspond to substantive associations exclusively regarding the male group. Lines marked by the letter "N" represent negative effects.