Deepening the educational relevance of Dąbrowski's Theory of Positive Disintegration: Pathway to autonomy – a Bayesian approach to validation

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Deepening the educational relevance of Dąbrowski's Theory of Positive Disintegration: Pathway to autonomy – a Bayesian approach to validation

Thesis submitted for the degree of Doctor of Education Sciences at the University of Antwerp to be defended by

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Supervisors:
Prof. dr. Peter Van Petegem
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Niki De Bondt
Antwerp, September 2025

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CHAPTER 1

GENERAL INTRODUCTION

GENERAL INTRODUCTION

Main objective and contribution of this doctoral research

This doctoral research focuses on the personal and contextual factors influencing surface versus deep learning and an autonomy orientation, illuminated from the perspective of the Theory of Positive Disintegration (TPD) (Dąbrowski, 1964, 1972b, 2015), which centers on personality growth and the attainment of autonomy, authenticity, and essence. In this way, it engages the TPD in educational research – which is virtually unique – and contributes to the existing comprehensive research on the personal and contextual correlates of the learning approach with the added value of bringing in emotive factors (overexcitabilities) that, moreover, provide a multilevel and dynamic growth perspective. The research was conducted among a sample of 516 higher education students with different personal (gender and intelligence) and contextual (prior education) characteristics and proceeds through the association of the TPD with Self-Determination Theory (SDT) (Deci & Ryan, 2000, 2002) – both theoretically and empirically, through the premise of the pursuit of autonomy and the learning patterns perspective on student learning (Vermunt & Donche, 2017), respectively. Furthermore, the research delves more deeply into the differential significance of the personality drivers in the TPD, i.e., the developmental potential and overexcitability, in relation to the five-factor model (FFM) personality traits (McCrae & Costa, 1987) that have been consistently used in established research on interrelationships between personality and the learning approach but have weak explanatory power (Chamorro-Premuzic & Furnham, 2009). Throughout the research, Bayesian structural equation modeling (BSEM) with informative, small-variance priors (Asparouhov & Muthén, 2014; Muthén & Asparouhov, 2012) is applied, which is still only marginally used in educational and psychological research (König & van de Schoot, 2018), despite its many advantages (Kruschke et al., 2012). This Bayesian approach to statistics is compared to a frequentist approach that has been consistently applied in empirical research on interrelationships between learning approaches and patterns *and* personal and contextual variables and is usually too strict (Muthén, 2013; Muthén & Asparouhov, 2013a). In this doctoral research, the TPD is explained in depth, with a focus on the developmental potential rather than overexcitabilities alone and the consideration of the empirical results within the overall framework of Dąbrowski's theory.

Figure 1.1 provides a schematic overview of the four studies included in this dissertation. Before presenting the research aims and rationales, we first discuss the theoretical frameworks and key concepts that underpin the studies, along with the major gaps in the literature and the main research questions that guided them.

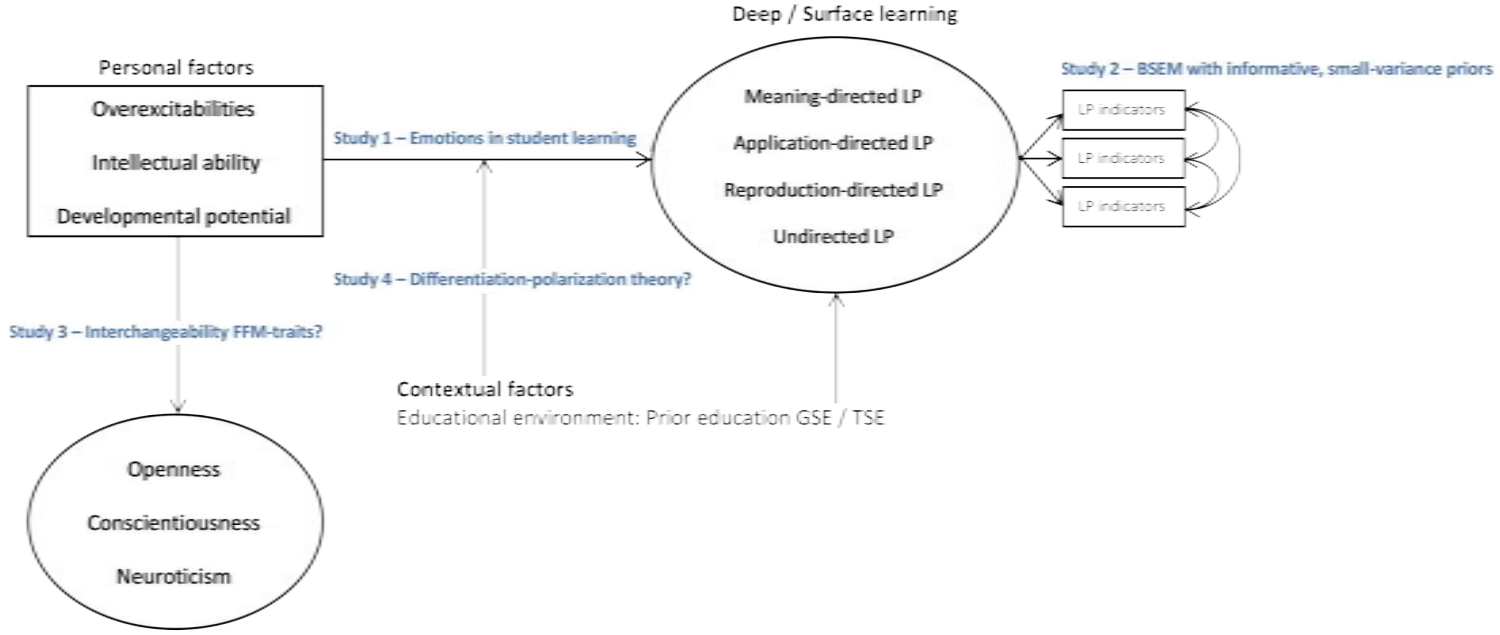

Figure 1.1. Schematic overview of the four studies included in this dissertation.
Note. LP = learning pattern; BSEM = Bayesian structural equation modeling; FFM = five-factor model; GSE = general secondary education; TSE = technical secondary education.

The Theory of Positive Disintegration

Kazimierz Dąbrowski (1902-1980), a Polish psychiatrist and psychologist, developed the TPD, which represents an organismic-dialectical, hierarchically structured theory of personality development, in which personality is defined as a "self-aware, self-chosen, self-affirmed, and self-determined unity of essential individual psychic qualities" (Dąbrowski, 2015, p. 290). Five developmental levels are distinguished: Primary Integration, Unilevel Disintegration, Spontaneous Multilevel Disintegration, Organized Multilevel Disintegration, and Secondary Integration. Personality is only achieved at the level of Secondary Integration (Dąbrowski, 1964, 2015).

The TPD presupposes inherent human integrative tendencies toward conscious, high value-based self-determinism and personal development, with essence as the ultimate purpose. However, this final goal is only achieved by a small number of people as it requires a dialectical process of multilevel disintegration in which the developing individual becomes deeply aware of: (a) the existence of various vertical (hierarchical) levels in external and internal reality, and (b) the need to choose the higher and true dimension. In this process of positive disintegration, the awareness of an antithesis between biological-social reality (accompanied by a cohesive mental structure aimed at satisfying low-instinctive biological and societal needs) and supra-instinctive necessity (referring to how life ought to be, i.e., absolutely truthful, alter-centric, and according to universal, objective moral values) leads to both external and, more significantly, inner conflict and tension that may cause the disintegration of the primitive mental organization and, subsequently, advance personality development (Dąbrowski, 1964, 1976, 2015).

Attaining multilevel disintegration and, ultimately, integration at a higher level, largely depends on an individual's developmental potential. This is determined by their level of innate psychic overexcitability and the presence of special abilities and talents, as well as autonomous dissolving and developmental dynamisms that exist within the inner psychic milieu, which cultivate personal growth (Dąbrowski, 1964, 1972b, 2015; Mendaglio, 2008; Tillier, 2018). At the level of Secondary Integration, the individual experiences inner peace, being driven by a personality ideal based on a personal hierarchy of values, which is derived from universal, objective moral values. Autonomy, authenticity, and empathy are fully developed (Dąbrowski, 1964, 1972b, 2015; Dąbrowski et al., 1970; Mendaglio, 2008; Tillier, 2018).

In addition to a strong developmental potential, the TPD emphasizes the importance of a supportive environment for facilitating personality development and the attainment of autonomy, as addressed in its concept of authentic education (Dąbrowski, 2015; Dąbrowski et al., 1970; Rankel, 2008). According to Dąbrowski (2015; Rankel, 2008), teachers and counselors should be acquainted with the TPD and educational systems should support the pursuit of the highest level of human functioning. By using the TPD, Dąbrowski aimed to reframe education and mental health, ultimately to advance mental health in society (Rankel, 2008). The TPD takes a dynamic perspective on mental health. Unlike the absence of mental disorders (Mika, 2008), according to Dąbrowski (1964, 2015), mental health reflects the progressive development of personality.

However, despite the TPD being a visionary theory of personality development that provides a vital regulatory perspective for moral development, inner growth, and mental health, the theory has only been validated to a limited degree. This is partly due to its complexity, as well as the limited accessibility of Dąbrowski's extensive body of work. Dąbrowski's discussion of authentic education is also not well known, due to this limited access (Dąbrowski, n.d., 2015), while the potential implication of the TPD for the field of education has been theoretically addressed by only a few authors (e.g., Daniels & Meckstroth, 2009; Hague, 1976; Rankel, 2008; Silverman, 2008; Tillier, 2006). Also, empirical research on the TPD – and its building blocks – in an educational context is virtually non-existent. Moreover, there are critical concerns that empirical research on the TPD *in any context* has focused only on overexcitability rather than developmental potential (Tillier, 2006) and also often fails to fully represent Dąbrowski's theory correctly and in depth (Tillier, 2009).

Overexcitability within the TPD

The concept of overexcitability refers to an above average responsiveness to stimuli due to a heightened sensitivity of the central nervous system, which generates a different, more intense, and more multifaceted experience of internal and external reality (Dąbrowski, 1970c, 1972b, 2015; Mendaglio, 2008; Piechowski, 1979, 1999, 2006; Tillier, 2018). Overexcitability constitutes the foundation of powerful perceptivity, which may lead to increased external and, especially, inner conflicts and tension. However, it also enables an individual to envision a higher, universal reality and to be deeply aware of what ought to be (Dąbrowski, 1970a). As such, overexcitability enhances the possibility

of inner mental transformation. The TPD distinguishes five forms of overexcitability – emotional, intellectual, imaginational, sensual, and psychomotor – the first three of which are considered essential to advance personality development (Dąbrowski, 1970a, 1996, 2015) and without which creativity, empathy, autonomy, and authenticity cannot develop (Dąbrowski et al., 1970).

The Overexcitability Questionnaire-Two and its properties

The Overexcitability Questionnaire-Two (OEQ-II) (Falk et al., 1999) is the most widely used self-reporting instrument for measuring the degree and nature of overexcitability. The OEQ-II consists of 50 items, equally representing the five forms of overexcitability. The instrument has been validated in a limited way, using a frequentist approach to statistics and yielding diverse results (Botella et al., 2015; He & Wong, 2014; Siu, 2010; Tieso, 2007b; Van den Broeck et al., 2014).

Multilevelness or a hierarchical organization of human development is the hallmark of Dąbrowski's personality theory (Dąbrowski, 2015; Tillier, 2018). According to the TPD, each form of overexcitability has a different expression depending on the level of personality development. Since the OEQ-II is primarily intended for use in groups (Falk et al., 1999) and the highest levels of personality development are reached by very few people (Dąbrowski, 1964, 2015), it can logically be observed that the items included in the instrument hardly reflect the higher – transcendental – levels.

Deep learning and an autonomy orientation

The concept of autonomy in the TPD and its link with Self-Determination Theory

At the fourth level of development (Organized Multilevel Disintegration) in the TPD, the dynamisms of autonomy and authentism become manifest in the developing individual. The TPD defines "autonomy" as a "dynamism of inner freedom. It signifies a consciously developed independence from lower drives and from the influences of the external environment" (Dąbrowski, 2015, p. 278). "Authenticity" is defined as "a high degree of unity of one's thinking, emotions, and activity," whereas "authentism" denotes "conscious activity in accordance with one's 'inner truth,' i.e., one's autonomously developed hierarchy of values" (Dąbrowski, 2015, p. 277).

The above-mentioned indicators of higher levels of human functioning in the TPD correspond quite closely to the concept of autonomy in SDT. SDT represents an organismic-dialectical metatheory that presupposes human integrative tendencies and centers on the dialectic between the active, autonomy-seeking human organism and the social environment which may support or impede this innate purpose (Deci & Ryan, 2000, 2002). In SDT, the concept of autonomy refers to volition and both reflective and active self-determination in concordance with one's personal values and integrated sense of self (Deci & Ryan, 2000).

According to both the TPD and SDT, the fulfillment of autonomy is fundamental for attaining eudaimonic well-being[1], full human functioning, and essence[2]. The external environment can have, however, a significant impact on the attainment of this human condition (Dąbrowski, 1964, 2015; Dąbrowski et al., 1970; Deci & Ryan, 2000, 2002).

Deep learning and its personal and contextual correlates

In particular, SDT focuses on the effects of the social environment on individuals' intrinsic motivation, with the latter giving rise to self-determined behavior according to inherent interests, as well as self-endorsed and self-affirmed values – or autonomy – leading to inner fulfillment and health (Deci & Ryan, 2002). Specifically with respect to the *educational environment,* intrinsic motivation constitutes an important characteristic of deep learning, the stimulation of which is one of the central goals of education (Entwistle, 1997). Deep-level processing of information – in which the objective is to understand – is characterized by the construction of meaning. In this process, intrinsic interest steers motivation. The features of deep learning also represent important developmental dynamisms for the attainment of higher levels of multilevel disintegration and autonomy in the TPD (Dąbrowski, 1964, 2015). In contrast, surface learning is characterized by a focus on memorization – with the intention to reproduce knowledge – and by extrinsic motivation (Entwistle, 1997; Tait & Entwistle, 1996).

1 In contrast to hedonic well-being, which refers to pleasure or happiness, eudaimonism focuses on "meaning and self-realization and defines well-being in terms of the degree to which a person is fully functioning" (Ryan & Deci, 2001, p. 141). Eudaimonic well-being consists of fulfilling one's true nature (Waterman, 1993) and reflects the ultimate human goal in SDT (Deci & Ryan, 2002) and the TPD.

2 According to Dąbrowski (1976, p. 134), "the essence of man is the unity of the conscious, the chosen, the affirmed and the developing major characteristics of individual personalities."

Various questionnaires have been developed to test these two modes of learning in students. Examples include the Approaches to Studying Inventory (ASI) (Entwistle & Ramsden, 1983), the Study Process Questionnaire (SPQ) (Biggs, 1987), the Inventory of Learning Styles (ILS) (Vermunt, 1994), and the Learning and Motivational Questionnaire (LEMO) (Donche et al., 2010), the latter two of which not only differentiate according to the way in which students process information along the surface/deep spectrum, but also measure their regulation strategies to address self-conscious reflection on studying. Empirical research indicates that learning approaches – as measured by the ASI and SPQ – and learning patterns – as gauged by the ILS and LEMO – are likely to be the result of the interplay between personal attributes and dynamic contextual influences (Entwistle & McCune, 2004; Vermunt, 1996; Vermunt & Donche, 2017; Vermunt & Vermetten, 2004).

A large part of the research on the influence of *personality* on the learning approach draws heavily on the FFM. The FFM is a comprehensive taxonomy of personality traits consisting of five factors (i.e., neuroticism, extraversion, openness to experience, conscientiousness, and agreeableness) that represent the basic dimensions of personality identified in analyses of standard personality measures (Costa & McCrae, 1992a; McCrae & Costa, 1987). However, the FFM-traits have weak explanatory power with regard to approaches to learning, with the most substantial relationship existing between openness and deep learning (Chamorro-Premuzic & Furnham, 2009). Furthermore, some researchers emphasize the importance of considering emotional aspects in the study of learning processes (Entwistle & McCune, 2004; Heikkilä et al., 2011) as research indicates that emotions are substantially related to learning approach, students' motivation, self-regulation, and academic achievement (Pekrun et al., 2002, 2011, 2017). More specifically, positive activating emotions (e.g., hope, pride, and enjoyment, including excitement [Pekrun et al., 2023]) seem to induce deep learning strategies and may strengthen motivation and self-regulation. Negative activating emotions (e.g., anxiety, anger, and shame), on the other hand, appear to lead to surface learning (Pekrun et al., 2002, 2011). Concomitantly, the question arises as to whether the emotive factor of overexcitability can be considered interchangeable with the FFM-traits. The scarce research on associations between these personal characteristics yields diverse results. More specifically, the studies by Limont et al. (2014) and Botella et al. (2015) reveal only weak to moderate relationships, in contrast to the study by Vuyk et al. (2016), which investigated associations between the six openness facets and

the five forms of overexcitability, revealing strong interrelationships. Moreover, Vuyk et al. (2016) argue that there is no justification for the existence of overexcitability as a separate research construct, given the strong research support for the FFM. All of the above-mentioned studies adopted a frequentist approach to statistics and none of the studies that made use of maximum likelihood (ML) estimation in their structural equation model generated good model fit, as measured by the chi-square statistic.

In addition to personal characteristics, *contextual* factors such as course-dependent and lecturer-dependent characteristics, as well as prior education and methods of assessment, also appear to influence the learning process (Donche et al., 2013; Entwistle & McCune, 2004). The scarce research on associations with prior education reveals that higher-level prior education is negatively related to reproduction-directed learning, and lower-level prior education is positively associated with a lack of regulation (Vermunt, 2005; Vermunt & Donche, 2017). An important determinant of the latter negative outcome appears to be the differential study culture that can be found in the various tracks of secondary education. The Differentiation-Polarization Theory (DPT) (Ball, 1981; Hargreaves, 1967; Lacey, 1970; Schafer & Olexa, 1971) posits that educational stratification (i.e., ability grouping or tracking) leads to a polarization of subcultures, with high- and low-ability groups respectively developing pro- and anti-school cultures. The latter is characterized by an undervaluation of educational achievement as a means of compensating for a loss of status. Moreover, this effect is reinforced by a less academically-oriented staff culture, in which lower-track teachers perceive their students as less competent and less teachable and have lower performance expectations, as a consequence of which they relax the learning content and didactics according to these presuppositions (Ball, 1981; Hargreaves, 1967; Ireson & Hallam, 2001; Murphy & Hallinger, 1989; Rosenbaum, 1976). The DPT has only been partially validated in Belgium (Van Houtte, 2004, 2006; Van Houtte & Stevens, 2010), and the findings have not been explored from the developmental perspectives of SDT and the TPD.

Bayesian structural equation modeling

Most educational and psychological questionnaires – like the OEQ-II – exhibit slight cross-loadings and measure additional minor factors beyond those embedded in the instruments, and they therefore cannot be appropriately approached by frequentist confirmatory factor analysis (CFA), which imposes exact parameter constraints. As

a consequence, ML CFA models usually generate poor data fit by postulating non-estimated parameters as exactly zero. Strategies aimed at compensating for this inadequacy are likely to rely on coincidence (MacCallum et al., 1992), and they are thus accompanied by a considerable risk of model misspecification (Muthén & Asparouhov, 2013b).

In contrast, BSEM allows for the inclusion of all cross-loadings and residual covariances in the model – which would lead to a non-identified model in a frequentist analysis – using strong informative priors with zero-mean and small variance (therefore allowing these parameters to vary slightly around zero-means), better reflecting substantive theory and leading to better model fit and more accurate inferences (Muthén & Asparouhov, 2012). According to substantive theory, cross-loadings and residual covariances in CFA models must be approximately zero. However, empirical research indicates that ML CFA models are too strict and do not meet the reality of the existence of small cross-loadings and minor correlated residuals in most psychological and educational instruments. Bayesian analysis makes it possible to incorporate this prior knowledge into parameter estimation. After all, in Bayesian statistics, the population parameter is treated as a random variable. This makes it possible to make probability statements about the value of this parameter – based on substantive theories or previous empirical findings – as reflected in its prior probability distribution. Drawing on Bayes' theorem, observed sampling data will revise this prior knowledge, thereby resulting in the posterior probability distribution of the parameter, which is proportional to the product of the likelihood and the prior distribution (Bolstad, 2007; Kaplan & Depaoli, 2012; Lee, 2007). Strong prior knowledge regarding the population parameter value (applied to CFA, it reflects the requirement for cross-loadings and correlated errors to be approximately zero) is indicated by a small variance of its prior distribution (allowing the aforementioned parameters in CFA to deviate from zero to a very limited extent). In this condition, the data have less impact on the posterior distribution (Muthén & Asparouhov, 2012).

Analogously, the BSEM approach can be applied to the investigation of scalar measurement invariance (MI) across different groups. Scalar MI, as characterized by invariant factor loadings and measurement intercepts across groups, is a prerequisite to compare factor means and factor intercepts (Millsap, 2011; Muthén & Asparouhov, 2013c). The BSEM approach to MI, which is described as approximate MI, offers a valid

alternative to the multi-group CFA approach to MI analysis with ML estimation, which usually results in insufficient fit due to small deviations from exact invariance. In the approximate invariance approach of BSEM, exact zero differences in factor loadings and measurement intercepts across groups are replaced by approximate zero differences based on zero-mean, small-variance priors (Asparouhov & Muthén, 2014; Muthén & Asparouhov, 2013a).

Despite its many advantages over the frequentist approach to statistics (Kruschke et al., 2012), the Bayesian approach remains marginally applied in educational and psychological research (König & van de Schoot, 2018). Moreover, the number of publications in any research domain using Bayesian approximate MI or the alignment optimization method with Bayes estimation to investigate scalar MI across groups is still very limited.

Research questions and sample

Research questions

Drawing on these gaps and opportunities in the research on the TPD and the personal and contextual correlates of deep versus surface learning, this doctoral dissertation addresses several key research questions (RQs), which are briefly specified below and then explained with reference to four studies:

RQs Study 1: Are the emotive factor of overexcitability and, more generally, the developmental potential – representing personality and autonomy drivers in the TPD – related to major indicators of deep learning and an orientation toward autonomy? Do they display stronger associations than the personality traits of the FFM, which does not provide a dynamic growth perspective? Furthermore, is the BSEM approach to statistics more appropriate than the frequentist approach that has been consistently applied in empirical research on the relationship between personality and the learning approach?

RQs Study 2: Applying BSEM with informative, small-variance priors, does the OEQ-II demonstrate good factorial validity and approximate scalar MI across gender? Moreover, compared to the frequentist approach, does the BSEM approach to factorial validation better represent substantive theory and avoid the problem of capitalizing on chance?

Furthermore, in line with the TPD's postulate that personality development involves the integration of multiple forms of overexcitability (Dąbrowski, 1976, 1996, 2015), do all five overexcitabilities load substantially onto a superordinate general construct of positive developmental potential?

RQs Study 3: Are overexcitabilities and, more generally, developmental potential interchangeable with the FFM-personality traits? Moreover, to what extent does the OEQ-II reflect a multilevel perspective consistent with the TPD's thesis of a hierarchical organization of personality development? Furthermore, is the BSEM approach to statistics more appropriate than the frequentist approach that has been consistently applied in research on the interrelationships between overexcitabilities and the FFM-traits?

RQs Study 4: Do students in different educational tracks and with varying educational backgrounds adopt different learning patterns in secondary and higher education, respectively? Based on our data from a large sample of higher education students, are there indications that support the applicability of the DPT in the Belgian context?

Sample

The OEQ-II was added to a large-scale longitudinal study (PROVANT) conducted in Flanders, which represents the Dutch-speaking part of Belgium, investigating the influence of learning patterns on 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 (M = 19.54 years; SD = 0.67) were in the second consecutive year of a program of higher education. In all, 516 students (318 women: 61.6%; 198 men: 38.4%) completed the OEQ-II online. Of these respondents, 356 (69%) had completed general secondary education (GSE) before entering higher education, while 132 (26%) had followed technical secondary education (TSE), 4% had followed vocational secondary education (VSE), and 1% had followed secondary education in the arts (ASE). Almost all of the participants (99%) spoke at least Dutch in the home, while a minority (20%) also used Arabic, Berber, Chinese, German, English, French, Italian, Spanish, or Turkish as their at-home language.

Four studies: Research aims and rationale

Study 1 – Emphasis on emotions in student learning: Analyzing relationships between overexcitabilities and the learning approach using Bayesian MIMIC modeling

Study 1 of this doctoral research contributes to the extant research on associations between *personality* and the learning approach by approximating personality using indicators of overexcitability, the relative presence of which is characteristic of the potential for advanced personality development and the attainment of autonomy according to the TPD. In this research, deep (versus surface) learning is approached through the learning patterns framework. A learning pattern can be described as "a coherent whole of learning activities that learners usually employ, their beliefs about learning and their learning motivation, a whole that is characteristic of them in a certain period of time" (Vermunt & Donche, 2017, p. 270). We made use of the LEMO, which is partially derived from the ILS, to measure the way in which students process information, as well as their regulation strategies and study motivation, in order to derive four learning patterns: the meaning-directed, application-directed, reproduction-directed, and undirected learning patterns (the first and latter two of which refer, respectively, to a deep and a surface approach) (Donche et al., 2010; Vermunt, 1994, 1996, 1998; Vermunt & Minnaert, 2003). In the LEMO, the conceptualization of study motivation is derived from SDT. More specifically, the conceptualization of the motivational variable of autonomous motivation – which is an indicator of the meaning-directed learning pattern – is derived from SDT's concept of intrinsic motivation (Donche et al., 2010). As a consequence, in our research, the association of the TPD with SDT is not only approached theoretically through the premise of the pursuit of autonomy, but also empirically through the learning patterns perspective on student learning.

Specifically, the aim of Study 1 is to investigate – among the samples of 318 female and 198 male higher education students – 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 the TPD, and using BSEM. In this way, an attempt is made to meet the demand from the scientific field to include personal differences other than the FFM-personality traits (Chamorro-Premuzic & Furnham, 2009) as well as emotive factors (Entwistle & McCune, 2004) in the study of

learning processes that may show stronger interrelationships. Although the study is exploratory, we primarily hypothesize a positive relationship between overexcitability and the meaning-directed learning pattern, based on empirically established positive associations between excitement and deep learning (Pekrun et al., 2002, 2011, 2023) and between openness and overexcitabilities, on the one hand (Vuyk et al., 2016), and openness and deep learning, on the other (Chamorro-Premuzic & Furnham, 2009). The hypothetical relationship is also based on theoretical correspondences between the attainment of higher levels of multilevel disintegration – which largely depends on the presence of a strong developmental potential, including overexcitabilities (Dąbrowski, 1964, 2015) – and some characteristics of meaning-directed learning.

Due to critical concerns that most of the empirical research on the TPD focuses only on overexcitability (Tillier, 2006, 2009) and the call from the scientific field for advanced research on all concepts related to the TPD in an integrated way (Mendaglio, 2012, 2022a; Mendaglio & Tillier, 2006), in addition to the five overexcitabilities, intellectual ability (as measured by the Prüfsystem für Schul- und Bildungsberatung Test 3 [PSB-3] [Horn, 1969]) and all interactions are included as covariates in the CFA models – in order to better reflect the developmental potential – with the hypothesis of a positive relationship with meaning-directed learning.

Finally, we hypothesize that BSEM with informative, small-variance priors will perform better than ML SEM, given the complexity of models which rely on learning questionnaire data.

Study 2 – Psychometric evaluation of the Overexcitability Questionnaire-Two applying Bayesian structural equation modeling (BSEM) and multiple-group BSEM-based alignment with approximate measurement invariance

All studies included in this dissertation apply a Bayesian analysis to address the problem of a frequentist approach in complex statistical models. Although BSEM is applied in the (higher order) CFA (with covariates) models in all four studies, using the Mplus software program (Muthén & Muthén, 1998-2017) and hypothesizing a better performance than ML SEM, Study 2 is entirely devoted to this Bayesian approach to statistics.

The main objective of Study 2 is to investigate – among the samples of 318 female and 198 male higher education students – the structural validity of the OEQ-II using BSEM with informative, small-variance priors, and to compare the results of this

Bayesian approach to that of a frequentist approach to validation. We hypothesize that the BSEM models will generate a good fit to the data because they may take into account the existence of trivial cross-loadings in the CFA model and many minor correlated residuals among the factor indicators.

Since the TPD postulates the conjunction of multiple overexcitabilities to arrive at personality development (Dąbrowski, 1976, 1996; Mendaglio, 2012, 2022a), a supplementary aim of Study 2 is to estimate a higher order model with the five overexcitability factors loading on a superordinate general construct of positive developmental potential. Based on the theoretical premise, we hypothesize that all of the five overexcitabilities will load substantially on the general latent construct of positive developmental potential.

The final aim of Study 2 is to investigate approximate invariance of measurement parameters across gender using BSEM. A frequentist approach to MI often proves to be too strict. Therefore, we hypothesize that a Bayesian approach will be a useful alternative for establishing approximate MI across groups.

Study 3 – A rationale for including overexcitability in talent research beyond the FFM-personality dimensions

As emphasized at the outset, a large part of the research on the extent and nature of associations between personality and the learning approach draws upon the FFM. Study 3, which expands on Study 1, therefore delves more deeply into the differential significance of overexcitability in relation to the established personality traits.

Specifically, the first aim of Study 3 is to investigate – among the samples of 318 female and 198 male higher education students – interrelationships between overexcitability, as measured by the OEQ-II, and the personality traits of neuroticism, openness, and conscientiousness, as gauged by the Neuroticism–Extraversion–Openness Five-Factor Inventory (NEO-FFI) (Costa & McCrae, 1992b), from the perspective of personality development according to the TPD, and using BSEM. The rationale behind this study is not only to examine the possible overlap between overexcitability and the FFM-traits, but also to contribute to the scarce research that yields diverse results. In light of the results of the studies by Botella et al. (2015), Limont et al. (2014), and Vuyk et al. (2016), we hypothesize only weak to moderate associations between the five forms of overexcitability and the personality traits of neuroticism, openness, and

conscientiousness, with the most substantial relationship concerning openness. We further hypothesize that BSEM will perform better than ML SEM, given the complexity of models which rely on personality questionnaire data.

The second objective is to investigate the possible presence of distinct factors within the variable of emotional overexcitability. A hierarchical organization of human development is the hallmark of the TPD and, according to Dąbrowski (1970c; Tillier, 2018), each form of overexcitability has a different manifestation depending on the developmental level, noting that overexcitabilities are non-existent at the level of Secondary Integration. 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 with regard to the emotional overexcitability items. Therefore, we hypothesize that a multi-factor exploratory structure will fit the data better than a one-factor structure. A multi-factor structure that reflects the multidimensional process of disintegration would diverge from the FFM, which does not include distinct levels of personality growth.

Study 3 further provides a theoretical discussion of the potential relevance of the concept of overexcitability and the TPD to the domain of giftedness and gifted education. Drawing on the OEQ-II, numerous studies on intensity in gifted and non-gifted individuals have demonstrated associations of intellectual giftedness[3] with intellectual (Bouchet & Falk, 2001; Carman, 2011; Harrison & Van Haneghan, 2011; Limont et al., 2014; Siu, 2010; Tieso, 2007a; Van den Broeck et al., 2014; Wirthwein et al., 2011; Wirthwein & Rost, 2011), imaginational (Carman, 2011; Harrison & Van Haneghan, 2011; Limont et al., 2014; Siu, 2010; Tieso, 2007a), emotional (Bouchet & Falk, 2001; Siu, 2010), sensual (Harrison & Van Haneghan, 2011; Limont et al., 2014; Siu, 2010; Van den Broeck et al., 2014), and psychomotor (Siu, 2010) overexcitability. Similar results were obtained (Ackerman, 1997; Gallagher, 1985; Miller et al., 1994; Pethö, 2022; Piechowski & Colangelo, 1984; Piechowski et al., 1985; Silverman & Ellsworth, 1981) using the open-ended Overexcitability Questionnaire (OEQ) (Lysy & Piechowski, 1983). Despite a positive association, existing research on the relationship between intellectual giftedness and overexcitability – drawing on both the OEQ and OEQ-II – yields diverse

3 The studies we refer to might be categorized within the gifted child paradigm, equating giftedness with high intellectual ability (Dai & Chen, 2021; Rinn, 2023).

results for the five forms of overexcitability. Furthermore, some authors argue that not all gifted individuals exhibit overexcitability (Mendaglio, 2022a; Tillier, 1998; Wells & Falk, 2021), which is consistent with the findings of the studies by Alias et al. (2013) and Gallagher (2022). Based on his clinical research, Dąbrowski (1949, 2015) also reported a substantial degree of overexcitability in groups of intellectually and artistically gifted young people, compared to a control group. Therefore, according to the TPD's propositions, gifted individuals appear to have more potential to arrive at autonomous and authentic personalities (Dąbrowski, 1949, 1970b, 2015; Tillier, 2002).

Study 4 – Are contextual rather than personal factors at the basis of an anti-school culture? A Bayesian analysis of differences in intelligence, overexcitability, and learning patterns between (former) lower and higher-track students

Study 4 delves deeper into the importance of a nurturing educational environment and its reciprocal linkages with emotions and learning effects. Specifically, the first aim of Study 4 – which extends Study 1 by addressing *contextual* factors that affect the learning approach – is to examine any personal differences in intelligence (as measured by the PSB-3) and overexcitabilities (as gauged by the OEQ-II) among the samples of 356 and 132 (former) GSE (higher track) and TSE (lower track) students, respectively. The second research aim is to investigate the consistency of these results with differences in mathematical and verbal achievement (as measured by identical performance tests [De Maeyer et al., 2003] that were administered when the students were at the start of their final year of secondary education, as did the PSB-3 and NEO-FFI) and learning patterns (as gauged by the LEMO), as well as differences in the influence of personal competence indicators on the learning approach among both tracks, all suggesting contextual, educational influences. The underlying rationale is, on the one hand, to contribute to the scarce research on associations between learning patterns and prior education and, on the other hand, to seek confirmation of the applicability of the DPT to Flanders.

The four studies, which all have been published in peer-reviewed international scientific journals, are presented in separate chapters.[4] The final chapter of this dissertation synthesizes the main outcomes of the four studies and provides a comprehensive discussion of them. It concludes with a listing of the key findings and discusses both the limitations of the studies and implications for educational research (mainly) and practice and avenues for future research.

4 This dissertation is a collection of related articles. As each chapter is written to be read on its own, some overlap between chapters is inevitable.

CHAPTER 2

STUDY 1:

Emphasis on emotions in student learning: Analyzing relationships between overexcitabilities and the learning approach using Bayesian MIMIC modeling

This chapter is based on:
De Bondt, N., & Van Petegem, P. (2017). Emphasis on emotions in student learning: Analyzing relationships between overexcitabilities and the learning approach using Bayesian MIMIC modeling. *High Ability Studies, 28*(2), 225–248. https://doi.org/10.1080/13598139.2017.1292897

ABSTRACT

The aim of this study is to investigate interrelationships between overexcitability and learning patterns, from the perspective of personality development according to Dąbrowski'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 Dąbrowski'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.

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, 1992b) 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, 1992b) – and the deep learning approach has been demonstrated in several studies (Chamorro-Premuzic & Furnham, 2009; Chamorro-Premuzic et al., 2007; Furnham et al., 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 et al., 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 et al., 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 et al., 2002, p. 97), and may strengthen motivation and self-regulation (Pekrun et al., 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 et al., 2002).

Authentic learning and personality

Dąbrowski's Theory of Positive Disintegration

Kazimierz Dąbrowski (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 Dąbrowski (1964, 2015; 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).

Dąbrowski 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 Dąbrowski, 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 (Dąbrowski, 1964, 2015; Mendaglio, 2008).

Overexcitabilities

According to Dąbrowski, the developmental potential of an individual depends in part on the extent and nature of psychic intensity. Dąbrowski 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 (Dąbrowski, 1964, 2015; Mendaglio, 2008).

Dąbrowski 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). Dąbrowski 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 et al., 1994), and that gifted individuals can be distinguished according to these three forms of overexcitability (Piechowski et al., 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 et al., 1999), and learning patterns, as gauged by the Learning and Motivational Questionnaire (LEMO) (Donche et al., 2010), from the perspective of personality development according to Dąbrowski'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 et al., 1992), with a large risk of model misspecification (Muthén & Asparouhov, 2013b). 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, 1992b). 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 et al., 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 Dąbrowski'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 et al., 2008; Vrugt & Oort, 2008). In Dąbrowski'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 (Dąbrowski, 1964, 2015; Mendaglio, 2008).

However, the five forms of overexcitability are not equally important with respect to the developmental process (Mendaglio, 2012). Dąbrowski considers emotional, intellectual, and imaginational overexcitability essential to advanced personality development (Dąbrowski, 1972b; 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 Dąbrowski'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).

MATERIALS 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 et al., 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 2.1, the Cronbach's alphas all exceed 80%, thus indicating good reliability, as well as consistency with the results of previous studies.

Table 2.1. 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

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 et al., 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 2.1).

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 2.1, 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.

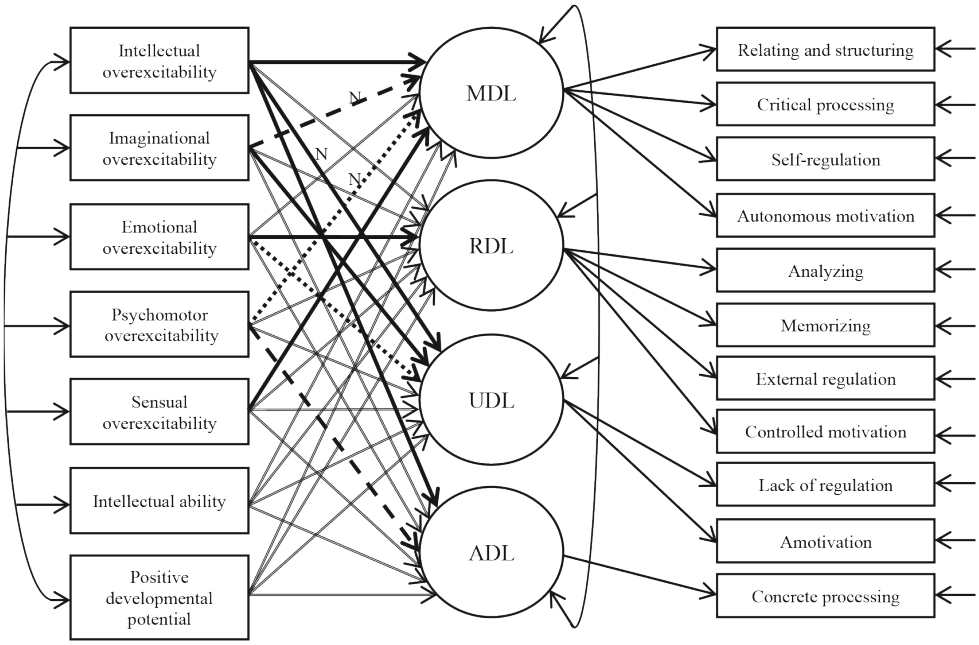

Figure 2.1. Multiple indicators, multiple causes model for females and males. *Note.* MDL = meaning-directed learning; RDL = reproduction-directed learning; UDL = undirected learning; ADL = application-directed learning. The bold lines represent significant – in the sense that the 95% Bayesian credibility 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.

Subsequently, a Bayesian analysis of the MIMIC model was performed with zero-mean and small-variance priors[5] 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 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[6] chain to describe the posterior distribution.

5 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 et al., 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).

6 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).

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 et al., 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 (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 2.1. 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 (see results for intellectual ability).

Maximum likelihood CFA with covariates

Table 2.2 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 2.2. 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.

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

2.2, omitting all non-significant[7] 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 2.3 (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 et al., 2007).

7 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 2.3. 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.

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 et al., 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.

Table 2.4 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 2.4. Bayesian MIMIC model estimation results for the structural parameters for females (n = 318) and males (n = 198).

Parameter	Estimate	Posterior *SD*	One-tailed *p*	95% Credibility Interval	
				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.

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 Dąbrowski'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 Dąbrowski'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 et al., 2002, 2011). Moreover, positive associations between anxiety and the use of rehearsal strategies were found in some studies (Pekrun et al., 2002). According to Dąbrowski, 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 Dąbrowski'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 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 et al., 2011).

According to Dąbrowski, 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 (Dąbrowski, 1964, 1972b; 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 et al., 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. Dąbrowski emphasizes the importance of a supportive environment for facilitating personality development in the case of moderate developmental potential (Mendaglio, 2008). Pekrun et al. (2002) also emphasize the importance of a nurturing educational environment and its reciprocal linkages with emotions and learning effects. In Dąbrowski'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 Dąbrowski, 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.

CHAPTER 3

STUDY 2:

Psychometric evaluation of the Overexcitability Questionnaire-Two applying Bayesian structural equation modeling (BSEM) and multiple-group BSEM-based alignment with approximate measurement invariance

This chapter is based on:
De Bondt, N., & Van Petegem, P. (2015). Psychometric evaluation of the Overexcitability Questionnaire-Two applying Bayesian structural equation modeling (BSEM) and multiple-group BSEM-based alignment with approximate measurement invariance. *Frontiers in Psychology, 6*, 1963. https://doi.org/10.3389/fpsyg.2015.01963

ABSTRACT

The Overexcitability Questionnaire-Two (OEQ-II) measures the degree and nature of overexcitability, which assists in determining the developmental potential of an individual according to Dąbrowski's Theory of Positive Disintegration. Previous validation studies using frequentist confirmatory factor analysis, which postulates exact parameter constraints, led to model rejection and a long series of model modifications. Bayesian structural equation modeling (BSEM) allows the application of zero-mean, small-variance priors for cross-loadings, residual covariances, and differences in measurement parameters across groups, better reflecting substantive theory and leading to better model fit and less overestimation of factor correlations. Our BSEM analysis with a sample of 516 students in higher education yields positive results regarding the factorial validity of the OEQ-II. Likewise, applying BSEM-based alignment with approximate measurement invariance, the absence of non-invariant factor loadings and intercepts across gender is supportive of the psychometric quality of the OEQ-II. Compared to males, females scored significantly higher on emotional and sensual overexcitability, and significantly lower on psychomotor overexcitability.

INTRODUCTION

Overexcitability within Dąbrowski's Theory of Positive Disintegration

Kazimierz Dąbrowski (1902-1980), a Polish psychiatrist and psychologist, developed the Theory of Positive Disintegration, which centers on heightened excitability in individuals, as well as on their drive, and their urge to resist conformity and complacency (Daniels & Piechowski, 2009). According to Dąbrowski (1964, 1972b; 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).

According to Dąbrowski, the developmental potential of an individual depends in part on the extent and nature of psychic intensity. Dąbrowski 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 (Dąbrowski, 1964, 1972b; Mendaglio, 2008). Dąbrowski distinguishes five forms of overexcitability. Psychomotor overexcitability represents "a surplus of energy or the expression of emotional tension through general hyperactivity" (Silverman, 2008, p. 160). Manifestations include an abundance of physical energy, work addiction, nervous habits, rapid speech, love of movement, 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). Dąbrowski considers the last three forms of overexcitability essential to advanced personality development (Dąbrowski, 1972b; Mendaglio, 2008).

The Overexcitability Questionnaire-Two and its psychometric properties

Falk et al. (1999) developed a self-report questionnaire to measure the degree and nature of overexcitability. The Overexcitability Questionnaire-Two (OEQ-II) continues to be used primarily in research positioned within the domain of giftedness. Numerous studies on intensity in gifted and non-gifted students have demonstrated associations of giftedness with intellectual (Bouchet & Falk, 2001; Carman, 2011; Harrison & Van Haneghan, 2011; Siu, 2010; Tieso, 2007a; Van den Broeck et al., 2014; Wirthwein et al., 2011; Wirthwein & Rost, 2011), imaginational (Carman, 2011; Harrison & Van Haneghan, 2011; Siu, 2010; Tieso, 2007a), and emotional (Bouchet & Falk, 2001; Siu, 2010) overexcitability. The OEQ-II has been translated into Turkish, Chinese, Korean, Spanish, French, and Dutch (Botella et al., 2015; Falk et al., 2008; He & Wong, 2014; Siu, 2010; Van den Broeck et al., 2014). Empirical research has revealed that emotional, intellectual, and imaginational overexcitability are important indicators and predictors of advanced personality development (Falk & Miller, 2009).

Despite the rising tendency in empirical research to use the OEQ-II as a supplementary measure of dispositional traits, the instrument has been validated in a limited way. Falk et al. (1999, p. 2) developed the easily administered and scored OEQ-II by incorporating the results of numerous prior studies on hyperexcitability, "including responses to deep reflex stimulation, open-ended responses to verbal stimuli, assessment in autobiographical material, and an open-ended questionnaire." The authors investigated the structural validity of the questionnaire via principal components factor analysis using varimax rotation. A stable and conceptually clear five-factor structure was retrieved with factor loadings above 0.50, and good internal consistency among the items indicative of the same factor was found for the two samples under study (Falk et al., 1999).

Van den Broeck et al. (2014) investigated the factorial structure of the OEQ-II (Dutch translation), using exploratory structural equation modeling (ESEM) (Asparouhov & Muthén, 2009) with weighted least squares estimation and oblique target rotation. The highly restrictive independent clusters model used in the confirmatory factor analysis (CFA), in which each indicator is allowed to load on only one factor and all non-target loadings are constrained to zero (Marsh et al., 2009), led to model rejection. Model testing using ESEM, in which the five correlated overexcitability factors were measured by each of the 50 items, yielded a partly satisfactory model fit. Modification indices were inspected in order to improve the model by including two residual covariances, ultimately leading to an acceptable fit to the data. This study further examined measurement invariance across intelligence levels and gender using an ESEM-Within-CFA approach (Marsh et al., 2013). This analysis established partial strict measurement invariance of the OEQ-II scores across the different groups. The researchers concluded that the non-invariant parameters do not considerably affect group comparisons because of their small proportionality.

Warne (2011) also investigated measurement invariance of the OEQ-II scores across gender using a multi-group CFA approach and maximum likelihood estimation, but the study could not establish metric invariance.

Botella et al. (2015) examined the structural validity of the French OEQ-II using CFA and maximum likelihood estimation. Instead of freeing "an important number of cross-loadings and residual covariances" (Botella et al., 2015, p. 211), the researchers first reduced the instrument to a 35-item version and concluded that a model with "five correlated factors with residual covariances" yields a better fit to the data compared to a "one second-order factor" model. Other studies that used CFA and maximum likelihood estimation to establish the construct validity of the OEQ-II also resulted in moderate model fit (He & Wong, 2014; Siu, 2010; Tieso, 2007b).

Bayesian structural equation modeling

In contrast to frequentist statistics, which ignores prior knowledge for hypothesis testing, Bayesian statistics relies on Bayes' theorem to update prior knowledge given the data. In maximum likelihood estimation, the parameters of the population are fixed but unknown, and the estimates of those parameters from a sample of the population are random but known. In Bayesian statistics the parameter of the population is considered

random, allowing probability statements to be made about its value, as expressed in the prior distribution. Using Bayes' theorem, observed sampling data will revise this prior knowledge, leading to the posterior distribution of the parameter (Bolstad, 2007; Kaplan & Depaoli, 2012; Lee, 2007). 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 et al., 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). The Bayesian credibility interval[8], based on the percentiles of the posterior distribution, allows direct probability statements about the parameter, in contrast to the confidence interval in frequentist theory, which is contingent on the hypothesis of extensive repeated sampling from the population (Bolstad, 2007; Kaplan & Depaoli, 2012;

8 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. In this study, which used Bayesian analysis as a pragmatic approach, a (null) hypothesis testing perspective (Arbuckle, 2013; Zyphur & Oswald, 2015) was used in parameter estimation by evaluating whether the 95% credibility interval of the model parameters encompassed zero. 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).

Zyphur & Oswald, 2015). The posterior distribution $P(\theta|z)$ yields maximum information about the parameter given the data – "unlike the point estimate and confidence interval in classical statistics, which provide no distributional information" (Kruschke et al., 2012, p. 725). Using a small variance prior, which reflects strong prior knowledge, the data will tend to contribute less information to the construction of the posterior distribution (Muthén & Asparouhov, 2012).

Recently, computational methods (e.g., the Gibbs algorithm) have been developed to draw random samples from the posterior distribution, allowing the practical use of Bayesian statistics (Bolstad, 2007), and leading to strong and increasing interest in this approach to statistics (Kruschke, 2015).

Meanwhile, Muthén and Asparouhov (2012) proposed an innovative approach to factor analysis using Bayesian structural equation modeling (BSEM), which better reflects substantive theory. Many psychological instruments cannot be adequately represented within a frequentist CFA approach, in which each item is allowed to load on one factor and all non-target loadings are fixed at zero (Marsh et al., 2009). Strategies to compensate for this inappropriateness may capitalize on chance (MacCallum et al., 1992), with a large risk of model misspecification (Muthén & Asparouhov, 2013b). In BSEM, parameter specifications of exact zeros are replaced by approximate zeros based on "informative, small-variance priors to reflect the researcher's theories and prior beliefs" (Muthén & Asparouhov, 2012, p. 316).

In the same way, Muthén and Asparouhov (2013a) propose the BSEM approach to measurement invariance analysis across different groups, in which exact zero differences in factor loadings and intercepts are replaced by approximate zero differences based on zero-mean, small-variance priors. "Measurement invariance is built on the notion that a measuring device should function in the same way across varied conditions, so long as those varied conditions are irrelevant to the attribute being measured" (Millsap, 2011, p. 1). With reference to psychological questionnaires, this implies that in order to test for mean differences across groups, the assumption of equivalent measurement of the underlying construct must be fulfilled. Scalar invariance, as characterized by invariant factor loadings and measurement intercepts, is a prerequisite to compare factor means and factor intercepts across groups (Millsap, 2011; Muthén & Asparouhov, 2013c; Vandenberg & Lance, 2000). The BSEM approach to measurement invariance is referred to as approximate measurement invariance

and provides a valuable alternative to the multi-group CFA approach to measurement invariance analysis with maximum likelihood estimation (Asparouhov & Muthén, 2014; Muthén & Asparouhov, 2013a), which mostly results in unsatisfactory fit due to minor deviations from exact invariance (Muthén & Asparouhov, 2012). Results of simulation studies indicate that BSEM with approximate measurement invariance is a suitable technique for proper estimation and comparison of factor means and variances across multiple groups that may have non-invariant measurement parameters with minor variance, "without relaxing the invariance specifications or deleting non-invariant items" (Muthén & Asparouhov, 2013a, p. 7; van de Schoot et al., 2013).

Aim of this study

The first and main objective of this study is to investigate the structural validity of the OEQ-II using BSEM with informative, small-variance priors, and to compare the results of this Bayesian approach to that of a frequentist approach to validation. We hypothesize that maximum likelihood CFA and ESEM models will generate poor data fit by postulating non-estimated parameters as exactly zero. The results of previous validation studies indicate that the OEQ-II – like most psychological instruments – exhibits slight cross-loadings and measures several supplementary minor personality factors in addition to the five overexcitabilities. 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 et al., 1992). 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 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.

The second aim of the study is to explore in greater depth the interrelationships between the five overexcitabilities by estimating a higher order model based on theoretical expectations and using Bayesian estimation. Mendaglio and Tillier (2006) strongly advocate the conceptualization of overexcitability within the overall context of development potential in future quantitative studies. According to Dąbrowski, an

individual's developmental potential is comprised of overexcitability, specific talents and abilities, and a strong autonomous drive to achieve individuality (Dąbrowski, 1964, 1972b; Mendaglio, 2008). However, the five forms of overexcitability are not equally important with respect to the developmental process (Mendaglio, 2012). Dąbrowski considers emotional, intellectual, and imaginational overexcitability essential to advanced personality development (Dąbrowski, 1972b; 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, "such that their energy is harnessed in the service of the developmental process" (Mendaglio, 2012, p. 212). The exclusive presence of psychomotor and sensual overexcitability constitutes negative developmental potential, which impedes the transcendence of biological needs and societal norms that is considered to be fundamental for the development of autonomy, authenticity, and empathy (Dąbrowski, 1972b; Mendaglio, 2012). Based on these theoretical considerations we hypothesize that all of the five overexcitabilities will load substantially on a superordinate general construct of positive developmental potential.

The final objective of this study is to investigate approximate invariance of measurement parameters across gender using BSEM. A CFA approach to measurement invariance often proves to be too strict, leading to model rejection and a long series of modifications of the model with a substantial risk of misspecification (Asparouhov & Muthén, 2014). Using an ESEM-Within-CFA approach, the study by Van den Broeck et al. (2014, p. 64) revealed partial strict measurement invariance across gender: "five items showed larger unique variances for girls than for boys, seven thresholds out of 200 were noninvariant, and only 12 out of 250 factor loadings were noninvariant." Because of the small proportionality of non-invariant parameters, we hypothesize that the BSEM approach will be a useful alternative to establish approximate measurement invariance across gender.

All analyses were carried out using the Mplus software program (Version 7.3; Muthén & Muthén, 1998-2012).

MATERIALS AND METHODS

Participants

The Overexcitability Questionnaire-Two (OEQ-II) (Falk et al., 1999) 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 self-report measure 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. 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. In all, 516 students (318 women: 61.6%; 198 men: 38.4%) completed the OEQ-II online. Of these respondents, 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. Two-thirds of the students were 19 years of age at the time of the survey, while 17% were 18 years old, 10% were 20 years old, and 6% were between 21 and 23 years of age. The study was executed in accordance with the guidelines of the Ethics Committee for the Social Sciences and Humanities of the University of Antwerp with written informed consent from all subjects.

Instrument

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." A high value on the scale of the items represents a high level of overexcitability.

Significant interrelationships have been found between gender and the extent and nature of overexcitability, as measured by the OEQ-II. A relatively strong association of

emotional and sensual overexcitability with the female gender appears to be a general empirical finding (Botella et al. 2015; Bouchet & Falk, 2001; He & Wong, 2014; Miller et al., 2009; Siu, 2010; Tieso, 2007a, 2007b; Treat, 2006; Van den Broeck et al., 2014; Wirthwein et al., 2011). There is also evidence of a stronger relationship between the dispositional traits of intellectual (Botella et al., 2015; Bouchet & Falk, 2001; Miller et al., 2009; Rinn et al., 2010; Siu, 2010; Treat, 2006; Van den Broeck et al., 2014) and psychomotor (Botella et al., 2015; Bouchet & Falk, 2001; He & Wong, 2014; Rinn et al., 2010; Treat, 2006; Van den Broeck et al., 2014) overexcitability and the male gender. Because of these interrelationships, statistical analyses will be performed for the different gender groups separately.

MCMC convergence

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, 1998-2012). 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, 2013), is evaluated via the potential scale reduction (PSR) convergence criterion (Gelman et al., 2014; Gelman & Rubin, 1992). The PSR criterion compares within- and between-chain variation of parameter estimates. 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, 1998-2012). With a large number of parameters, a PSR value of less than 1.100 for each parameter indicates that convergence of the MCMC sequence has been obtained (Muthén & Muthén, 1998-2012).

Convergence of the MCMC algorithm in distribution is assessed via monitoring of the posterior distributions by trace and autocorrelation plots (Muthén & Muthén, 1998-2012). Posterior parameter trace plots display the sampled parameter values over time. Quick up-and-down fluctuations and absence of long-term trends in the plot indicate rapid convergence in distribution (Arbuckle, 2013; Kaplan & Depaoli, 2012).

Autocorrelation plots also display the degree of non-independence of successive posterior draws in the MCMC chains (Kaplan & Depaoli, 2012; Muthén & Muthén, 1998-

2012). An estimated correlation between the sampled parameter values reaching zero indicates convergence (Arbuckle, 2013).

Analyses

Before performing a Bayesian analysis of the OEQ-II model, a maximum likelihood analysis was carried out for comparison purposes. Using maximum likelihood estimation, a CFA model was tested – according to the OEQ-II's hypothesized latent factor loading pattern for the 50 observed variables – and an exploratory factor analysis (EFA) for five factors was performed using ESEM with oblique Geomin rotation. In the ESEM model, the five correlated factors were measured by each of the 50 factor indicators and the residuals were not correlated.

Subsequently, a Bayesian analysis was performed using the CFA model, albeit with informative, small-variance priors for the cross-loadings in the model and uncorrelated residuals. 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. Applying the Bayes estimator and Gibbs algorithm, two independent MCMC chains with 10,000 iterations were used to describe the posterior distribution. The factor variances were fixed at one to set the metric of the factors, and standardized variables were analyzed.

In the next step, a Bayesian analysis was performed using informative, small-variance priors for cross-loadings and residual covariances in the CFA model. In this BSEM analysis, normal prior distributions $N(0, 0.01)$ were used for the cross-loadings, admitting ignorable effect sizes (Muthén & Asparouhov, 2012). An inverse-Wishart prior distribution $IW(0, df)$ with $df = 56$ was applied for the correlated residuals, corresponding to prior zero-means and variances of 0.01 (MacKinnon, 2008). In this 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 chain to describe the posterior distribution. A sensitivity analysis was carried out, in which the effect of varying the prior variances of the residual covariances on the parameter estimates and model fit was investigated.

In relation to the second aim of this study, a higher order model was estimated – according to the hypothesized latent factor loading pattern, as represented in Figure 3.1 – using BSEM with informative, small-variance priors for the cross-loadings $\lambda \sim N(0, 0.01)$ and residual covariances $\delta \sim IW(0, 56)$ in the measurement model. In the hypothetical model, the latent variable of positive developmental potential was operationalized according to the five overexcitability factors.

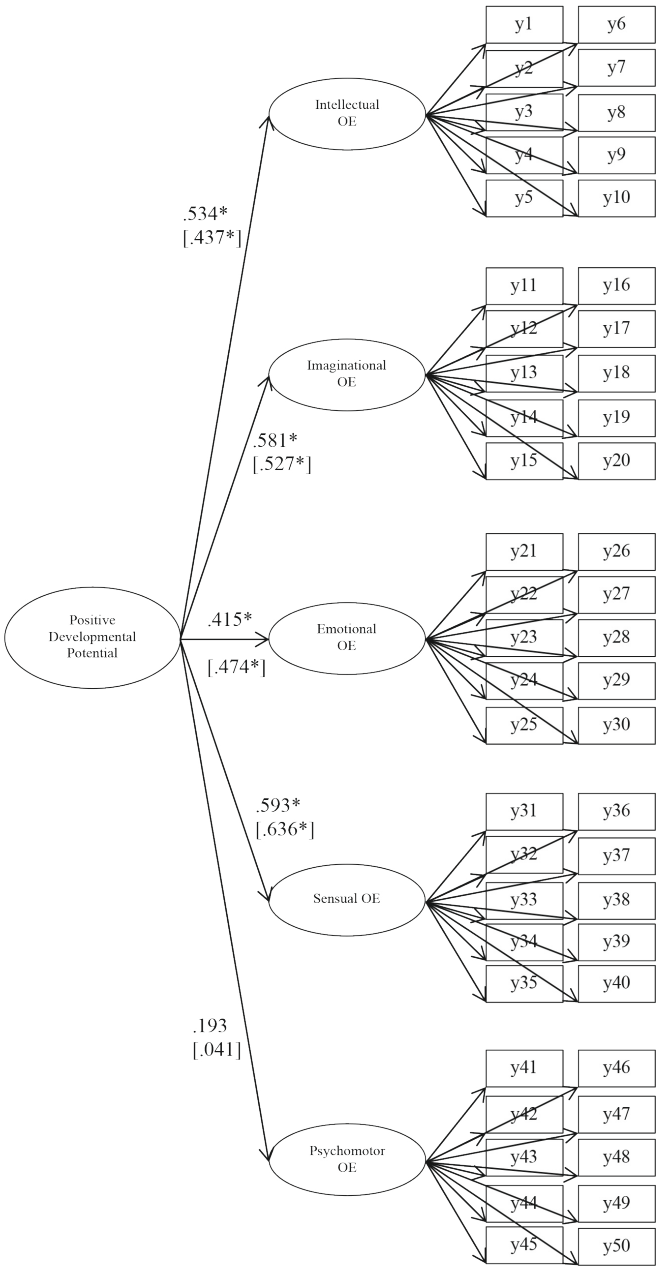

Figure 3.1. Higher order BSEM model with informative, small-variance priors for cross-loadings and residual covariances for the Overexcitability Questionnaire-Two (OEQ-II; Falk et al., 1999) data for females and males (second-order factor loadings are added within parentheses).
Note. OE = overexcitability; BSEM = Bayesian structural equation modeling.
* Significance at the 5% level in the sense that the 95% Bayesian credibility interval does not cover zero.

Finally, a Bayesian multiple-group model with approximate measurement invariance (Muthén & Asparouhov, 2013a) was carried out. One categorical latent variable with two known classes (i.e., male and female) was specified in this BSEM model. Normally distributed priors $N(0, 0.01)$ were utilized for differences in intercepts and factor loadings across groups. Non-informative or diffuse priors were used for factor means, variances, and covariances across groups with the exception of factor means and variances in the male group, which were set at zero and one, respectively. Residuals were correlated, using an inverse-Wishart prior distribution $IW(0, 16)$, corresponding to prior zero-means and variances of 0.01. Analyses were executed for each overexcitability factor and the alignment optimization method with Bayes estimation (Asparouhov & Muthén, 2014) was applied, which optimizes alignment "of the measurement parameters, factor loadings and intercepts/thresholds according to a simplicity criterion that favors few non-invariant measurement parameters," and subsequently adjusts "the factor means and variances in line with the optimal alignment" (Muthén & Muthén, 2013, p. 2). The alignment optimization method provides a solution to a parameterization indeterminacy, in which (few) non-invariant parameters are underestimated and (many) invariant parameters are overestimated, due to non-normally distributed deviations from a parameter average over groups resulting in the misestimation of factor means and variances (Muthén & Asparouhov, 2013a). In this BSEM multiple-group analysis, every tenth iteration was saved with a maximum and minimum number of iterations for each of two MCMC chains of 50,000 and 1,000, respectively, using the Gelman-Rubin PSR < 1.05 criterion (Gelman & Rubin, 1992).

Model fit assessment

The following fit measures were used as a means of evaluating the quality of the fit of both CFA and EFA models: 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 models, 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, 1998-2012; Scheines et al., 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 (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 five overexcitability factors are reported per gender group in Table 3.1. The 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).

Table 3.1. Descriptive statistics per overexcitability factor for females and males.

	Females					Males				
	IOE	**ImOE**	**EOE**	**SOE**	**POE**	**IOE**	**ImOE**	**EOE**	**SOE**	**POE**
Mean	3.450	2.809	3.737	3.295	3.233	3.540	2.708	3.162	3.112	3.380
Standard Deviation	0.591	0.779	0.572	0.736	0.714	0.538	0.663	0.617	0.691	0.700
Skewness	-0.035	0.220	-0.245	-0.147	0.105	0.161	0.148	-0.097	0.041	-0.253
Kurtosis	0.102	-0.195	-0.153	-0.175	-0.217	-0.128	-0.245	0.148	0.054	-0.094

Note. IOE = intellectual overexcitability; ImOE = imaginational overexcitability; EOE = emotional overexcitability; SOE = sensual overexcitability; POE = psychomotor overexcitability.

Confirmatory and exploratory factor analysis

Table 3.2 shows the chi-square statistic, CFI, and RMSEA for the evaluation of both maximum likelihood CFA and EFA models. Highly significant chi-square statistics,

RMSEA values of more than 0.05, and CFI values of less than .90 all indicate that the CFA and EFA models for females and males fit the data poorly. Moreover, as represented in Table 3.3, the hypothesized five factor pattern is not fully recovered by the EFA results for females and males. Several significant (at the 5% significance level) cross-loadings on other latent factors can be detected. The hypothesized factor loading pattern is not well captured by the EFA model, possibly due to the existence of many minor correlated residuals among the factor indicators (Muthén & Asparouhov, 2012), as can be expected from inspection of the modification indices.

Table 3.2. Maximum likelihood CFA and EFA model testing results for females (n = 318) and males (n = 198).

Model	χ^2	*df*	*p*-value	RMSEA	CFI
Females					
CFA	2565	1165	0.000	0.061	0.767
EFA	1934	985	0.000	0.055	0.842
Males					
CFA	2174	1165	0.000	0.066	0.712
EFA	1660	985	0.000	0.059	0.807

Note. CFA = confirmatory factor analysis; EFA = exploratory factor analysis; *df* = degrees of freedom; RMSEA = root mean square error of approximation; CFI = comparative fit index.

Table 3.3. Maximum likelihood EFA model estimation results for females (n = 318) and males (n = 198).

Factor Loadings										
	Females					**Males**				
	F1	**F2**	**F3**	**F4**	**F5**	**F1**	**F2**	**F3**	**F4**	**F5**
y1	**0.467***	0.086	-0.120	-0.018	-0.058	**0.405***	0.163	0.101	-0.021	-0.034
y2	0.011	**0.135***	0.041	0.030	0.023	-0.042	**0.263***	-0.041	0.079	0.032
y3	**0.498***	-0.031	0.117	0.153*	-0.024	**0.550***	-0.041	0.026	-0.017	-0.123
y4	**0.599***	0.038	0.029	-0.055	0.018	**0.476***	-0.080	0.027	0.221*	-0.064
y5	**0.504***	0.044	0.016	0.146*	0.003	**0.443***	-0.013	0.133	0.021	-0.170*
y6	**0.589***	0.073	0.061	-0.060	-0.007	**0.425***	0.251*	0.005	0.042	-0.113
y7	**0.667***	-0.115*	-0.100	-0.002	0.126*	**0.652***	-0.023	-0.101	0.070	0.088
y8	**0.610***	-0.003	0.162*	0.113*	-0.056	**0.607***	-0.012	0.145*	0.068	-0.069
y9	**0.575***	-0.004	0.034	0.169*	0.013	**0.558***	0.079	0.121	-0.142	0.058
y10	**0.685***	-0.031	0.102	-0.044	0.014	**0.694***	0.050	-0.001	0.112	0.025
y11	0.008	**0.480***	0.084	0.075	-0.026	**0.361***	0.291*	-0.010	-0.047	-0.045
y12	0.006	**0.631***	0.110	0.011	0.051	0.223*	**0.429***	0.025	0.144	-0.147*
y13	-0.052	**0.466***	0.173*	0.059	-0.085	0.254*	**0.382***	0.037	-0.048	0.058
y14	0.037	**0.569***	-0.058	0.040	-0.076	-0.041	**0.582***	0.023	-0.072	0.066
y15	0.029	**0.664***	0.074	-0.068	0.099*	0.005	**0.442***	0.001	0.157	-0.084
y16	-0.011	**0.725***	0.010	-0.027	0.026	0.084	**0.744***	-0.039	-0.017	0.029
y17	0.062	**0.570***	-0.048	0.044	0.038	0.082	**0.563***	-0.110	-0.019	0.171*
y18	0.000	**0.504***	0.119	-0.055	0.032	-0.252*	**0.506***	0.002	0.272*	-0.037
y19	0.045	**0.546***	0.212*	-0.029	0.101*	-0.123	**0.455***	0.026	0.425*	0.017
y20	0.076	**0.410***	0.353*	-0.014	-0.082	0.180*	**0.354***	-0.022	0.255*	-0.117
y21	0.236*	-0.012	0.041	**0.577***	0.038	0.104	-0.082	**0.571***	-0.059	-0.001
y22	-0.132	0.303*	-0.106	**0.402***	-0.007	0.061	-0.010	**0.492***	-0.046	0.001
y23	0.036	-0.023	0.010	**0.477***	0.125*	-0.007	-0.024	**0.571***	-0.058	0.078
y24	0.172*	0.147*	-0.038	**0.185***	0.184*	0.025	**0.270***	0.079	0.248*	0.140*
y25	0.012	**0.537***	-0.140*	0.412*	-0.068	0.101	0.359*	**0.389***	0.012	-0.012
y26	0.143*	0.008	0.051	**0.605***	0.051	0.021	0.005	**0.847***	0.029	0.006
y27	-0.020	0.406*	0.027	**0.468***	0.062	-0.175*	**0.471***	0.311*	0.118	-0.074
y28	0.240*	0.323*	-0.052	**0.486***	-0.061	0.179*	0.039	**0.351***	0.082	0.028
y29	-0.101	-0.084	0.210*	**0.633***	0.009	0.038	-0.105	**0.507***	0.041	-0.016
y30	0.126	0.138*	0.050	**0.347***	0.031	-0.040	0.110	**0.462***	0.220*	0.045

Table 3.3. *Continued.*

Factor Loadings										
	Females					**Males**				
	F1	**F2**	**F3**	**F4**	**F5**	**F1**	**F2**	**F3**	**F4**	**F5**
y31	0.188*	0.025	**0.465***	-0.071	0.188*	0.308*	-0.076	-0.001	**0.465***	-0.007
y32	0.134*	0.037	**0.583***	-0.132*	-0.025	0.068	0.015	0.046	**0.644***	-0.067
y33	0.189*	0.004	**0.555***	-0.088	-0.018	-0.071	0.072	0.127*	**0.756***	-0.058
y34	-0.056	0.208*	**0.264***	0.114	0.111*	0.133	0.094	0.090	**0.179***	0.084
y35	-0.038	0.221*	**0.657***	-0.040	0.005	0.003	0.325*	-0.054	**0.543***	0.008
y36	0.252*	0.032	**0.472***	0.113*	0.028	0.185*	0.061	0.227*	**0.420***	0.107
y37	-0.023	-0.073	**0.741***	0.141*	-0.021	0.153	-0.028	0.033	**0.462***	0.042
y38	0.000	0.026	**0.834***	0.062	-0.001	0.184*	-0.043	-0.029	**0.794***	0.008
y39	0.056	0.030	**0.692***	0.029	-0.036	0.233*	0.091	-0.061	**0.453***	0.110
y40	0.184*	0.033	**0.495***	0.030	0.027	-0.002	0.037	0.189*	**0.392***	0.124
y41	0.282*	0.058	**-0.295***	-0.019	0.289*	0.255*	-0.097	-0.014	-0.093	**0.342***
y42	0.007	-0.072	-0.058	0.093*	**0.753***	0.145*	-0.082	-0.033	0.036	**0.799***
y43	-0.019	-0.104*	0.001	0.041	**0.832***	-0.012	-0.112	-0.013	0.118*	**0.871***
y44	-0.057	-0.034	0.003	0.058	**0.751***	0.009	-0.007	0.127*	-0.029	**0.789***
y45	0.098	0.065	-0.045	-0.181*	**0.614***	-0.072	-0.007	0.009	0.087	**0.594***
y46	-0.032	0.195*	0.042	-0.016	**0.419***	-0.083	0.180*	0.155	-0.094	**0.353***
y47	-0.073	0.275*	0.114*	-0.064	**0.503***	-0.131	0.293*	0.029	0.023	**0.579***
y48	-0.049	0.063	-0.041	0.149*	**0.612***	-0.009	0.136	0.131	-0.177*	**0.514***
y49	0.073	-0.097	0.053	0.013	**0.691***	-0.040	-0.037	0.215*	0.076	**0.408***
y50	0.086	0.058	-0.002	-0.036	**0.707***	0.066	0.040	-0.071	-0.150*	**0.653***
Factor Correlations										
	Females					**Males**				
	F1	**F2**	**F3**	**F4**	**F5**	**F1**	**F2**	**F3**	**F4**	**F5**
F1	1.000					1.000				
F2	0.292*	1.000				0.036	1.000			
F3	0.345*	0.325*	1.000			0.226*	0.228*	1.000		
F4	0.082	0.057	0.083	1.000		0.252*	0.344*	0.252*	1.000	
F5	0.133*	0.114*	0.010	0.126*	1.000	-0.040	-0.056	0.139	-0.038	1.000

Note. EFA = exploratory factor analysis; F1 = factor 1; F2 = factor 2; F3 = factor 3; F4 = factor 4; F5 = factor 5. The standardized coefficients in bold represent factor loadings that are the largest for each factor indicator.
*$p < .05$.

BSEM with informative, small-variance priors for cross-loadings

Table 3.4 presents the fit results of the BSEM model with informative, small-variance priors for cross-loadings for both gender groups. The 95% CIs for the difference between the observed and replicated chi-square values do not cover zero, and the PP*p*s are smaller than 0.05, both indicating unsatisfactory model fit. The results of this BSEM model, which are not reported, still reveal significant[9] (in the sense that the 95% Bayesian credibility interval does not encompass zero) but fewer cross-loadings and slightly higher major factor loadings, as compared with the EFA model. Increasing the variance of the prior distributions of the cross-loadings does not alter the fit results considerably. We may assume that the OEQ-II measures several supplementary minor personality factors in addition to the five overexcitabilities. On the one hand, freeing all residual covariances would lead to a non-identified model (Muthén & Asparouhov, 2012), which in Bayesian analysis may hinder MCMC convergence; on the other hand, modifying the model using modification indices in a frequentist analysis may capitalize on chance (MacCallum et al., 1992), with a large risk of model misspecification (Muthén & Asparouhov, 2013b).

Table 3.4. Bayesian model testing results for females (n = 318) and males (n = 198).

Model	PP *p*	95% CI
Females		
CFA with cross-loadings	0.000	770.367-994.541
CFA with cross-loadings and residual covariances	0.767	-199.724-93.706
Males		
CFA with cross-loadings	0.000	448.610-682.850
CFA with cross-loadings and residual covariances	0.905	-248.311-50.020

Note. PP *p* = posterior predictive probability; CI = confidence interval; CFA = confirmatory factor analysis.

9 As previously mentioned in footnote 8, a hypothesis testing perspective was used in this study. 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.

BSEM with informative, small-variance priors for cross-loadings and residual covariances

Subsequently, a Bayesian analysis was performed using informative, small-variance priors for cross-loadings and residual covariances. As represented in Table 3.4, the 95% CIs for the difference between the observed and the replicated chi-square values cover zero and the PP*p*s are 0.767 and 0.905 for the female and male group, respectively, both indicating good model fit. Figure 3.2A presents the distribution of the difference between the observed and the replicated chi-square values for the female group. The matching scatterplot (see Figure 3.2B), with the majority of the points plotted along the 45 degree line, indicates satisfactory model fit for the observed data.

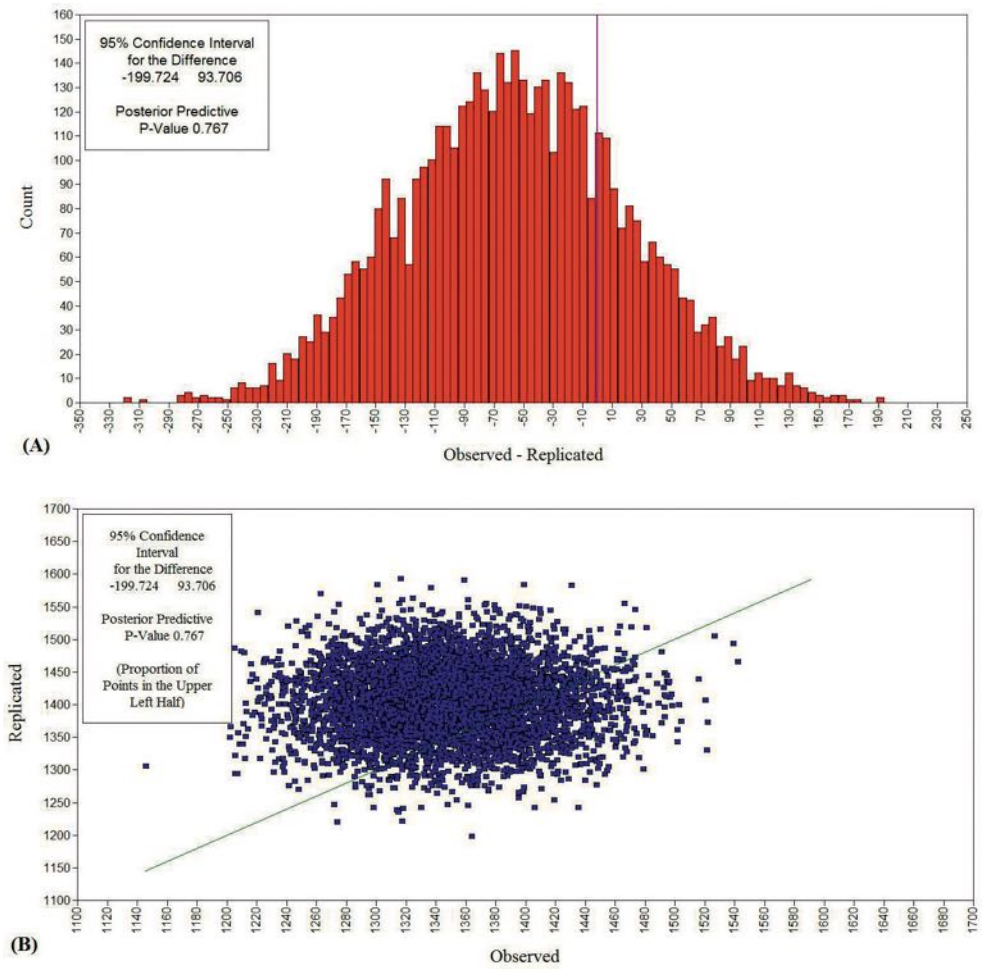

Figure 3.2. Bayesian posterior predictive checking distribution plot (A) and scatterplot (B) for the Bayesian model with small-variance priors for cross-loadings and residual covariances for females. *Note.* In the posterior predictive checking distribution plot, the chi-square statistic for the observed data is marked by the vertical line, which corresponds to a zero value on the *x*-axis. The matching scatterplot allows determining the PP*p* as the proportion of points above the 45 degree line.

Good MCMC convergence was established for the two models. The PSR value smoothly decreased over the iterations, reaching a value of 1.010 after half of the iterations. Additionally, the stability of the parameter estimates across the iterations was verified. Figure 3.3 presents posterior parameter trace and autocorrelation plots for the loading of item y10 on the intellectual overexcitability factor for the male group. The trace plot (see Figure 3.3A) displays a stable, horizontal band for the parameter

presented, indicating convergence of the MCMC algorithm in distribution. The autocorrelation plot (see Figure 3.3B) displays low autocorrelation or approximate non-independence of successive posterior samples. The posterior parameter trace and autocorrelation plots for the other parameters included in the models (not reported) were also indicative of good convergence in distribution.

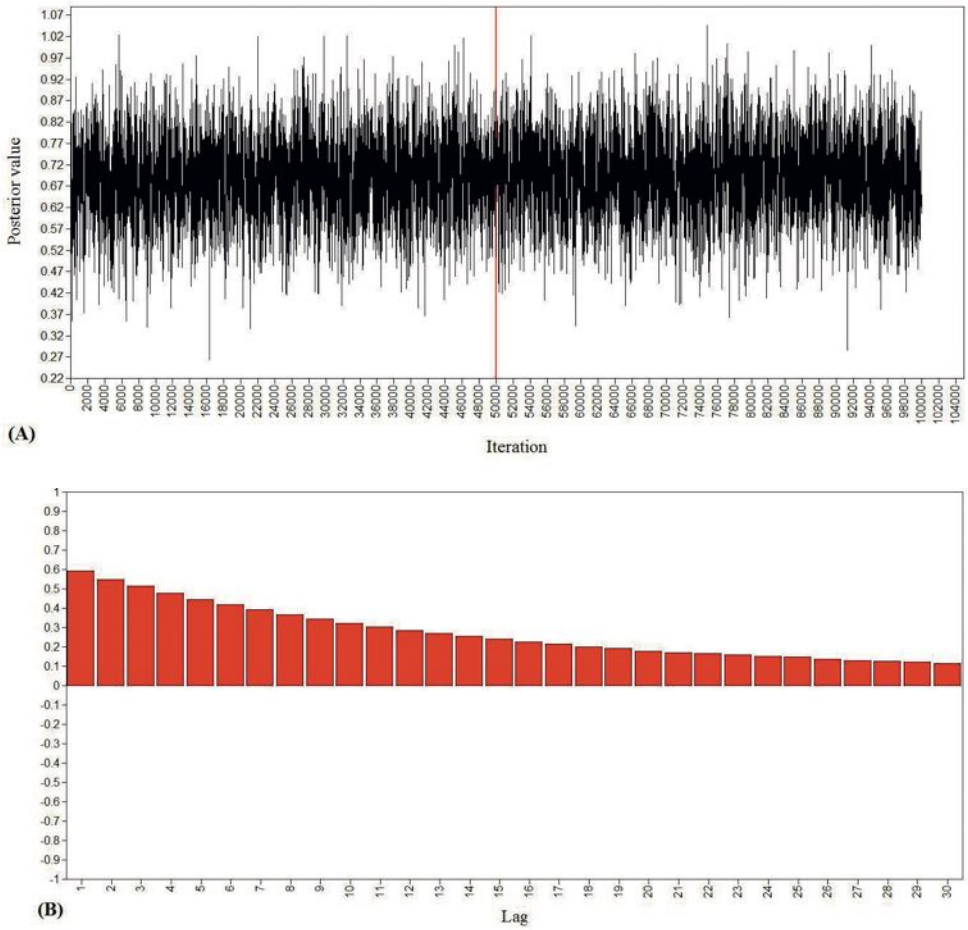

Figure 3.3. Bayesian posterior parameter trace plot (A) and autocorrelation plot (B) for the loading of item y10 on intellectual overexcitability in the Bayesian model with small-variance priors for cross-loadings and residual covariances for males.
Note. The *x*-axis of the posterior parameter trace plot displays the iterations of the MCMC procedures and the *y*-axis shows the corresponding parameter values. The vertical line represents the burn-in phase at 50,000 iterations. The iterations on the right-hand side of the vertical line determine the posterior distribution of the loading estimate.

Thus, the results of both BSEM models can be reliably interpreted. With the exception of one non-significant (in the sense that the 95% Bayesian credibility interval encompasses zero) major factor loading, the hypothesized factor loading pattern was fully recovered, with substantial target loadings and only one significant cross-loading (in the male group), as displayed in Table 3.5 (in Mplus, the reported estimates are the medians of their posterior distributions). Many minor residual covariances were found to be significant at the 5% level, particularly 49 (i.e., 4%) for the female group, with an average absolute residual correlation (range) of 0.221 (-0.254 to 0.532), and 68 (i.e., 5.55%) for the male group, with an average absolute residual correlation (range) of 0.241 (-0.294 to 0.462). Excluding these residual correlations may lead to the poor fit of the previously studied models (Cole et al., 2007), and unsatisfactory loading pattern recovery in the ESEM model (Muthén & Asparouhov, 2012). The Bayesian factor correlations are located in order of magnitude between the maximum likelihood EFA (smallest values, see Tables 3.3 and 3.5) and CFA (largest values, not reported) correlations. However, according to theory, the factors are predicted to correlate to a considerable level. Table 3.5 shows weak to moderate factor correlations.

Table 3.5. Bayesian model estimation results for females (n = 318) and males (n = 198) using small-variance priors for cross-loadings and residual covariances.

Factor Loadings										
	Females					**Males**				
	IOE	**ImOE**	**EOE**	**SOE**	**POE**	**IOE**	**ImOE**	**EOE**	**SOE**	**POE**
y1	**0.456***	0.025	-0.004	-0.042	-0.035	**0.530***	0.069	0.028	-0.041	0.013
y2	**0.078**	0.060	0.046	0.007	0.005	**0.178**	0.021	-0.011	0.024	-0.003
y3	**0.587***	0.015	0.031	0.039	-0.013	**0.611***	-0.004	-0.019	-0.047	-0.047
y4	**0.576***	0.001	0.023	0.031	0.003	**0.615***	-0.034	-0.001	0.041	-0.014
y5	**0.634***	-0.021	0.051	-0.016	0.008	**0.617***	-0.050	0.035	-0.018	-0.085
y6	**0.655***	0.035	-0.070	0.042	-0.007	**0.555***	0.061	0.003	0.031	-0.060
y7	**0.689***	-0.040	-0.028	-0.121	0.073	**0.728***	-0.025	-0.103	-0.016	0.076
y8	**0.619***	0.028	0.044	0.099	-0.054	**0.680***	-0.030	0.060	0.041	-0.030
y9	**0.649***	-0.033	0.070	0.002	0.011	**0.574***	0.022	0.039	-0.039	0.074
y10	**0.703***	0.026	-0.038	0.024	-0.010	**0.663***	0.048	-0.006	0.068	0.028
y11	-0.030	**0.688***	-0.002	-0.040	0.008	0.032	**0.563***	0.018	0.004	-0.031

Table 3.5. *Continued.*

Factor Loadings										
	Females					Males				
	IOE	**ImOE**	**EOE**	**SOE**	**POE**	**IOE**	**ImOE**	**EOE**	**SOE**	**POE**
y12	-0.002	**0.729***	0.012	-0.022	0.020	0.014	**0.681***	0.011	0.035	-0.082
y13	-0.042	**0.684***	-0.015	0.003	-0.058	-0.003	**0.648***	-0.013	-0.024	0.046
y14	-0.001	**0.488***	0.040	-0.016	-0.034	0.006	**0.404***	0.047	-0.048	0.031
y15	0.027	**0.681***	-0.005	-0.036	0.085	0.024	**0.475***	-0.015	0.009	-0.017
y16	0.009	**0.688***	0.001	-0.045	0.000	0.044	**0.666***	0.008	-0.092	0.026
y17	0.019	**0.505***	0.044	-0.003	0.026	-0.020	**0.563***	-0.033	-0.058	0.112
y18	-0.021	**0.497***	0.016	0.060	0.006	-0.075	**0.424***	0.017	0.042	-0.017
y19	0.069	**0.513***	0.024	0.112	0.043	0.017	**0.404***	0.034	0.191*	-0.001
y20	0.039	**0.608***	-0.007	0.140	-0.077	0.001	**0.607***	0.009	0.080	-0.092
y21	0.071	-0.047	**0.650***	0.006	0.009	0.011	0.006	**0.565***	-0.066	0.045
y22	-0.067	0.042	**0.422***	-0.040	0.008	-0.017	-0.053	**0.652***	-0.052	-0.033
y23	-0.054	-0.033	**0.540***	-0.021	0.056	-0.018	-0.050	**0.584***	-0.041	0.036
y24	0.083	0.029	**0.347***	-0.029	0.109	0.038	0.051	**0.359***	0.062	0.076
y25	-0.022	0.126	**0.567***	-0.031	-0.058	0.031	0.049	**0.629***	0.039	-0.031
y26	0.003	-0.059	**0.723***	-0.011	-0.010	0.057	-0.011	**0.750***	-0.017	0.045
y27	-0.027	0.092	**0.628***	-0.005	0.036	-0.088	0.121	**0.588***	-0.013	-0.075
y28	0.098	0.066	**0.596***	0.027	-0.034	0.029	0.035	**0.474***	0.076	0.019
y29	-0.067	-0.122	**0.640***	0.044	-0.026	-0.018	-0.073	**0.572***	0.035	-0.004
y30	0.059	0.007	**0.457***	0.026	0.014	0.012	0.005	**0.546***	0.085	-0.004
y31	0.049	-0.005	-0.051	**0.614***	0.125	0.009	-0.045	-0.041	**0.709***	-0.035
y32	0.014	-0.020	-0.071	**0.692***	-0.018	0.020	0.025	-0.043	**0.671***	-0.025
y33	0.045	-0.010	-0.026	**0.648***	-0.022	-0.015	0.010	0.056	**0.679***	-0.013
y34	-0.094	0.026	0.087	**0.444***	0.060	0.044	-0.014	0.049	**0.363***	0.016
y35	-0.042	0.090	-0.006	**0.693***	-0.020	0.015	0.106	0.003	**0.540***	0.014
y36	0.091	0.009	0.042	**0.623***	0.020	0.029	0.036	0.084	**0.604***	0.076
y37	-0.033	-0.022	0.042	**0.694***	-0.038	-0.017	-0.064	-0.009	**0.679***	0.005
y38	-0.031	0.004	0.041	**0.790***	-0.025	0.038	-0.017	-0.004	**0.787***	-0.039
y39	0.012	-0.004	-0.022	**0.732***	-0.030	0.023	0.055	-0.030	**0.591***	0.048
y40	0.032	0.024	-0.009	**0.622***	0.025	-0.044	0.032	0.066	**0.491***	0.041
y41	0.091	-0.017	0.006	-0.062	**0.356***	0.091	-0.047	0.013	-0.023	**0.421***

Table 3.5. *Continued.*

Factor Loadings										
	Females					**Males**				
	IOE	**ImOE**	**EOE**	**SOE**	**POE**	**IOE**	**ImOE**	**EOE**	**SOE**	**POE**
y42	-0.045	-0.047	0.043	-0.004	**0.729***	0.017	0.019	-0.040	0.034	**0.758***
y43	-0.013	-0.063	-0.008	-0.008	**0.796***	-0.036	-0.041	-0.016	0.046	**0.802***
y44	-0.034	0.049	-0.029	-0.034	**0.761***	-0.016	-0.009	0.093	-0.030	**0.752***
y45	0.020	0.038	-0.076	-0.021	**0.673***	-0.024	0.014	-0.058	0.023	**0.700***
y46	0.006	0.075	0.020	0.022	**0.524***	-0.038	0.042	0.028	-0.007	**0.529***
y47	-0.046	0.099	0.020	0.105	**0.564***	0.016	0.021	-0.010	0.029	**0.675***
y48	-0.003	0.000	0.058	-0.048	**0.707***	-0.019	0.010	0.022	-0.020	**0.634***
y49	0.048	-0.103	0.001	0.050	**0.730***	0.045	-0.039	0.100	-0.011	**0.542***
y50	0.014	0.029	0.000	0.029	**0.716***	-0.019	-0.010	-0.063	-0.036	**0.670***
Factor Correlations										
	Females					**Males**				
	IOE	**ImOE**	**EOE**	**SOE**	**POE**	**IOE**	**ImOE**	**EOE**	**SOE**	**POE**
IOE	1.000					1.000				
ImOE	0.343*	1.000				0.334*	1.000			
EOE	0.336*	0.368*	1.000			0.318*	0.367*	1.000		
SOE	0.471*	0.506*	0.288*	1.000		0.462*	0.476*	0.426*	1.000	
POE	0.163	0.144	0.215*	0.071	1.000	-0.042	-0.022	0.166	0.035	1.000

Note. IOE = intellectual overexcitability; ImOE = imaginational overexcitability; EOE = emotional overexcitability; SOE = sensual overexcitability; POE = psychomotor overexcitability. 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.

A sensitivity analysis was carried out, investigating the effects of varying the prior variances of the residual covariances on the PP*p* and the lower and upper bounds of the 95% CI for the difference in chi-square statistic for the observed and synthetic data. This analysis also checked the variability of the parameter estimates. Unless the research sample is extremely small, or the model and/or prior distribution are strongly contradicted by the data, the results of the Bayesian analysis will change very little when the variance of the prior distribution is altered (Arbuckle, 2013). Table 3.6

presents the Bayesian model fit results under varying prior variance conditions for the male group, and also presents the standardized estimate of the factor loading of item y1 on the latent variable of intellectual overexcitability. Initially, an inverse-Wishart prior *IW*(0, 56) was used for the residual covariances, corresponding to prior zero-means and variances of 0.0111 (*SD* = 0.1054). Augmenting the degrees of freedom for the parameters that are assumed to follow an inverse-Wishart distribution will decrease the variance of the prior distribution or increase the degree of prior knowledge included in the model. The extent to which the prior variance can be reduced is monitored through the PP*p*. In the framework of this residual correlations sensitivity analysis, both a less informative prior with *df* = 54 (corresponding to a prior variance of 0.0833) and more informative priors with *df* = 66, 76 and 86 (corresponding to prior variances of 0.0003, 0.0001, and < 0.0001, respectively) were used. Applying a strong informative prior with *df* = 73 (corresponding to a prior variance of 0.0001) yielded excellent model fit, as indicated by a PP*p* of 0.515. However, for both gender groups, the results of the sensitivity analysis indicate that different priors for the residual covariances do not alter the estimation of the factor loadings considerably. Additionally, with rather large sample sizes, the choice of the prior variance is less important as the data contribute more information to the construction of the posterior distribution (Muthén & Asparouhov, 2012).

Table 3.6. Bayesian model testing results for males using small-variance priors for cross-loadings and varying prior variance conditions for residual covariances, and corresponding estimation results for the factor loading of item y1 on intellectual overexcitability.

Model			**Parameter**			**95% Credibility Interval**	
df	**PP *p***	**95% CI**	**Loading λ_1**	**Posterior *SD***	**One-tailed *p***	**Lower 2.5%**	**Upper 2.5%**
54	0.914	-256.198-44.962	0.526	0.102	0.000	0.314	0.712
56	0.905	-248.311-50.020	0.530	0.104	0.000	0.312	0.716
66	0.728	-204.914-101.821	0.537	0.099	0.000	0.330	0.718
73	0.515	-163.316-153.099	0.539	0.096	0.000	0.340	0.715
76	0.414	-132.449-171.688	0.536	0.098	0.000	0.334	0.719
86	0.108	-60.272-257.655	0.544	0.094	0.000	0.347	0.716

Note. *df* = degrees of freedom; PP *p* = posterior predictive probability; CI = confidence interval; *SD* = standard deviation.

BSEM higher order model

With respect to the female group, the 95% CI for the difference between the observed and the replicated chi-square values covers zero, with a lower bound of -197.241 and an upper bound of 92.474, and the PP*p* is 0.757, both indicating good model fit. The same conclusion can be drawn for the male group (PP*p* = 0.884, Δ observed and replicated χ^2 95% CI [-246.146, 59.556]). A steadily decreasing PSR value, with a value close to 1 for the last few tens of thousands of iterations, as well as convergence plots showing tight horizontal bands for the parameters, and autocorrelation plots displaying low dependence in the chain, are all indicative of good MCMC convergence.

The hypothesized loading pattern depicted in Figure 3.1 is only partially recovered for both gender groups. Psychomotor overexcitability can be distinguished from the other forms of overexcitability, as indicated by the non-significant factor loading on the general latent construct of positive developmental potential. Regarding the measurement model, all intended factor loadings – with the exception of the loading of item y2 on intellectual overexcitability, as in the previous BSEM models – were substantive. Nonetheless, some cross-loadings were found to deviate substantially from zero, particularly 6 for the female group, with an average loading of 0.175, and 2 for the male group, with an average loading of 0.224. Many minor residual covariances were found to be significant at the 5% level, particularly 34 for the female group, with an average absolute residual correlation (range) of 0.233 (-0.252 to 0.532), and 47 for the male group, with an average absolute residual correlation (range) of 0.248 (-0.279 to 0.476). Parameter estimates for the structural components in the model are presented in Figure 3.1.

Omitting the cross-loadings in the hierarchical model and using informative, small-variance priors for the residual covariances $\delta \sim IW(0, 56)$ in the measurement model also yields satisfactory model fit for both the female (PP*p* = 0.634, Δ observed and replicated χ^2 95% CI [-168.305, 123.630]) and male groups (PP*p* = 0.800, Δ observed and replicated χ^2 95% CI [-215.656, 88.242]), in contrast to a model that only has cross-loadings with even less strict prior variances ($\lambda \sim N(0, 0.09)$ corresponding to 95% cross-loading limits of ±0.59), which leads to a low PP*p* (< 0.05). However, in the structural model for the female group, all target loadings are significant, although the loading of the psychomotor overexcitability factor on the latent variable of positive developmental potential must be considered small ($\lambda = 0.261$). Not permitting cross-loadings in the measurement model

considerably increases the number of non-trivial residual covariances (158 for females, and 124 for males) and inflates parameter estimates.

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 et al., 2002). The DIC values generated by the first higher order model and the second hierarchical model were 40490.867 and 40459.584 for the female group, and 25991.245 and 25956.312 for the male group, respectively. Although the difference in DIC is small, the models that only included residual covariances produced the smallest DIC values. However, the models with more constraints led to considerably more significant residual covariances (and, as a consequence, lower DIC values), making model comparison more difficult. Our results correspond to previous studies mentioning higher loadings on a second-order latent variable and inflated first-order factor correlations in the case of more strict models (Golay et al., 2013).

Multiple-group BSEM-based alignment with approximate measurement invariance

Table 3.7 presents the results of the BSEM multiple-group approximate measurement invariance analysis with zero-means and decreasing variances for the prior distributions of differences in factor loadings and intercepts across gender. The extent to which the prior variance can be reduced is monitored through the PP*p*. "If the prior variance is small relative to the magnitude of non-invariance, PPP will be lower than if the prior variance corresponds better to the magnitude of non-invariance" (Muthén & Asparouhov, 2013a, p. 21). Analyses were executed for each overexcitability factor, since configural invariance had already been established (see BSEM models with informative, small-variance priors for cross-loadings and residual covariances). For the intellectual overexcitability data a prior variance for the measurement parameters of 0.01 results in a PP*p* of 0.540. Decreasing the prior variance does not alter the PP*p* substantially. A prior variance of 0.000000001 – resulting in an excellent PP*p* of 0.559 – entails a strong informative prior belief that 95% of the distribution of non-invariance is situated within the range of [-0.000062; +0.000062], which represents an extremely small range around zero.

Scalar invariance, as characterized by invariant factor loadings and measurement intercepts, is a prerequisite to compare factor means across groups (Millsap, 2011; Muthén

& Asparouhov, 2013c; Vandenberg & Lance, 2000). For intellectual overexcitability, the factor loadings and intercepts are all invariant, regardless of the simulated prior variance, and none of the groups show a significantly (at the 5% significance level) different factor mean. For the construct of imaginational overexcitability, the use of a prior variance of 0.01 and 0.000000001 generates PP*p*s of 0.392 and 0.225, respectively. The factor loadings and intercepts are all invariant, and none of the groups show a significantly different factor mean. For emotional overexcitability, a prior variance of 0.01, 0.001, and smaller, results in PP*p*s of 0.500, 0.441, and 0.402, respectively. The factor loadings and intercepts are all invariant, and the male group shows a significantly smaller factor mean. For sensual overexcitability, a prior variance of 0.01, 0.001, and smaller, results in PP*p*s of 0.598, 0.491, and approximately 0.450, respectively. The factor loadings and intercepts are all invariant, and the male group shows a significantly smaller factor mean. For the psychomotor overexcitability data a prior variance of 0.01 results in a PP*p* of 0.518. The factor loadings are all invariant, although the intercept of item y50 ("I thrive on intense physical activity, e.g. fast games and sports") is non-invariant across gender. Decreasing the prior variance to 0.001 or smaller, still produces an acceptable PP*p* of 0.235 and approximately 0.160, respectively, and leads the non-invariance of the intercept of y50 to disappear. The factor loadings and intercepts are all invariant and the female group shows a significantly smaller factor mean.

According to the acceptable PP*p*s and corresponding CIs even under strict conditions (i.e., the use of prior distributions with extremely small variances of 0.000000001), we may conclude that approximate scalar measurement invariance is supported by the data for each of the overexcitability latent variables.

Table 3.7. Model fit coefficients of multiple-group BSEM-based alignment with approximate measurement invariance per overexcitability factor using varying prior variances.

Prior variance σ^2	Intellectual OE		Imaginational OE		Emotional OE		Sensual OE		Psychomotor OE	
	PP *p*	95% CI	PP *p*	95% CI	PP *p*	95% CI	PP *p*	95% CI	PP *p*	95% CI
0.01	0.540	-42.660-52.130	0.392	-38.731-46.347	0.500	-49.966-38.545	0.598	-48.852-43.248	0.518	-59.937-40.278
0.001	0.589	-51.289-40.207	0.275	-32.969-56.720	0.441	-45.894-44.876	0.491	-38.249-43.758	0.235	-34.540-51.567
0.0001	0.578	-47.817-40.790	0.232	-35.467-72.492	0.402	-45.185-48.596	0.455	-34.207-48.716	0.157	-29.045-62.081
0.00001	0.559	-47.853-44.884	0.232	-37.887-72.639	0.392	-46.726-47.701	0.455	-33.556-50.392	0.157	-28.902-63.374
0.000001	0.559	-48.030-46.511	0.232	-39.102-70.930	0.402	-46.654-47.810	0.455	-33.668-51.832	0.167	-29.122-63.611
0.0000001	0.559	-48.083-47.011	0.225	-33.007-59.420	0.402	-46.508-47.884	0.455	-33.740-52.255	0.167	-29.234-63.665
0.00000001	0.559	-48.098-47.165	0.225	-33.042-59.346	0.402	-46.448-47.911	0.446	-33.761-52.384	0.167	-29.274-63.680
0.000000001	0.559	-48.103-47.214	0.225	-33.053-59.322	0.402	-46.428-47.920	0.446	-33.768-52.425	0.157	-29.287-63.685

Note. BSEM = Bayesian structural equation modeling; OE = overexcitability; PP *p* = posterior predictive probability; CI = confidence interval.

DISCUSSION

The first aim of this study was to validate the factorial structure of the OEQ-II using Bayesian estimation in comparison with the frequentist approach to validation. 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, which better reflects substantive theory. The analysis yielded positive results regarding the factorial validity of the OEQ-II, in contrast to the maximum likelihood CFA and EFA models which could not generate a satisfactory model fit. The hypothesized factor loading pattern was not fully recovered by the EFA results, due to the existence of many minor residual covariances. Freeing all residual covariances in a frequentist analysis would lead to a non-identified model. Alternatively, modifying the model using modification indices may capitalize on chance (MacCallum et al., 1992), with a large risk of model misspecification (Muthén & Asparouhov, 2013b). However, Bayesian analysis allows for all residual covariances to be inserted into the model using zero-mean, small-variance prior distributions, therefore overriding the problem of non-identification. Moreover, the BSEM approach "informs about model modification when all parameters are freed and does so in a single-step analysis" (Muthén & Asparouhov, 2012, p. 313). BSEM led to good model fit, as evaluated by means of Posterior Predictive Checking, which is less susceptible to slight, negligible model misspecifications compared to the chi-square statistic for assessing model fit (Muthén & Asparouhov, 2012). It also led to less inflated factor correlations compared to CFA, and satisfactory loading pattern recovery with substantial target loadings.

However, one major factor loading, namely the loading of item y2 ("I can take difficult concepts and translate them into something more understandable") on the latent factor of intellectual overexcitability, was not found to be substantive (although the standardized coefficient of the loading was the largest for this item). Although the content of y2 is consistent with the content of the other items that load significantly on the latent variable of intellectual overexcitability, perhaps a higher standard is required to yield the response of agreement. The level of conceptual difficulty is not defined in more detail and can be interpreted differently by various people. The study by Van den Broeck et al. (2014) also revealed a low but significant factor loading ($\lambda = .33$) for the respective item. Future validation studies of the OEQ-II will have to affirm how

y2 compares relative to the other factor indicators and in relation to the construct of intellectual overexcitability.

Regarding the results of the higher order model, we may conclude that the construct of psychomotor overexcitability, as captured by the OEQ-II, behaves differently to intellectual, imaginational, emotional, and sensual overexcitability. The latter forms of overexcitability all load substantially on the superordinate latent variable of positive developmental potential. According to Dąbrowski's theory, the presence of only psychomotor and/or sensual overexcitability in an individual hinders advanced development (Dąbrowski, 1972b; Mendaglio, 2012). However, according to the results of this study, the construct of sensual overexcitability is strongly related to three of the most important drivers of personality growth. Piechowski (2013, p. 105) stated that under emotional tension, psychomotor overexcitability can be manifested as "compulsive talking and chattering, impulsive actions, nervous habits (tics, nail biting), workaholism, acting out," and sensual overexcitability can be expressed as "overeating, self-pampering, sex as pacifier and escape, buying sprees, desire to be in the limelight." Only one item of the OEQ-II is related to the expression of psychomotor or sensual overexcitability under difficult emotional circumstances (i.e., "When I am nervous, I need to do something physical"). All of the items representing sensual overexcitability are expressed in a positive way, and are indicative of a very perceptive personality, as are the other three forms of overexcitability which are considered essential to advanced personality development. The 40 items of the OEQ-II representing intellectual, imaginational, emotional, and sensual overexcitability seem to be indicative of a conscious, complex, creative, deeply emotionally engaged, sensitive, and perceptive personality with a strong susceptibility to wonder. Psychomotor overexcitability, as represented by the OEQ-II, does not have that same kind of spirit, but is more neutral and related to intense physical activity and competitiveness. Mendaglio and Tillier (2006) rightly emphasize the importance of further elaborating the empirical research on developmental potential by incorporating specific talents and abilities, dynamisms, and features of the environment alongside overexcitabilities in future studies. The results of this study also demonstrate the importance of more thoroughly examining the specific, possibly mediational role of psychomotor overexcitability in the process of personality growth, as viewed from the perspective of Dąbrowski's theory.

Results of simulation studies indicate that approximate measurement invariance with highly precise priors outperforms full and partial measurement invariance in the case of (many) small differences in measurement parameters across groups (van de Schoot et al., 2013). In our study, which applied BSEM-based alignment with approximate measurement invariance, the absence of non-invariant factor loadings and intercepts across gender was indicative of the psychometric quality of the OEQ-II. The results of our study revealed a significantly higher score for females on emotional and sensual overexcitability, and a significantly lower score on the construct of psychomotor overexcitability compared to males. These results are mostly consistent with the findings of the previous studies mentioned above. However, no difference could be established in the level of intellectual overexcitability across both gender groups. The rather intellectual homogeneity of the sample may explain this result.

BSEM is an innovative and flexible approach to statistics, allowing the application of zero-mean, small-variance priors for cross-loadings, residual covariances, and differences in measurement parameters across groups, which leads to better model fit and less overestimation of factor correlations compared to CFA (which postulates exact parameter constraints and is usually too strict) (Fong & Ho, 2014; Muthén, 2013; Muthén & Asparouhov, 2013a).

More generally, 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). Even in the case of very limited prior knowledge (non-informative prior) with little influence on the posterior distribution, the Bayesian credibility interval nevertheless allows direct probability statements about the parameter values given the data (Kruschke et al., 2012).

With regard to the limitations of this study, we have to note that although the BSEM approach to factorial validation and measurement invariance analysis 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. Muthén and Asparouhov (2012) rightly emphasize the difficulty of balancing the need for small-variance priors for cross-loadings and small prior variances for

residual covariances, which is supported by the results of the sensitivity analysis of the higher order model in this study. Moreover, the degree of susceptibility of the PP*p* to model misspecification warrants further research. This is of major importance given the strong influence of small-variance priors on the posterior parameter distributions, even in medium-sized samples. Furthermore, the susceptibility of the PP*p* to specific model features, the number of variables, and variable distributions needs to be investigated in more detail (Muthén & Asparouhov, 2012). One reviewer rightly stressed the limitation of the use of rather small sample sizes in this study – especially with regard to the male sample – according to standard criteria applied in conventional CFA and SEM analyses. Although the PP*p* has been found to perform better with small sample sizes than the maximum likelihood chi-square statistic, and to be less prone to negligible model misspecifications (Muthén & Asparouhov, 2012), the susceptibility of the PP*p* to the number of observations as well as the performance of BSEM estimation under varied sample sizes (and model features) should definitely be examined further. Future BSEM studies should investigate which sample size is required according to the number of degrees of freedom included in the model in order to ensure optimum performance. However, preliminary studies indicate that Bayesian SEM performs better with small sample sizes than does maximum likelihood SEM (Lee & Song, 2004).

In any case, using Bayesian analysis, either as a pragmatic or meta-analytic approach, it is crucial to perform sensitivity analyses which investigate the effect of varying the means and variances of prior distributions on the parameter estimates and model fit. The performance of the alignment optimization method under varied conditions also needs to be investigated further, as it represents a novel technique for measurement invariance analysis under certain assumptions.

A second limitation of this study is the use of a convenience sample to simultaneously investigate the factorial structure of the OEQ-II, as well as approximate measurement invariance of factor loadings and intercepts across gender. Future studies should preferably use independent randomized samples to cross-validate the OEQ-II and investigate (approximate) measurement invariance across varied conditions.

Apart from this, the results of our study coincide with the findings of the study by Van den Broeck et al. (2014), and are supportive of the psychometric quality of the OEQ-II.

The Mplus scripts for the main BSEM analyses in this study are available as Supplementary Material (see Appendix A).

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CHAPTER 4

STUDY 3:

A rationale for including overexcitability in talent research beyond the FFM-personality dimensions

This chapter is based on:
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ABSTRACT

The aim of this study is to provide – first theoretically and, subsequently, through an empirical analysis – a rationale for including the concept of overexcitability in talent research, beyond the five-factor model personality traits. Moreover, the empirical part of this study makes use of an innovative statistical method to address the problem of a frequentist approach to statistics in complex trait models which are based on personality questionnaire data. This study offers insight into the differential significance of overexcitability in relation to the established personality traits, emphasizing Dąbrowski's dynamic approach to personality and the key contribution of overexcitability in the developmental process. Furthermore, implications for the field of giftedness are discussed.

INTRODUCTION

Kazimierz Dąbrowski (1902-1980), a Polish psychiatrist and founder of the Theory of Positive Disintegration (TPD), emphasizes the importance of investigating interrelationships between outstanding abilities, psychoneuroses, and personality in children and young people. Dąbrowski further stresses the lack of studies examining the correlation between these characteristics, which he regards as qualities on the road to humanity (Dąbrowski, 2015). The TPD represents a hierarchically structured and dynamic theory of personality development, in which personality is defined as "[a] self-aware, self-chosen, self-affirmed, and self-determined unity of essential individual psychic qualities" (Dąbrowski, 2015, p. 290) and is only attained at the final level of the developmental process. 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 special abilities, talents, and autonomous inner forces that cultivate growth (dynamisms) (Dąbrowski, 1964, 2015; Mendaglio, 2008; Tillier, 2018).

Dąbrowski's Theory of Positive Disintegration

According to the TPD, personality is usually achieved through a process of disintegration in which awareness of a discrepancy between biological and social actuality (determinism) on the one hand and supra-biological necessity on the other hand (the latter refers to how life should be, i.e., absolutely truthful, alter-centric, and according to the moral imperative) gives rise to external but especially internal conflicts that may cause the disintegration of the primitive mental organization (Dąbrowski, 2015).

The TPD distinguishes five levels of development, which are not sequential, age-related, or universal (Mendaglio, 2008). The first developmental level (Primary Integration) refers to a cohesive mental structure that is dominated by primitive instincts and is characterized by egocentrism, conformity, a low level of (self-)consciousness, and a limited critical attitude. It is present in high levels in the average person and, according to Dąbrowski, it reflects a low level of mental health. Individuals who are endowed with sufficient developmental potential, or who are in favorable conditions (for example in the period of maturation), are able to achieve disintegration and possibly advanced development. In this process, dissolving dynamisms (more specifically, ambivalences

and ambitendencies at the second level [Unilevel Disintegration] and, subsequently, at the third level [Spontaneous Multilevel Disintegration] – when one becomes aware of the existence of an authentic hierarchy of values – anxiety about oneself, dissatisfaction with oneself, feelings of shame and guilt, and feelings of inferiority towards oneself) cause intense negative emotions, and weaken and ultimately destroy primary integration. Attaining the fourth level of development (Organized Multilevel Disintegration) – which is characterized by the conscious self-organization of the course of development – depends largely on the presence of developmental dynamisms (e.g., self-awareness, subject-object attitude[10], the Third Factor[11], self-education, and autopsychotherapy), which reduce the distress by moving toward an ideal and creating a new mental structure. Higher-level emotions are experienced, thus leading to the conscious creation of a hierarchy of values. Higher values are pursued, and a strong sense of responsibility toward oneself and others is developed, along with a strong sense of justice and empathy. Dissolving and developmental dynamisms ultimately constitute an internal mental environment (Inner Psychic Milieu) that is self-directed and free of conflict. 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, which is derived from universal, objective moral values. Autonomy, authenticity, and empathy are fully developed. Only a few people achieve the highest level of human development (Dąbrowski, 1964, 1970b, 2015; Mendaglio, 2008; Tillier, 2018).

The concept of overexcitability within the TPD

According to Dąbrowski, the developmental potential of an individual depends in part on the extent and nature of psychic intensity. Overexcitability refers 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 (Dąbrowski, 1970c, 2015; Mendaglio, 2008; Tillier, 2018). Dąbrowski

10 Subject-object in oneself refers to the process of looking at oneself critically and from a distance (the self as object) and approaching the other as subject, with empathy and compassion (Dąbrowski, 2015).

11 The Third Factor can be considered a conscious self-determinism in which the individual is directed by an inner voice and personal values that reflect a high moral level. The First and Second Factors refer to the constitutional endowment and social environment, respectively (Dąbrowski, 2015).

distinguishes five forms of increased psychic excitability – emotional, intellectual, imaginational, psychomotor, and sensual – whose most essential manifestations and characteristics are listed in Table 4.1. Dąbrowski considers the first three forms of overexcitability essential to advanced personality development, with emotional overexcitability constituting the key driver of alter-centrism (Dąbrowski, 1970a, 2015). On the one hand, overexcitability or "nervousness" may lead to inner and external conflicts and tension. On the other hand, it constitutes the foundation of powerful perceptivity, which enables an individual to envision a higher, universal reality (Dąbrowski, 1970a). As such, overexcitability may contribute to a higher awareness of what should be, as well as to contemplation and the approximation of a higher, truthful reality.

Table 4.1. Essential characteristics of overexcitabilities.

Intellectual overexcitability • intensified activity of the mind • asking penetrating questions • reflective thought • problem solving • searching for truth and understanding • conceptual and intuitive integration • interest in abstraction and theory	**Emotional overexcitability** • intense connectedness with others • experience things deeply • strong affective and somatic expressions • sensitivity in relationships • responsiveness to others • well-differentiated feelings toward self	**Psychomotor overexcitability** • intense physical activity • work addiction • nervous habits • rapid speech • impulsiveness • competitiveness • urge to action
Imaginational overexcitability • visualize events very well • ingenuity • fantasy • need for novelty and variety • poetic and dramatic perception		**Sensual overexcitability** • enhanced receptivity of the senses • aesthetic appreciation • sensuality • pleasure in being the center of attention

Note. Adapted from Daniels and Piechowski (2009).

The Overexcitability Questionnaire-Two (OEQ-II) (Falk et al., 1999) is the most widely used self-reporting instrument for measuring the degree and nature of overexcitability.

Implications for the field of giftedness

Numerous studies on intensity in gifted and non-gifted students have demonstrated associations of giftedness with intellectual (Bouchet & Falk, 2001; Carman, 2011; Harrison & Van Haneghan, 2011; Siu, 2010; Tieso, 2007a; Van den Broeck et al., 2014; Wirthwein et al., 2011; Wirthwein & Rost, 2011), imaginational (Carman, 2011; Harrison & Van Haneghan, 2011; Siu, 2010; Tieso, 2007a), and emotional (Bouchet & Falk, 2001; Siu, 2010) overexcitability. Based on systematic research, Dąbrowski also reports a substantial degree of overexcitability, as well as psychoneurotic symptoms in groups of intellectually and artistically gifted young people, as compared to a control group (Dąbrowski, 2015). This is in line with the results of some recent studies that demonstrate a significant positive relationship between high intelligence and both mood and anxiety disorders (Gale et al., 2013; Harrison & Van Haneghan, 2011; Karpinski et al., 2018; MacCabe et al., 2010). Unconventionally, Dąbrowski defines psychoneuroses (e.g., depression and existential anxiety) as syndromes emerging from internal and external conflicts arising from the awareness of the discrepancy between "what is" and "what ought to be" (Dąbrowski, 1970a, 1972a). He regards psychoneuroses as qualities in the process of personality development, however, if they occur at a sufficiently high level, meaning that they are in conjunction with excellent mental capabilities, overexcitabilities, and developmental dynamisms, including self-consciousness, the Third Factor, creativity, self-education, and autopsychotherapy (Dąbrowski, 1970a, 1970c, 2015). In this condition, overexcitability and psychoneuroses enhance the possibility of inner mental transformation and, according to Dąbrowski, they are a necessary element of an individual's psychic enrichment (Dąbrowski, 1970a, 2015; Dąbrowski & Joshi, 1972). Moreover, they serve as a prophylactic against psychotic disorders (Dąbrowski, 1970a). It is only through the awareness of a different, higher, truthful reality (through intuition [Dąbrowski, 1970b] and creative search [1972a]) and through cognizance, understanding, and acceptance of the tension that may result from its contrast with actuality (through autopsychotherapy [2015]), that one can consciously embrace the road to self-perfection, alter-centrism, and essence. Psychoneuroses are non-existent at the level of Secondary Integration (Dąbrowski, 1970c; Dąbrowski & Piechowski, 1969).

Implications for gifted education

With their inherent characteristics, therefore, gifted individuals appear to have more potential to arrive at autonomous and strong personalities (Dąbrowski, 1970b, 2015; Tillier, 2002). Dąbrowski nevertheless emphasizes the importance of guidance of the process of personality development by an "adviser" who is personally characterized by a strong personality, and who first evaluates both the developmental potential and actual level of the individual (Dąbrowski, 2015). According to Dąbrowski, the maturation period is well suited for this purpose, given the inherent intensification of disintegrative symptoms and increased brain plasticity during this period. The adviser should ideally raise awareness of the existence of multilevel contradictions in an individual caused by, on the one hand, the presence of instinctive motives aimed at self-preservation, and on the other hand, the necessity of alter-centrism, deep identification, and conscious empathy. The adviser strengthens positive developmental traits and encourages self-insight, identification, empathy, moral responsibility, and self-determinism based on high moral values (Dąbrowski, 2015). This process of authentic education (Rankel, 2008) is then gradually taken over by a process of self-education, in which the individual becomes aware of his/her own personality ideal and the necessity of approaching this ideal. Through critical and objective self-examination and the conscious perception of the higher and lower within themselves, while simultaneously becoming aware of a higher, true reality, individuals can develop a personal hierarchy of values and aims. The personality ideal is activated by means of the Third Factor, which acts as an active consciousness that rejects the lower, instinctive dimension and affirms the higher, true one (Dąbrowski, 2015). Further progress in the process of self-education will ultimately allow room for what might be called transformational education, in which the individual takes on an exemplary and value-directing leading role in society. According to Dąbrowski, gifted individuals are ideally suited to create normative patterns. In addition to having a deeper awareness of a hierarchy of values, they possess a more uniform interpretation of the highest level, which indicates the existence of a universal hierarchy of values (Dąbrowski, 1970b, 2015).

Relationships between overexcitabilities and personality traits

Despite Dąbrowski's call for empirical research on interrelationships between overexcitability, personality, abilities and psychoneuroses, such studies are virtually

non-existent. Based on an assumed level of conceptual congruence (Gallagher, 2013), three studies (which are discussed below) have investigated associations between overexcitability and the five-factor model (FFM) personality traits. The FFM is a comprehensive taxonomy of personality traits, consisting of five factors that represent the basic dimensions of personality identified in analyses of standard personality measures (Costa & McCrae, 1992a; McCrae & Costa, 1987). In this context, personality refers to the relatively stable style of thinking, feeling, and acting that is characteristic of an individual (Costa et al., 1995). Although the FFM has developed into a dominant paradigm in personality psychology (Costa & McCrae, 1995), it is still an evolving scientific construct (Costa & McCrae, 1992a). The five personality factors are defined according to a large set of specific traits or facets (Costa & McCrae, 1992b). The neuroticism factor may be described as the tendency to experience negative affects such as depression, anxiety, and anger, and it also includes the disturbed thoughts and behaviors that accompany emotional instability (McCrae & Costa, 1987, 1989). The extraversion factor can be described as the predisposition to experience positive emotions and to be active, sociable, and dominant, while the openness factor is characterized by active imagination, aesthetic sensitivity, attentiveness to inner feelings, preference for variety, and intellectual curiosity (Costa & McCrae, 1992b; McCrae & Costa, 1989). The factor of conscientiousness is defined by organization, perseverance, meticulousness, and need for performance, whereas the agreeableness factor is characterized by sympathy, trust, cooperation, and altruism (McCrae & Costa, 1989).

Limont et al. (2014) investigated interrelationships between overexcitability and personality, as measured by the 60-item NEO Five-Factor Inventory (NEO-FFI) (Costa & McCrae, 1992b), applying maximum likelihood (ML) estimation in five structural equation models with each of the personality traits as the sole dependent variable. This study, which generated only partially good model fit (despite the low complexity of the models), reveals only weak to moderate relationships between the five forms of overexcitability and personality traits. Vuyk et al. (2016) investigated associations between the six openness facets (i.e., fantasy, aesthetics, feelings, actions, ideas, and values) – as measured by the 240-item NEO Personality Inventory-3 (NEO-PI-3) (McCrae et al., 2005) – and overexcitability, applying robust ML exploratory structural equation modeling (ESEM). In their joint-factor model, six factors (which correspond

to hypothesized relationships between fantasy and imaginational overexcitability, aesthetics and sensual overexcitability, feelings and emotional overexcitability, actions and psychomotor overexcitability, ideas and intellectual overexcitability, and to an unrelated facet of values) were measured by each of the 50 overexcitability indicators and 45 openness indicators (three items were removed from the model in order to achieve convergence). The ESEM model demonstrated weak model fit, as measured by the chi-square statistic ($p < 0.00001$) and comparative fit index (CFI = .790), and a more or less recovered hypothesized factor loading pattern, with substantial target loadings and many significant cross-loadings. Despite the poor model fit, the authors conclude that "openness facets and OEs [i.e., overexcitabilities] appear to represent the same construct" (Vuyk et al., 2016, p. 205). They further claim that there is no justification for the existence of overexcitability as a separate research construct, given the strong research support for the FFM. Finally, a study by Botella et al. (2015, p. 217) provides evidence of only a few, predominantly weak to moderate positive (Pearson) correlations between overexcitabilities and personality traits, from which the authors deduce that "OE [i.e., overexcitability] and the Big Five model are two different views of personality, and their combination might enhance the understanding of the development of personality."

Empirical study

The first aim of this study is to investigate interrelationships between overexcitability, as measured by the OEQ-II, and the personality traits of neuroticism, openness, and conscientiousness, as gauged by the NEO-FFI, applying Bayesian structural equation modeling (BSEM) with informative, small-variance priors (Muthén & Asparouhov, 2012). All of the existing three studies on interrelationships between overexcitabilities and personality traits adopted a frequentist approach to statistics. None of the above-mentioned studies that made use of ML estimation in their structural equation model generated good model fit, as measured by the chi-square statistic. A Bayesian approach to statistics might have been more appropriate, given the complexity of trait models which rely on personality questionnaire data. Results of validation studies indicate that most personality instruments exhibit slight cross-loadings and measure several supplementary minor factors in addition to the postulated personality 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 et al., 1992), with a large risk of model misspecification (Muthén & Asparouhov, 2013b). We hypothesize that the BSEM model will generate a good fit to the data, as it is capable of taking into account the existence of trivial cross-loadings 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 prior distributions[12], therefore overriding the problem of non-identification. More specifically, cross-loadings and residual covariances will not be fixed at exactly zero (as in ML CFA), but will be able to deviate slightly from zero, using strong informative priors with zero-mean and small variance. This will enhance the model with the *a priori* research-driven information that ML CFA models are too strict and do not meet the reality of the existence of small cross-loadings and minor correlated residuals in most psychological instruments. Using a small-variance prior, which reflects strong prior knowledge (i.e., according to substantive theory, cross-loadings and residual covariances must be approximately zero), the data will tend to contribute less information to the construction of the posterior distribution (Muthén & Asparouhov, 2012). In light of the results of the studies by Botella et al. (2015), Limont et al. (2014), and Vuyk et al. (2016), we hypothesize weak to moderate associations between the five forms of overexcitability and the personality traits of neuroticism, openness, and conscientiousness, with the most substantial relationship concerning openness.

12 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 et al., 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).

As posited in the theoretical analysis, the TPD does not regard intelligence as negligible. The awareness of a discrepancy between a lower and higher reality, as well as the perception of a transcendental objectivity (through intuition) requires higher mental capabilities (Dąbrowski, 2015). Intelligence may also be an active driver of the third factor, thereby giving rise to conscious, highly value-based auto-determinism. The developmental process, however, is directed by higher-level emotions. Nonetheless, intelligence and higher-level emotions cooperate closely at high levels of psychic functioning (Dąbrowski, 1970b, 1970c). When combined with a high level of overexcitability and strong developmental dynamisms, intelligence may thus function as a catalyst if used in the service of the developmental process. Therefore, we additionally hypothesize a moderation effect of intellectual ability on the influence of overexcitability on personality.

Furthermore, Dąbrowski (2015) states that "[n]one of the forms of hyperexcitability [...] develops in isolation. As a rule these are mixed forms with predominance of this or that form. They are disintegrating factors and, in conjugation with mental hyperexcitability [i.e., intellectual overexcitability], permit preparation for higher forms of disintegration and secondary integration" (p. 75). "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). Therefore, and in reference to the study by Vuyk et al. (2016), we further hypothesize a substantial relationship between positive developmental potential – which represents in our study the interaction between the five overexcitabilities – and the personality trait of openness.

The second aim of this study is to investigate the possible presence of distinct factors within the variable of emotional overexcitability, applying ESEM with ML estimation. A hierarchical organization of human development is the hallmark of the TPD and, according to Dąbrowski, each form of overexcitability has a different expression, depending on the level of personality development (Dąbrowski, 1970c; Tillier, 2018). Although the OEQ-II does not define the five overexcitability factors according to a set of hierarchically structured facets, a multiple-level perspective can clearly be distinguished with regard to emotional overexcitability. For example, the item "I am deeply concerned about others" is situated on a higher, more humane and abstract

level in the process of personal development in comparison with the item "I can feel a mixture of different emotions all at once." Therefore, we hypothesize that a two-factor exploratory structure will fit the data better than a one-factor structure. A two-factor structure that reflects the multidimensional and multi-stage process of disintegration would diverge from the FFM model, which does not include distinct levels of personality growth.

MATERIALS AND METHODS

Participants

The OEQ-II and NEO-FFI were added to a large-scale study conducted in Flanders (i.e., the Dutch-speaking part of Belgium) that investigated the influence of learning patterns on both academic performance and the successful transition from secondary to higher education. In all, 516 students (318 women: 61.6%; 198 men: 38.4%) completed the three measures discussed below. The respondents (M = 19.54 years; SD = 0.67) were in the second consecutive year of a program of higher education (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). Almost all of the participants (99%) spoke at least Dutch in the home, while a minority (20%) also used Arabic, Berber, Chinese, German, English, French, Italian, Spanish, or Turkish as their at-home language. Many of these individuals could be considered talented, given their prior education and continued participation in higher education. The study was executed in accordance with the guidelines of the Ethics Committee for the Social Sciences and Humanities of the university with written informed consent from all subjects.

Measures

Overexcitabilities

The OEQ-II consists of 50 items (equally representing the five forms of overexcitability) that 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 et al., 2014) and approximate scalar

measurement invariance across gender (De Bondt & Van Petegem, 2015). In this study, as represented in Table 4.2, the Cronbach's alphas all exceed 0.80, thus indicating good reliability, as well as correspondence to the results of previous studies.

Because of significant relationships between gender and overexcitability – in other words, a higher score for females on emotional and sensual overexcitability and a lower score on psychomotor overexcitability relative to males (Bouchet & Falk, 2001; De Bondt & Van Petegem, 2015; Van den Broeck et al., 2014) – statistical analyses will be performed for the different gender groups separately.

Table 4.2. Descriptive statistics for females and males and Cronbach's alphas.

		Females				Males			
Variable	***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
Neuroticism	.840	3.026	0.616	-0.050	-0.191	2.588	0.616	0.120	-0.405
Openness to experience	.709	3.263	0.520	0.211	-0.138	3.145	0.517	0.524	0.020
Conscientiousness	.744	3.587	0.484	-0.124	-0.471	3.500	0.440	-0.053	-0.337
Intellectual ability	.828	31.310	4.157	-0.501	0.198	31.200	4.172	-0.656	0.378

Personality traits

An abbreviated Dutch version of the NEO-FFI, which operationalizes the FFM, was used to measure three major dimensions of personality: neuroticism, openness, and conscientiousness (Hoekstra et al., 1996). Each of these three traits is measured by a scale consisting of twelve items that are scored along a five-point Likert scale with response options ranging from "Strongly disagree" to "Strongly agree." In the present data set, all Cronbach's alphas for the NEO-FFI factors were higher than 0.70 indicating an acceptable level of internal consistency.

Intellectual ability

Intellectual ability was 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 0.80, thus indicating good internal consistency.

Analyses

Using the Mplus software program (Version 7.4; Muthén & Muthén, 1998-2017), a multiple-indicators, multiple-causes (MIMIC) model (Jöreskog & Goldberger, 1975) was utilized, in which latent variables (in this case, personality traits) are predicted by observed variables (in this case, the dispositional traits of overexcitabilities that actively drive personality according to the TPD). Before performing a Bayesian analysis of the MIMIC model, as represented in Figure 4.1, a frequentist analysis was carried out for comparison purposes. Using ML estimation, a CFA model with covariates was tested with the five overexcitability indicators, positive developmental potential (which represents the interaction between the five forms of overexcitability and which is obtained by multiplying them), and intellectual ability as observed independent variables, with all of the personality trait indicators as observed dependent variables, and with neuroticism, openness, and conscientiousness as latent dependent variables. All personality trait factors were regressed on all of the covariates in the MIMIC model.

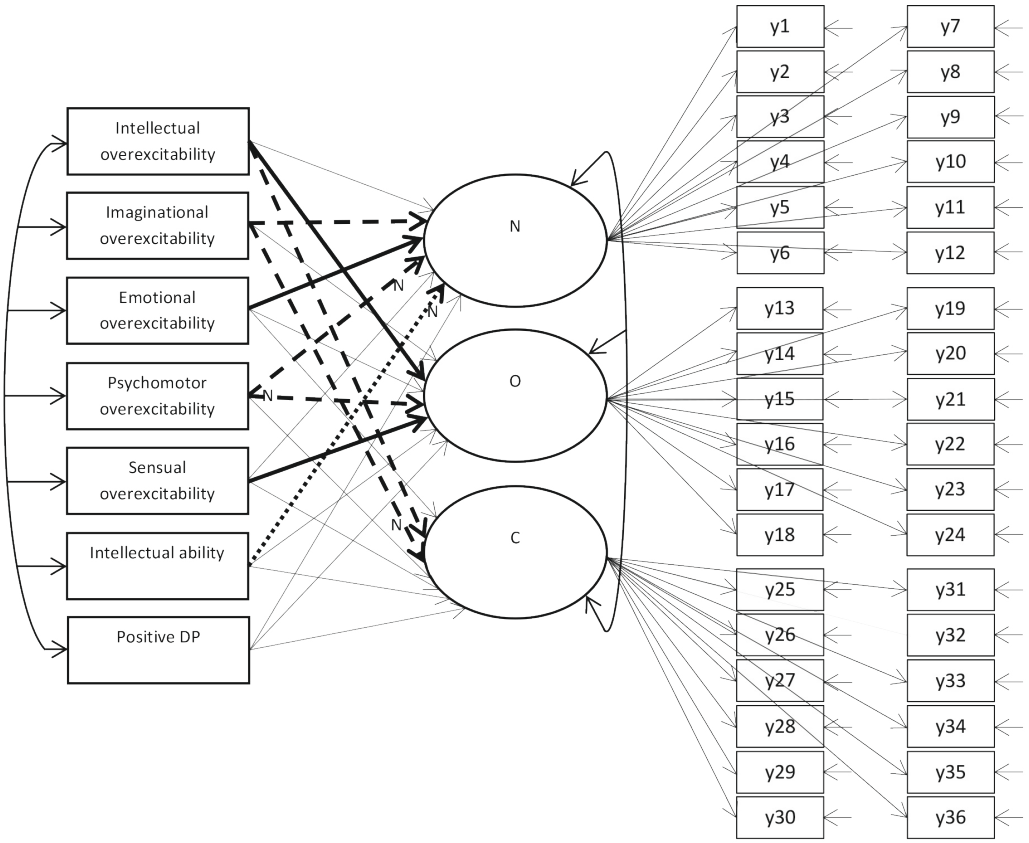

Figure 4.1. Multiple indicators, multiple causes model for females and males.
Note. N = neuroticism; O = openness; C = conscientiousness; DP = developmental potential. The bold lines represent significant – in the sense that the 95% Bayesian credibility interval does not cover zero – relationships for both female and male Bayesian models with zero-mean, small-variance priors for cross-loadings and residual covariances in the measurement model. 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.

Subsequently, a Bayesian analysis of the MIMIC model was performed with zero-mean and small-variance priors 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 a large 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* = 42 was applied for the correlated residuals, corresponding to prior zero-means and variances of 0.0111 (*SD* = 0.1054). In 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[13] chain to describe the posterior distribution. With regard to all these specifications we have adhered to the recommendations of Muthén and Asparouhov (2012). Standardized variables were analyzed.

Finally, in order to investigate the possible presence of distinct factors within the variable of emotional overexcitability, an exploratory factor analysis for two factors was performed – using ML ESEM with oblique Geomin rotation – and compared to a one-factor structure. In the ESEM models, the two correlated factors were measured by each of the 10 factor indicators and the residuals were not correlated.

Model fit assessment

The following fit measures were used to evaluate the fit of the ML CFA and ESEM models: 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 models, 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, 1998-2017). The simulated data should approximately match the observed data if the model fits the data. The Posterior Predictive *p*-value (PP*p*)

13 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, 1998-2017). 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, 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, 1998-2017).

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 (Muthén & Asparouhov, 2012).

RESULTS

Descriptive statistics

Descriptive summary statistics for the overexcitability indicators, personality traits, and intellectual ability are reported per gender group in Table 4.2. 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 scale measuring conscientiousness, which could be expected, given the higher intellectual profile of the respondents.

ML MIMIC

Table 4.3 shows the chi-square statistic, CFI, and RMSEA for the evaluation of the frequentist MIMIC models. Significant chi-square statistics, RMSEA values of more than 0.05, and CFI values of less than 0.90 all indicate that both female and male models fit the data poorly.

Table 4.3. ML and Bayesian MIMIC model testing results for females (n = 318) and males (n = 198).

Model	χ2	*df*	*p*-value	RMSEA	CFI	PP *p*	95% CI
Females							
ML-MIMIC	1732.395	822	< 0.0001	0.059	0.688		
BSEM-MIMIC						0.108	-42.581-189.744
Males							
ML-MIMIC	1364.909	822	< 0.0001	0.058	0.645		
BSEM-MIMIC						0.165	-62.605-181.482

Note. ML = maximum likelihood; 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; BSEM = Bayesian structural equation modeling.

BSEM MIMIC

Subsequently, a Bayesian analysis of the MIMIC model was performed. The 95% CIs for the difference between the observed and the replicated chi-square values cover zero and the PP*p*s are 0.141 and 0.581 for the female and male group, respectively, both indicating good model fit. However, the covariate of intellectual ability is only weakly negatively indicative of neuroticism for males (β = -0.240, p < 0.01). Moreover, it has no significant (significant in the sense that the 95% Bayesian credibility interval[14] does not cover zero) interactive effect on the influence of each of the overexcitabilities on the three personality dimensions in the male group. Likewise, the covariate of positive developmental potential has no significant effect on any of the personality traits. Consequently, both variables were dropped from the Bayesian MIMIC model. 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 et al., 2002). The DIC values generated by the full model and

14 The Bayesian credibility interval, based on the percentiles of the posterior distribution, allows direct probability statements about the parameter, in contrast to the confidence interval in frequentist theory, which is contingent on the hypothesis of extensive repeated sampling from the population (Bolstad, 2007; Kaplan & Depaoli, 2012; Zyphur & Oswald, 2015). 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 0.05).

the more parsimonious model were 36439.131 and 34056.584 for the female group, and 20672.984 and 19758.881 for the male group, respectively. Thus, the more parsimonious models produced the smallest DIC values. As presented in Table 4.3, omitting the variables of intellectual ability and positive developmental potential from the Bayesian MIMIC model yields satisfactory fit for both the female (PPp = 0.108, Δ observed and replicated χ^2 95% CI [-42.581, 189.744]) and male groups (PPp = 0.165, Δ observed and replicated χ^2 95% CI [-62.605, 181.482]). Figure 4.2A presents the distribution of the difference between the observed and the replicated chi-square values for the male group. The matching scatterplot (see Figure 4.2B), with the majority of the points plotted along the 45 degree line, indicates satisfactory model fit for the observed data.

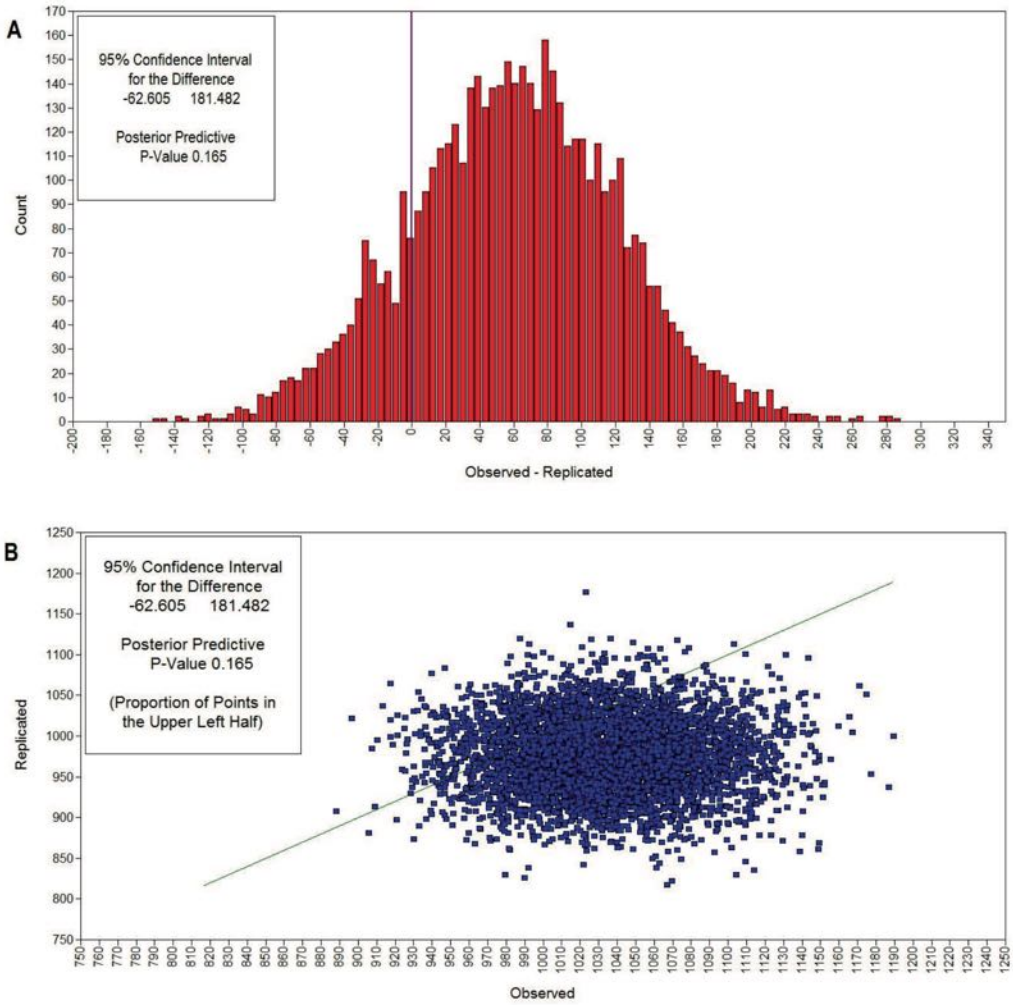

Figure 4.2. Bayesian posterior predictive checking distribution plot (A) and scatterplot (B) for the Bayesian MIMIC model for males.
Note. In the posterior predictive checking distribution plot, the chi-square statistic for the observed data is marked by the vertical line, which corresponds to a zero value on the *x*-axis. The matching scatterplot allows determining the PP*p* as the proportion of points above the 45 degree line.

Good McMC convergence was established for the two models. The PSR values smoothly decreased over the iterations, reaching a value close to 1 for the last few tens of thousands of iterations. Thus, the results of both BSEM models can be reliably interpreted. With the exception of only a small number of non-significant major factor loadings, the hypothesized factor loading pattern is fully recovered with substantial

target loadings and only one non-trivial cross-loading (in both gender groups), as displayed in Table 4.4 (in Mplus, the reported estimates are the medians of their posterior distributions). 68 (i.e., 11%) 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 et al., 2007).

Table 4.4. Bayesian MIMIC model estimation results for the measurement parameters for females (n = 318) and males (n = 198).

Factor Loadings						
	Females			**Males**		
	N	**O**	**C**	**N**	**O**	**C**
y1	**0.487***	-0.002	0.056	**0.833***	-0.058	0.054
y2	**0.582***	-0.007	0.021	**0.352***	0.024	0.035
y3	**0.522***	-0.003	-0.014	**0.606***	0.049	0.009
y4	**0.576***	0.020	0.001	**0.541***	0.056	-0.016
y5	**0.683***	-0.015	0.053	**0.702***	0.016	0.014
y6	**0.643***	0.000	-0.018	**0.550***	0.015	0.022
y7	**0.618***	0.011	0.046	**0.659***	0.001	-0.101
y8	**0.464***	0.014	-0.014	**0.178**	-0.003	-0.068
y9	**0.506***	-0.013	-0.038	**0.444***	-0.042	-0.030
y10	**0.588***	-0.003	-0.013	**0.592***	0.030	0.039
y11	**0.431***	-0.006	-0.093	**0.294***	-0.109	-0.009
y12	**0.524***	0.008	-0.038	**0.254**	0.021	-0.022
y13	0.061	**0.302***	-0.204*	-0.046	**0.834***	-0.049
y14	0.002	0.031	**-0.048**	-0.066	0.009	**-0.141**
y15	0.006	**0.734***	-0.007	-0.013	**0.642***	0.064
y16	-0.023	**0.417***	0.064	-0.023	**0.321***	0.023
y17	0.012	**0.675***	0.015	0.027	**0.632***	-0.025
y18	0.017	**0.446***	0.006	0.030	**0.045**	0.022
y19	0.041	**0.306***	0.013	0.140	**0.288***	0.112
y20	-0.006	**-0.136**	-0.028	-0.078	**0.206**	-0.051
y21	0.000	**0.719***	-0.034	0.054	**0.677***	-0.018
y22	-0.026	**0.424***	0.033	-0.020	**0.332***	0.005

Table 4.4. *Continued.*

Factor Loadings						
	Females			**Males**		
	N	**O**	**C**	**N**	**O**	**C**
y23	-0.062	**0.503***	0.036	-0.078	**0.546***	0.011
y24	0.001	**0.557***	0.007	0.024	**0.565***	0.034
y25	0.033	-0.015	**0.645***	0.099	-0.009	**0.827***
y26	-0.019	0.019	**0.479***	-0.141	0.016	**0.385***
y27	0.034	-0.009	**0.559***	-0.007	-0.030	**0.440***
y28	0.021	-0.007	**0.419***	0.082	0.012	**0.406***
y29	-0.005	0.011	**0.414***	-0.134	0.080	**0.584***
y30	-0.019	-0.022	**0.502***	0.058	-0.066	**0.555***
y31	0.035	0.009	**0.405***	0.128	-0.035	**0.488***
y32	0.015	0.004	**0.513***	0.017	0.017	**-0.081**
y33	-0.006	0.007	**0.518***	**-0.025**	-0.108	-0.023
y34	-0.031	0.022	**0.281***	-0.084	-0.009	**0.256**
y35	-0.065	-0.004	**0.702***	-0.170*	-0.131	**0.600***
y36	0.037	0.003	**0.098**	0.096	0.085	**0.404***
Factor Correlations						
	Females			**Males**		
	N	**O**	**C**	**N**	**O**	**C**
N	1.000			1.000		
O	0.050	1.000		0.147	1.000	
C	-0.306*	0.029	1.000	-0.017	-0.061	1.000

Note. MIMIC = multiple-indicators, multiple-causes; N = neuroticism; O = openness; C = conscientiousness. 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 4.5 presents the estimation results for the substantive structural parameters for both gender groups (see also Figure 4.1). As hypothesized, intellectual overexcitability is indicative of openness for both females ($\beta = 0.301$, $p < 0.001$) and males ($\beta = 0.275$, $p < 0.01$). Moreover, it is a supplementary indicator of conscientiousness but only for the female group ($\beta = 0.184$, $p < 0.01$). As expected, sensual overexcitability is

indicative of openness ($\beta = 0.454$, $p < 0.001$ for females, and $\beta = 0.245$, $p < 0.01$ for males). Psychomotor overexcitability is negatively related to neuroticism ($\beta = -0.174$, $p < 0.01$) and openness ($\beta = -0.175$, $p < 0.001$) but only for the female group. Furthermore, emotional overexcitability is an indicator of neuroticism ($\beta = 0.318$, $p < 0.001$ for females, and $\beta = 0.327$, $p < 0.001$ for males), while imaginational overexcitability is indicative of neuroticism ($\beta = 0.271$, $p < 0.001$) and negatively indicative of conscientiousness ($\beta = -0.472$, $p < 0.001$), but only for females.

Table 4.5. Bayesian MIMIC model estimation results for the significant 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					
Neuroticism regressed on					
imaginational overexcitability	0.271	0.071	< 0.001	0.129	0.407
emotional overexcitability	0.318	0.063	< 0.001	0.192	0.438
psychomotor overexcitability	-0.174	0.058	< 0.01	-0.285	-0.057
Openness regressed on					
intellectual overexcitability	0.301	0.056	< 0.001	0.189	0.409
psychomotor overexcitability	-0.175	0.049	< 0.001	-0.270	-0.080
sensual overexcitability	0.454	0.055	< 0.001	0.343	0.557
Conscientiousness regressed on					
intellectual overexcitability	0.184	0.072	< 0.01	0.042	0.323
imaginational overexcitability	-0.472	0.067	< 0.001	-0.594	-0.334
Males					
Neuroticism regressed on					
emotional overexcitability	0.327	0.083	< 0.001	0.158	0.484
Openness regressed on					
intellectual overexcitability	0.275	0.085	< 0.01	0.104	0.433
sensual overexcitability	0.245	0.092	< 0.01	0.059	0.419

Note. MIMIC = multiple-indicators, multiple-causes.

We can conclude that intellectual, psychomotor (negative parameter), and sensual overexcitability account for 45.1% of the variance in openness for the female group. For the male group, 25.6% of the variance in openness can be explained by intellectual and sensual overexcitability. Emotional, psychomotor (negative parameter), and imaginational overexcitability (the latter two only with respect to females) account for 19.9% and 15.0% of the variance within the trait of neuroticism for females and males, respectively. In addition, intellectual and imaginational overexcitability (negative parameter) account for 21.2% of the variance within conscientiousness for the female group.

ML ESEM

As expected, a two-factor exploratory structure [$\chi 2$ ($df = 26$, $n = 318$) = 56.614, $p < 0.001$, RMSEA = 0.061 (low = 0.039, high = 0.083), and CFI = 0.955 for the female group, and $\chi 2$ ($df = 26$, $n = 198$) = 55.549, $p < 0.001$, RMSEA = 0.076 (low = 0.048, high = 0.103), and CFI = 0.930 for the male group] fits the data better than a one-factor structure [$\chi 2$ ($df = 35$, $n = 318$) = 160.760, $p < 0.0001$, RMSEA = 0.106 (low = 0.090, high = 0.123), and CFI = 0.815 for females, and $\chi 2$ ($df = 35$, $n = 198$) = 131.047, $p < 0.0001$, RMSEA = 0.118 (low = 0.097, high = 0.140), and CFI = 0.772 for males].

Similar results were obtained for both gender groups. As presented in Table 4.6, two factors can clearly be distinguished: the first (F1) and second factor (F2) may represent the catalyst role that emotional overexcitability may play at a respectively higher and lower level in the course of personality development. For example, the items "I am deeply concerned about others," "It makes me sad to see a lonely person in a group," and "I feel other people's feelings" all load significantly on F1. Thus, the first factor may be indicative of the emergence of empathy in the phase of Organized Multilevel Disintegration. In contrast, all of the items that load significantly on F2 (e.g., "I can feel a mixture of different emotions all at once," "I have strong feelings of joy, anger, excitement, and despair," and "I worry a lot") may reflect the mixed feelings or ambivalences that emerge in the phase of Unilevel Disintegration.

Table 4.6. Maximum likelihood ESEM model estimation results for females (n = 318) and males (n = 198).

Factor Loadings				
	Females		**Males**	
	F1	**F2**	**F1**	**F2**
y6	**0.556***	0.144	**0.428***	0.096
y9	0.032	**0.406***	0.196*	**0.431***
y11	**0.721***	-0.159	**0.406***	0.143
y17	0.039	**0.318***	-0.006	**0.414***
y26	-0.184	**0.837***	-0.010	**0.808***
y31	**0.790***	0.008	**1.118***	-0.003
y35	0.030	**0.654***	0.081	**0.550***
y41	0.160	**0.532***	0.113	**0.368***
y44	**0.383***	0.209	**0.083**	0.057
y49	0.217	**0.270***	**0.380***	0.247*
Factor Correlations				
	Females		**Males**	
	F1	**F2**	**F1**	**F2**
F1	1.000		1.000	
F2	0.574*	1.000	0.421*	1.000

Note. ESEM = exploratory structural equation modeling; F1 = factor 1; F2 = factor 2. The standardized coefficients in bold represent factor loadings that are the largest for each factor indicator.
*$p < 0.05$.

DISCUSSION

The main objective of this study was to investigate interrelationships between overexcitability and neuroticism, openness, and conscientiousness, applying BSEM. BSEM is an innovative and flexible approach to statistics, allowing the application of zero-mean, small-variance priors for cross-loadings and residual covariances, which leads to better model fit and less overestimation of factor correlations compared to ML CFA (which postulates exact parameter constraints and is usually too strict) (Fong & Ho, 2014; Muthén, 2013; Muthén & Asparouhov, 2013a).The analysis yielded positive results

regarding the fit of the models, in contrast to the ML MIMIC models which could not generate a satisfactory model fit, due to the existence of many minor cross-loadings and residual covariances in the measurement model.

The results of both BSEM MIMIC models indicate that overexcitability is weakly related to the three personality traits examined with one exception (i.e., a moderate association with openness for females, as inferred from the explained variance). None of the above-mentioned studies that investigated associations between overexcitabilities and the FFM-personality traits took possible gender differences into account. Despite similarities in substantive structural parameter estimates for females and males (i.e., non-trivial associations between intellectual and sensual overexcitabilities and openness, and between emotional overexcitability and neuroticism), this study also reveals clear differences in both gender groups regarding significant parameter values and explained variance.

Furthermore, based on the similarities and differences identified between overexcitability and personality traits, we cannot deduce any conceptual equivalence of or interchangeability between overexcitability and openness, despite the moderate relationship for females. Moreover, the interaction term "positive developmental potential" had no substantive effect on any of the personality traits. The results of this study do not support the assertion of the Vuyk et al. (2016) study, but rather concur with the findings of Botella et al. (2015) and Limont et al. (2014). This does not preclude a potential understanding of the overexcitability scores within the framework of a widely accepted personality taxonomy. However, classifying overexcitabilities within the five-factor taxonomy must take into account the variety of distinctive facets from which all five broad personality dimensions are comprised, in order to interpret overexcitability from a pattern of convergent and discriminant relationships. After all, most of the overexcitability scales have loadings on more than one personality factor, and clear correspondences in content between overexcitability and various discrete facets (e.g., the anxiety, depression, and self-consciousness facets of neuroticism, all facets – excluding actions – of openness, the altruism and tender-mindedness facets of agreeableness, and in some sense the dutifulness facet of conscientiousness) may be assumed. However, divergences may also be expected, which derive from different conceptual origins and a different approach to personality. As stated by McCrae and Costa (1989, p. 23), "The five-factor model is not based on any single theory of personality,

but has been shown to encompass scales that operationalize a number of theoretical perspectives." Furthermore, "[t]he five-factor model is purely descriptive, it does not explain the origins of personality nor the mechanisms that account for individual differences" (McCrae & Costa, 1989, p. 34). In contrast, Dąbrowski's personality theory assumes a hierarchical organization of personal development, and personality is only achieved at the level of Secondary Integration. Few reach this highest level of human development (Dąbrowski, 2015; Mendaglio, 2008; Tillier, 2018).

The results of the ML ESEM models clearly reveal this multiple-phase perspective. Just as F2 may reflect a dissolving dynamism in the transitional phase between primary integration and disintegration, F1 may mirror a developmental dynamism, which reduces distress by moving toward a personality ideal. Neither human growth, entelechy, positive mental health nor a multidimensional perspective on personality development are tapped by the NEO-FFI scales or FFM. Moreover, as inferred from Table 4.5, the openness scale of the NEO-FFI seems to primarily reflect the "Intellect" factor (Goldberg, 1990), with an emphasis on intellectual curiosity and aesthetic sensitivity – not to be confused with intelligence, as indicated by the results of the BSEM models and in accordance with previous research (Costa & McCrae, 1992a). In the same way, the core dimension of the neuroticism factor in the FFM is negative emotionality, and thus mainly corresponds with lower levels of development according to Dąbrowski's theory. In contrast to emotional overexcitability, the personality trait of neuroticism does not include higher level constructs such as syntony, identification, and empathy. In this context, McCrae and Costa (1987, p. 87) state that "[v]irtually all theorists would concur in the centrality of negative affect to neuroticism; the question is whether other features also define it." Moreover, they add that "[v]iewing Neuroticism solely as negative affectivity may prevent a recognition of its broader motivational and interpersonal aspects" (Costa & McCrae, 1988, p. 264).

Although multidimensionality can clearly be deduced from the results of the ESEM models regarding emotional overexcitability, a multi-stage perspective is much less clear with respect to the other forms of overexcitability. According to Dąbrowski, however, each form of overexcitability has a different expression, depending on the level of personality development (Dąbrowski, 1970c; Tillier, 2018). It would therefore be interesting to consider a hierarchically structured questionnaire that goes beyond the five-factor static taxonomic model of personality and can be used in future

research on dynamic developmental processes of personality in accordance with the TPD. Organizing the OEQ-II according to a set of hierarchically structured facets may offer better insight into the implicit theoretical basis and differential significance of overexcitability in relation to the established personality traits. It may also elucidate relationships between higher levels of personality development and some positioning in the FFM while also enabling an explanation of the dynamic operation of traits and facilitating further empirical investigation of the TPD.

In any case, overexcitability is a major concept. In addition to revealing that emotional, intellectual, and imaginational overexcitability are important indicators of personality development (Falk & Miller, 2009; Lysy & Piechowski, 1983; Miller et al., 1994), empirical studies have indicated that intellectual overexcitability, as measured by the OEQ-II, is particularly strongly interrelated with the deep learning approach (De Bondt & Van Petegem, 2017). This close relationship could not be demonstrated when using the FFM-personality traits (Chamorro-Premuzic & Furnham, 2009).

Furthermore, the introduction refers to an important association between overexcitability, as measured by the OEQ-II, and giftedness, as well as to the greater potential of gifted individuals to arrive at autonomous and authentic personalities. With their intensity, sensitivity, heightened reflectivity, and consciousness, along with their state of being different and their awareness thereof, combined with their innate urge to strive for authenticity, gifted individuals experience the discrepancy between what is and what ought to be more intensely. This makes them potentially more vulnerable to inner conflicts and tension. Because of the same attributes, along with their creativity and penchant for self-determinism, however, gifted individuals have a greater capacity than anyone else to find the path to absolute meaningfulness and even ultimately to inspire others, and help them grow along the road to humanity. This is the greatest and most valuable human contribution and, by their very nature, gifted individuals appear to be the very best in this respect.

With regard to the development of a strong personality, however, Dąbrowski emphasizes the importance of authentic education, which encourages individuals to transcend mediocrity and to develop their own personal hierarchies of values and aims, which they are then taught to realize (Rankel, 2008).

With regard to the limitations of this study, we have to note that although the BSEM approach to factorial validation better represents substantive theory, 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 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). Even in the case of very limited prior knowledge (non-informative prior) with little influence on the posterior distribution, the Bayesian credibility interval nevertheless allows direct probability statements about the parameter values given the data.

A second limitation of this study is the use of a brief version of the Revised NEO Personality Inventory (NEO-PI-R) (Costa & McCrae, 1992b) to determine only three personality traits. The NEO-FFI lacks the rich detail of the 240-item NEO-PI-R, which assesses 30 facets that define the five factors. Furthermore, a more complete grasp of latent constructs such as personality and overexcitability would require additional in-depth research on their neurobiological foundations.

To conclude, the results of this study provide clear evidence of similarities and differences for the OEQ-II scales when interrelated with the NEO-FFI scales. However, it should be noted that the interrelationships are not sufficiently strong to suggest that broader based personality instruments may serve as a substitute when a more comprehensive insight into human personality, its developmental course, and evolutionary significance is required.

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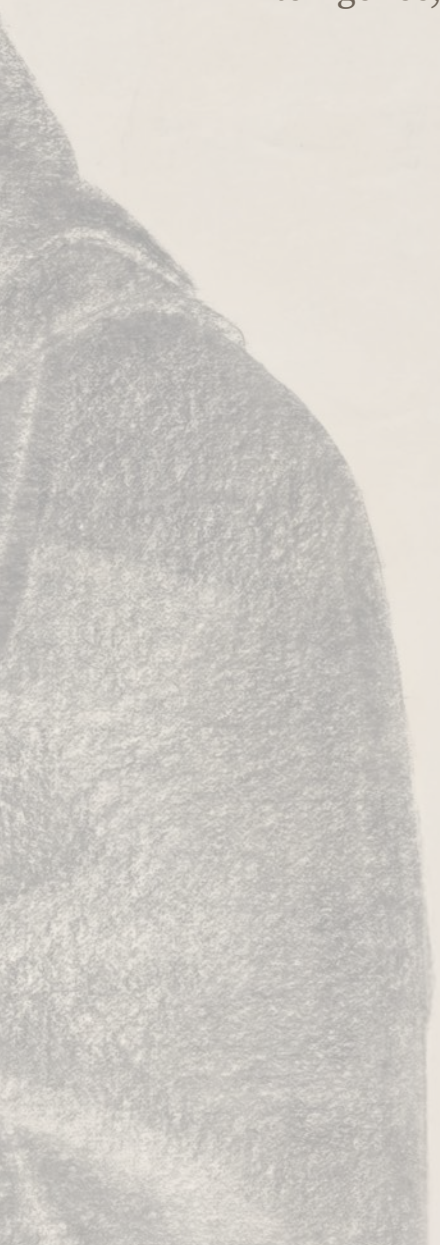
CHAPTER 5

STUDY 4:

Are contextual rather than personal factors at the basis of an anti-school culture? A Bayesian analysis of differences in intelligence, overexcitability, and learning patterns between (former) lower and higher-track students



This chapter is based on:
De Bondt, N., Donche, V. & Van Petegem, P. (2020). Are contextual rather than personal factors at the basis of an anti-school culture? A Bayesian analysis of differences in intelligence, overexcitability, and learning patterns between (former) lower and higher-track students. *Social Psychology of Education, 23*, 1627–1657. https://doi.org/10.1007/s11218-020-09597-5

ABSTRACT

Research indicates that educational stratification may lead to a lower-track school culture of futility and a less academically-oriented culture among lower-track teachers, leading to both reduced study involvement and lower educational achievement among their students. This study investigated whether an anti-school culture in the lower tracks (in this study, in technical secondary education [TSE; $n = 132$] in comparison with general secondary education [GSE; $n = 356$]) has a solid basis that is supported by *personal*, ontological differences in intelligence and developmental potential (i.e., overexcitability, according to the Theory of Positive Disintegration [TPD]). In addition, this study examined the consistency of these results with differences in mathematical and verbal achievement, the use of cognitive processing and metacognitive regulation strategies, and study motivation, as well as differences in the influence of personal competence indicators on the learning approach, all suggesting *contextual*, educational influences. A Bayesian analysis was applied to address the problem of a frequentist approach in complex statistical models. This study does not primarily reveal competence differences between both tracks (as indicated by no substantive differences in overexcitability and intelligence between respectively former GSE and TSE students and GSE and TSE boys), but rather substantial differences in verbal and mathematical performance, as well as regulatory/motivational problems among former TSE students, corroborating to some extent the abovementioned consequences of academic differentiation. The results are further elucidated from the perspective of self-determination theory and the TPD.

INTRODUCTION

The principal aim of tracking or ability grouping in secondary education is both to prepare students for different final competencies and to offer them a trajectory in accordance with their cognitive abilities and interests (Schafer & Olexa, 1971). However, in Flanders, which represents the Dutch-speaking part of Belgium, no systematic screening for intelligence or other competencies is carried out at the start of (and during) secondary education. Nor are the personal interests of the students assessed in depth at the outset. Moreover, empirical research in Belgium has shown that the effects of tracking are not unequivocally beneficial for the lower ability groups. On the contrary, educational stratification would lead in the lower tracks to impaired study involvement (Van Houtte, 2006; Van Houtte & Stevens, 2010), reduced achievement (Stevens & Vermeersch, 2010; Van de gaer et al., 2006; Van Houtte, 2004), lower self-esteem (Van Houtte, 2005), as well as to an increased sense of futility (Van Houtte & Stevens, 2010). Similar results are obtained in other countries (Gamoran & Mare, 1989; Hallinan & Kubitschek, 1999; Kerckhoff, 1986; Vanfossen et al., 1987).

An important determinant of these negative outcomes appears to be the differential study culture that can be found in the various education tracks. The differentiation-polarization theory states that academic differentiation leads to a polarization of subcultures in which high- and low-ability groups develop a pro- and anti-school culture, respectively (Ball, 1981; Hargreaves, 1967; Lacey, 1970; Schafer & Olexa, 1971). In a hierarchically structured education system based on academic achievements, the lower-track students try to compensate for their loss of status by adopting an anti-school attitude (Hargreaves, 1967) that is characterized by an undervaluation of educational achievements (Ball, 1981; Hargreaves, 1967; Lacey, 1970; Rosenbaum, 1976; Schafer & Olexa, 1971). Moreover, this effect is reinforced by a less academically-oriented staff culture, in which lower-track teachers perceive their students as less competent and less teachable and have lower performance expectations (Ball, 1981; Hargreaves, 1967; Ireson & Hallam, 2001; Murphy & Hallinger, 1989; Rosenbaum, 1976). Consequently, they relax the learning content and didactics according to these presuppositions, which ultimately compromises students' achievements and future perspectives.

The differentiation-polarization theory is equally applicable to Belgium. Secondary education in Flanders comprises six years of study (grades 7-12, ages 12-18), the last

four years of which are organized according to four different education tracks. General secondary education (GSE) represents the academic track that provides a theoretical program which prepares students for higher education, while vocational secondary education (VSE) offers a practical curriculum that immediately prepares students for a specific practical profession. Technical secondary education (TSE) and arts secondary education (ASE) provide, in addition to a theoretical program, technical and artistic courses, respectively, that prepare students for both immediate professional practice and participation in higher education. Academic differentiation would lead to a less study-oriented culture among students of TSE and VSE (lower status), compared to GSE (higher status), and to both a less academically-oriented culture among lower-track teachers (Van Houtte, 2004, 2006) and a TSE/VSE school culture of futility, which govern, respectively, the lower educational achievement and reduced study involvement of TSE/VSE students (Van Houtte, 2004; Van Houtte & Stevens, 2010).

The aim of this research is to investigate whether an anti-school culture in the lower tracks (in this study, in TSE in comparison with GSE) has a solid basis that is supported by real *personal* differences in intelligence and developmental potential (i.e., overexcitability, according to Dąbrowski's Theory of Positive Disintegration [TPD] [Dąbrowski, 1964, 2015]). Are these results consistent with any differences in mathematical and verbal achievement among both tracks that may indicate *contextual*, educational influences? Further, Van Houtte and Stevens (2010) point to a culture of low motivation in TSE and VSE tracks. This study therefore also investigates whether there are differences in study motivation between (former) TSE and GSE students, and whether they process information and regulate their study process differently. In other words, do they apply different learning patterns that might explain differing degrees of study involvement? Furthermore, the differential influence of personal competence indicators (including overexcitability) on learning patterns is investigated. These research questions are mainly addressed through a Bayesian approach to statistics, which is still marginally applied in educational research (König & van de Schoot, 2018), despite its many advantages over the frequentist approach (Kruschke et al., 2012). Before presenting this study, we first introduce the concepts of learning patterns, overexcitability, and Bayesian structural equation modeling (BSEM) (Muthén & Asparouhov, 2012).

Learning patterns and its correlates with personal and contextual factors

A learning pattern can be described as "a coherent whole of learning activities that learners usually employ, their beliefs about learning and their learning motivation, a whole that is characteristic of them in a certain period of time" (Vermunt & Donche, 2017, p. 270). The Inventory of Learning Styles (ILS) (Vermunt, 1994) has been developed to test learning patterns in higher education and addresses both information processing and self-conscious reflection on studying. The present study uses the Learning and Motivational Questionnaire (LEMO) (Donche et al., 2010), which is derived from the ILS, to measure the way in which students process information, as well as their regulation strategies and study motivation.

With regard to information processing, the surface/deep dichotomy describes important differences in the ways in which students learn (Marton & Säljö, 1976). A surface approach to learning is characterized by a focus on memorization, with the intention to reproduce knowledge. In contrast, a deep approach, in which the objective is to understand, is characterized by the construction of meaning by relating concepts, by exploring underlying patterns and principles, and by critical argumentation (Entwistle, 1997).

The learning process is also affected by the extent of self-regulation, which is characterized by the independent planning of learning activities, monitoring progress, testing, diagnosing problems, and engaging in repair activities, evaluation, and reflection (Vermunt & van Rijswijk, 1988). External regulation and lack of regulation concern, respectively, the regulation of the learning process by external sources and regulatory difficulties (Vermunt & Vermetten, 2004).

Motivation is also an important determinant of an individual's study approach and learning process (Entwistle & McCune, 2004; Vermunt & Donche, 2017). In the LEMO, the conceptualization of study motivation is derived from Self-Determination Theory (SDT) (Deci & Ryan, 2000, 2002). SDT represents an organismic-dialectical metatheory that presupposes human integrative tendencies and centers on the dialectic between the active, autonomy-seeking human organism and the social environment which may support or impede this innate purpose. SDT presupposes a self-determination continuum in which different types of motivation can be distinguished according to the extent to which they operate autonomously (Deci & Ryan, 2000, 2002). At one end of the continuum is the condition of amotivation in which there is no intention to act. At

the other end resides intrinsic motivation that gives rise to self-determined behavior in which one autonomously chooses to perform an activity in function of inherent interest. In between reside various types of extrinsic motivation, which can be considered non-autotelic and more or less instrumental to the attainment of externally defined goals and values (Deci & Ryan, 2000, 2002; Ryan & Connell, 1989).

The LEMO yields four learning patterns (Donche et al., 2010). The *meaning-directed learning pattern* is characterized by the intention to acquire understanding (thus reflecting a deep approach) through the relation, structuring, and critical processing of information, as well as by self-regulation and autonomous motivation (the latter reflects a personal interest in learning and desire to study, both of which are related to intrinsic motivation and more autonomous forms of extrinsic motivation in SDT). In contrast, *reproduction-directed learning* is characterized by the use of a surface approach, with an emphasis on the memorization and analysis of information as process characteristics, as well as by external regulation and controlled motivation (the latter reflects an experienced duty to study and relates to less autonomous forms of extrinsic motivation in SDT). The *undirected learning pattern* is determined by both a lack of regulation and amotivation, while *application-directed learning*, which is related to deep learning (Vermunt, 1998), is characterized by the concrete processing of information.

A learning pattern is likely to be the result of interplay between personal attributes and dynamic contextual influences (Vermunt, 1996; Vermunt & Donche, 2017; Vermunt & Vermetten, 2004). Regarding *personal* factors, empirical studies have indicated that *inter alia* personality and gender are related to learning patterns (Vermunt & Donche, 2017). Personality, as measured by the five-factor model (FFM) personality traits (McCrae & Costa, 1987), is only weakly to moderately interrelated with learning patterns (Vermunt & Donche, 2017), with the most substantial relationship between openness to experience and deep learning (Chamorro-Premuzic & Furnham, 2009). With regard to gender, a study by Severiens and Ten Dam (1997) points to a higher score for women and men on, respectively, reproduction-directed learning and undirected learning, although the differences are small. Other studies do not show consistent relationships (Vermunt, 2005).

Research has also demonstrated that *contextual* factors, such as course-dependent and lecturer-dependent characteristics, as well as prior education and methods of assessment, affect the learning process (Donche et al., 2013; Entwistle & McCune,

2004). The scarce research on associations with prior education reveals that higher prior education is negatively related to reproduction-directed learning, and lower prior education is positively associated with a lack of regulation (Vermunt, 2005; Vermunt & Donche, 2017).

The concept of overexcitability within the TPD

The TPD represents an organismic and dynamic theory of personality development, in which personality is defined as "[a] self-aware, self-chosen, self-affirmed, and self-determined unity of essential individual psychic qualities" (Dąbrowski, 2015, p. 290) and is only attained at the final level of the developmental process. The TPD presupposes innate integrative human tendencies toward conscious, high value-based self-determination and personal development, with essence as the ultimate purpose. However, this final goal is only achieved by a few people as it requires a process of positive disintegration in which awareness of a discrepancy between biological and social actuality on the one hand and supra-biological necessity on the other hand (the former refers to a cohesive mental structure aimed at meeting biological needs and conforming to societal norms; the latter refers to how life ought to be, i.e., absolutely truthful, alter-centric, and according to universal, objective moral values) gives rise to external and internal conflicts that may cause the disintegration of the primitive mental organization (Dąbrowski, 2015). Only in the presence of sufficient developmental potential (which is determined by a high level of overexcitability, special abilities and talents, and a strong autonomous drive to achieve individuality) can one reach further disintegration and, subsequently, advanced development (Dąbrowski, 2015; Mendaglio, 2008; Tillier, 2018).

The concept of overexcitability refers to enhanced psychic intensity or an above average responsiveness to stimuli, due to heightened sensitivity of the central nervous system (Dąbrowski, 1970c, 2015; Mendaglio, 2008). It constitutes the foundation of powerful perceptivity, which may lead to increased external but especially inner conflicts and tension. But it also enables an individual to envision a higher, universal reality and to be deeply aware of what should be (Dąbrowski, 1970a). As such, overexcitability enhances the possibility of inner mental transformation. Moreover, it is a necessary element of an individual's psychic enrichment (Dąbrowski, 1970a, 2015; Dąbrowski & Joshi, 1972). The TPD distinguishes five forms of overexcitability. *Psychomotor*

overexcitability is characterized by an abundance of physical energy, hyperkinesia, and "an immediacy of reaction and capacity for action; it is a 'permanent' psychomotor readiness" (Dąbrowski, 2015, p. 75). *Sensual overexcitability* involves enhanced receptivity of the senses and strong sensory and esthetic experiences (Dąbrowski, 2015; Daniels & Piechowski, 2009). *Intellectual overexcitability* is characterized by intensified mental activity, searching for truth and understanding, conceptual and intuitive integration, independent and critical thinking, and an interest in abstraction and theory. *Emotional overexcitability* involves the capacity for strong attachments and deep relationships, identification and empathy, as well as the ability to experience things deeply, strong somatic and affective expressions, and well-differentiated feelings toward self (Daniels & Piechowski, 2009). It "constitutes the ground for compassion, pity, anxiety about others and about one's own thread of life" (Dąbrowski, 2015, p. 211). *Imaginational overexcitability* is characterized by the capacity for strong visualization, prospection and retrospection, as well as by ingenuity, fantasy, intense dreams, illusions, and visionary powers (Dąbrowski, 2015; Daniels & Piechowski, 2009). Dąbrowski (2015) states that "[n]one of the forms of hyperexcitability [...] develops in isolation. As a rule these are mixed forms with predominance of this or that form. They are disintegrating factors and, in conjugation with mental hyperexcitability [i.e., intellectual overexcitability], permit preparation for higher forms of disintegration and secondary integration[15]" (p. 75). The TPD postulates the necessary conjunction of the five overexcitabilities to arriving at personality development. Positive developmental potential includes all five forms of overexcitability, although intellectual, emotional, and imaginational overexcitability support the transformation of the lower forms of overexcitability, i.e., sensual and psychomotor overexcitability (Dąbrowski, 1976; Mendaglio, 2012).

Furthermore, special abilities and talents are also part of an individual's developmental potential. According to Dąbrowski (2015), "the activities of intelligence, the activities of thinking, are instrumental activities of the aspirational and affectional dynamisms. Disintegration of these dynamisms disintegrates also the thinking activities connected with them. Love, unselfishness, conscious ability to sacrifice oneself,

15 The TPD distinguishes five levels of development, which are not sequential, age-related, or universal (Mendaglio, 2008): primary integration, unilevel disintegration, spontaneous multilevel disintegration, organized multilevel disintegration, and secondary integration (for full explanation see Dąbrowski, 2015). Personality is only achieved at the level of secondary integration.

contemplative activity, all purify, elevate, and broaden our thinking, introducing it to a more objective area" (p. 119). The developmental process is guided by higher-level emotions. Nevertheless, intelligence and higher-level emotions collaborate closely at a high level of psychic functioning (Dąbrowski, 1970b, 1970c). If combined with a high level of overexcitability and strong developmental dynamisms (more specifically, self-consciousness, subject-object attitude[16], the personality ideal[17], and the Third Factor[18]), intelligence could function as a catalyst if used in the service of the developmental process.

Bayesian structural equation modeling

Educational research continues to make only marginal use of Bayesian statistics (König & van de Schoot, 2018), despite its many advantages over the frequentist approach to statistics (Kruschke et al., 2012). For example, most educational and psychological questionnaires exhibit slight cross-loadings and measure additional minor factors beyond those embedded in the instruments, and they therefore cannot be appropriately approached by frequentist confirmatory factor analysis (CFA), which imposes exact parameter constraints. Strategies aimed at compensating for this inadequacy are likely to rely on coincidence (MacCallum et al., 1992), and they are thus accompanied by a considerable risk of model misspecification (Muthén & Asparouhov, 2013b). In contrast, BSEM allows for the inclusion of all cross-loadings and residual covariances in the model – which would lead to a non-identified model in a frequentist analysis – using strong informative priors with zero-mean and small variance (therefore allowing these parameters to vary slightly around zero-means), better reflecting substantive theory

16 Subject-object in oneself refers to the process of looking at oneself critically and objectively and approaching the other subjectively, with empathy and compassion (Dąbrowski, 2015).

17 At higher levels of development, the individual becomes aware of his/her own personality ideal and the necessity of approaching this ideal. Through critical and objective self-examination and the conscious perception of the higher and lower within herself/himself, while simultaneously becoming aware of a higher, true reality (through intuition), the individual can construct a personal hierarchy of values, which is derived from universal, objective moral values (Dąbrowski, 2015).

18 The personality ideal is activated by means of the Third Factor, which can be considered a highly conscious, high value-based self-determinism that rejects the lower, instinctive dimension and affirms the higher, authentic one. The First Factor refers to the constitutional endowment, while the Second Factor points to the social environment (Dąbrowski, 2015).

and leading to better model fit and more accurate inferences (Muthén & Asparouhov, 2012).

Analogously, the BSEM approach can be applied to the investigation of scalar measurement invariance (MI) across different groups, in which exact zero differences in factor loadings and measurement intercepts across groups are replaced by approximate zero differences based on zero-mean, small-variance priors[19]. The BSEM approach to MI, which is described as approximate MI, offers a valid alternative to the multi-group CFA approach to MI analysis with maximum likelihood (ML) estimation, which usually results in insufficient fit due to small deviations from exact invariance (Asparouhov & Muthén, 2014).

MATERIALS AND METHODS

Participants

The instruments discussed below were added to a large-scale longitudinal study conducted in Flanders investigating the influence of learning patterns on the successful transition from secondary to higher education. This study focuses on a sample of 356 (232 women; 124 men; M = 19.39 years; SD = 0.52) and 132 (67 women; 65 men; M = 19.69 years; SD = 0.78) students who were in the second consecutive year of a program of higher education and had completed, respectively, general and technical secondary education before entering higher education. The study was executed in accordance with the guidelines of the Ethics Committee for the Social Sciences and Humanities of the university with written informed consent from all subjects.

19 In contrast to frequentist approaches, the population parameter is treated as random in Bayesian statistics. This makes it possible to make probability statements about the value of this parameter, based on substantive theories or previous empirical findings, as reflected in its prior probability distribution. Drawing on Bayes' theorem, observed sampling data will revise this prior knowledge, thereby resulting in the posterior probability distribution of the parameter (which is proportional to the product of the likelihood and the prior distribution) (Bolstad, 2007; Kaplan & Depaoli, 2012; Lee, 2007). Strong prior knowledge regarding the population parameter value (applied to CFA and scalar MI, it reflects the requirement for cross-loadings, correlated errors, and differences in factor loadings and intercepts across groups to be approximately zero) is indicated by a small variance of its prior distribution (allowing the aforementioned parameters in CFA and MI to deviate from zero to a very limited extent). In this condition, the data have less impact on the posterior distribution (Asparouhov & Muthén, 2014; Muthén & Asparouhov, 2012).

Measures

Overexcitabilities

The Overexcitability Questionnaire-Two (OEQ-II) (Falk et al., 1999) was used in this study, which is the most widely utilized self-reporting instrument for measuring the degree and nature of overexcitability. The OEQ-II consists of 50 items (equally representing the five forms of overexcitability) that are scored along a five-point Likert scale with response options ranging from "Not at all like me" to "Very much like me." A high value on the scale of the items represents a high level of overexcitability. The OEQ-II demonstrates good factorial validity and approximate scalar MI across gender (De Bondt & Van Petegem, 2015).

Learning patterns

The LEMO is composed of the Inventory of Learning Styles-Short Version (ILS-SV) (Donche & Van Petegem, 2008) and abbreviated versions of the Academic Self-Regulation Questionnaire (SRQ-A) (Ryan & Connell, 1989; Vansteenkiste et al., 2009) and Academic Motivation Scale (AMS) (Vallerand et al., 1992) to measure cognitive processing and metacognitive regulation strategies (ILS-SV; 20 and 14 items, respectively), as well as study motivation (SRQ-A and AMS; 12 and 3 items, respectively). All items are scored along a five-point Likert scale. A high value on the scale of the items represents a high level of the variable concerned.

Intellectual ability

Intellectual ability was measured by the Prüfsystem für Schul- und Bildungsberatung Test 3 (PSB-3) (Horn, 1969), which represents a non-verbal, time-limited intelligence test that is composed of 40 items.

Mathematical and verbal achievement

The mathematical performance test (24 items) and readability test (25 items) contain functional arithmetic and reading skills tasks that measure the proper functioning in society or in a future work situation (De Maeyer et al., 2003).

The PSB-3 and performance tests were conducted two years earlier, when the respondents were at the start of their final year of secondary education.

Analyses

The factorial structure of the OEQ-II had already been validated, using BSEM and yielding positive results, in contrast to an ML CFA analysis which could not generate a satisfactory model fit, due to the existence of trivial cross-loadings and many minor correlated residuals among the factor indicators (De Bondt & Van Petegem, 2015). In addition, approximate scalar MI across gender was established. The present study investigates approximate MI of factor loadings and intercepts across education tracks, using the Mplus software program (Version 8.3; Muthén & Muthén, 1998-2017). Scalar invariance, as characterized by invariant factor loadings and measurement intercepts across groups, is a requirement for comparing group factor means (Millsap, 2011; Muthén & Asparouhov, 2013c). First, in order to establish configural invariance, a CFA model – according to the OEQ-II's hypothesized latent factor loading pattern for the 50 observed variables – was tested for both GSE and TSE groups, albeit using BSEM with informative, small-variance priors for cross-loadings and residual covariances. Target loadings with non-informative priors – i.e., normally distributed priors with a mean of zero and a large 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 used. An inverse-Wishart prior distribution $IW(0, df)$ with $df = 56$ was utilized for the residual covariances, corresponding to prior zero-means and variances of 0.01. Every tenth iteration was used – in order to reduce autocorrelation between successive posterior draws – with a total of 100,000 iterations and one MCMC[20] chain to describe the posterior distribution. With regard to all these specifications we have adhered to the recommendations of Muthén & Asparouhov (2012). Standardized variables were analyzed. Subsequently, approximate scalar MI across education tracks was tested. Analyses were carried out for each overexcitability factor and the alignment

20 Bayesian analysis uses Markov chain Monte Carlo (MCMC) algorithms to iteratively extract random samples from the posterior distribution of the model parameters (Muthén & Muthén, 1998-2017). MCMC convergence of posterior parameters, which denotes that sufficient samples have been extracted from the posterior distribution to precisely estimate the posterior parameter values, is assessed using the potential scale reduction (PSR) convergence criterion (Gelman & Rubin, 1992). The PSR criterion compares within- and between-chain variation of parameter estimates. 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 indicates perfect convergence (Kaplan & Depaoli, 2012; Muthén & Muthén, 1998-2017).

optimization method with Bayes estimation (Asparouhov & Muthén, 2014) was applied. Normal prior distributions $N(0, 0.01)$ were used for differences in factor loadings and intercepts across tracks. Inverse-Wishart prior distributions $IW(0, 16)$ were applied for the correlated residuals, corresponding to prior zero-means and variances of 0.01. Every tenth iteration was saved with a maximum and minimum number of iterations for each of two MCMC chains of 50,000 and 1,000, respectively, using the Gelman-Rubin PSR[19] < 1.05 criterion (Gelman & Rubin, 1992). A sensitivity analysis was carried out, in which the effect of decreasing the variance of the prior distributions for differences in intercepts and factor loadings on the model fit was investigated.

In relation to the second main objective of this study, a multiple-indicators, multiple-causes (MIMIC) model (Jöreskog & Goldberger, 1975) was used, in which latent variables (in this case, learning patterns) are predicted by observed variables (in this case, in a first MIMIC model education track and gender, and in a second MIMIC model, as represented in Figure 5.1, the five overexcitabilities, positive developmental potential [which represents the interaction between the five forms of overexcitability], and intellectual ability). All learning pattern factors were regressed on all of the covariates and Bayesian estimation was used with informative, small-variance priors for the cross-loadings $\lambda \sim N(0, 0.01)$ and residual covariances $\delta \sim IW(0, 17)$ in the measurement model. Every 10th iteration was used with a total of 100,000 iterations and one MCMC chain.

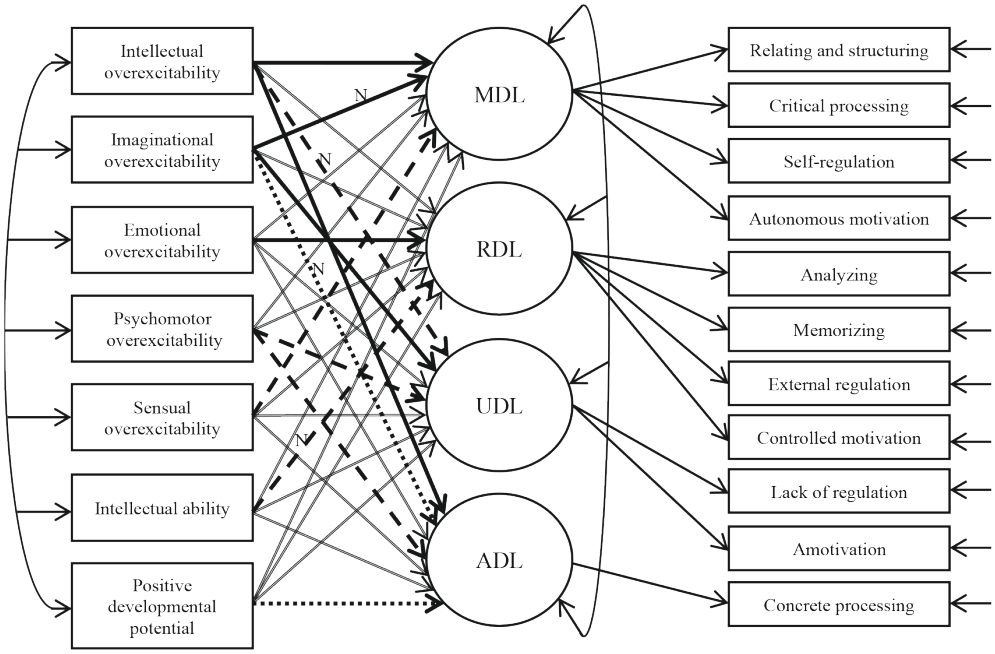


Figure 5.1. Multiple indicators, multiple causes model for GSE and TSE (MIMIC model 2).
Note. MDL = meaning-directed learning; RDL = reproduction-directed learning; UDL = undirected learning; ADL = application-directed learning. The bold lines represent significant – in the sense that the 95% Bayesian credibility interval does not cover zero – relationships for both GSE and TSE Bayesian models with zero-mean, small-variance priors for cross-loadings and residual covariances in the measurement model. The dashed lines represent non-trivial relationships with regard to the GSE group, while the dotted lines correspond to substantive associations exclusively regarding the TSE group. Lines marked by the letter "N" represent negative effects.

In the first MIMIC model, direct effects were included to test for measurement intercept non-invariance (Muthén & Asparouhov, 2012). To this end, all factor indicators were regressed on both covariates, using normally distributed priors with a mean of zero and a variance of 0.01 (in order to loosen the hypothesis of exact MI without capitalizing on chance). Regarding the second MIMIC model, an ML analysis and a Bayesian analysis with small-variance priors only for cross-loadings $\lambda \sim N(0, 0.01)$ were also carried out for comparison purposes. Furthermore, sensitivity analyses were performed, in which the effect of varying the prior variances of the cross-loadings (BSEM-MIMIC with cross-loadings) and residual covariances (BSEM-MIMIC with cross-loadings and residual covariances) on the parameter estimates and model fit were investigated. Finally, a moderation effect of intellectual ability on the influence of overexcitability

on the learning approach was examined. The present study extends previous research mainly demonstrating a strong association between intellectual overexcitability and deep learning (De Bondt & Van Petegem, 2017). This relationship was explained by correspondences between the attainment of higher levels of multilevel[21] disintegration and characteristics of the deep learning approach such as self-regulation, autonomous motivation, structuring, and critical processing. The focus of (the second part of) the present study is on the differential impact of personal competence factors (including overexcitability) on the learning approach for GSE and TSE.

Model fit assessment

The chi-square statistic, comparative fit index (CFI; Bentler, 1990), and root mean square error of approximation (RMSEA; Steiger, 1990) were used to evaluate the fit of the ML-MIMIC models. A non-significant chi-square value, a CFI value close to 1 (Hu & Bentler, 1995), and a RMSEA value of 0.05 or less (Browne & Cudeck, 1989) all indicate a close fit of the model.

For the BSEM models, fit assessment was performed using Posterior Predictive Checking in which – as provided for in Mplus – the likelihood-ratio chi-square for the observed data is compared to the chi-square based on synthetic data acquired by means of draws of parameter values from the posterior distribution (Asparouhov & Muthén, 2010; Muthén & Muthén, 1998-2017). The simulated data should approximately resemble the observed data if the model fits the data. The Posterior Predictive *p*-value (PP*p*) measures the proportion of the chi-square values of the replicated data that is greater than that of the observed data. A low PP*p* (< 0.05) points to a poor model fit, while 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 synthetic data that contains zero positioned close to the middle of the interval – indicates excellent model fit (Muthén & Asparouhov, 2012).

21 Dąbrowski's concept of multilevelness refers to the various vertical levels in the external and internal reality of which developing individuals become aware during the multilevel disintegration phase, the attainment of which depends largely on the presence of a high level of overexcitability (Dąbrowski, 2015; Mendaglio, 2008). The level of organized multilevel disintegration is characterized by the structuring of a universal (and consciously derived personal) hierarchy of values (through creativity, intuition, and higher-level emotions) and by the conscious, autonomous self-organization of the course of development (by means of the Third Factor) (Dąbrowski, 1970b, 1972a, 2015).

RESULTS

Descriptive statistics

Descriptive statistics for the overexcitability and learning pattern indicators, mathematical and verbal performance, and intellectual ability, as well as significant results of preliminary independent samples *t*-tests comparing GSE and TSE, are reported in Table 5.1 – these analyses were carried out using SPSS (Version 25; Arbuckle, 2017). Compared to GSE students, TSE students score significantly lower on both mathematical ($MD = 2.263$, $t = 5.593$, $p < 0.001$) and verbal ($MD = 1.709$, $t = 6.215$, $p < 0.001$) performance tests, as well as on the variables of intellectual ability ($MD = 0.892$, $t = 2.122$, $p < 0.05$) and controlled motivation ($MD = 0.276$, $t = 3.280$, $p < 0.01$), and significantly higher on the variables of concrete processing ($MD = -0.194$, $t = -3.009$, $p < 0.01$), lack of regulation ($MD = -0.263$, $t = -3.359$, $p < 0.001$), and amotivation ($MD = -0.153$, $t = -1.973$, $p < 0.05$; this result should be interpreted cautiously given the increased values for skewness and kurtosis).

All Cronbach's alphas indicate an acceptable level of internal consistency except for the verbal achievement variable, which has a low reliability coefficient (the performance tests results were not used for further statistical analysis).

Table 5.1. Descriptive statistics and significant results of independent samples *t*-tests comparing GSE and TSE.

		GSE				TSE				
	α	**Mean**	***SD***	**Skewness**	**Kurtosis**	**Mean**	***SD***	**Skewness**	**Kurtosis**	***MD***
Intellectual overexcitability	.800	3.485	0.574	0.177	0.023	3.482	0.552	-0.266	-0.183	
Imaginational overexcitability	.835	2.741	0.739	0.329	-0.013	2.800	0.697	-0.054	-0.228	
Emotional overexcitability	.822	3.506	0.676	-0.225	-0.111	3.513	0.607	-0.306	-0.267	
Sensual overexcitability	.862	3.231	0.743	-0.027	-0.149	3.175	0.655	-0.007	-0.095	
Psychomotor overexcitability	.863	3.291	0.706	0.047	-0.225	3.269	0.746	-0.219	-0.346	
Relating and structuring	.709	3.693	0.626	-0.473	0.151	3.619	0.613	-0.246	-0.541	
Critical processing	.732	3.476	0.695	-0.300	0.260	3.397	0.754	-0.582	0.149	
Self-regulation	.690	2.937	0.754	0.050	-0.358	2.916	0.802	0.200	-0.068	
Autonomous motivation	.833	3.743	0.664	-0.405	0.152	3.634	0.754	-0.370	-0.045	
Analyzing	.687	3.407	0.697	-0.127	-0.207	3.479	0.732	-0.358	0.121	
Memorizing	.733	3.375	0.807	-0.319	-0.143	3.443	0.786	-0.370	0.017	
External regulation	.619	3.662	0.558	-0.183	0.008	3.750	0.486	-0.158	0.199	
Controlled motivation	.800	2.880	0.824	-0.228	-0.394	2.604	0.833	0.078	-0.360	0.276** *t*=3.280
Lack of regulation	.741	2.483	0.753	0.371	-0.157	2.746	0.807	-0.125	-0.389	-0.263*** *t*=-3.359
Amotivation	.882	1.442	0.708	1.831	3.027	1.595	0.889	1.692	2.303	-0.153* *t*=-1.973
Concrete processing	.646	3.475	0.616	-0.155	-0.233	3.670	0.679	0.002	-0.565	-0.194** *t*=-3.009

Table 5.1. *Continued.*

		GSE				TSE				
	α	**Mean**	***SD***	**Skewness**	**Kurtosis**	**Mean**	***SD***	**Skewness**	**Kurtosis**	***MD***
Intellectual ability	.823	31.651	4.021	-0.625	0.607	30.759	4.214	-0.428	-0.079	0.892* *t*=2.122
Mathematical achievement	.792	13.201	4.010	-0.123	-0.631	10.937	3.686	0.166	-0.884	2.263*** *t*=5.593
Verbal achievement	.513	19.182	2.521	-0.587	-0.120	17.472	3.020	-0.593	0.029	1.709*** *t*=6.215

Note. GSE = general secondary education; TSE = technical secondary education; *SD* = standard deviation; *MD* = mean difference.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

As represented in Table 5.2, significant mean differences in the variables of intellectual ability, controlled motivation, and lack of regulation can be attributed to differences between females in both tracks, while the mean difference in concrete processing is mainly attributable to differences between males in GSE and TSE.

Table 5.2. Significant results of independent samples *t*-tests for males and females comparing GSE and TSE.

	GSE		TSE		
	Mean	***SD***	**Mean**	***SD***	***MD***
Males					
Imaginational overexcitability	2.631	0.662	2.850	0.610	-0.219* *t*=-2.226
External regulation	3.464	0.576	3.672	0.528	-0.207* *t*=-2.412
Concrete processing	3.457	0.609	3.703	0.708	-0.246* *t*=-2.492
Mathematical achievement	15.032	3.595	12.138	3.330	2.894*** *t*=5.376
Verbal achievement	19.537	2.398	18.153	2.791	1.383*** *t*=3.539
Females					
Controlled motivation	2.933	0.828	2.542	0.916	0.390** *t*=3.316
Lack of regulation	2.496	0.764	2.854	0.832	-0.357** *t*=-3.305
Intellectual ability	31.756	4.051	30.375	4.237	1.382* *t*=2.384
Mathematical achievement	12.212	3.879	9.718	3.654	2.494*** *t*=4.597
Verbal achievement	18.991	2.570	16.781	3.109	2.210*** *t*=5.782

Note. GSE = general secondary education; TSE = technical secondary education; *SD* = standard deviation; *MD* = mean difference.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Approximate MI of overexcitability factors across education tracks

The CFA models with small-variance priors for cross-loadings and residual covariances yielded an acceptable fit, as indicated by PP*p*s of 0.750 (Δ observed and replicated χ^2 95% CI [-193.946, 95.446]) and 0.985 (Δ observed and replicated χ^2 95% CI [-327.655, -15.153]) for the GSE and TSE group, respectively. Good MCMC convergence was achieved for

both models. The PSR value steadily decreased over the iterations, reaching a value of 1.010 after half (TSE) and three quarters (GSE) of the iterations. Additionally, the stability of the parameter estimates across the iterations was verified and established. With the exception of one and two non-substantive (in the sense that the 95% Bayesian credibility interval[22] encompasses zero) target factor loadings in the GSE and TSE group, respectively, the hypothesized factor loading pattern was fully retrieved, with substantial target loadings and only one non-trivial cross-loading (in both groups – the estimation results are not reported).

Table 5.3 presents the results of the approximate MI analysis with zero-means and decreasing variances for the prior distributions of differences in factor loadings and intercepts across education tracks. For intellectual overexcitability a prior variance of 0.01 results in a PP*p* of 0.509. Decreasing the prior variance does not alter the PP*p* substantially. Similar results are obtained for the other forms of overexcitability. For each of the overexcitability latent variables, the factor loadings and intercepts are all invariant, regardless of the simulated prior variance (even under strict conditions), and none of the groups show a significantly (in the sense that the 95% Bayesian credibility interval does not cover zero) different factor mean.

22 The Bayesian credibility interval can be derived directly from the percentiles of the posterior distribution, allowing probability statements about the parameter. In this study, a (null) hypothesis testing perspective (Arbuckle, 2017; Zyphur & Oswald, 2015) was used in parameter estimation by evaluating whether the 95% credibility interval of the model parameters included zero. If the 95% Bayesian credibility interval of a parameter does not cover zero, the null (condition) can be rejected as improbable, and as a result, the parameter is considered significant (which is indicated by a one-tailed Bayesian *p*-value below 0.05). A hypothesis testing perspective was also used to assess the model fit (Levy, 2011).

Table 5.3. Model fit coefficients of multiple-group BSEM-based alignment with approximate measurement invariance per overexcitability factor using decreasing prior variances.

Prior variance σ^2	Intellectual OE		Imaginational OE		Emotional OE		Sensual OE		Psychomotor OE	
	PP *p*	95% CI	PP *p*	95% CI	PP *p*	95% CI	PP *p*	95% CI	PP *p*	95% CI
0.01	0.509	-49.952-43.088	0.539	-49.599-38.008	0.578	-54.207-35.098	0.546	-50.213-46.363	0.570	-59.557-42.132
0.001	0.580	-51.712-41.622	0.409	-41.528-46.055	0.553	-45.932-42.819	0.447	-42.868-59.491	0.539	-45.548-46.107
0.0001	0.525	-49.876-41.494	0.384	-37.455-47.214	0.543	-46.859-43.068	0.368	-42.910-57.190	0.451	-41.315-46.135
0.00001	0.508	-49.500-42.575	0.375	-36.896-47.944	0.536	-46.155-42.995	0.362	-41.343-56.229	0.431	-40.547-43.673
0.000001	0.500	-49.259-42.941	0.371	-36.937-48.003	0.508	-48.546-42.941	0.368	-41.303-57.242	0.431	-40.395-44.011
0.0000001	0.500	-49.175-43.054	0.371	-36.946-48.006	0.508	-48.516-42.919	0.368	-41.310-57.543	0.431	-40.355-44.122
0.00000001	0.500	-49.147-43.089	0.371	-36.948-48.006	0.508	-48.506-42.912	0.375	-41.313-57.636	0.441	-40.344-44.157
0.000000001	0.500	-49.138-43.100	0.371	-36.949-48.032	0.508	-48.503-42.910	0.375	-41.314-57.665	0.441	-40.340-44.168

Note. BSEM = Bayesian structural equation modeling; OE = overexcitability; PP *p* = posterior predictive probability; CI = confidence interval.

MIMIC model 1

As represented in Table 5.4, good model fit was established for MIMIC model 1 with learning pattern data from higher education (PPp = 0.161, Δ observed and replicated χ^2 95% CI [-20.102, 61.420]), as well as good MCMC convergence. With the exception of one non-substantive major factor loading (i.e., the loading of controlled motivation on the reproduction-directed learning factor), the hypothesized factor loading pattern for the LEMO[23] was fully recovered (the estimation results of the measurement model are not reported). None of the direct effects were significant at the 5% level, which demonstrates (approximate) MI of intercepts and thus indicates that the intercepts of the learning pattern factor indicators do not differ for gender and education track. Gender predicts the meaning- (β = 0.125, p < 0.05) and reproduction-directed learning pattern (β = 0.300, p < 0.001), with females showing a substantially higher score. Education track is indicative of the undirected (β = 0.204, p < 0.001) and application-directed learning pattern (β = 0.142, p < 0.01), with a substantively higher score for TSE.

23 BSEM CFA models with small-variance priors for cross-loadings and residual covariances – according to the LEMO's hypothesized factor loading pattern for the 49 observed variables – yielded a satisfactory fit, as indicated by PPps of 0.542, 0.548, 0.508, and 0.508 for the meaning-, reproduction-, application-, and undirected-learning pattern, respectively. All intended factor loadings – with the exception of the loading of item y19 and y27 on, respectively, the latent variable of concrete processing and external regulation – were substantive, with no significant (at the 5% level) cross-loadings and 15 (i.e., 4%) non-trivial correlated errors.

Table 5.4. ML and Bayesian MIMIC model testing results for GSE (n = 356) and TSE (n = 132).

Model	χ^2	*df*	*p*-value	RMSEA	CFI	PP *p*	95% CI
MIMIC model 1						0.161	-20.102-61.420
MIMIC model 2							
GSE							
ML-MIMIC	374.840	88	< 0.0001	0.096	0.772		
BSEM-MIMIC with cross-loadings						0.000	96.674-202.880
BSEM-MIMIC with cross-loadings and residual covariances						0.109	-20.090-88.106
TSE							
ML-MIMIC	206.266	88	< 0.0001	0.101	0.770		
BSEM-MIMIC with cross-loadings						0.000	43.317-149.700
BSEM-MIMIC with cross-loadings and residual covariances						0.238	-35.543-75.330

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

MIMIC Model 1 with learning pattern data collected from the same participants (n = 462; 335 GSE, 127 TSE) at the start of their final year of secondary education (PPp = 0.177, Δ observed and replicated χ^2 95% CI [-22.274, 58.333]) – allowing cross-validation – yielded the same results regarding the LEMO's hypothesized latent factor loading pattern with no substantive direct effects and demonstrating a substantially higher score for females and males on, respectively, reproduction-directed learning (β = 0.256, p < 0.001) and application-directed learning (β = -0.128, p < 0.05), as well as a substantively higher score for TSE on the application-directed learning pattern (β = 0.192, p < 0.001).

As (former) GSE and TSE students differ structurally in their learning approach, further statistical analyses will be performed for the different education tracks separately.

MIMIC model 2

ML-MIMIC

As represented in Table 5.4, significant chi-square values, RMSEA values of more than 0.05, and CFI values of less than .90 all indicate that the frequentist GSE and TSE models fit the data poorly.

BSEM-MIMIC with cross-loadings

The PP*p*s are smaller than 0.05 for both models, indicating unsatisfactory model fit (see Table 5.4). Increasing the variance of the prior distributions of the cross-loadings – to the point that MCMC convergence is hindered – does not alter the fit results substantially (not reported). We may assume that the LEMO, like most learning questionnaire instruments, measures several supplementary minor learning approach factors in addition to the four latent factors included in the structural model.

BSEM-MIMIC with cross-loadings and residual covariances

As displayed in Table 5.4, good model fit was found for both the GSE (PP*p* = 0.109, Δ observed and replicated χ^2 95% CI [-20.090, 88.106]) and TSE groups (PP*p* = 0.238, Δ observed and replicated χ^2 95% CI [-35.543, 75.330]). Good MCMC convergence was established for the two models. With the exception of one non-substantive major factor loading (again the loading of controlled motivation on the reproduction-directed learning factor in the TSE group), the hypothesized factor loading pattern for the LEMO is fully recovered, as displayed in Table 5.5 (in Mplus, the reported estimates are the medians of their posterior distributions).

Table 5.5. Bayesian MIMIC model 2 estimation results for the measurement parameters for GSE (n = 356) and TSE (n = 132) using small-variance priors for cross-loadings and residual covariances.

Factor Loadings	**GSE**				**TSE**			
	MDL	**RDL**	**UDL**	**ADL**	**MDL**	**RDL**	**UDL**	**ADL**
Relating and structuring	**0.819***	0.027	-0.044	-0.042	**0.870***	0.014	0.000	0.006
Critical processing	**0.871***	-0.053	0.003	0.039	**0.809***	-0.052	0.027	0.048
Self-regulation	**0.556***	0.023	0.104	0.026	**0.643***	0.042	0.040	-0.016
Autonomous motivation	**0.646***	0.029	0.003	0.024	**0.775***	0.018	-0.061	-0.033
Analyzing	0.121	**0.618***	-0.138	-0.016	0.053	**0.797***	-0.065	-0.010
Memorizing	-0.033	**0.753***	0.038	-0.012	-0.035	**0.776***	0.065	-0.019
External regulation	-0.006	**0.581***	-0.076	-0.032	-0.023	**0.668***	-0.016	0.023
Controlled motivation	-0.038	**0.664***	0.170	0.060	0.032	0.077	0.053	**0.106**
Lack of regulation	0.059	0.015	**0.909***	-0.013	0.034	0.026	**0.916***	0.025
Amotivation	-0.081	-0.032	**0.608***	-0.004	-0.100	-0.075	**0.427***	0.063
Concrete processing	0.009	0.001	-0.016	**0.913***	-0.004	-0.005	-0.005	**0.937***
Factor Correlations	**GSE**				**TSE**			
	MDL	**RDL**	**UDL**	**ADL**	**MDL**	**RDL**	**UDL**	**ADL**
MDL	1.000				1.000			
RDL	0.040	1.000			0.208	1.000		
UDL	-0.297*	0.149	1.000		-0.196	0.119	1.000	
ADL	0.175	-0.014	-0.059	1.000	0.410*	0.028	-0.070	1.000

Note. MIMIC = multiple indicators, multiple causes; GSE = general secondary education; TSE = technical secondary education; 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 5.6 presents the estimation results for the substantive structural parameters for both education tracks. Intellectual overexcitability is indicative of meaning-directed learning for both the GSE (β = 0.632, p < 0.001) and TSE groups (β = 0.464, p < 0.001). Moreover, it is negatively related to undirected learning but only for GSE (β = -0.327, p < 0.001), and it is a supplementary indicator of application-directed learning (β = 0.333, p < 0.001 for GSE, and β = 0.445, p < 0.001 for TSE). In contrast, imaginational overexcitability

is negatively related to meaning-directed learning (β = -0.166, p < 0.05 for GSE, and β = -0.284, p < 0.05 for TSE) and positively related to undirected learning (β = 0.260, p < 0.01 for GSE, and β = 0.355, p < 0.05 for TSE). It is also negatively indicative of application-directed learning but only for TSE (β = -0.380, p < 0.01). Furthermore, emotional overexcitability is an indicator of reproduction-directed learning (β = 0.389, p < 0.001 for GSE, and β = 0.318, p < 0.01 for TSE), while psychomotor overexcitability is indicative of undirected (β = 0.145, p < 0.05) and application-directed learning (β = 0.173, p < 0.01), but only for GSE. Sensual overexcitability predicts the meaning-directed learning pattern, but only for the GSE group (β = 0.146, p < 0.01). Further, intellectual ability is negatively related to reproduction-directed learning but only for GSE (β = -0.116, p < 0.05), and positive developmental potential predicts the application-directed learning pattern only with respect to the TSE group (β = 0.623, p < 0.01).

Table 5.6. Bayesian MIMIC model 2 estimation results for the significant structural parameters for GSE (n = 356) and TSE (n = 132).

Parameter				**95% Credibility Interval**	
	Estimate	**Posterior *SD***	**One-tailed *p***	**Lower 2.5%**	**Upper 2.5%**
GSE					
Meaning-directed learning regressed on					
Intellectual overexcitability	0.632	0.049	< 0.001	0.530	0.725
Imaginational overexcitability	-0.166	0.073	< 0.05	-0.306	-0.023
Sensual overexcitability	0.146	0.061	< 0.01	0.027	0.263
Reproduction-directed learning regressed on					
Intellectual ability	-0.116	0.055	< 0.05	-0.221	-0.008
Emotional overexcitability	0.389	0.064	< 0.001	0.259	0.510
Undirected learning regressed on					
Intellectual overexcitability	-0.327	0.082	< 0.001	-0.482	-0.157
Imaginational overexcitability	0.260	0.091	< 0.01	0.077	0.434
Psychomotor overexcitability	0.145	0.067	< 0.05	0.012	0.275
Application-directed learning regressed on					
Intellectual overexcitability	0.333	0.090	< 0.001	0.147	0.498
Psychomotor overexcitability	0.173	0.067	< 0.01	0.042	0.302

Table 5.6. *Continued.*

Parameter	Estimate	Posterior *SD*	One-tailed *p*	95% Credibility Interval	
				Lower 2.5%	Upper 2.5%
TSE					
Meaning-directed learning regressed on					
Intellectual overexcitability	0.464	0.095	< 0.001	0.267	0.641
Imaginational overexcitability	-0.284	0.123	< 0.05	-0.524	-0.041
Reproduction-directed learning regressed on					
Emotional overexcitability	0.318	0.112	< 0.01	0.092	0.530
Undirected learning regressed on					
Imaginational overexcitability	0.355	0.157	< 0.05	0.032	0.646
Application-directed learning regressed on					
Intellectual overexcitability	0.445	0.102	< 0.001	0.233	0.632
Imaginational overexcitability	-0.380	0.127	< 0.01	-0.623	-0.125
Positive developmental potential	0.623	0.216	< 0.01	0.194	1.041

Note. MIMIC = multiple indicators, multiple causes; GSE = general secondary education; TSE = technical secondary education; *SD* = standard deviation.

Intellectual, imaginational (negative parameter), and sensual overexcitability (the latter only with respect to GSE) account for 45.5% and 42.9% of the variance in meaning-directed learning for the GSE and TSE group, respectively. In addition, emotional overexcitability and intellectual ability (negative parameter and only with respect to GSE) account for 19.8% and 25.1% of the variance within reproduction-directed learning for the GSE and TSE group, respectively. Furthermore, imaginational overexcitability accounts for 20.4% of the variance within undirected learning for the TSE group, while imaginational, intellectual (negative parameter), and psychomotor overexcitability explain 17.5% of the variance within this learning pattern for the GSE group. For the TSE group, 43.7% of the variance in application-directed learning can be explained by intellectual, imaginational (negative parameter), and positive developmental potential, whereas 23.7% of the variance within this learning pattern is explained by intellectual and psychomotor overexcitability for the GSE group.

Table 5.7 presents the Bayesian model fit results under varying prior variance conditions for the residual covariances for the TSE group, and also shows the standardized estimate of the factor loading of autonomous motivation on the latent variable of meaning-directed learning. At first, an inverse-Wishart prior *IW*(0, *df*) with *df* = 17 was used for the residual covariances, corresponding to prior zero-means and variances of 0.0111 (*SD* = 0.1054). Increasing the degrees of freedom will reduce the variance of the prior distribution. The extent to which the prior variance can be decreased is examined by means of the PP*p*. Both a less informative prior with *df* = 15 (corresponding to a prior variance of 0.0833) and more informative priors with *df* = 19, 21, 24, 29, 34 and 44 (corresponding to prior variances of 0.0036, 0.0016, 0.0006, 0.0002, 0.0001, and < 0.0001, respectively) were used. Applying a strong informative prior with *df* = 44 still yields acceptable model fit, as indicated by a PP*p* of 0.075. However, for both education tracks, the results of the sensitivity analysis indicate that different priors for the residual correlations do not affect the estimation of the factor loadings substantively.

Table 5.7. BSEM-MIMIC model 2 testing results for TSE (n = 132) using small-variance priors for cross-loadings $\lambda \sim N(0, 0.01)$ and varying prior variance conditions for residual covariances, and corresponding estimation results for the factor loading of autonomous motivation on meaning-directed learning.

Model			**Parameter**			**95% Credibility Interval**	
df	**PP *p***	**95% CI**	**Loading λ_4**	**Posterior *SD***	**One-tailed *p***	**Lower 2.5%**	**Upper 2.5%**
15	0.246	-35.966-72.948	0.773	0.106	0.000	0.548	0.964
17	0.238	-35.543-75.330	0.775	0.105	0.000	0.553	0.964
19	0.235	-35.955-74.484	0.778	0.104	0.000	0.557	0.966
21	0.229	-34.607-75.263	0.780	0.103	0.000	0.557	0.966
24	0.208	-33.995-76.096	0.781	0.103	0.000	0.562	0.969
29	0.182	-30.191-80.590	0.785	0.102	0.000	0.571	0.970
34	0.150	-26.833-84.335	0.788	0.102	0.000	0.574	0.974
44	0.075	-13.410-98.737	0.792	0.100	0.000	0.584	0.976

Note. BSEM = Bayesian structural equation modeling; MIMIC = multiple indicators, multiple causes; TSE = technical secondary education; *df* = degrees of freedom; PP *p* = posterior predictive probability; CI = confidence interval; *SD* = standard deviation.

Finally, including interaction terms in the BSEM-MIMIC model (which are obtained by multiplying the variable of intellectual ability with each of the substantial overexcitability indicators) yields good model fit for both the GSE (PPp = 0.167, Δ observed and replicated χ^2 95% CI [-34.487, 100.809]) and TSE groups (PPp = 0.181, Δ observed and replicated χ^2 95% CI [-34.601, 93.988]). Intellectual ability has only a substantive interactive effect on the influence of imaginational overexcitability on the undirected-learning pattern for both groups (β = -0.146, p < 0.05 for GSE, and β = -0.230, p < 0.01 for TSE).

DISCUSSION

Research in Belgium has indicated that educational stratification leads to a TSE/VSE school culture of futility and a less academically-oriented culture among lower-track teachers, leading to both lower study involvement and less educational achievement among TSE/VSE students (Van Houtte, 2004, 2006; Van Houtte & Stevens, 2010).

This study, which initially compared competence and performance indicators between GSE and TSE, revealed significant differences in mathematical and verbal achievement and intellectual ability, in favor of GSE students. However, a further breakdown by gender did not show a significant intelligence mean difference between boys of GSE and TSE (in contrast to highly significant differences on both performance tests between GSE and TSE boys and girls).

Further, former GSE and TSE students did not differ substantively in the degree and nature of overexcitability, which constitutes an essential element of an individual's potential to arrive at high levels of personality development, according to the TPD. Overexcitability increases the possibility of inner mental transformation, which paves the way for achieving higher levels of human functioning, as characterized by autonomy, authenticity, and empathy, and consequently, according to Dąbrowski, mental health (Dąbrowski, 2015; Dąbrowski & Joshi, 1972).

This study further investigated the influence of education track (GSE/TSE) on the learning approach (MIMIC model 1) and, subsequently, the differential impact of intelligence and overexcitability on learning patterns in both tracks (MIMIC model 2). MIMIC model 1 revealed a substantively higher score for former TSE students on both undirected and application-directed learning compared to GSE. More specifically, the

results of the preliminary *t*-tests indicated that the differences in lack of regulation (undirected learning) and concrete processing (application-directed learning) are on average attributable to girls and boys, respectively (although these results should be interpreted cautiously due to small and divergent sample sizes).

The results of MIMIC model 2 revealed that personal competence indicators substantially explain an individual's learning pattern, but that dynamic contextual influences are at least as important. The latter can be deduced from the unexplained variance in the model as well as the differential results for both tracks. Despite similarities in substantive structural parameter estimates for GSE and TSE (i.e., substantial positive associations between intellectual overexcitability and meaning- and application-directed learning, between emotional overexcitability and reproduction-directed learning, and between imaginational overexcitability and undirected learning, as well as a non-trivial negative relationship between imaginational overexcitability and the meaning-directed learning pattern), this study also shows clear differences in both tracks in terms of significant parameter values and explained variance. First, intellectual ability is negatively indicative of reproduction-directed learning, but only for GSE. This is in line with previous studies that either found no relationship of intelligence with the learning approach (Diseth, 2002; Furnham et al., 2009; von Stumm & Furnham, 2012) or a weak to moderate positive association with deep learning (Chamorro-Premuzic & Furnham, 2008). However, in our study a moderating effect of intellectual ability on the influence of imaginational overexcitability on the undirected learning approach was established for both tracks. Second, a substantively positive and negative relationship was found between, respectively, the variables of "positive developmental potential" and imaginational overexcitability and the application-directed learning pattern, but only for the TSE group. As already mentioned, application-directed learning is associated with deep learning (Vermunt, 1998) – Table 5.5 shows a substantive correlation between the factors of meaning- and application-directed learning for TSE ($r = 0.41$, $p < 0.05$), in contrast to GSE – which in turn is theoretically related to the attainment of higher levels of personal development (De Bondt & Van Petegem, 2017). Concrete processing is characterized by "applying subject matter by connecting it to one's own experiences" (Vermunt, 2005, p. 213) and the TPD emphasizes the necessity of independent action in accordance with one's personal hierarchy of values and aims, which is derived from conscious and affective experiences and "a true sense of morality" (Dąbrowski, 2015, p.

9). In a sense, both interactive effects mentioned above confirm the stimulating effect of a combination of heightened levels of various forms of overexcitability and (cognitive) ability to arrive at a stronger developmental potential and, subsequently, higher levels of personality development.

Further, we can conclude that intellectual overexcitability is associated with deep learning (which is most strongly expressed in the GSE track) and imaginational overexcitability is related to surface learning. The latter applies to both tracks but the variable of imaginational overexcitability influences the learning approach more strongly in the TSE track (to be inferred from the standardized beta coefficients in the BSEM-MIMIC models). The TSE group did not show a significantly different factor mean regarding imaginational overexcitability. However, a further breakdown by gender in the preliminary *t*-tests revealed a substantially higher degree of imaginational overexcitability for former TSE boys compared to ex-GSE boys (see Table 5.2). No significant difference could be established for girls. This result (as well as the higher score on concrete processing for TSE boys) raises the question whether there is a larger representation of visual-spatial learners (Silverman, 2002) in the group of TSE boys, which may also explain performance differences given the educational context (despite identical non-verbal intelligence levels). Wai and Kell (2017) point to the existence of a large group of unidentified visual-spatial thinkers who are less verbally and mathematically talented and stress the social and individual importance of identifying, developing, and valuing spatial talent. After all, spatial ability is related to STEM (science, technology, engineering, and mathematics) performance (Lubinski, 2010; Wai & Kell, 2017) and Lubinski (2010, p. 344) speaks of "an under-utilized pool of talent for meeting the complex needs of an ever-growing technological world" and refers to its distinctive motivational covariates. Although the relationship of visual-spatial thinking with imaginational overexcitability is still unexplored, visualization (Lubinski, 2010) and imagination (Daniels & Meckstroth, 2009) are undeniably related to scientific discovery. In addition, several studies have demonstrated associations of imaginational overexcitability with giftedness (Carman, 2011; Harrison & Van Haneghan, 2011; Siu, 2010; Tieso, 2007a), which in turn is related to creative contributions (Park et al., 2008).

Thus, the results of this study show that the lower competence and performance expectations of TSE teachers and schools are not fully justified and may even be at the root of their students' lower performance (by imposing lower standards) and

regulatory/motivational problems, as indicated by the lower performance test results and higher scores for undirected learning indicators, respectively. According to SDT, the social environment is particularly relevant as it can have a positive or negative impact on an individual's intrinsic motivation, psychological growth, and well-being by promoting or hindering the perceived satisfaction of basic needs, especially autonomy and competence (Deci & Ryan, 2000, 2002). The question then arises as to what extent the innate, universal needs for autonomy (which refers to both reflective and active self-determining in concordance with one's personal values and integrated sense of self [Deci & Ryan, 2000]) and in particular competence (which refers to the aptitude to intervene effectively in the external and internal environment and to generate value-creating effects within it [Deci & Ryan, 2000]) can be fulfilled, given a school culture of futility with a flawed belief in the capacities of its population that is not based on proper screening. In contrast to the latter, the TPD emphasizes the importance of a culture of "authentic education" in which an adviser (e.g., a teacher), who is personally characterized by a strong personality, thoroughly evaluates the developmental potential of an individual and encourages developing her/his own personal hierarchy of values and aims (Dąbrowski, 2015; Rankel, 2008). The adviser raises awareness of the existence of multilevel contradictions in an individual and encourages self-awareness, empathy, moral responsibility, and self-determinism based on high moral values, paving the way to personal growth that reflects the ultimate goal in authentic education (Dąbrowski, 2015). This study shows that former GSE and TSE students do not differ substantially in their level of overexcitability, which, according to the TPD, is an essential component of an individual's developmental potential whose strong presence is a pre-requisite for achieving autonomy, the fulfillment of which – according to both the TPD and SDT – is fundamental for attaining eudaimonic well-being, full human functioning, and essence (Dąbrowski, 2015; Deci & Ryan, 2000, 2002). However, former TSE students scored substantially higher on undirected learning indicators, which rather points to an impersonal causality orientation (Deci & Ryan, 1985), as characterized by the lack of intentional behavior and its regulation. According to SDT, a strong autonomous orientation (which refers to the regulation of behavior according to inherent interests and self-endorsed and self-affirmed values) across situational contexts is the result of meeting fundamental psychological needs (Deci & Ryan, 2000, 2002). The results of MIMIC Model 1 with learning pattern data from secondary education did not reveal

a substantively higher score for TSE (compared to GSE) on undirected learning. The origin of ex-TSE students' higher scores on undirected learning in higher education may be partially due to context-dependent factors such as larger adaptation requirements (being less prepared for higher educational requirements) and a history of teaching that is less responsive to basic needs (being less encouraged to intervene in one's environment in a self-determining, effective and value-creating way, which typifies a school culture of futility or hopelessness).

Limitations

Finally, we have to note that this study is mainly limited by the use of small sample sizes according to standard criteria used in conventional CFA and SEM analyses (moreover, a larger sample could differentiate not only by educational track but also by gender). Although the PP*p* has been found to outperform the ML chi-square statistic under small sample sizes and to be less sensitive to minor model misspecifications (Muthén & Asparouhov, 2012), further research is required into the sensitivity of the PP*p* to the number of observations as well as the robustness of BSEM estimation under varied sample sizes. However, preliminary studies show that BSEM performs better with small sample sizes than does ML SEM (Lee & Song, 2004). A second limitation of this study is the use of the concept of imaginational overexcitability as a proxy for spatial ability. Third, this study was conducted among a (relatively homogeneous) group of students of higher education, as a result of which the research findings cannot be extrapolated to the entire population of (former) TSE and GSE students.

Conclusions

Despite its limitations, this study contributes to the existing research on the consequences of educational stratification by primarily revealing regulatory/motivational problems among former TSE students, as well as substantial differences in verbal and mathematical performance among GSE and TSE students (both suggesting contextual, educational influences), rather than personal competence differences between both tracks (as indicated by no substantive differences in overexcitability and intelligence between respectively former GSE and TSE students and GSE and TSE boys). The results of this study appear to confirm the theoretically presupposed and empirically validated consequences of academic differentiation: the lower performance

scores and regulatory problems of (former) lower-track students seem to have their origins in a previous anti-school culture characterized by reduced study requirements and impaired fostering of fundamental human needs for autonomy and competence, thus confirming the differentiation-polarization theory. As a consequence, the necessity of a culture of need-supportive and authentic high-standard education aimed at all students with confidence in their potential and innate integrative tendencies cannot be overemphasized in order to promote personal growth, autonomy, and hence well-being.

CHAPTER 6

GENERAL DISCUSSION AND CONCLUSIONS

GENERAL DISCUSSION AND CONCLUSIONS

The purpose of this doctoral research was to explore in depth the interrelations between deep versus surface learning – approached through the learning patterns framework – and the personal and contextual factors influencing it, illuminated from the perspective of Dąbrowski's Theory of Positive Disintegration (TPD) (Dąbrowski, 1964, 1972b, 2015), which focuses on personal growth and the attainment of autonomy, authenticity, and essence. The TPD represents an organismic and hierarchically[24] structured theory of personality development, in which personality is defined as "[a] self-aware, self-chosen, self-affirmed, and self-determined unity of essential individual psychic qualities" (Dąbrowski, 2015, p. 290) and is only attained at the highest level of the developmental process (i.e., the level of Secondary Integration). According to the TPD, personality is usually achieved through a process of multilevel disintegration in which strong awareness of a discrepancy between biological-social reality on the one hand and supra-biological necessity on the other hand (the former refers to a cohesive mental structure aimed at meeting biological needs and conforming to societal norms; the latter refers to how life should be, i.e., absolutely truthful, alter-centric, and according to universal, objective moral values) gives rise to external but especially internal conflicts and tension that may cause the disintegration of the primitive mental organization and, subsequently, advance personality development. Achieving the highest level of human development – or enacting the personality ideal[25] – depends

24 The concept of "hierarchization" in the TPD refers to "[t]he process of developing or activating different emotional levels. It stems from conflicts of value which reflect the existence of feelings corresponding to higher and lower values (i.e. more preferred vs. less preferred choices). A hierarchy of values is a hierarchy of higher and lower levels of emotions" (Dąbrowski, 2015, p. 283).

25 Dąbrowski (2015, p. 103) argues that the personality ideal "embraces, synthetizes in itself, as it were, all the most essential positive, more or less general, and also individual traits," and must be conceived as a "transcendental but concrete" ideal that can be attained through the process of positive disintegration (1976, p. 131). More specifically, the personality ideal gradually emerges at the level of multilevel disintegration due to an increasing self-awareness through the perception and elaboration of intense emotional experiences that provides insight into the higher and lower self. In this way, the personality ideal is empirically derived. Dąbrowski (1964, 1970b) also refers to the personality ideal as a normative concept that can only be captured globally through intuition. A particular strength relating to the intuitive perception of the personality ideal concerns the disintegrative states of suffering, nervousness, psychoneuroses, and contemplation, as well as the religious attitude and the quality of truthfulness (Dąbrowski, 2015).

largely on an individual's developmental potential, which is determined by their level of innate psychic overexcitability and the presence of special abilities, talents, and autonomous inner dynamisms that cultivate personal growth (Dąbrowski, 1964, 1972b, 2015; Mendaglio, 2008; Tillier, 2018). "Overexcitability" is the English translation of the Polish term "nadpobudliwość," which corresponds to the ability to be super-stimulated or "super-stimulability" (Piechowski, 1999). Overexcitability leads to a "deeper, more vivid, and more acutely sensed" experience of life – it creates an "intense aliveness" (Daniels & Piechowski, 2009, p. 9). The TPD distinguishes five forms of overexcitability – emotional, intellectual, imaginational, sensual, and psychomotor – the first three of which are considered essential to advance personality development (Dąbrowski, 1970a, 1996, 2015) and without which creativity, empathy, autonomy, and authenticity cannot develop (Dąbrowski et al., 1970).

In synopsis, this doctoral research investigated the influence of overexcitability and, more generally, the developmental potential – representing personality and autonomy drivers in the TPD – on the use of cognitive processing and metacognitive regulation strategies in the learning process and study motivation (as conceptualized by Self-Determination Theory [SDT] [Deci & Ryan, 2000, 2002], which is associated with the TPD through the premise of the pursuit of autonomy[26]) among 516 higher education students with different personal (gender [318 women; 198 men] and intelligence) and contextual (prior education) characteristics. As such, it considered emotive factors in the study of the learning approach, which have only received marginal attention in established empirical research (Entwistle & McCune, 2004; Heikkilä et al., 2011), although they are likely to induce autonomous motivation (and, more generally, deep learning) and authentic self-determined activity – as empirically substantiated by Pekrun et al. (2002) (and consistent with Pekrun's [2006, 2018] Control-Value Theory propositions) and theoretically postulated in the TPD (see also footnotes 24 and 25), respectively – whereby the former leads to the latter, as validated by SDT (Deci & Ryan, 2000).

Specifically, the purpose of *Study 1* was to contribute to the existing comprehensive research on the *personal* correlates of deep versus surface learning characteristics by

26 It should be recalled that the construct of autonomy in SDT (i.e., self-determination in concordance with one's personal values) quite closely corresponds to the dynamism of autonomy in the TPD (i.e., self-determination based on universal, objective moral values) (Dąbrowski, 2015; Deci & Ryan, 2000).

taking the perspective of the TPD. Established research on interrelationships between personality and the learning approach typically measures personality using the five-factor model (FFM) personality traits, i.e., neuroticism, extraversion, openness to experience, conscientiousness, and agreeableness (Costa & McCrae, 1992a; McCrae & Costa, 1987), which, however, have weak explanatory power with respect to learning approaches (Chamorro-Premuzic & Furnham, 2009). Study 1 approached personality with indicators of overexcitability, the presence of which is characteristic of the potential for advanced personality development and the attainment of autonomy according to the TPD. It should be reemphasized that Dąbrowski conceives the concept of personality in an unconventional way. Personality, as defined in the TPD, must be shaped, is value-based and is only achieved by a few people (Mendaglio, 2008). Moreover, inner growth into essence does not cease upon reaching the highest level of development (Piechowski, 2008). The following key research question was posed: Are the emotive factor of overexcitability and, more generally, the developmental potential related to major indicators of deep learning and an orientation toward autonomy? Moreover, do they show stronger associations than the FFM-traits, which do not offer a dynamic growth perspective?

Given that empirical research on the relationship between personality and the learning approach heavily relies on the FFM, *Study 3* – which expands on Study 1 – further examined the differential significance of overexcitability in relation to the established personality traits. Moreover, Study 3 was intended *inter alia* a response to the publication by Vuyk et al. (2016), both methodologically and in terms of content. Vuyk et al. (2016) argue that there is no justification for the existence of overexcitability as a separate research construct, given the substantial associations between the six openness facets and overexcitabilities that they identified in their maximum likelihood (ML) exploratory SEM joint-factor model and the strong research support for the FFM. Therefore, Study 3 aimed to determine whether overexcitability and, more generally, developmental potential are interchangeable with the FFM-traits of neuroticism, conscientiousness, and – especially – openness. Furthermore, Study 3 examined the extent to which the Overexcitability Questionnaire-Two (OEQ-II) (Falk et al., 1999) reflects the hierarchical perspective of the TPD. A multi-facet structure that reflects the multilevel process of disintegration would diverge from the FFM, which does not include distinct levels of personality growth.

Study 4 – which extends Study 1 by addressing *contextual* factors that affect deep versus surface learning – contributed to the existing research on the importance of a nurturing educational environment and its reciprocal linkages with emotions and learning effects. The rationale of this study was, on the one hand, to contribute to the scarce research on associations between learning patterns and prior education, and on the other hand, to verify the Differentiation-Polarization Theory (DPT) (Ball, 1981; Hargreaves, 1967; Lacey, 1970; Schafer & Olexa, 1971), which states that educational stratification (i.e., ability grouping or tracking) leads to a polarization of subcultures in which higher- and lower-track students develop a pro- and anti-school culture, respectively. Specifically, Study 4 addressed the following research questions: Do students in different educational tracks and with varying educational backgrounds adopt different learning patterns in secondary and higher education, respectively? Based on our data from a large sample of higher education students, are there indications that support the applicability of the DPT in the Belgian context?

Throughout the research, Bayesian structural equation modeling (BSEM) (Muthén & Asparouhov, 2012) was applied, which is still only marginally used in educational and psychological research (König & van de Schoot, 2018), and this approach was compared to a frequentist approach to statistics. BSEM is an innovative and flexible approach to statistics that allows the application of zero-mean, small-variance priors for cross-loadings, residual covariances, and differences in measurement parameters across groups, better reflecting substantive theory and leading to better model fit and more accurate inferences compared to a frequentist analysis (which postulates exact parameter constraints and is usually too strict) (Asparouhov & Muthén, 2014; Muthén & Asparouhov, 2012). Using BSEM with informative, small-variance priors, *Studies 2 and 4* investigated the factorial validity of the OEQ-II and approximate scalar measurement invariance (MI) of overexcitability factors across gender and education tracks, respectively. In accordance with the TPD's postulate that personality development involves the integration of multiple forms of overexcitability, *Study 2* also examined whether all five overexcitabilities substantially load onto a superordinate general construct of positive developmental potential. *Throughout all four studies*, the appropriateness of the BSEM approach to factorial validation was evaluated compared to the frequentist approach that has been consistently applied in empirical research

on the interrelationships between learning approaches and patterns *and* personal and contextual variables, as well as between overexcitabilities and the FFM-traits.

The main outcomes of the four studies are discussed below.

Overexcitabilities and deep learning, including an orientation toward autonomy (Study 1)

The aim of Study 1 was to investigate – among the samples of 318 female and 198 male higher education students – interrelationships between overexcitabilities, as measured by the OEQ-II, and learning patterns, as gauged by the Learning and Motivational Questionnaire (LEMO) (Donche et al., 2010), from the perspective of personality development according to the TPD. Based on, first, theoretical correspondences between the attainment of higher levels of multilevel disintegration in the TPD – which depends largely on the presence of a strong developmental potential, including overexcitabilities (Dąbrowski, 1964, 2015) – and characteristics of meaning-directed, deep learning[27] and, second, the empirically established positive relationship between excitement and deep learning (Pekrun et al., 2002, 2011, 2023), Study 1 primarily hypothesized substantial positive associations between the five overexcitabilities and the meaning-directed learning pattern. Due to critical concerns that most of the empirical research on the TPD focuses only on overexcitability (Tillier, 2006, 2009), in addition to the five overexcitabilities, intellectual ability (as measured by the Prüfsystem für Schul- und Bildungsberatung Test 3 [PSB-3] [Horn, 1969]) and all interactions were included as covariates in the Bayesian confirmatory factor analysis (CFA) models – in order to better reflect the developmental potential – with the hypothesis of a positive relationship with meaning-directed learning.

The results of Study 1 clearly demonstrated that overexcitability is related to learning patterns, with the most substantial relationship occurring with deep learning, although

27 In addition to the association pointed out in the studies via the dynamisms of autonomy and self-control and the characteristic of a critical attitude, the relationship with the cognitive processing strategy of "relating and structuring" is expressed in Dąbrowski's thesis of increased systematizing at higher levels of personal development in order to arrive at one's personality ideal. The fourth level of the developmental process (i.e., Organized Multilevel Disintegration) is indeed characterized by creative systematization, which represents the "[r]eshaping of the unordered disintegrative process into an ordered and ever more consciously controlled process" (Dąbrowski, 2015, p. 129) by means of "systematizing dynamisms" such as subject-object in oneself and the Third Factor (1970b, p. 13).

not all forms of overexcitability were substantively indicative of meaning-directed learning. Intellectual, imaginational (negative parameter), and sensual overexcitability accounted 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 could be explained by intellectual, psychomotor (negative parameter), and sensual overexcitability. This close relationship could not be demonstrated when using the FFM-personality traits (Chamorro-Premuzic & Furnham, 2009; von Stumm & Furnham, 2012; Zhang, 2003). In their ML CFA with covariates study, Chamorro-Premuzic and Furnham (2009) showed that only openness had a significant effect on learning approaches (as measured by the Study Process Questionnaire [SPQ] [Biggs, 1987]), with a positive and negative effect on deep and surface learning, respectively, although it accounted for only 18% of the variance in each factor.

It was mainly intellectual overexcitability that appeared to be particularly strongly interrelated to deep learning (as inferred from the substantial positive associations between intellectual overexcitability and meaning- and application-directed learning). Since a correlation matrix of indicator variables has not been included in the studies, Table 6.1 presents, for the entire sample, the bivariate correlations between the indicators of overexcitability, openness, neuroticism, and conscientiousness (the latter three as measured by the NEO Five-Factor Inventory [NEO-FFI] [Costa & McCrae, 1992b]) and the four meaning-directed learning pattern indicators, intellectual ability, and mathematical and verbal achievement test scores.[28] Table 6.1 shows that of all the variables, intellectual overexcitability is most strongly related to the four indicators of meaning-directed learning, which all represent personality-inducing dynamisms and characteristics in the TPD.[29] Although the FFM-trait of openness is also indicative of

28 The OEQ-II and LEMO were conducted when the participants were in the second consecutive year of a program of higher education, while the NEO-FFI, PSB-3, and achievement tests were conducted two years earlier, when the respondents were at the start of their final year of secondary education. A full correlation matrix of indicator variables for the entire sample is presented in Appendix B.

29 Table 6.1 also shows intellectual overexcitability to be weakly positively related to intellectual ability (r = 0.098, p < 0.05), as well as to mathematical (r = 0.109, p < 0.05) and verbal (r = 0.118, p < 0.01) achievement. In contrast, emotional overexcitability is weakly negatively correlated with mathematical (r = -0.250, p < 0.01) and verbal (r = -0.139, p < 0.01) achievement, although unrelated to intellectual ability (the latter also applies to imaginational, sensual, and psychomotor overexcitability which in turn are not significantly related to achievement, except for a weak negative correlation of psychomotor overexcitability with verbal achievement [r = -0.125, p < 0.01]).

meaning-directed learning, it does not prove to be more strongly associated with the four respective indicators than sensual overexcitability. These results are consistent with the findings of a study by von Stumm and Furnham (2012), which demonstrated that Typical Intellectual Engagement[30] (TIE) (Goff & Ackerman, 1992) was strongly indicative of the deep learning approach (as measured by the SPQ), in contrast to the FFM-traits (which in their study showed no significant relationships with the deep approach). Daniels and Meckstroth (2009, p. 43) state that "[c]hildren with intellectual overexcitability have almost insatiable curiosity, as well as a voracious appetite and capacity for intellectual effort and stimulation. [...] Driven by wide and deep interests, they relentlessly probe the unknown." Intellectual overexcitability appears to be an important driver of intrinsic motivation and other indicators of deep learning and an autonomy orientation according to both the TPD and SDT (as derived from the results of Study 1), and conceptually more or less corresponds to TIE and Need for Cognition[31] (NFC) (Cacioppo et al., 1996; Cohen et al., 1955). The TPD assumes, however, a prospective dynamic and hierarchical perspective (see also below).

30 TIE has been defined as "a personality construct that represents an individual's aversion or attraction to tasks that are intellectually taxing and is thus related to acculturative and purposeful development and expression of certain intellectual abilities" (Ackerman et al., p. 276).

31 NFC refers to an individual's "tendency to engage in and enjoy effortful cognitive activity" (Cacioppo et al., 1996, p. 197).

Table 6.1. Pearson correlation coefficients between achievement variables, intellectual ability, overexcitability, openness, neuroticism, and conscientiousness, and meaning-directed learning pattern indicators.

	Variables	*N*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Mathematical achievement	502														
2	Verbal achievement	498	0.484**													
3	Intellectual ability	500	0.350**	0.248**												
4	Intellectual overexcitability	516	0.109*	0.118**	0.098*											
5	Emotional overexcitability	516	-0.250**	-0.139**	0.008	0.250**										
6	Sensual overexcitability	516	-0.057	-0.019	0.054	0.435**	0.356**									
7	Imaginational overexcitability	516	-0.051	-0.033	0.082	0.322**	0.380**	0.500**								
8	Psychomotor overexcitability	516	-0.005	-0.125**	-0.045	0.099*	0.147**	0.053	0.089*							
9	Openness	478	0.056	0.171**	0.107*	0.437**	0.185**	0.536**	0.299**	-0.108*						
10	Neuroticism	479	-0.160**	-0.067	-0.117*	-0.002	0.413**	0.100*	0.255**	-0.065	0.062					
11	Conscientiousness	471	-0.087	-0.049	-0.092*	0.096*	0.072	-0.067	-0.228**	0.043	0.025	-0.213**				
12	Relating and structuring	516	0.037	0.064	0.011	0.476**	0.184**	0.254**	0.051	0.026	0.287**	-0.046	0.182**			
13	Critical processing	516	0.155**	0.141**	-0.003	0.552**	0.095*	0.297**	0.108*	-0.002	0.315**	-0.099*	0.095*	0.679**		
14	Self-regulation	516	-0.051	-0.048	0.014	0.313**	0.193**	0.249**	0.132**	-0.036	0.260**	-0.018	0.181**	0.426**	0.440**	
15	Autonomous motivation	516	-0.043	0.015	-0.003	0.410**	0.192**	0.314**	0.062	0.020	0.304**	-0.078	0.257**	0.458**	0.366**	0.394**

Note. $*p < 0.05$; $**p < 0.01$.

According to the TPD, multiple forms of overexcitability must manifest in order to contribute to personality shaping (Dąbrowski, 1976, 1996, 2015). However, the results of Study 1 showed that emotional, imaginational, and psychomotor overexcitability are not substantively indicative of deep learning. Emotional overexcitability was instead related to surface learning, as it was the only explanatory factor for reproduction-directed learning in both gender groups and even indicative of undirected learning with regard to the male group.[32] Imaginational overexcitability was also found to be an indicator of undirected learning and, like psychomotor overexcitability, was not positively indicative of meaning-directed learning; all of which contributed to a non-substantive effect of the interaction term "positive developmental potential." As further emphasized in the discussion of Study 4, qualitative learning is affected not only by personal attributes but also by interactive learning-environment conditions (Entwistle et al., 2003; Pekrun, 2006; Pekrun et al., 2002, 2023). As explained in his concept of authentic education, Dąbrowski (2015; Rankel, 2008) also emphasizes the importance of a nurturing educational environment for facilitating personality development and the attainment of autonomy. Therefore, the results of Study 1 (more specifically, the unexplained variance in the models along with the differential results for the five forms of overexcitability) may support an argument for accommodating learning-environment adaptations – such as creating a learning environment that provides safety, strengthens self-confidence, and is affirmative, with ample opportunity for movement and physical activity, and that provides a whole view and encourages creative imagination (Daniels & Meckstroth, 2009; Falk & Miller, 2009) – in alignment with emotional, psychomotor, and imaginational overexcitability, respectively, to enhance deep learning. However, the finding that not all overexcitabilities contribute significantly positively to deep learning and an autonomy orientation might also be partially explained by the lack of a multilevel

32 Although the results of Study 1 revealed that emotional overexcitability is not indicative of deep learning, Table 6.1 shows significant weak positive correlations – to the same degree as the trait of conscientiousness – with each of the four meaning-directed learning pattern indicators. It should further be noted that emotional overexcitability and neuroticism appear to be distinct constructs. Although the FFM-trait of neuroticism correlates moderately positively with emotional overexcitability ($r = 0.413$, $p < 0.01$), it shows no associations with the meaning-directed learning pattern indicators (with the exception of a weak negative correlation with critical processing [$r = -0.099$, $p < 0.05$]) and a negative association with intellectual ability ($r = -0.117$, $p < 0.05$), in contrast to emotional overexcitability (see Table 6.1). The core dimension of neuroticism is negative emotionality, and mainly corresponds with lower levels of development according to the TPD.

perspective. Multilevelness or a hierarchical organization of human development is the hallmark of Dąbrowski's personality theory (Dąbrowski, 2015; Tillier, 2018). According to the TPD, each form of overexcitability has a different expression depending on the level of personality development. Higher levels of psychic functioning are fueled by the presence of developmental dynamisms and *higher-level* overexcitabilities in conjunction with intelligence (Dąbrowski, 1970b, 1970c; Tillier, 2018). Since the OEQ-II is primarily intended for use in groups and the highest levels of personality development are achieved by very few people, it can logically be observed that the items included in the instrument hardly reflect the higher – transcendental – levels. In the same sense, it should be noted that most of the items of the LEMO's meaning-directed learning pattern indicators do not extend beyond a school context and are not directly related to moral development or more advanced levels of deep learning. In Study 1, the covariate of intellectual ability had also no substantive effect on any of the learning patterns, the latter of which corresponds to previous studies that mentioned no substantive relationships between intelligence and approaches to learning (Diseth, 2002; Furnham et al., 2009; von Stumm & Furnham, 2012), in contrast to a study by Chamorro-Premuzic and Furnham (2008), which indicated a weak to moderate positive relationship between intelligence and the deep learning approach.[33]

The multilevel perspective on overexcitabilities is further addressed when discussing the results of Study 3.

Bayesian structural equation modeling (all four studies – mainly Study 2)

The main objective of Study 2 was to investigate – among the samples of 318 female and 198 male higher education students – the structural validity of the OEQ-II using BSEM with informative, small-variance priors, and to compare the results of this Bayesian approach to that of a frequentist approach to validation. The results of Study 2 (and Study 4) revealed that the OEQ-II demonstrates good factorial validity. Applying BSEM

33 Table 6.1 also reveals no significant correlations between the four indicators of meaning-directed learning and intellectual ability, which in turn is positively correlated with mathematical ($r = 0.350$, $p < 0.01$) and verbal ($r = 0.248$, $p < 0.01$) achievement that seems to correlate only with critical processing ($r = 0.155$, $p < 0.01$ for mathematics, and $r = 0.141$, $p < 0.01$ for reading) within the deep approach. The latter is in line with the results of empirical research that provides no evidence of a strong, consistent relationship between deep learning and academic achievement (Boyle et al., 2003; Busato et al., 1998; Diseth, 2003; Duff et al., 2004; Furnham et al., 2009; Heikkilä et al., 2011; Komarraju et al., 2011; Vermunt, 2005).

with zero-mean, small-variance priors for cross-loadings and residual covariances led to good model fit for both the female and male groups, in contrast to the ML CFA and exploratory FA models and BSEM models with only cross-loadings. We may assume that the OEQ-II measures several supplementary minor personality factors in addition to the five overexcitabilities. On the one hand, freeing all residual covariances would lead 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 et al., 1992), with a large risk of model misspecification (Muthén & Asparouhov, 2013b). BSEM led to less inflated factor correlations compared to ML CFA, and satisfactory factor loading pattern recovery with substantial target loadings.

Since the TPD postulates the conjunction of the five overexcitabilities to arrive at personality development (Dąbrowski, 1976, 1996; Mendaglio, 2012), a supplementary aim of Study 2 was to estimate a higher order model with the five overexcitability factors loading on a superordinate general construct of positive developmental potential. The BSEM models with zero-mean, small-variance priors for both cross-loadings and residual covariances and only for correlated residuals led to good model fit for both gender groups and satisfactory factor loading pattern recovery in the measurement model. Regarding the structural model, all target loadings were substantive (in the BSEM model with only residual covariances for the female group), except for the loading of the psychomotor overexcitability factor on the variable of positive developmental potential (in the BSEM models with both cross-loadings and residual covariances). In their seminal paper, Muthén and Asparouhov (2012) rightly emphasize the difficulty of balancing the need for small-variance priors for cross-loadings and small prior variances for residual covariances, which thus appears to be supported by the results of the higher order Bayesian CFA models. While cross-loadings model meaningful relationships between items and non-target factors, residual covariances model common sources of impact on the indicators that are independent of the factors embedded in the model. Asparouhov et al. (2015) emphasize that the BSEM approach to CFA is not only intended to test the model, but is primarily designed to examine the sources of difference between the hypothesized CFA model and the data – in a single-step analysis – and thus provide guidance for any necessary model modifications. Several scholars have made recommendations for good practice on conducting Bayesian analysis and on the steps to follow when performing a sensitivity analysis of priors

(Arts et al., 2021; Asparouhov et al., 2015; Depaoli & van de Schoot, 2017; Depaoli et al., 2020; Levy & McNeish, 2023; Muthén & Asparouhov, 2012; Robitzsch, 2022; van Erp et al., 2018).[34]

Although BSEM is increasingly used in CFA analyses, the number of publications using Bayesian approximate MI or the alignment optimization method with Bayes estimation in order to investigate scalar MI across groups is still very limited. Using the OEQ-II data, the final aim of Study 2 was to investigate invariance of measurement parameters across gender applying BSEM with strong informative priors. To our knowledge, this study was the first to perform BSEM-based alignment with approximate MI based on real data (in this case, for each of the overexcitability latent variables), except for the exemplary applications as presented in Asparouhov and Muthén (2014) (Byrne & van de Vijver, 2017). The absence of non-invariant factor loadings and measurement intercepts across gender (and education tracks in Study 4) was indicative of the psychometric quality of the OEQ-II. The results revealed a substantively higher score for females on emotional and sensual overexcitability, and a substantially lower score on the construct of psychomotor overexcitability compared to males.

Finally, it should be noted that throughout all four studies, BSEM performed better than ML SEM.

Overexcitabilities in relation to the FFM-personality traits (Study 3)

Using the samples of 318 female and 198 male higher education students, the results of Study 3, based on BSEM analyses with good model fit – in contrast to the weak fit reported in the frequentist study by Vuyk et al. (2016) – did not demonstrate a strong interrelationship between overexcitability (as measured by the OEQ-II) and openness to experience (as gauged by the NEO-FFI). Instead, overexcitability appeared to be

34 In conjunction with this, new methods have been developed to construct Bayesian and BSEM models. A recent important implementation in the Mplus software program (Muthén & Muthén, 1998-2017) is the new method to calculate the BSEM fit index Posterior Predictive *p*-value (PP*p*) in the presence of missing data (Asparouhov & Muthén, 2021a). In earlier versions of Mplus (as used in the four studies), missing data are imputed during Markov chain Monte Carlo (MCMC) estimation and these perfectly fitting imputed data are used as if they represent observed data, thereby weakening the power to detect model misspecification. In the new PP*p* method, the replicated data sets are generated with the same missing data (which are imputed as missing values) as the observed data set, without compromising the speed of computation (Asparouhov & Muthén, 2021a). It should be noted, however, that the missing data for the OEQ-II were very limited (< 0.20%). The missing data for the LEMO amounted to only 0.20%.

weakly related to the three personality traits examined (i.e., neuroticism, openness, and conscientiousness), with one exception, namely a moderate association with openness for females. Only intellectual and sensual overexcitability were substantially positively indicative of openness (for both females and males). Moreover, the interaction term "positive developmental potential" had no substantive effect on any of the personality traits, nor was there an interaction effect of intellectual ability with respect to the influence of overexcitability on personality, indicating a different approach to personality in the TPD compared to the FFM – a multidimensional perspective on personality development is not tapped by the FFM. Thus, the results of Study 3 did not confirm any conceptual equivalence of, or interchangeability between, overexcitability and openness and did not support the assertion of the Vuyk et al. (2016) study, but rather concurred with the findings of Botella et al. (2015), Limont et al. (2014), and more recently Gallagher (2022) and the theoretical considerations of Grant (2021). It seems to be clear that both constructs – although related to each other – are distinct.[35]

A supplementary objective of Study 3 was to investigate the possible presence of distinct factors within the variable of emotional overexcitability consistent with the TPD's assumption of a hierarchical organization of personal development, in which each form of overexcitability has a different manifestation depending on the developmental level (Dąbrowski, 1970c; Tillier, 2018). As hypothesized, a two-factor exploratory structure fitted the data better than a one-factor structure, and the two factors that could be distinguished might represent the catalyst role that emotional overexcitability can play at a higher and lower level in the course of personality development. However, a multilevel perspective was much less clear with respect to the other forms of overexcitability.

Contextual influences and deep learning (Study 4)

The first objective of Study 4 was to examine any *personal* differences in intelligence (as measured by the PSB-3) and overexcitabilities (as gauged by the OEQ-II) among (former) general and technical secondary education (GSE [$n = 356$] and TSE [$n = 132$], respectively) students in order to investigate whether the claimed anti-school culture in the lower

35 Incidentally, Pekrun et al. (2023) recently included the five personality traits in their theoretical framework of antecedents and outcomes of achievement emotions, in addition to positive activating emotions such as excitement.

tracks (TSE) (Ball, 1981; Hargreaves, 1967; Lacey, 1970; Schafer & Olexa, 1971) has a solid basis. With the exception of a significant intelligence mean difference between girls from GSE and TSE (in favor of GSE), no personal competence differences between the tracks could be identified, as evidenced by the absence of substantive differences in overexcitability and intelligence between, respectively, former GSE and TSE students and GSE and TSE boys. The second research aim was to examine the consistency of these results with differences in mathematical and verbal achievement (as measured by identical performance tests that were administered at the start of the final year of secondary education, as did the PSB-3) and learning patterns (as measured by the LEMO), as well as differences in the influence of personal competence indicators on the learning approach among both tracks, all suggesting *contextual*, educational influences. The results showed that, compared to GSE students, TSE students scored significantly lower on the mathematical and verbal performance tests. A further breakdown by gender did not change the results. Furthermore, education track was found to be indicative of the learning pattern applied, both in higher and secondary education, with a substantively higher score for (former) TSE students on the application-directed learning pattern. However, former TSE students also scored substantially higher on undirected learning once they were in higher education. In addition, a differential impact of overexcitabilities on learning patterns among former TSE and GSE students was established.

Overall, but limited to our select sample of higher education students, it can be concluded that the lower personal competence expectations of lower-track teachers and schools (Ball, 1981; Hargreaves, 1967; Ireson & Hallam, 2001; Murphy & Hallinger, 1989; Rosenbaum, 1976) are not fully justified and may even partly underlie their students' lower performance (by imposing lower standards) and regulatory/motivational problems, as indicated by the lower verbal and mathematical performance test results and higher scores for undirected learning indicators, respectively. Lower-track prior education is clearly related to undirected learning. However, this relationship could not be established using learning pattern data from secondary education. Consequently, the cause of ex-TSE students' higher scores on undirected learning in higher education may partly lie in context-dependent factors such as higher adaptation requirements (being less prepared for higher educational demands) and even a history of teaching that is less responsive to SDT's fundamental human needs of autonomy and competence (being

less encouraged to intervene in one's environment in a self-determining, effective and value-creating way, which typifies an anti-school culture). Thus, the results of Study 4 appear to be in line with the DPT, although we should note that other contextual factors – such as socioeconomic status, cultural background, at-home language, and field of study – may have also contributed to the differential results for both tracks.

Concluding key findings (1) and implications for educational research and practice, limitations of the studies, and avenues for future research (2)

Overexcitabilities and deep learning, including an orientation toward autonomy
(1) The results of Study 1 showed that intellectual overexcitability is strongly positively related to key indicators of deep learning and an orientation toward autonomy – and does so more strongly than the FFM-traits (see Table 6.1). However, although the TPD postulates the conjunction of multiple overexcitabilities *at a high level* of development and intelligence to arrive at authentism (Dąbrowski, 1970a, 1970c, 1996, 2015), not all forms of overexcitability were found to be substantially indicative of deep learning and its autonomy-promoting indicators. In addition, the interaction term "positive developmental potential" and the covariate of intellectual ability had no substantive effects on any of the learning patterns, including the meaning-directed learning pattern. (2) In the case of moderate developmental potential (as characterized by the presence of several but not all forms of overexcitability and, concurrently, not only sensual and psychomotor overexcitability [Mendaglio, 2008]), the TPD emphasizes the importance of a nurturing social environment – as addressed in its concept of authentic education – for facilitating personal development and the attainment of autonomy (Dąbrowski, 2015; Dąbrowski et al., 1970; Rankel, 2008), the latter of which is consistent with SDT's propositions (Deci & Ryan, 2000, 2002). Therefore, the results of Study 1, which could only confirm the TPD to a certain extent, may support an argument for, on the one hand, accommodating learning-environment adaptations primarily in alignment with emotional, imaginational, and psychomotor overexcitability (at any level) to enhance deep learning, and on the other hand, the organization of overexcitabilities into a hierarchical factor model to further explore the relationships between the level of personality development and some positioning with respect to the surface/deep learning spectrum (taking into account higher-level aspects of deep learning that

may be relevant in the search for meaning), given a certain learning environment. Bidirectional causation between overexcitability at various levels and indicators of deep learning at different levels of complexity, with an interactive effect of aspects of the learning environment, was not investigated in Study 1 and represents an important avenue for future research given the primordial impact of emotive factors on motivation and indicators of authentism, as emphasized by the TPD and in line with contemporary approaches to the science of emotions (Mendaglio, 2008, 2022a; Pekrun, 2006, 2018) and as evidenced by the results of our research. Furthermore, considering intellectual overexcitability in a hierarchical manner[36] may further differentiate it from concepts such as TIE and NFC. As such, it would allow the investigation of both quantitative *and* qualitative between-person variations in "super-stimulability," as well as an examination of its within-person dynamic operation (growth) across time in stimulating learning-environment conditions.

Bayesian structural equation modeling

(1) Applying BSEM, the results of Studies 2 and 4 revealed that the OEQ-II demonstrates good factorial validity and approximate scalar MI across gender and education tracks, respectively. Moreover, throughout the studies of this dissertation, BSEM with informative, small-variance priors performed better than ML SEM. Compared to the frequentist approach, the Bayesian approach to statistics proved to be more appropriate, given the complexity of models which rely on personality and learning questionnaire data. The BSEM approach to factorial validation and MI analysis better represented substantive theory and avoided the need for a long series of model modifications that would bear the substantial risk of model misspecification.

(2) Educational research continues to make only marginal use of Bayesian statistics (König & van de Schoot, 2018), despite its many advantages over the frequentist approach

36 Intellectual overexcitability at a high – transcendental – level of development could be reflected in, among other aspects, the characteristic expressed in the statement: "I need to know and understand what's universal, the truth, and the coherence of things" (De Bondt & Van Petegem, 2025). In contrast, intellectual overexcitability at lower developmental levels could be reflected in the characteristics expressed in the statements: "I have a great thirst for knowledge and I am curious" (Primary Integration), "I question everything, which can sometimes lead to doubts and extensive repeated contemplation of problems" (Unilevel Disintegration), and "I am introspective by nature, I contemplate my feelings and thoughts, and I feel the need to monitor my thinking" (Spontaneous Multilevel Disintegration).

to statistics. Bayesian analysis makes it possible to incorporate prior information into parameter estimation, and is well suited for testing complex, non-linear models with non-normal distributions, regardless of sample size. Even in the case of very limited prior knowledge with little influence on the posterior distribution, the Bayesian credibility interval nevertheless allows direct probability statements about the parameter values given the data (Kruschke et al., 2012). The results of all four studies indicate the strong potential for the increasing use of Bayesian modeling in educational and psychological research.

We have applied BSEM at a very early stage, but should note that it is an innovative method that requires further research. In particular, the performance of BSEM estimation and posterior predictive checking under varied sample sizes and model features should be examined further (Asparouhov & Muthén, 2021b; Muthén & Asparouhov, 2012), as well as determine the sample size from which it is relevant to use the Bayesian versions of the approximate fit indices of root mean square error of approximation (RMSEA; Steiger, 1990), comparative fit index (CFI; Bentler, 1990), and the Tucker–Lewis index (TLI; Bentler & Bonett, 1980; Tucker & Lewis, 1973), as recently implemented in Mplus (Asparouhov & Muthén, 2021a; Garnier-Villarreal & Jorgensen, 2020). Approximate fit indices may be used to bypass a shortcoming of strict testing procedures such as the chi-square fit test, which can dismiss a model even in case of minor model misspecifications. They are especially beneficial when the sample size is large and many minor discrepancies between the data and the model are rendered statistically significant. In earlier (and current) versions of Mplus (as used in the four studies), model fit assessment in BSEM is performed using the PP*p*, which is based on the likelihood-ratio chi-square statistic. However, at large sample sizes, the PP*p* behaves similarly to the ML chi-square, making it relevant in that case to use the Bayesian versions of the approximate fit indices RMSEA, CFI, and TLI, instead of the PP*p*, to construct approximate well-fitting BSEM models with less extensive modifications (Asparouhov & Muthén, 2021a).

Furthermore, Studies 2 and 4 applied BSEM with alignment optimization to examine approximate MI across groups. However, no comparison was made with frequentist approaches to MI analysis. Comparing the employed technique with alternative methods for establishing (approximate) scalar MI using the same data would be a worthwhile endeavor. Such a comparison could include full and partial MI (based on

ML or Bayesian estimation), approximate MI, partial approximate MI, and alignment optimization (also using ML or Bayesian estimation). Approximate MI should not be used when full MI holds in the population. Simulation studies have shown that partial MI tends to outperform approximate MI when large differences exist in only one or few measurement parameters. Conversely, approximate MI outperforms full or partial MI when there are numerous small differences in measurement parameters across groups (van de Schoot et al., 2013). The approximate invariance approach of BSEM may be preferable under the assumption of a high degree of minor non-invariance, where opposing non-invariance patterns largely cancel each other out (Muthén & Asparouhov, 2013a). However, when substantial parameter deviations exists, the BSEM small-variance prior for parameter differences tends to shrink the deviating parameter toward the group average, resulting in biased estimates of factor means and variances (Muthén & Asparouhov, 2013a; van de Schoot et al., 2013). The alignment optimization method offers a solution to this issue of parameterization indeterminacy (Asparouhov & Muthén, 2023). By employing a component loss function, it identifies solutions with many approximately invariant measurement parameters across groups and a few non-invariant parameters (Asparouhov & Muthén, 2014, 2023; Leitgöb et al., 2023). The advantage of BSEM-based alignment, as used in our studies, over the BSEM approach to MI without alignment lies in its improved interpretability. Alignment estimates are derived by minimizing the number of non-invariant parameters, whereas BSEM estimates are obtained by minimizing the variability of parameter estimates across groups. Consequently, alignment typically yields more interpretable results, as fewer non-invariant parameters are identified (Asparouhov & Muthén, 2014). As Asparouhov and Muthén (2014, p. 1) note, the alignment method "essentially automates and greatly simplifies measurement invariance analysis. The method also provides a detailed account of parameter invariance for every model parameter in every group." The decision to use full, partial, approximate MI, or alignment optimization should be made on a case-by-case basis, depending on the dataset and research context (Seddig & Leitgöb, 2018).

Overexcitabilities in relation to the FFM-personality traits

(1) The results of Study 3 did not confirm any conceptual equivalence of overexcitability and the FFM-personality trait of openness (and this applied even more strongly to

neuroticism and conscientiousness) and did not support the assertion of the Vuyk et al. (2016) study, but rather concurred with the findings of Botella et al. (2015), Gallagher (2022), and Limont et al. (2014). It seems to be clear that overexcitability and openness – although related to each other – are distinct constructs. Furthermore, drawing on the OEQ-II, a multilevel perspective that was in accordance with the TPD's thesis of a hierarchical organization of personality development could only be distinguished with regard to emotional overexcitability.

(2) Given the results of Study 3, first, it is worthwhile to further explore the interrelationship and substantial difference between openness (according to the comprehensive 240-item Revised NEO Personality Inventory [NEO-PI-R] [Costa & McCrae, 1992b] instead of the brief NEO-FFI, as used in our research) and overexcitability. Overexcitability could be a temperamental/emotive driver of the FFM-trait of openness and its characteristics of intellectual curiosity, esthetic sensitivity, active imagination, attentiveness to inner feelings, and preference for variety (Costa & McCrae, 1992b; McCrae & Costa, 1989). According to the TPD, the characteristic of open-mindedness represents one of the "particular positive values" that combined with universal positive values constitute the personality ideal. In contrast, overexcitabilities represent emotive factors that are likely to induce authentism and authentic self-determined activity and, moreover, provide a multilevel and dynamic growth perspective (Dąbrowski, 2015). A more comprehensive grasp of both constructs requires additional in-depth research on their neurobiological foundations. Furthermore, future research might explore the relationship between distinctive facets (and sub-facets) of *all five* broad personality dimensions and overexcitabilities in greater depth, in order to interpret overexcitability from a pattern of convergent and discriminant relationships.

Second, it is important to further explore the interrelationships between overexcitabilities and intellectual ability from the perspective of personality development according to the TPD (which Study 3 only considered theoretically). This is needed because the existing research on associations of giftedness with overexcitabilities yields diverse results, which, moreover, are not always considered from the perspective of Dąbrowski's theory (Mendaglio, 2012, 2022a). According to the TPD, overexcitability and high-mental capabilities are essential constituents of an individual's developmental potential, and they play a key role in personality growth and the attainment of authenticity and autonomy (Dąbrowski, 1964, 1972b, 2015). Moreover,

multiple forms of overexcitability must manifest in order to contribute to the shaping of personality (Dąbrowski, 1976, 1996, 2015). Using data from the same sample (although slightly reduced; $n = 500$) as Studies 1, 2, and 3, De Bondt and Van Petegem (2025) sought to confirm the empirically established relationships between overexcitabilities and intellectual giftedness (Bouchet & Falk, 2001; Gallagher, 1985; Pethö, 2022; Piechowski et al., 1985; Silverman & Ellsworth, 1981; Siu, 2010; Tieso, 2007a). However, a correlation matrix of indicator variables showed intellectual ability (as measured by the PSB-3) to be weakly positively related to only one form of overexcitability (as gauged by the OEQ-II), that is, intellectual overexcitability (see also Table 6.1). Nevertheless, when comparing the best performers (> 95th percentile) on the PSB-3 with the rest of the sample, significant mean differences in the variables of imaginational, sensual, and psychomotor overexcitability were established, with higher scores for the high performers on the intelligence test and large effect sizes. A simulation study of independent samples *t*-tests was carried out and demonstrated the conjunction of high-intellectual ability and the presence of higher levels (degrees) of multiple forms of overexcitability. However, from the results of the simulation study, it could also be observed that the association of overexcitability with high-intellectual ability did not show a consistent pattern. Moreover, the small leading groups of best performers on the PSB-3 did not score significantly higher on all three forms of overexcitability – emotional, intellectual, imaginational – which are considered essential to advance personality development according to the TPD (Dąbrowski, 1970a, 1996, 2015), or on all five overexcitabilities more generally (De Bondt & Van Petegem, 2025). Furthermore, emotional overexcitability did not show significant mean differences between the distinct groups, which is in line with the scarce studies demonstrating a substantial association of this form of overexcitability – as measured by the OEQ-II – with intellectual giftedness (Bouchet & Falk, 2001; Siu, 2010).

The scientific field has called for advanced research on all concepts related to the TPD in an integrated way (Mendaglio, 2012, 2022; Mendaglio & Tillier, 2006). Therefore, future research should not only clarify the relationship between overexcitability and giftedness using larger samples and a more comprehensive set of instruments, but also incorporate dynamisms into the construct of developmental potential. Moreover, it should investigate the interactive effects of conducive environmental conditions on the interrelationships between multilevel overexcitabilities and intelligence and the

attainment of autonomy (an aspect that we only considered theoretically in this doctoral research).

In this context, as mentioned above, it would be interesting to consider a hierarchically structured overexcitability questionnaire that goes beyond the five-factor *static* taxonomic model of personality and can be used in future research on *dynamic* developmental processes of personality in accordance with the TPD. Such a questionnaire would also facilitate further empirical investigation of the TPD. *Emotional overexcitability at a high – transcendental – level of development* could be reflected in, among other aspects, the characteristic expressed in the statement: "Love is absolute and I accept it fully." *Higher-level intellectual and imaginational overexcitability* could be reflected in attributes such as those expressed in the statements: "I need to know and understand what's universal, the truth, and the coherence of things" and "Wonder coincides with the meaning of existence," respectively. *Sensual and psychomotor overexcitability at a high level of development* could be reflected in characteristics such as those expressed in the statements: "I feel the connection between myself and the universe" and "I strive for the highest human attitude and act accordingly," respectively. In contrast, *emotional overexcitability at lower developmental levels* could be reflected in the characteristics expressed in the statements: "I like having other people around me" (Primary Integration), "I am shy by nature, I have a strong affective memory, and sometimes I experience symptoms such as blushing, sweating or a feeling of tension in different parts of my body" (Unilevel Disintegration), and "I have strong sense of self-awareness, I am self-critical, and I evaluate and assess myself regularly" (Spontaneous Multilevel Disintegration) (De Bondt & Van Petegem, 2025). Incorporating a hierarchy into instruments that measure overexcitability would also make it possible to infer any stronger associations with giftedness. Moreover, a Bayesian approach to validation of this complex "growth modeling questionnaire" would add value over the frequentist approach.

Contextual influences and deep learning

(1) The results of Study 4 revealed regulatory/motivational problems among former lower-track students (once they were in higher education), as well as a substantial lower verbal and mathematical performance (as measured by identical performance tests) at the start of their final year of secondary education compared to higher-track

students, rather than personal competence differences between both tracks. Thus, the results of Study 4 appear to be in line with the DPT: the lower performance scores and regulatory problems of (former) lower-track students could partially have their origins in a (previous) anti-school culture characterized by reduced study requirements and impaired fostering of SDT's fundamental human needs for autonomy and competence. (2) However, it should be noted that Study 4 is limited by the use of rather small sample sizes, which did not allow simultaneous differentiation by gender or specificity of prior education (field of study) in the BSEM analyses. Moreover, only two time points were considered in these cross-sectional analyses and a limited set of instruments was used to measure students' competencies and skills. Furthermore, we only considered one educational contextual factor and not aspects of the home environment, such as socioeconomic status, cultural background, and at-home language. In addition, a substantial limitation concerns not having used independent randomized samples in Studies 1 and 4 that would have allowed cross-validation. Finally, the study was conducted among a relatively homogeneous group of students of higher education, as a result of which the research findings cannot be extrapolated to the entire population of (former) TSE and GSE students. Yet, for this very reason, the results are remarkable. The results of Study 4 substantiate the necessity of further research on interactive effects of conducive learning-environment conditions – as characterized by a culture of need-supportive and authentic high-standard education – on the interrelationships between emotions and learning effects. Furthermore, teachers and schools must become familiar with SDT and the TPD and understand the mechanisms underlying personal flourishing. Moreover, considering the results of Study 4, systematic screening for intelligence or other competencies at the start of secondary education (or preferably earlier), as well as a thorough assessment of students' personal interests, developmental potential, and learning approach, are warranted.

Finally, it would be valuable to further explore some important similarities between SDT and the TPD, as well as the potential contribution of the latter to the highly validated SDT. The TPD and SDT both represent organismic theories rooted in humanistic and positive psychology in which the self is viewed as a process of integration. Both theories presuppose innate integrative human tendencies which lead to a unification of cognitive, affective, and behavioral faculties. Strong awareness provides insight into emotional experiences, which directs the process of self-determination and autonomous regulation. This occurs in close

cooperation with cognitive functions that allow the individual to act in accordance with personal, self-endorsed values (Brown & Ryan, 2003; Dąbrowski, 1970b, 1970c; Ryan, 1995; Schultz & Ryan, 2015). SDT and the TPD both emphasize the essential influence of awareness in development and the attainment of eudaimonic well-being. Only through self-awareness and consciously reflecting on one's own behavior and testing it against personal values can one establish self-regulation and attain personal growth and autonomy (Schultz & Ryan, 2015). However, the TPD adds a moral normative component and the necessary implication of having achieved a more advanced level of human development (Dąbrowski, 1964, 2015). In this sense, the TPD complements SDT by inserting a morality-based hierarchy into the external (and internal) reality which an individual can become aware of and should be guided by. More specifically, the TPD stresses the importance of the conscious independence of the lower levels of the external and internal environment. This occurs through the process of positive disintegration that consciously develops moral judgment and is then guided by it, also in action. Thus, the TPD goes beyond emphasizing subjective valuations of personal fulfillment. Rather, its focus is on objective criteria for eudaimonia, as defined by those with a great capacity for wisdom. This enables it to explain how wisdom can help human beings cope with more difficult and unfulfilling life events. Ryan et al. (2019, p. 127) note that "wisdom has not been a direct focus of SDT, either conceptually or empirically," with the reason being "the careful growth of the formal theory, and SDT's conservative tenets of making no errors of commission" (2019, p. 124). However, they also emphasize the hope and expectation that as research in the field of wisdom develops (further), important and strong connections to central SDT-constructs will be demonstrable. The personality ideal, as defined by the TPD, encompasses the concept of wisdom. When fundamental needs are considered at different hierarchical levels in SDT, at the highest level autonomy reflects wisdom. Perhaps a validation of the theory from the hierarchical perspective of the TPD – with presupposition of an objective moral norm and the possible positive contribution of inner conflict and suffering to personal growth – has yet to be initiated. In this context, the TPD may be of value in interpreting SDT's key concepts at the highest level of personal development.

General conclusion

Despite the limitations of this doctoral research, it engaged the TPD in educational research on interrelationships between personal and contextual factors and the learning approach

– with the added value of bringing in emotive factors that display stronger associations compared to the FFM-traits and, moreover, provide a unique multilevel and dynamic growth perspective. The research proceeded through the association of the TPD with SDT – both theoretically and empirically, through the premise of the pursuit of autonomy and the learning patterns perspective on student learning, respectively – and was able to provide support for some hypotheses (e.g., substantive positive associations of intellectual and sensual overexcitability with indicators of deep learning and an autonomy orientation; a substantial influence of prior education on learning patterns and their association with personality drivers in the TPD, in line with the DPT) but not for all of them (e.g., the lack of a substantial positive association with deep learning for emotional, imaginational, and psychomotor overexcitability). Furthermore, the Bayesian approach to validation was found to add value over the frequentist approach. Throughout all four studies, BSEM with informative, small-variance priors performed better than frequentist SEM. The Bayesian approach to statistics proved to be more appropriate, given the complexity of models which rely on personality and learning questionnaire data. The BSEM approach to factorial validation and MI analysis better represented substantive theory and avoided the problem of capitalizing on chance. Moreover, by applying BSEM, the OEQ-II demonstrated good factorial validity and approximate scalar MI across gender and education tracks.

The TPD was also explained accurately and in depth, with a focus on the developmental potential rather than overexcitabilities alone and the consideration of the empirical results within the overall framework of Dąbrowski's theory (Mendaglio, 2022b). Moreover, the research delved more deeply into the differential significance of the personality drivers in the TPD in relation to the FFM-traits and could not statistically substantiate any conceptual equivalence. Finally, the concept of authentic education was further briefly theoretically explored in the context of giftedness. The TPD provides a meaningful regulatory perspective for the attainment of autonomy at the highest level and consequently eudaimonic well-being and essence – a finality too vital not to explore further.

CHAPTER 7

SUMMARY

DUTCH SUMMARY

Het doel van dit doctoraatsonderzoek was om de onderlinge relaties tussen diep versus oppervlakkig leren en de persoonlijke en contextuele factoren die dit beïnvloeden te onderzoeken vanuit het perspectief van Dąbrowski's Theorie van Positieve Desintegratie (TPD) (Dąbrowski, 1964, 1972b, 2015) die zich richt op persoonlijke groei en het bereiken van autonomie, authenticiteit en essentie. De TPD vertegenwoordigt een hiërarchisch gestructureerde en dynamische theorie van persoonlijkheidsontwikkeling, waarin persoonlijkheid wordt gedefinieerd als een "zelfbewuste, zelfgekozen, zelf-bevestigde en zelf-gedetermineerde eenheid van essentiële individuele psychische kwaliteiten" en pas wordt bereikt op het hoogste niveau van het ontwikkelingsproces (Dąbrowski, 2015). Het bereiken van dit hoogste niveau van menselijke ontwikkeling – of het verwezenlijken van het persoonlijkheidsideaal – hangt grotendeels af van het ontwikkelingspotentieel van een individu, dat wordt bepaald door het niveau van aangeboren over-exciteerbaarheid en de aanwezigheid van bijzondere capaciteiten en talenten en autonome innerlijke dynamieken die persoonlijke groei cultiveren (Dąbrowski, 1964, 1972b, 2015; Mendaglio, 2008; Tillier, 2018). De TPD onderscheidt vijf vormen van over-exciteerbaarheid (of super-stimuleerbaarheid [Piechowski, 1999]) – emotioneel, intellectueel, imaginatief, sensorisch en psychomotorisch – waarvan de eerste drie als essentieel worden beschouwd om persoonlijkheidsontwikkeling te bevorderen (Dąbrowski, 1970a, 1996, 2015) en zonder welke empathie, autonomie en authenticiteit zich niet kunnen ontwikkelen (Dąbrowski et al., 1970). In de TPD verwijst autonomie naar een bewust, op hoge morele waarden gebaseerd zelf-determinisme (Dąbrowski, 2015).

Ondanks dat de TPD een visionaire theorie van persoonlijkheidsontwikkeling is die een zinvol en belangrijk regulatief perspectief biedt voor de morele ontwikkeling, innerlijke groei en mentale gezondheid, is ze slechts in beperkte mate gevalideerd. Dit is deels te wijten aan de complexiteit ervan, maar ook aan de beperkte toegankelijkheid van het uitgebreid oeuvre van de Poolse psychiater en psycholoog Kazimierz Dąbrowski (1902-1980). Ook de mogelijke implicatie van de TPD voor het domein van onderwijs werd slechts door enkele auteurs theoretisch behandeld (Daniels & Meckstroth, 2009; Hague, 1976; Rankel, 2008; Silverman, 2008; Tillier, 2006) en empirisch onderzoek naar de TPD – en haar bouwstenen – in een onderwijscontext is vrijwel onbestaand.

Bovendien heerst de kritische bezorgdheid dat het empirisch onderzoek naar de TPD, in welke context ook, zich louter richt op over-exciteerbaarheid in plaats van het ruimere ontwikkelingspotentieel (Tillier, 2006) en ook vaak de theorie van Dąbrowski niet geheel juist en diepgaand weergeeft (Tillier, 2009).

Op basis van deze lacunes en opportuniteiten in het onderzoek naar de TPD, was het hoofddoel van dit doctoraat te onderzoeken hoe Dąbrowski's theorie met haar uitgangspunt van het streven naar autonomie kan bijdragen aan het bestaand uitgebreid onderwijsonderzoek naar de persoonlijke en contextuele correlaten van diepe versus oppervlakkige leerkenmerken zoals benaderd vanuit het leerpatronenraamwerk (Donche et al., 2010; Vermunt, 1994, 1996, 1998; Vermunt & Minnaert, 2003). In tegenstelling tot oppervlakkig leren, kenmerkt het diepgaand leren zich door een focus op betekenisconstructie – met de intentie om te begrijpen – en intrinsieke motivatie (Entwistle, 1997; Tait & Entwistle, 1996). De kenmerken van diep leren vertegenwoordigen ook belangrijke ontwikkelingsdynamieken voor het bereiken van hogere niveaus van persoonlijkheidsontwikkeling en autonomie in de TPD (Dąbrowski, 1964, 2015). Empirisch onderzoek geeft aan dat leerbenaderingen en leerpatronen waarschijnlijk het resultaat zijn van de interactie tussen persoonlijke kenmerken en dynamische contextuele omgevingsinvloeden (Entwistle & McCune, 2004; Vermunt, 1996; Vermunt & Donche, 2017; Vermunt & Vermetten, 2004).

Het onderzoek verliep via de associatie van de TPD met Zelfdeterminatietheorie (ZDT) (Deci & Ryan, 2000, 2002) die beide hun oorsprong hebben in de humanistische en positieve psychologie en de verwezenlijking van autonomie als fundamenteel beschouwen voor het bereiken van eudaimonisch welzijn en essentie (Dąbrowski, 1964, 2015; Deci & Ryan, 2000, 2002). De externe omgeving kan echter een belangrijke invloed uitoefenen op het bereiken van deze menselijke conditie (Dąbrowski, 1964, 2015; Dąbrowski et al., 1970; Deci & Ryan, 2000, 2002). In het bijzonder richt ZDT zich op het effect van de externe omgeving op de menselijke intrinsieke motivatie, die aanleiding geeft tot zelf-gedetermineerd gedrag volgens inherente interesses, evenals zelf-onderschreven en zelf-bevestigde waarden – of autonomie – wat leidt tot innerlijke vervulling en welzijn (Deci & Ryan, 2002).

Meer specifiek onderzocht dit doctoraat de invloed van over-exciteerbaarheid en meer algemeen het ontwikkelingspotentieel – die persoonlijkheids- en autonomiedrivers in de TPD vertegenwoordigen (Dąbrowski, 2015) – op het gebruik

van cognitieve verwerkings- en metacognitieve regulatiestrategieën in het leerproces en studiemotivatie (zoals afgeleid van ZDT) – waarvan de onderlinge samenhang diverse leerpatronen binnen het spectrum oppervlakkig/diep leren weerspiegelen (Vermunt & Donche, 2017) – bij 516 studenten in het hoger onderwijs met verschillende *persoonlijke* (gender [318 vrouwen; 198 mannen] en intelligentie – Studie 1) en *contextuele* (vooropleiding – Studie 4) kenmerken. Als zodanig werden emotieve factoren betrokken in de studie van de leerbenadering, die slechts marginale aandacht hebben gekregen in het gevestigd empirisch onderzoek (Entwistle & McCune, 2004; Heikkilä et al., 2011) hoewel ze waarschijnlijk autonome motivatie en authentieke zelf-gedetermineerde activiteit induceren – zoals respectievelijk empirisch onderbouwd door Pekrun et al. (2002) (in consistentie met Pekrun's Controle-Waarde Theorie (CWT) [Pekrun, 2006, 2018]) en theoretisch gepostuleerd in de TPD (Dąbrowski, 2015) – waarbij het eerste aanleiding geeft tot het laatste, zoals gevalideerd door ZDT (Deci & Ryan, 2000).

Doorheen het onderzoek werd gebruik gemaakt van Bayesiaanse structurele vergelijkingsmodellering (BSEM) (Muthén & Asparouhov, 2012) wat nog maar in heel beperkte mate wordt toegepast in onderzoek in het domein van de onderwijswetenschappen en psychologie (König & van de Schoot, 2018) en deze benadering werd vergeleken met een frequentistische benadering van statistiek (alle vier studies – voornamelijk Studie 2). BSEM is een innovatieve en flexibele benadering van statistiek die de toepassing van priors met nul als gemiddelde en een kleine variantie voor kruisladingen, residuele covarianties en verschillen in parameters tussen groepen mogelijk maakt, wat leidt tot een betere weerspiegeling van de substantieve theorie, betere modelfit en accuratere inferenties in vergelijking met een frequentistische analyse (die exacte parameterbeperkingen postuleert en meestal te strikt is) (Asparouhov & Muthén, 2014; Muthén & Asparouhov, 2012).

Aangezien het gevestigd onderzoek naar onderlinge relaties tussen persoonlijkheid en leerbenadering doorgaans persoonlijkheid meet met behulp van het Vijf-Factoren Model (FFM) (McCrae & Costa 1987) dat echter een zwakke verklaringskracht vertoont met betrekking tot de leeraanpak (Chamorro-Premuzic & Furnham, 2009), onderzochten we ook de differentiële betekenis van over-exciteerbaarheid in relatie tot de FFM-persoonlijkheidskenmerken openheid, consciëntieusheid en neuroticisme (Studie 3).

Alzo betrok dit doctoraat de TPD in het onderwijsonderzoek naar de onderlinge relaties tussen persoonlijke en contextuele factoren en de leerbenadering – met de

meerwaarde van de inbreng van emotieve factoren die sterkere associaties vertonen in vergelijking met de FFM-persoonlijkheidskenmerken en bovendien een uniek multilevel en dynamisch groeiperspectief bieden. Het onderzoek verliep via de associatie van de TPD met ZDT – zowel theoretisch als empirisch, respectievelijk via de premisse van het streven naar autonomie en het leerpatronenperspectief op het leren van studenten – en kon ondersteuning bieden voor sommige vooropgestelde hypothesen (e.g., substantiële positieve associaties van intellectuele en sensorische over-exciteerbaarheid met indicatoren van diep leren en een autonomieoriëntatie; een substantiële invloed van de contextuele factor vooropleiding op leerpatronen en hun associatie met persoonlijkheidsdrivers in de TPD, in lijn met de Differentiatie-Polarisatie Theorie [DPT] [Ball, 1981; Hargreaves, 1967; Lacey, 1970; Schafer & Olexa, 1971]) maar niet voor allemaal (e.g., het ontbreken van een substantiële positieve associatie van diep leren met emotionele, imaginatieve en psychomotorische over-exciteerbaarheid).

Bovendien bood de Bayesiaanse valideringsmethode een meerwaarde ten opzichte van een frequentistische benadering. In de vier studies presteerde BSEM met informatieve, kleine-variantie priors beter dan frequentist SEM en bleek de Bayesiaanse statistiek meer geschikt gegeven de complexiteit van modellen die gebaseerd zijn op data van persoonlijkheids- en leervragenlijsten. De BSEM-benadering van factoriële validatie en analyse van meetinvariantie reflecteerde beter de substantieve theorie en voorkwam de noodzaak van een uitgebreide reeks van sequentiële modelaanpassingen die het aanzienlijk risico van modelmisspecificatie met zich mee zou brengen. Onder toepassing van BSEM vertoonde de Overexcitability Questionnaire-Two (OEQ-II) (Falk et al., 1999), i.e. het meest gebruikt zelfrapporteringsinstrument voor het meten van de mate en aard van over-exciteerbaarheid, een goede factoriële validiteit en approximatieve scalaire meetinvariantie over gender en opleidingsniveau heen.

De TPD werd diepgaand toegelicht, met een focus op het gehele ontwikkelingspotentieel in plaats van alleen over-exciteerbaarheid en de interpretatie van de empirische resultaten binnen het geheel van de theorie van Dąbrowski (Mendaglio, 2022b). Bovendien ging het onderzoek dieper in op de differentiële betekenis van de persoonlijkheidsdrivers in de TPD in vergelijking met de FFM-persoonlijkheidskenmerken en het kon geen conceptuele equivalentie statistisch onderbouwen. Tot slot werd het concept van “authentiek onderwijs” in de TPD verder beknopt theoretisch verkend in de context van begaafdheid.

De TPD biedt een betekenisvol regulatief perspectief voor het bereiken van autonomie op het hoogste niveau en bijgevolg eudaimonisch welzijn en essentie – een finaliteit te essentieel om niet verder te verkennen.

ENGLISH SUMMARY

The purpose of this doctoral research was to explore in depth the interrelations between deep versus surface learning and the personal and contextual factors influencing it, illuminated from the perspective of Dąbrowski's Theory of Positive Disintegration (TPD) (Dąbrowski, 1964, 1972b, 2015), which focuses on personal growth and the attainment of autonomy, authenticity, and essence. The TPD represents a hierarchically structured and dynamic theory of personality development, in which personality is defined as a "self-aware, self-chosen, self-affirmed, and self-determined unity of essential individual psychic qualities" (Dąbrowski, 2015, p. 290) and is only attained at the highest level of the developmental process. Achieving the highest level of human development – or enacting the personality ideal – depends largely on an individual's developmental potential, which is determined by their level of innate psychic overexcitability and the presence of special abilities, talents, and autonomous inner dynamisms that cultivate personal growth (Dąbrowski, 1964, 1972b, 2015; Mendaglio, 2008; Tillier, 2018). The TPD distinguishes five forms of overexcitability (or "super-stimulability" [Piechowski, 1999]) – emotional, intellectual, imaginational, sensual, and psychomotor – the first three of which are considered essential to advance personality development (Dąbrowski, 1970a, 1996, 2015) and without which empathy, autonomy, and authenticity cannot develop (Dąbrowski et al., 1970). In the TPD, the concept of autonomy refers to a conscious, high value-based self-determinism (Dąbrowski, 2015).

However, despite the TPD being a visionary theory of personality development that provides a vital regulatory perspective for moral development, inner growth, and mental health, the theory has only been validated to a limited degree. This is partly due to its complexity, as well as the limited accessibility of the extensive body of work of the Polish psychiatrist and psychologist Kazimierz Dąbrowski (1902-1980). Also, the potential implication of the TPD for the field of education has been theoretically addressed by only a few authors (e.g., Daniels & Meckstroth, 2009; Hague, 1976; Rankel, 2008; Silverman, 2008; Tillier, 2006), while empirical research on the TPD – and its building blocks – in an educational context is virtually non-existent. Moreover, there are critical concerns that empirical research on the TPD *in any context* has focused only on overexcitability rather than developmental potential (Tillier, 2006) and also often fails to fully represent Dąbrowski's theory correctly and in depth (Tillier, 2009).

Drawing on these gaps and opportunities in the research on the TPD, the main purpose of this doctorate was to investigate how Dąbrowski's theory with its premise of the pursuit of autonomy can contribute to the existing comprehensive research on the personal and contextual correlates of deep versus surface learning characteristics approached through the learning patterns framework (Donche et al., 2010; Vermunt, 1994, 1996, 1998; Vermunt & Minnaert, 2003). In contrast to surface learning, deep learning is characterized by the construction of meaning – with the intention to understand – and by intrinsic motivation (Entwistle, 1997; Tait & Entwistle, 1996). The features of deep learning also represent important developmental dynamisms for the attainment of higher levels of personality development and autonomy in the TPD (Dąbrowski, 1964, 2015). Empirical research indicates that learning approaches and patterns are likely to be the result of the interplay between personal attributes and dynamic contextual influences (Entwistle & McCune, 2004; Vermunt, 1996; Vermunt & Donche, 2017; Vermunt & Vermetten, 2004).

The research proceeded through the association of the TPD with Self-Determination Theory (Deci & Ryan, 2000, 2002). The TPD and SDT are both organismic theories rooted in humanistic and positive psychology, which consider the attainment of autonomy as fundamental for eudaimonic well-being and essence (Dąbrowski, 1964, 2015; Deci & Ryan, 2000, 2002). The external environment can have, however, a significant impact on the attainment of this human condition (Dąbrowski, 1964, 2015; Dąbrowski et al., 1970; Deci & Ryan, 2000, 2002). In particular, SDT focuses on the effects of the external environment on individuals' intrinsic motivation, with the latter giving rise to self-determined behavior according to inherent interests, as well as self-endorsed and self-affirmed values – or autonomy – leading to inner fulfillment and health (Deci & Ryan, 2002).

More specifically, this doctoral research investigated the influence of overexcitability and, more generally, developmental potential – representing personality and autonomy drivers in the TPD (Dąbrowski, 2015) – on the use of cognitive processing and metacognitive regulation strategies in the learning process and study motivation (as conceptualized by SDT) – the interrelation of which reflects various learning patterns within the surface/deep learning spectrum (Vermunt & Donche, 2017) – among 516 higher education students with different *personal* (gender [318 women; 198 men] and intelligence – Study 1) and *contextual* (prior education – Study 4) characteristics. As such,

it considered emotive factors in the study of the learning approach, which have only received marginal attention in established empirical research (Entwistle & McCune, 2004; Heikkilä et al., 2011), although they are likely to induce autonomous motivation (and, more generally, deep learning) and authentic self-determined activity – as empirically substantiated by Pekrun et al. (2002) (and consistent with Pekrun's [2006, 2018] Control-Value Theory [CVT] propositions) and theoretically postulated in the TPD (Dąbrowski, 2015), respectively – whereby the former leads to the latter, as validated by SDT (Deci & Ryan, 2000).

Throughout the research, Bayesian structural equation modeling (BSEM) (Muthén & Asparouhov, 2012) was applied, which is still only marginally used in educational and psychological research (König & van de Schoot, 2018), and this approach was compared to a frequentist approach to statistics (all four studies – mainly Study 2). BSEM is an innovative and flexible approach to statistics that allows the application of zero-mean, small-variance priors for cross-loadings, residual covariances, and differences in measurement parameters across groups, better reflecting substantive theory and leading to better model fit and more accurate inferences compared to a frequentist analysis (which postulates exact parameter constraints and is usually too strict) (Asparouhov & Muthén, 2014; Muthén & Asparouhov, 2012).

Since established research on interrelationships between personality and the learning approach typically measures personality using the five-factor model (FFM) personality traits (McCrae & Costa 1987), which, however, have weak explanatory power with respect to learning approaches (Chamorro-Premuzic & Furnham, 2009), we also examined the differential significance of overexcitability in relation to the FFM-traits of openness, conscientiousness, and neuroticism (Study 3).

Thus, this doctoral research engaged the TPD in educational research on interrelationships between personal and contextual factors and the learning approach – with the added value of bringing in emotive factors that display stronger associations compared to the FFM-personality traits and, moreover, provide a unique multilevel and dynamic growth perspective. The research proceeded through the association of the TPD with SDT – both theoretically and empirically, through the premise of the pursuit of autonomy and the learning patterns perspective on student learning, respectively – and was able to provide support for some hypotheses (e.g., substantive positive associations of intellectual and sensual overexcitability with indicators of deep learning and an

autonomy orientation; a substantial influence of the contextual factor of prior education on learning patterns and their association with personality drivers in the TPD, in line with the Differentiation-Polarization Theory [DPT] [Ball, 1981; Hargreaves, 1967; Lacey, 1970; Schafer & Olexa, 1971]) but not for all of them (e.g., the lack of a substantial positive association with deep learning for emotional, imaginational, and psychomotor overexcitability).

Furthermore, the Bayesian approach to validation was found to add value over the frequentist approach. Throughout all four studies, BSEM with informative, small-variance priors performed better than frequentist SEM. The Bayesian approach to statistics proved to be more appropriate, given the complexity of models which rely on personality and learning questionnaire data. The BSEM approach to factorial validation and measurement invariance (MI) analysis better represented substantive theory and avoided the need for a long series of sequential model modifications that would bear the substantial risk of model misspecification. Moreover, by applying BSEM, the Overexcitability Questionnaire-Two (OEQ-II) (Falk et al., 1999), i.e., the most widely utilized self-reporting instrument for measuring the degree and nature of overexcitability, demonstrated good factorial validity and approximate scalar MI across gender and education tracks.

The TPD was explained in depth, with a focus on the developmental potential rather than overexcitabilities alone and the consideration of the empirical results within the overall framework of Dąbrowski's theory (Mendaglio, 2022b). Moreover, the research delved more deeply into the differential significance of the personality drivers in the TPD in relation to the FFM-traits and could not statistically substantiate any conceptual equivalence. Finally, Dąbrowski's concept of "authentic education" was further briefly theoretically explored in the context of giftedness.

The TPD provides a meaningful regulatory perspective for the attainment of autonomy at the highest level and consequently eudaimonic well-being and essence – a finality too vital not to explore further.

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APPENDICES

APPENDICES

Appendix A

Supplementary material Study 2: Input syntax.

1 BSEM with informative, small-variance priors for cross-loadings and residual covariances – Mplus code

```
TITLE:      BSEM on OEQ-II data – females
DATA:       FILE = Data.dat;
VARIABLE:   NAMES =
            Gender
            y1-y50;
            usevariables y1-y50;
            ! 5-point scale from 1 “Not at all like me” to 5 “Very much like me”
            missing are all (-99);
            ! grouping is Gender (0=g1 1=g2);
            ! Gender = 0 for males and 1 for females
            useobs = Gender eq 1;
DEFINE:     standardize y1-y50;
ANALYSIS:   estimator = Bayes;
            process = 2;
            chain = 1;
            fbiter = 100000;
            thin=10;
MODEL:      fi by y1-y10*;
            fim by y11-y20*;
            fe by y21-y30*;
            fs by y31-y40*;
            fps by y41-y50*;
            fi-fps with fi-fps;
            fi-fps @1;
            ! x-loadings:
            fi by y11-y50*0 (i1-i40);
```

```
                fim by y1-y10*0 (im1-im10)
                y21-y50*0 (im11-im40);
                fe by y1-y20*0 (e1-e20)
                y31-y50*0 (e21-e40);
                fs by y1-y30*0 (s1-s30)
                y41-y50*0 (s31-s40);
                fps by y1-y40*0 (ps1-ps40);
                ! residual covariances:
                y1-y50 (p1-p50);
                y1-y50 with y1-y50 (p51-p1275);
MODEL PRIORS:
                i1-i40~N(0,0.01);
                im1-im40~N(0,0.01);
                e1-e40~N(0,0.01);
                s1-s40~N(0,0.01);
                ps1-ps40~N(0,0.01);
                p1-p50~IW(1,56);
                p51-p1275~IW(0,56);
OUTPUT:         tech1 tech8 stdy;
PLOT:           type = plot2;
```

2 Multiple-group BSEM-based alignment with approximate measurement invariance – Mplus code

```
TITLE:          BSEM MI on OEQ-II data – intellectual overexcitability
DATA:           FILE = Data MI.dat;
VARIABLE:       NAMES = u y1-y50 group;
                USEVARIABLES = y1-y10 group;
                missing are all (-99);
                CLASSES = c(2);
                KNOWNCLASS = c(group = 1-2);
ANALYSIS:       TYPE =MIXTURE;
                ESTIMATOR = BAYES;
                process = 2;
                biter = (1000);
                thin = 10;
                align = fixed(BSEM);
MODEL:          %OVERALL%
                f BY y1-y10* (lam#_1-lam#_10);
                [y1-y10] (nu#_1-nu#_10);
                y1-y10 (p#_1-p#_10);
                y1-y10 with y1-y10;
MODEL PRIORS:
                do(1,10) diff(lam1_#-lam2_#)~N(0,0.01);
                do(1,10) diff(nu1_#-nu2_#)~N(0,0.01);
                do(1,2) p#_1~iw(1,16);
                do(1,2) p#_2~iw(1,16);
                do(1,2) p#_3~iw(1,16);
                do(1,2) p#_4~iw(1,16);
                do(1,2) p#_5~iw(1,16);
                do(1,2) p#_6~iw(1,16);
                do(1,2) p#_7~iw(1,16);
                do(1,2) p#_8~iw(1,16);
                do(1,2) p#_9~iw(1,16);
                do(1,2) p#_10~iw(1,16);
```

```
OUTPUT:          TECH1 TECH8;
PLOT:            TYPE =PLOT2;
```

Appendix B

Pearson correlation coefficients between achievement variables, intellectual ability, overexcitability, openness, neuroticism, and conscientiousness, and learning pattern indicators.

	N	1	2	3	4	5	6	7	8	9	10
1	502										
2	498	0.484**									
3	500	0.350**	0.248**								
4	516	0.109*	0.118**	0.098*							
5	516	-0.250**	-0.139**	0.008	0.250**						
6	516	-0.057	-0.019	0.054	0.435**	0.356**					
7	516	-0.051	-0.033	0.082	0.322**	0.380**	0.500**				
8	516	-0.005	-0.125**	-0.045	0.099*	0.147**	0.053	0.089*			
9	478	0.056	0.171**	0.107*	0.437**	0.185**	0.536**	0.299**	-0.108*		
10	479	-0.160**	-0.067	-0.117*	-0.002	0.413**	0.100*	0.255**	-0.065	0.062	
11	471	-0.087	-0.049	-0.092*	0.096*	0.072	-0.067	-0.228**	0.043	0.025	-0.213**
12	516	0.037	0.064	0.011	0.476**	0.184**	0.254**	0.051	0.026	0.287**	-0.046
13	516	0.155**	0.141**	-0.003	0.552**	0.095*	0.297**	0.108*	-0.002	0.315**	-0.099*
14	516	-0.051	-0.048	0.014	0.313**	0.193**	0.249**	0.132**	-0.036	0.260**	-0.018
15	516	-0.043	0.015	-0.003	0.410**	0.192**	0.314**	0.062	0.020	0.304**	-0.078
16	516	-0.019	-0.113*	-0.100*	0.158**	0.165**	0.123**	0.018	-0.090*	0.029	0.077
17	516	-0.180**	-0.119**	-0.108*	-0.018	0.294**	0.129**	0.085	0.047	-0.024	0.164**
18	516	-0.096*	-0.082	-0.019	-0.010	0.205**	0.012	-0.040	0.016	-0.121**	0.012
19	516	0.041	0.046	-0.018	0.003	0.234**	0.063	0.190**	0.132**	0.038	0.233**
20	516	-0.192**	-0.305**	-0.097*	-0.121**	0.180**	0.080	0.204**	0.107*	-0.086	0.257**
21	516	0.005	-0.082	-0.055	-0.167**	-0.037	-0.038	0.227**	0.039	-0.081	0.138**
22	516	-0.032	-0.059	-0.012	0.388**	0.135**	0.231**	0.161**	0.191**	0.121**	-0.073

Note. 1 = mathematical achievement; 2 = verbal achievement; 3 = intellectual ability; 4 = intellectual overexcitability: 5 = emotional overexcitability; 6 = sensual overexcitability; 7 = imaginational overexcitability; 8 = psychomotor overexcitability; 9 = openness; 10 = neuroticism; 11 = conscientiousness; 12 = relating and structuring; 13 = critical processing; 14 = self-regulation; 15 = autonomous motivation; 16 = analyzing; 17 = memorizing; 18 = external regulation; 19 = controlled motivation; 20 = lack of regulation; 21 = amotivation; 22 = concrete processing.
*$p < 0.05$; **$p < 0.01$.

11	12	13	14	15	16	17	18	19	20	21
0.182**										
0.095*	0.679**									
0.181**	0.426**	0.440**								
0.257**	0.458**	0.366**	0.394**							
0.179**	0.275**	0.235**	0.223**	0.206**						
0.106*	0.058	-0.002	0.063	0.125**	0.414**					
0.200**	0.100*	0.022	-0.057	0.140**	0.389**	0.458**				
-0.100*	-0.007	-0.018	-0.008	-0.014	0.040	0.163**	0.104*			
-0.191**	-0.168**	-0.149**	0.050	-0.169**	0.028	0.202**	0.094*	0.167**		
- -0.164**	-0.283**	-0.164**	-0.067	-0.414**	-0.089*	-0.042	-0.200**	0.322**	0.325**	
0.090	0.400**	0.370**	0.343**	0.299**	0.093*	0.050	0.131**	-0.025	0.029	-0.199**

AUTHOR CONTRIBUTIONS

Study 1 **Emphasis on emotions in student learning: Analyzing relationships between overexcitabilities and the learning approach using Bayesian MIMIC modeling**

De Bondt, N.: Conception of the study, setup of the method, data analyses, drafting and revision of the manuscript, article reviewing and editing before and after journal submission, proof correction for publication.

Van Petegem, P.: Data acquisition, feedback on the study conception and method, critical feedback on the manuscript.

Study 2 **Psychometric evaluation of the Overexcitability Questionnaire-Two applying Bayesian structural equation modeling (BSEM) and multiple-group BSEM-based alignment with approximate measurement invariance**

De Bondt, N.: Conception of the study, setup of the method, data analyses, drafting and revision of the manuscript, article reviewing and editing before and after journal submission, proof correction for publication.

Van Petegem, P.: Data acquisition, feedback on the study conception and method, critical feedback on the manuscript.

Study 3 **A rationale for including overexcitability in talent research beyond the FFM-personality dimensions**

De Bondt, N.: Conception of the study, setup of the method, data analyses, drafting and revision of the manuscript, article reviewing and editing before and after journal submission, proof correction for publication.

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De Maeyer, S.: Critical feedback on the manuscript.

Donche, V.: Data acquisition.

Study 4 **Are contextual rather than personal actors at the basis of an anti-school culture? A Bayesian analysis of differences in intelligence, overexcitability, and learning patterns between (former) lower and higher-track students**

De Bondt, N.: Conception of the study, setup of the method, data analyses, drafting and revision of the manuscript, article reviewing and editing before and after journal submission, proof correction for publication.

Van Petegem, P.: Data acquisition, feedback on the study conception and method, critical feedback on the manuscript.

Donche, V.: Data acquisition, critical feedback on the manuscript.