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# 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.

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## 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.

Are contextual rather than personal factors at the basis of an anti-school culture?

Keywords: educational stratification, learning patterns, overexcitability within the theory of positive disintegration, Bayesian structural equation modeling, approximate measurement invariance, self-determination theory

## 1. 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 and 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 and Stevens, 2010), reduced achievement (Stevens and Vermeersch, 2010; Van de gaer, Pustjens, Van Damme, and De Munter, 2006; Van Houtte, 2004), lower self-esteem (Van Houtte, 2005), as well as to an increased sense of futility (Van Houtte and Stevens, 2010). Similar results are obtained in other countries (Gamoran and Mare, 1989; Hallinan and Kubitschek, 1999; Kerckhoff, 1986; Vanfossen, Jones, and Spade, 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 and 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 and 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 and Hallam, 2001; Murphy and 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 and 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 Dabrowski's theory of positive disintegration [TPD] [Dabrowski, 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 and van de Schoot, 2018), despite its many advantages over the frequentist approach (Kruschke, Aguinis, and Joo, 2012). Before presenting this study, we first introduce the concepts of learning patterns, overexcitability, and Bayesian structural equation modeling (BSEM) (Muthén and Asparouhov, 2012).

### 1.1. 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 and 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, Van Petegem, Van de Mosselaer, and Vermunt, 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 and 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 and van Rijswijk, 1988). External regulation and lack of regulation concern, respectively, the regulation of the learning process by external sources and regulatory difficulties (Vermunt and Vermetten, 2004).

Motivation is also an important determinant of an individual's study approach and learning process (Entwistle and McCune, 2004; Vermunt and Donche, 2017). In the LEMO, the conceptualization of study motivation is derived from self-determination theory (SDT) (Deci and 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 and 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 and Ryan, 2000, 2002; Ryan and Connell, 1989).

The LEMO yields four learning patterns (Donche, Van Petegem, Van de Mosselaer, and Vermunt, 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 and Donche, 2017; Vermunt and Vermetten, 2004). Regarding *personal* factors, empirical studies have indicated that *inter alia* personality and gender are related to learning patterns (Vermunt and Donche, 2017). Personality, as measured by the five-factor model (FFM) personality traits (McCrae and Costa, 1987), is only weakly to moderately interrelated with learning patterns (Vermunt and Donche, 2017), with the most substantial relationship between openness to experience and deep learning (Chamorro-Premuzic and 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, De Maeyer, Coertjens, Van Daal, and Van Petegem, 2013; Entwistle and 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 and Donche, 2017).

**1.2. 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" (Dabrowski, 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 (Dabrowski, 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 (Dabrowski, 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 (Dabrowski, 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 (Dabrowski, 1970a). As such, overexcitability enhances the possibility of inner mental transformation. Moreover, it is a necessary element of an individual's psychic enrichment (Dabrowski, 1970a, 2015; Dabrowski and 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" (Dabrowski, 2015, p. 75). *Sensual overexcitability* involves enhanced receptivity of the senses and strong sensory and esthetic experiences (Dabrowski, 2015; Daniels and 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 and Piechowski, 2009). It "constitutes the ground for compassion, pity, anxiety about others and about one's own thread of life" (Dabrowski, 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 (Dabrowski, 2015; Daniels and Piechowski, 2009). Dabrowski (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[1]" (p. 75). The TPD postulates the necessary conjunction of the five overexcitabilities to arriving at personality development. Positive

[1] 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 Dabrowski, 2015). Personality is only achieved at the level of secondary integration.

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 (Dabrowski, 1976; Mendaglio, 2012).

Furthermore, special abilities and talents are also part of an individual's developmental potential. According to Dabrowski (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, 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 (Dabrowski, 1970b, 1970c). If combined with a high level of overexcitability and strong developmental dynamisms (more specifically, self-consciousness, subject-object attitude[2], the personality ideal[3], and the Third Factor[4]), intelligence could function as a catalyst if used in the service of the developmental process.

### 1.3. Bayesian Structural Equation Modeling

Educational research continues to make only marginal use of Bayesian statistics (König and van de Schoot, 2018), despite its many advantages over the frequentist approach to statistics (Kruschke, Aguinis, and Joo, 2012). For example, most educational and psychological

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

[3] 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 (Dabrowski, 2015).

[4] 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 (Dabrowski, 2015).

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, Roznowski, and Necowitz, 1992), and they are thus accompanied by a considerable risk of model misspecification (Muthén and Asparouhov, 2013a). 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 and 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[5]. 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 and Muthén, 2014).

## 2. Method

### 2.1. Participants

[5] 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 and 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 and Muthén, 2014; Muthén and Asparouhov, 2012).

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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.

### 2.2. Measures

#### 2.2.1. Overexcitabilities

The Overexcitability Questionnaire-Two (OEQ-II) (Falk, Lind, Miller, Piechowski, and Silverman, 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 and Van Petegem, 2015).

#### 2.2.2. Learning patterns

The LEMO is composed of the Inventory of Learning Styles-Short Version (ILS-SV) (Donche and Van Petegem, 2008) and abbreviated versions of the Academic Self-Regulation Questionnaire (SRQ-A) (Ryan and Connell, 1989; Vansteenkiste, Sierens, Soenens, Luyckx, and Lens, 2009) and Academic Motivation Scale (AMS) (Vallerand, Pelletier, Blais, Briere, Senecal, and Vallieres, 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.

**2.2.3. 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.

**2.2.4. 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, Rymenans, Daems, Van Petegem, and Van den Bergh, 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.

**2.3. 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 and 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 and 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 and Asparouhov, 2013b). 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 and 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[6] 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. Subsequently, approximate scalar MI across education tracks was tested. Analyses were carried out for each overexcitability factor and the alignment optimization method with Bayes estimation (Asparouhov and 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[6] < 1.05 criterion (Gelman and 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.

[6] Bayesian analysis uses Markov chain Monte Carlo (MCMC) algorithms to iteratively extract random samples from the posterior distribution of the model parameters (Muthén and 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 and 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 and Depaoli, 2012; Muthén and Muthén, 1998-2017).

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In relation to the second main objective of this study, a multiple-indicators, multiple-causes (MIMIC) model (Jöreskog and 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 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 $10^{th}$ iteration was used with a total of 100,000 iterations and one MCMC chain.

(Figure 1)

In the first MIMIC model, direct effects were included to test for measurement intercept non-invariance (Muthén and 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 and Van Petegem, 2017). This relationship was explained by correspondences between the attainment of higher levels of multilevel[7] 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.

### 2.3.1. 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 and Bentler, 1995), and a RMSEA value of 0.05 or less (Browne and 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 and Muthén, 2010; Muthén and 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 and Asparouhov, 2012).

## 3. Results

[7] Dabrowski'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 (Dabrowski, 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) (Dabrowski, 1970b, 1972, 2015).

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### 3.1. 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 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 1)

As represented in Table 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 2)

### 3.2. 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 $\chi^2$ 95% CI [-193.946, 95.446]) and 0.985 (Δ observed and replicated $\chi^2$ 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[8] 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 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.

(Table 3)

### 3.3. MIMIC model 1

As represented in Table 4, good model fit was established for MIMIC model 1 with learning pattern data from higher education (PP*p* = 0.161, $\Delta$ observed and replicated $\chi^2$ 95% CI [-20.102, 61.420]), as well as good MCMC convergence. With the exception of one non-

[8] 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 and 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).

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[9] 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- ($\beta = 0.125$, $p < 0.05$) and reproduction-directed learning pattern ($\beta = 0.300$, $p < 0.001$), with females showing a substantially higher score. Education track is indicative of the undirected ($\beta = 0.204$, $p < 0.001$) and application-directed learning pattern ($\beta = 0.142$, $p < 0.01$), with a substantively higher score for TSE.

(Table 4)

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 (PP$p$ = 0.177, Δ observed and replicated $\chi^2$ 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 ($\beta = 0.256$, $p < 0.001$) and application-directed learning ($\beta = -0.128$, $p < 0.05$), as well as a substantively higher score for TSE on the application-directed learning pattern ($\beta = 0.192$, $p < 0.001$).

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

### 3.4. MIMIC model 2

[9] 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 PP*p*s 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.

### 3.4.1. ML-MIMIC

As represented in Table 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.

### 3.4.2. BSEM-MIMIC with cross-loadings

The PP*p*s are smaller than 0.05 for both models, indicating unsatisfactory model fit (cf. Table 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.

### 3.4.3. BSEM-MIMIC with cross-loadings and residual covariances

As displayed in Table 4, good model fit was found for both the GSE (PP$p$ = 0.109, Δ observed and replicated $\chi^2$ 95% CI [-20.090, 88.106]) and TSE groups (PP$p$ = 0.238, Δ observed and replicated $\chi^2$ 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 (in Mplus, the reported estimates are the medians of their posterior distributions).

(Table 5)

Table 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 ($\beta$ = 0.632, $p$ < 0.001) and TSE groups ($\beta$ = 0.464, $p$ < 0.001). Moreover, it is negatively related to undirected learning but only for GSE ($\beta$ = -0.327, $p$ < 0.001), and it is a supplementary indicator of application-directed learning ($\beta = 0.333$, $p < 0.001$ for GSE, and $\beta = 0.445$, $p < 0.001$ for TSE). In contrast, imaginational overexcitability is negatively related to meaning-directed learning ($\beta = -0.166$, $p < 0.05$ for GSE, and $\beta = -0.284$, $p < 0.05$ for TSE) and positively related to undirected learning ($\beta = 0.260$, $p < 0.01$ for GSE, and $\beta = 0.355$, $p < 0.05$ for TSE). It is also negatively indicative of application-directed learning but only for TSE ($\beta = -0.380$, $p < 0.01$). Furthermore, emotional overexcitability is an indicator of reproduction-directed learning ($\beta = 0.389$, $p < 0.001$ for GSE, and $\beta = 0.318$, $p < 0.01$ for TSE), while psychomotor overexcitability is indicative of undirected ($\beta = 0.145$, $p < 0.05$) and application-directed learning ($\beta = 0.173$, $p < 0.01$), but only for GSE. Sensual overexcitability predicts the meaning-directed learning pattern, but only for the GSE group ($\beta = 0.146$, $p < 0.01$). Further, intellectual ability is negatively related to reproduction-directed learning but only for GSE ($\beta = -0.116$, $p < 0.05$), and positive developmental potential predicts the application-directed learning pattern only with respect to the TSE group ($\beta = 0.623$, $p < 0.01$).

(Table 6)

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 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 7)

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 (PP*p* = 0.167, Δ observed and replicated $\chi^2$ 95% CI [-34.487, 100.809]) and TSE groups (PP*p* = 0.181, Δ observed and replicated $\chi^2$ 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 ($\beta = -0.146$, $p < 0.05$ for GSE, and $\beta = -0.230$, $p < 0.01$ for TSE).

**4. Discussion**

Are contextual rather than personal factors at the basis of an anti-school culture?

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 and 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 Dabrowski, mental health (Dabrowski, 2015; Dabrowski and 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, Monsen, and Ahmetoglu, 2009; von Stumm and Furnham, 2012) or a weak to moderate positive association with deep learning (Chamorro-Premuzic and 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 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 and 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" (Dabrowski, 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 (cf. Table 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 and 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 and Meckstroth, 2009) are undeniably related to scientific discovery. In addition, several studies have demonstrated associations of imaginational overexcitability with giftedness (Carman, 2011; Harrison and Van Haneghan, 2011; Siu, 2010; Tieso, 2007), which in turn is related to creative contributions (Park, Lubinski, and Benbow, 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 and 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 and 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 and 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 (Dabrowski, 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 (Dabrowski, 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 (Dabrowski, 2015; Deci and Ryan, 2000, 2002). However, former TSE students scored substantially higher on undirected learning indicators, which rather points to an impersonal causality orientation (Deci and 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 and 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).

### 4.1. Limitations

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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 and 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 and 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.

### 4.2. 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.

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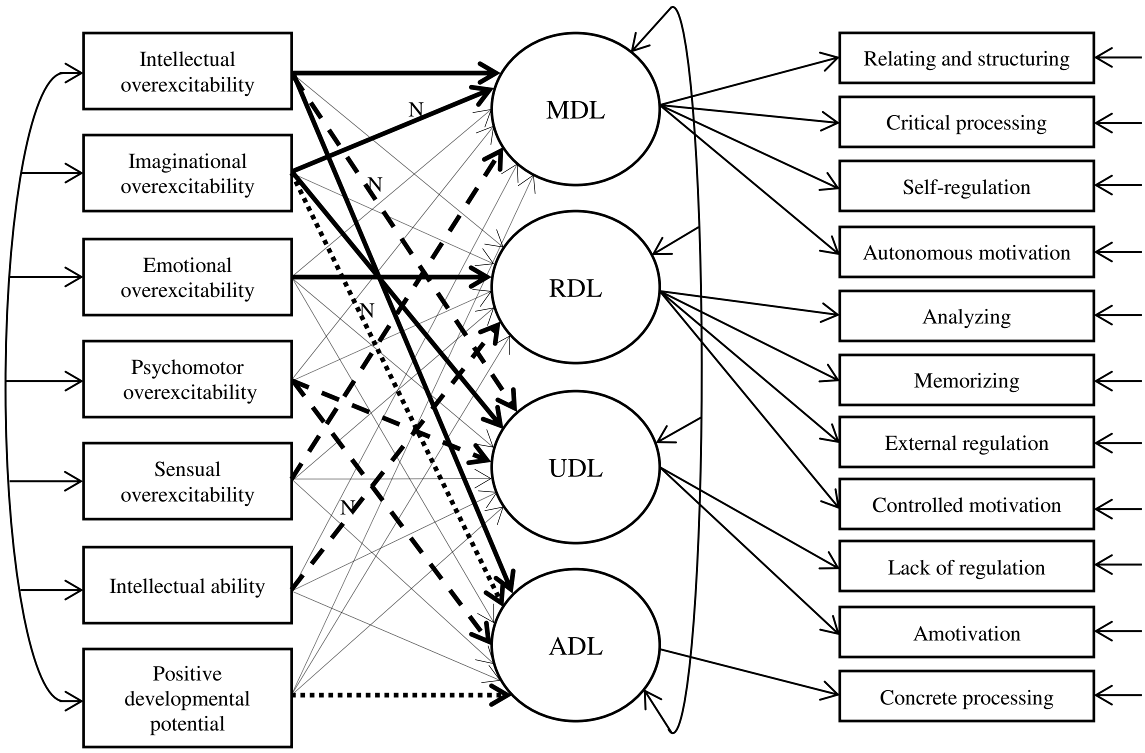


**Figure 1.** Multiple indicators, multiple causes model for GSE and TSE (MIMIC model 2).

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.

**Table 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 |
| 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.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

**Table 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.

**Table 3.** Model fit coefficients of multiple-group BSEM-based alignment with approximate measurement invariance per overexcitability factor using decreasing prior variances.

| Prior | Intellectual OE | | Imaginational OE | | Emotional OE | | Sensual OE | | Psychomotor OE | |
|---|---|---|---|---|---|---|---|---|---|---|
| variance $\sigma^2$ | 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.

**Table 4.** ML and Bayesian MIMIC model testing results for GSE ($n$ = 356) and TSE ($n$ = 132).

| Model | $\chi^2$ | *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.

**Table 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 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 |
| **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.

**Table 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 $\lambda_4$** | **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.