Motivation at school: Differentiation between and within school subjects matters in the prediction of academic achievement

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Abstract

School motivation is a multidimensional concept. It can be qualitatively defined by various sources of regulation as well as by the school subject to which it pertains. Based on self-determination theory, we postulate that motivation types vary in terms of quality (from lower to higher quality these types are: external, introjected, identified, and intrinsic) and that higher motivational quality predicts positive outcomes. In this study, we examined school subject differentiation in motivational quality and prediction patterns of academic achievement. Results from bi-factor ESEM examining differences in motivational quality within a subject (French, math, and English as a second language) showed that high general levels of motivation in math and English predicted achievement, and more so in the corresponding school subject. Intrinsic motivation for a school subject was generally positively associated with achievement, but only in the corresponding school subject, whereas introjected and external regulations for most school subjects negatively predicted achievement in the corresponding school subject, but also in the other ones. Results from bi-factor ESEM examining differences in motivation levels for distinct school subjects for a given motivation type showed that general levels of intrinsic and external regulations across school subjects predicted achievement positively and negatively, respectively, in all school subjects, while intrinsic motivation, but also identified regulation, had positive subject-specific associations with achievement. The specificity of intrinsic and identified motivations and non-specificity of introjected and external motivations point toward various recommendations in school motivation research and practice. While assessment of autonomous motivations should be subject-specific, assessment of controlled motivations could be general with no loss of predictive power.

1. Introduction

According to some motivational theories, such outcomes as achievement and performance are best predicted by motivational variables measured at the same level of generality (Bandura, 1997; Vallerand, 1997). For example, a measure of motivation specificto math, and not a global measure of motivation at school, should be the best predictor of math achievement (Huang, 2012). Indeed, global measures do not consider the complexity and variation of self-perceptions, and this could impair the ability to understand and predict behavior (Ajzen, 2005; Marsh & Yeung, 1998). Therefore, scales measuring important areas of life would be more useful than global scales for understanding the consequences pertaining to area-specific self-related constructs. In addition, when motivation toward a specific school subject, for example, is being measured, it is expected to be less correlated with outcomes (e.g., achievement) in non-corresponding school subjects (Bong, 2002; Guay et al., 2010).

Such specificity principles (i.e., level of specificity–global vs. specific–and area of specificity–maths vs. French–, for example) imply that knowledge of the determinants of students' achievement relies on an understanding of subject-bound dynamics. In various studies stemming from different motivational theories (i.e., self-efficacy theory, achievement goal theory, expectancy value theory, and self-concept theory), researchers have applied these principles (see Wentzel & Wigfield, 2009, for a literature review of each theory) and have shown that a large portion of motivational variance is specific to school subjects (Bong, 2001; Shen, McCaughtry, & Martin, 2008). However, our survey of the field reveals a dearth in self-determination theory (SDT; Ryan & Deci, 2007) research testing the specificity principles, limiting the understanding of motivational dynamics. More specifically, motivations derived from SDT have been assessed in various school subjects, but only a few researchers have done so simultaneously across school subjects (Chanal & Guay, 2015; Guay et al., 2010), possibly because of the degree of complexity of such a research endeavor. Indeed, within SDT, qualitatively distinct motivation types exist that may differ among school subjects as well as in their relations to outcomes within a given school subject. In this study, we analyze, among those proposed by SDT, four types of motivation (intrinsic, identified, introjected, and external) toward three school subjects (French, math, and English as a second language). Our main research endeavor, which aligns with a collective effort to better understand how motivation predicts achievement (Guay et al., 2010; Linnenbrink & Pintrich, 2002; Mega, Ronconi, & De Beni, 2014), is to uncover fundamental processes in the way each type of motivation toward various school subjects predicts academic achievement in these subjects and others. Our analysis could lead to important discoveries regarding area (types of school subjects) and level specificity (global vs. specific) of motivation and broaden our understanding of student motivation and the associated outcomes. More precisely, the predictive power of various types of motivation could be increased when simultaneously taking into account (1) their specificity to school subjects as well as (2) their communalities in terms of global motivation (see Fig. 1).

1.1. Self-determination theory and academic motivation

In SDT, motivation is defined as the reasons underlying a behavior. Applied to education, it refers to the reasons students engage in various school activities (Ryan & Deci, 2000). It is possible to distinguish among various types of motivation that differ in terms of self-determination (i.e., the extent to which a behavior originates from the self). Intrinsic motivation refers to engaging in an activity for its own sake, for the pleasure and satisfaction it provides (Ryan & Deci, 2000). Extrinsic motivation refers to engaging in an activity for instrumental reasons rather than for its intrinsic qualities. According to SDT, there are various types of extrinsic motivation that differ in terms of self-determination. From low to high self-determination, these are external regulation, introjected regulation, identified regulation, and integrated regulation (Ryan & Deci, 2000).

External regulation occurs when a behavior is motivated by the desire to obtain a reward or avoid punishment. Introjected regulation refers to behaviors performed in response to internal pressures, such as obligation or guilt: the individual somewhat endorses the reasons for doing something, but in a controlled manner. Identified regulation is observed when individuals identify with the reasons for performing a behavior, or when they personally find it important. This is a self-determined form of extrinsic motivation, because the behavior originates from the self in a non-contingent manner. Integrated regulation occurs when the identified regulation is congruent with other values and needs. The behavior is therefore performed because it is part of who the person is. However, this form of regulation requires individuals to have formed a coherent identity (Deci, Ryan, & Williams, 1996), such that they can identify with the importance of a behavior and reciprocally assimilate that identification with other aspects of their coherent sense of self. Consequently, this type of extrinsic motivation is not assessed in studies on children and adolescents such as this one.

Thus, in SDT, motivation types are located along a self-determination continuum reflecting motivational quality, rather than motivational intensity. Motivation types are therefore expected to relate to each other in a quasi-simplex-like pattern, with stronger positive correlations between adjacent motivations than between distant ones. For example, identified regulation and intrinsic motivation should be positively and moderately correlated, and this correlation should be stronger than the one between intrinsic motivation and introjected regulation. In previous research, the self-determination continuum was supported for types of motivation toward school in general (Otis, Grouzet, & Pelletier, 2005; Ryan & Connell, 1989; Vallerand, Blais, Brière, & Pelletier, 1989, 1992, 1993). Furthermore, this continuum also reflects how each motivation type affects various school outcomes. For example, students who endorse autonomous types of motivation (intrinsic and identified regulation) are more persistent and cognitively involved in their tasks, experience more positive emotions, and have better grades, whereas students who are motivated in a controlled fashion (introjected and external) are less persistent, are more distracted, experience more negative emotions (anxiety), and obtain lower grades (Guay, Lessard, & Dubois, 2016; Guay, Ratelle, &Chanal, 2008). With these findings, researchers have underscored the importance of developing intrinsic and identified motivations rather than introjected or external regulations during the school years.

Based on theory and results, many researchers have claimed that motivational quality matters, more so than motivational intensity (Ratelle, Guay, Vallerand, Larose, & Senécal, 2007; Vansteenkiste, Sierens, Soenens, Luyckx, & Lens, 2009). However, statistical issues arise from research testing this proposition, which was done within the confines of confirmatory factor analyses (CFA; Guay, Morin, Litalien, Valois, & Vallerand, 2015) or profile analyses (Ratelle et al., 2007) that do not offer a stringent test of this hypothesis. In these two methods, type-specific factors are estimated without prior removal of the variance shared among all items of the scale. In other words, although SDT motivation items assess various types of motivation, the scores on the same items may also reflect a general factor of motivation. This factor would represent motivation intensity, which could differentially predict achievement in comparison with specific components. In previous research testing employees' work motivation, researchers have estimated a global factor in order to assess quantity of self-determined motivation and has supported the hypothesis that qualitatively distinct motivation types predict work outcomes over and above the G-factor (Howard, Gagné, Morin, & Forest, 2016). Similar findings have been observed in physical activity as well (Gunnell & Gaudreau, 2015), although motivational intensity predicted goal-consistent behavior more strongly than motivational quality did.

1.2. The differential examination of school motivation

There are two approaches to the differential examination of school motivation. The first is to examine motivation across various school subjects. As previously stated, this has been done from several theoretical standpoints (e.g., goal theory, self-efficacy theory, self-concept, and the expectancy-value model) focusing primarily on such disciplines as writing, reading and math (Bong, 2001; Green, Martin, & Marsh, 2007). We refer to this motivational differentiation as between-subject differentiation. Another approach is to examine school motivation as a multidimensional concept that illustrates varying reasons underlying engagement in a given school subject. SDT substantiates this approach by distinguishing among various types of motivation. We refer to this motivational differentiation as within-subject differentiation.

In this study, we wanted to combine both approaches by measuring each type of motivation for each school subject, while taking into account the common variance (i.e., a global factor of motivation) associated with these items in each school subject. We also wanted to test how these components fared in the prediction of academic achievement. Conducting such an analysis to untangle specific and common variance is relevant because, if motivational quality matters more than motivational intensity, each type of motivation should be a stronger predictor of achievement than the G_w-factor (see Fig. 1; a global factor related to within-subject differentiation, representing a global indicator of various types of motivation within a specific subject). Thus, to support previous research stressing the importance of motivation quality, our analyses should first show that, compared with introjected and external regulations, intrinsic and identified motivations within a given school subject will predict achievement more positively in this subject. Second, the G_w-factor of motivation should not be a better predictor of achievement in a corresponding subject than intrinsic or identified motivation because it is expected mostly to mirror motivational intensity.

As previously mentioned, few SDT researchers have examined types of school motivation toward various school subjects simultaneously. Some support has been obtained for an effect of between-subject differentiation (i.e., area specificity of motivation) with respect to intrinsic motivation toward reading, math, social studies and science (Gottfried, 1985, 1990). More specifically, students engage in various activities that schools offer as an opportunity to discover at a relatively early age which activities they do or do not enjoy. Students' intrinsic motivation differentiation across school subjects is evidenced by correlational patterns, whereby intrinsic motivation for a given school subject is more strongly associated with other motivational constructs within that school subject than with motivational constructs for other school subjects (Gottfried, 1985, 1990). Other researchers (Eccles, Wigfield, Harold, & Blumenfeld, 1993; Green et al., 2007) have also shown that "valuing of school subject" had lower between-subject correlations than more "trait-like" academic constructs, such as school anxiety.

In this study, we wanted to replicate the school subject differentiation effect obtained for intrinsic motivation and extend our focus to how identified, introjected, and external regulations are differentiated across subjects and in their relations to educational outcomes. Because these regulations are phenomenologically distinct from intrinsic motivation, we postulated that intensity in differentiation effects (or area specificity) would differ across motivation types. We expected school subject differentiation to be stronger at the higher end of the self-determination continuum (intrinsic motivation) and lower as selfdetermination declines. Intrinsic motivation should be more area-specific in its predictions than the facets of extrinsic motivation because intrinsic motivation originates autotelically, arising from the inherent satisfaction in the action and presumably energizing behavior circumscribed to the interest. In contrast, extrinsic motivation relies on contingent outcomes that are separable from the action. Identified regulation should be less area-specific in its predictions than intrinsic motivation. This is because, although this regulatory process is somewhat tied to the inherent characteristics of the activity, it is nevertheless governed mostly by the endorsement of cultural values (Deci & Ryan, 1985). In fact, students may understand relatively early that reading, writing, and math are all important for their development as individuals, and that identified goals enabled by success in one subject can be pursued in other ones as well. Weaker area specificity in identified motivation should translate into higher cross-subject outcome prediction (e.g., identified motivation in French predicting math grades). Finally, we posited that introjected and external regulations would predict outcomes across school subjects equally because they involve management of internal and external impetuses that should operate independently of the school subject, affecting outcomes in all subjects at once. This hypothesis is in line with previous findings obtained in children and adolescent samples showing that correlations among intrinsic motivations toward various school subjects are weaker than correlations among identified regulations, which are in turn weaker than correlations among introjected and external regulations (Chanal & Guay, 2015; Guay et al, 2010).

Because autonomous motivations (intrinsic and identified) are hypothesized to be more specific, we postulated that their relations with achievement would be stronger in corresponding school subjects than in non-corresponding ones. We also expected to find more positive relations with achievement in a given school subject for these motivations than for controlled ones (introjected and external), reflecting the higher quality of autonomous motivations. In addition to hypotheses testing area-specific predictions of motivation, we also tested level-specific hypotheses by extracting a G_b-factor (see Fig. 1), which is a global factor in between-subject differentiation models estimated among items of a single type of motivation for three school subjects (e.g., general introjected regulation across French, math, and English), and examining how its general prediction compared to that of specific factors. The G_b-factor extracted from intrinsic or identified regulation should be less correlated with achievement in the three school subjects than subject-specific factors because area-specific predictions should entail better predictions from the according-level factors. However, because we expect introjected and external regulations to be less differentiated across subjects, the G_b-factor related to these constructs—a higher-level, global indicator of these motivation types—should be more cor-related with achievement than subject-specific factors.

1.3. Overview and hypotheses

In this study, we aimed to examine high school students' motivation differentially by estimating the effects of both within- and between- subject motivational differentiation while taking into account the common variance across motivation types. We believe that the within- and between-subject differentiation effects of motivation, estimated while taking into account general factors, are so conceptually central that our findings may be used to refine our understanding of the relations between important constructs involved in students' achievement and of how determinants affect students' levels of autonomous and controlled motivations in learning situations. More specifically, at the within-subject level, if a G_w-factor is more predictive of achievement than the specific factors, such findings might call into question the focus on motivation quality advocated by SDT. Furthermore, until now, most researchers have considered types of motivation (intrinsic, iden- tified, introjected, and external) in a given school subject as equally specific. However, if some types of motivation are differentiated across school subjects, and thus more area-specific, researchers should be specific in their assessment and should design interventions that are unique to each school subject. If some are undifferentiated, we can dispense with measuring them specifically, which can help reduce the length of some questionnaires. In addition, future research and interventions on undifferentiated types of motivation should be directed toward antecedents that are not subject-specific.

In this study, two general perspectives are proposed under which many different hypotheses between types of regulation for the three school subjects and achievement in those school subjects are tested. These hypotheses are all presented in Table 1. In the within-subject differentiation perspective, we expected the following relations for each school subject: (a) the G_w-factor (see Fig. 1) will be related to achievement in corresponding subjects in a positive manner (+), but not associated with achievement in other school subjects (0); (b) intrinsic motivation in a given school subject will be associated positively and moderately to achievement in the corresponding school subject (++), but not associated to achievement in non-corresponding school subjects (0); (c) a similar pattern is expected for identified regulation, but the magnitude of specific relations should be smaller than for intrinsic motivation (+); (d) introjected regulation should be associated negatively to achievement in all subjects (−; undifferentiated), but to a lesser degree than external regulation (−−). For the between-subject differentiation perspective, we expected the following relations for each regulation: (a) the G_b-factor (see Fig. 1) should be associated (positively (+) or negatively (−) depending on the regulation type) to achievement in school subjects, but in an undifferentiated way; (b) intrinsic and identified regulations should have specific factor relations that are subject-specific and positive, though stronger for intrinsic (++) than for identified regulation (+); (c) introjected and external regulations should have specific factor relations that are negative and undifferentiated, though stronger for external (−−) than for introjected (−). Although the two perspectives (i.e., within and between-subject differentiation) lead to similar predictions between motivation and achievement, it is important to highlight that the ways there are tested are sharply different. In within-subject analyses, each regulation type competes with the others as well as with motivation intensity (G_w- factor) to predict achievement, whereas in the between-subject, only one motivation type is assessed, but has to compete with its measurement in other subjects as well as with its global level at school (G_b- factor). Thus, both hypothesis offer the possibility to test more stringently the differentiation of types of regulation.

2. Method

2.1. Participants, study Design, and procedures

Data were obtained from a study on adolescents' academic achievement, motivation, and personal relationships. The Quebec Ministry of Education provided us with a random sample of 4000 high school students for the 2007–2008 school year. The students were representative of those in grades 7, 8, and 9 attending the 423 French public high schools (in the province of Quebec, Canada). The researchers mailed a consent form and a questionnaire to the students and their parents. Of all the students, 1404 (666 boys, 738 girls; Mage = 13.74, SD = 1.09) returned a completed questionnaire. On average, fathers (21%) and mothers (28%) had completed at least a college degree, and 66% of the students lived with both parents. A high proportion of the students (95%) were born in Quebec, and 99% of them had French as their mother tongue. The Quebec high school system comprises five years of schooling. The students were in their first (32%), second (36%), or third year of high school (32%). The institutional review board of our University has approved this project.

2.2. Measures

2.2.1. Motivation at school

The original Academic Motivation Scale (AMS) includes seven subscales, each containing four items representing a possible reason (or regulation) for engaging in school-related academic activities. We assessed types of regulations toward French, math, and English school subjects using a version of the AMS that was slightly adapted to address engagement in school subjects (Vallerand et al., 1989; French version). Items are scored on a five-point ordinal scale ranging from 1 (strongly disagree) to 5 (strongly agree).

In this study, we retained the following four subscales in our questionnaire: intrinsic regulation for knowledge (e.g., Because I experience pleasure and satisfaction while learning new things in this course), identified regulation (e.g., Because eventually this course will enable me to enter the job market in a field that I like), introjected regulation (e.g., To prove myself that I am able to succeed in this course), and external regulation (e.g., To have a better salary later on). Numerous studies have supported the factorial, convergent, and divergent validity, and the scale score reliability of the AMS (Vallerand et al., 1989, 1992, 1993). Table 2 presents means, standard deviations, as well as factor loadings and item uniquenesses based on three first- order CFA factor solutions involving four correlated latent constructs. Scale score reliability estimates were computed from the CFA standardized parameter estimates in within-subject differentiation models, using McDonald's (1970) omega. Compared with traditional scale score reliability estimates (e.g., alpha), omega has the advantage of taking into account the strength of the association between items and constructs as well as item-specific measurement errors (Sijtsma, 2009a,b). More precisely, the omega directly applies reliability formulas, which define reliability as true score variance divided by total variance (sum of true score variance and error variance), to latent variable modeling, where variance is split between factor loadings ("true" variance) and uniquenesses ("error" variance). In the measurement models, the 12 scale score reliability estimates were approximately 0.87 (from 0.796 to 0.919) for the four types of regulation in the three school subjects. Bivariate correlations between latent factors are presented in Table 3.

2.2.2. *Achievement in school subjects*

Achievement in the three school subjects was assessed based on the official report cards produced by each high school. Scores on this variable could range from zero to 100.

2.3. Data analysis

2.3.1. Model fit

All models were estimated using Mplus (Version 7.4; Muthén & Muthén, 2012) and were tested using the maximum likelihood robust (MLR) estimation method. To ascertain the adequacy of model fit, we used the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root-mean-square error of approximation (RMSEA), the standardized root mean square residual (SRMR), as well as the $\chi 2$ test statistic. The CFI and TLI usually vary on a 0-to-1 continuum (although the TLI could be greater than 1 because of sampling, this is rarely the case in practice; Bollen & Curran, 2006) in which values greater than 0.90 and 0.95 respectively reflect acceptable and excellent fit to the data (Schumacker & Lomax, 1996). Browne and Cudeck (1993) suggest that RMSEAs below 0.05 are indicative of a “close fit” and that values up to 0.08 represent reasonable errors of approximation. Similarly, SRMR values should be less than 0.08. Whereas the TLI, SRMR and RMSEA contain a “penalty” for a lack of parsimony, the CFI does not. When new parameters are added, the latter may indicate an improved fit due simply to chance.

Missing data averaged less than 1% (see Table 2). To account for missing data in the structural equation modeling (SEM) analyses, fullinformation maximum likelihood (FIML) was used to compute the product of individual likelihood functions to estimate analysis parameters. Using a FIML procedure under MLR for treating missing data is considered superior to listwise deletion and other ad hoc methods, such as mean substitution (Davey, Shanahan, & Schafer, 2001; Peugh & Enders, 2004), and is now common in the general SEM framework.

2.3.2. CFA versus ESEM

The basic assumption behind CFA is that items load on their respective factors (i.e., main loading), with no cross-loading on other latent factors (Marsh et al., 2009). This procedure is consistent with the restrictive independent cluster model (ICM) of CFA and has the advantage of motivating researchers to develop parsimonious models. However, ICM-CFA requires strong measurement assumptions, which do not always hold with real phenomena. More specifically, a measurement instrument may yield many cross-loadings (normally much weaker than main loadings) that are consistent with the underlying theory. The ICM-CFA approach of setting cross-loadings to zero may therefore lead researchers to specify a parsimonious model that does not fit the data well. Similarly, incorporating small cross-loadings in a model provides some control for the fact that items are imperfect indicators of a construct and thus present some degree of irrelevant association with the other constructs included in the measure—a form of systematic measurement error. More importantly, when cross-loadings, even small ones, are not estimated, the only way for the model to adapt to these associations between specific indicators and other constructs is through overestimation of latent factor correlations, which occurs in many CFA applications (Asparouhov & Muthén, 2009; Marsh et al., 2009; Morin, Marsh, & Nagengast, 2013). An exploratory structural equation modeling (ESEM) approach overcomes these limitations because, like in exploratory factor analysis (EFA), it freely estimates all rotated cross-loadings between indicators and latent factors. Moreover, ESEM conveniently follows the same guidelines as CFA in terms of fit indices, standard errors, and tests of significance, and shares the SEM framework flexibility (correlated residuals, tests of invariance, etc.). The ESEM therefore provides synergy between CFA, EFA, and SEM (Marsh, Morin, Parker, & Kaur, 2014) and is easily integrated in a bifactor model framework (Morin, Arens, & Marsh, 2016).

Given the theoretical simplex structure of motivation (Howard, Gagné, & Bureau, 2017) where motivation factors are ordered from an autonomous extreme to an external one, cross-loadings are expected between adjacent factors. Cross-loadings are also expected to get smaller, and eventually negative, as factors become more separated on the motivation continuum (Guay et al., 2015). Thus, not estimating cross-loadings could lead to inflated relations among motivation components, especially those that are adjacent on the continuum. For this reason, we expect ESEM models to represent the data with less bias.

2.3.3. *Bi-factor model*

The bi-factor model assumes that all items developed for a given multidimensional instrument could be grouped under a general factor (i.e., the G-factor), representing a conceptual broad factor, in addition to being grouped under their corresponding latent construct (see Fig. 2 for an example applied to within-subject motivational differentiation). The G-factor thus extracts the common variance among all items developed to assess clustered dimensions, making such predefined scale dimensions more uniquely specified. This is different from typical second-order models where the global factor predicts latent factors that in turn predict items. Structurally, the second-order model does not allow the global factor to predict scale items singularly, as with bifactor estimation, but merely to weigh preexisting dimensional patterns. The bi-factor model is quite flexible, offering the possibility to integrate, for example, outcomes to assess the predictive power of the G-factor and the specific latent factors. The bi-factor model can be tested with both CFA and ESEM.

Factor loadings of the current bi-factor models can be meaningfully interpreted. High factor loadings for all items on the G_w-factor (i.e., at the within-subject level, where four motivation types for a specific school subject are included in a model) mean that the G_w-factor captures the quantity of motivation for a given school subject (e.g., math). Alternatively, higher G_w-factor loadings for the autonomous items compared to the controlled ones implies that the G_w-factor assesses motivation quality for a given school subject. At the between-subject differentiation level (where one motivation type for three different school subjects is included in the model), high factor loadings on the G_b-factor for all items mean that the G_b-factor captures a broader level of motivation across the three school subjects (e.g., a general level of intrinsic motivation irrespective of the school subject). In all model types, the loadings connecting each specific latent dimension to the items represent the net effect (purged from the G-factor variance) of the latent construct.

In bi-factor models, there is no ovariance estimated among specific latent factors, in this case the four regulation types for a given school subject (e.g., math intrinsic, math identified, math introjected, and math external) or the three different school subjects for a single type of regulation (e.g., intrinsic for French, math, and English), as well as between the G-factor and specific factors. Uncorrelated factors (specific and general) are a critical condition for sound interpretation of results. If specific factors were allowed to correlate, then distribution of item variance would not follow patterns postulated by the bi-factor model (i.e., that any general common variance is attributed to the general factor and any specific common variance is attributed to specific factors). The ESEM bi-factor models were estimated following an orthogonal Target rotation, while first-order ESEM models were estimated following regular Target rotation. Target rotations are used in ESEM methodology because they allow for an a priori specification of target factor loadings to maximize while keeping cross-loading at low levels (Morin et al., 2016).

3. Results

3.1. Within-subject differentiation

As Marsh et al. (2009) recommended, we began with a CFA to verify the appropriateness of the a priori four-factor structure underlying the responses to the AMS (i.e., factor validity). If the analysis revealed adequate and similar fit indices for both CFA and ESEM models, there would be little advantage to pursuing ESEM analyses because the ESEM model is less parsimonious than the CFA model—although an ESEM model could still provide a more exact representation of the factor correlations (for a review, see Morin et al., 2013). Indeed, as Morin et al. (2016) recommend, decisions regarding the choice between ESEM and CFA models should not be solely based on the model fit indices, but it is also important to take parameter estimates (factor loadings and factor correlations) as well as substantive theory into account. Thus, for each school subject, we tested six models (see Table 4). In the first model, we tested the four-factor structure of the instrument using CFAs. In the second one, we tested a CFA bi-factor model, whereas in the third one we simply included, in the CFA bi-factor model, grades in the three school subjects regressed on all latent factors. For the fourth, fifth, and sixth models, we tested the three above-mentioned models in an ESEM framework (where all cross-loadings are estimated).

For each school subject, the three CFA models resulted in CFI, TLI, SRMR and RMSEA values that were all in the acceptable range (see Table 4). For ESEM models, the fit indices were superior to those obtained with CFA, notably for the RMSEA values, and all indicated good model fit. Thus, the ESEM solutions for all three school subjects provided better fit indices than the alternative CFA models. Moreover, parameter estimates in the ESEM solutions (factor loadings and factor correlations) were in line with the motivational differentiation hypothesis derived from SDT. With regards to factor correlations, however, most factor correlations from the CFA solution were similar to those obtained in the ESEM solution. This could lead us to conclude that the ESEM solution provides few advantages over the CFA one.

However, one correlation appears to be relatively inflated in CFA, that is, the one between intrinsic motivation and introjected regulation in the French school subject. Indeed, this correlation in CFA is 0.61, whereas in ESEM it is 0.54. Because we want to minimize biased factors (i.e., when some cross-loadings are not estimated between motivational factors) as much as possible when predicting achievement in each school subject and for the other reasons stated above, we kept the bifactor ESEM solutions testing our hypotheses (see models 6w, 12w, and 18w in Table 4).

In Table 5, we provide means for the target loadings and for the cross-loadings, standard deviations (SD), omega (ω) and omega hierarchical/subscale (ωh/ωs), and loading ranges for G_w, intrinsic, identified, introjected, and external regulations for each school subject (French, math, and English). Both reliability estimates provide valuable but different information on factor validity. Although omega gives a reliability estimate on a latent factor by itself, omega hierarchical/subscale considers multiple loadings to a specific item to be part of the total variance of this item (Gignac & Watkins, 2013). Thus, general and specific latent factors are in competition as it comes to sharing total variance leading to lower overall reliability estimates. Omega and omega hierarchical/subscale therefore imply two different takes on reliability, with the latter evaluating reliability in contrast to other factors defined by the same items in the model rather than factor reliability in isolation. While some authors argue against omega hierarchical/subscale because they violate the convention that all that is not included in reliability estimates should be error variance (Perreira et al., 2018), they argue that if it is to be reported, it should be reported along with omega. Interestingly, all omega (ω) values for all factors are "acceptable" according to common guidelines that reliability should be above 0.70, although the cutoff criteria is of questionable origin (Lance, Butts, & Michels, 2006). Omega hierarchical/subscale shows that $G_w$factors explain a fair amount of shared variance with reliability estimates around 0.70. Specific factors in this model explain lower amounts of shared variance which confirms that they should be interpreted as specific factors purged from commonality with other motivational constructs. Also, all target loadings are higher than the cross-loadings on other types of regulation for all school subjects. The three G_w-factors are interpreted based on motivational intensity rather than motivation quality because most loadings are high on the G_w-factor, except for external regulation where the mean loadings is lower (see Table 6). While one may argue that such results could also signify that the $G_w$factor captures a certain degree of motivational quality, this conceptual stance is not supported by the data since all other loadings from introjected, identified, and intrinsic items are high and mostly equivalent. If the G_w-factor really captured a certain degree of motivational quality, then we should have observed a clearer pattern of loading where intrinsic item loadings would be higher than identified ones, and identified would be higher than introjected ones, and finally introjected would be higher than external ones (i.e., intrinsic > identified > introjected > external).

Also, paths connecting each motivational factor (G_w, intrinsic, identified, introjected, and external) to grades in the three school subjects are presented. For French, the G_w-factor did not significantly predict achievement. However, the specific variance in intrinsic motivation positively and significantly predicted achievement in this school subject, whereas external regulation for French negatively and significantly predicted achievement in the three school subjects. Noteworthy, the coefficient of the path connecting intrinsic motivation in French to grades in this school subject is higher than the path coefficients connecting intrinsic motivation in French to grades in noncorresponding school subjects, thereby providing support for the specificity of this motivational construct. However, the path connecting external regulation in French to grades in this school subject was not higher than the paths connecting this motivational construct to grades in non-corresponding school subjects, thereby providing support for our hypothesis regarding the non-specificity of its effect. In this school subject, it also appears that motivational quality matters more than motivational intensity since the G_w-factor does not predict achievement over the specific factors.

The pattern of results for math was different from that obtained for French. The common variance among items captured by the G_w-factor positively predicted math achievement, meaning that motivational intensity significantly and positively predicted math achievement. Interestingly, the G_w-factor in math predicted achievement in noncorresponding school subjects as well, although its prediction of math achievement was the strongest. In addition, the specific variance in introjected and external regulation negatively predicted math achievement. However, as expected, these relations were not specific because external and introjected regulations in math predicted grades to a similar extent in non-corresponding school subjects. It thus appears that, for math, the two processes were at play, such that both motivational intensity and motivational quality had predictive power.

For English, the G_w-factor also predicted achievement positively and significantly in all subjects, whereas introjected and external regulations negatively predicted general achievement. Moreover, intrinsic motivation positively and significantly predicted achievement in this school subject. As in the case for math, it appears that both motivational intensity and motivational quality had the power to predict achievement. Finally, as in the case for French, the results for English showed both the specificity of intrinsic motivation and the non-specificity of controlled regulations.

3.2. Between-subject differentiation

The same procedure as above was used to verify the appropriateness of the three-factor structure underlying the responses for a given motivational construct across the three school subjects. Thus, for each regulation type, we tested six models (see Table 7): a CFA, a bi-factor CFA, a bi-factor CFA predicting grades in each school subject, as well as three analogous models using the ESEM framework.

Each set of models, pertaining to a specific regulation type, yielded similar observations: the CFAs resulted in CFI, TLI, SRMR and RMSEA values that were in the acceptable range, except for analyses pertaining to introjected regulation where the CFA bi-factor model with grades showed poor fit to the data. For the ESEM models, the fit indices, which were generally superior to those obtained with CFA, all indicated good model fit. However, with models pertaining to intrinsic motivation and identified regulation, some CFA bi-factor models had slightly superior fit. Still, we decided to select the bi-factor ESEM solutions for the following reasons: (a) fit indices were not sharply different between CFA and ESEM, (b) controlled regulations ESEM models, although presenting low target and high non-target loadings, still presented high target and G_b-factor loadings than CFA models meaning better defined factors in ESEM, and (c) to be consistent with others solutions selected in this study. Moreover, parameter estimates (factor loadings and factor correlations) were, in this case too, in line with the motivational differentiation hypothesis derived from SDT. Consequently, we kept the bi-factor ESEM solution that predicted achievement (see models 6b, 12b, 18b and 24b in Table 7).

In Table 8, we provide means for the target loadings and for the cross-loadings, standard deviations (SD), omega (ω) and omega hierarchical and subscale (ωh/ωs), and ranges for G_b, French, math, and English loadings for each regulation type (intrinsic, identified, introjected, and external). Reliability estimates show that the G_b-factors have high omega (ω) values ($M\omega$=0.94). However, only controlled regulations have high omega hierarchical values (0.91 and 0.87, compared to 0.77 and 0.68 for autonomous motivations models). These estimates suggest that G_b-factors for controlled regulations capture most of the variance shared with subject-specific factors, leading to less reliable specific factors in these models. Still, omega (ω) values for these factors are all above 0.50 which is in line with more lenient guidelines recently suggested for reliability in bi-factor models (Perreira et al., 2018) and suggests that these models still present interpretable specific factors. The four G_b-factors are interpreted based on global factors reflecting the common variance across school subjects for a given regulation type (e.g., global intrinsic motivation). Because the range of target loadings on the G_b-factors was not very wide, we do not present it in a separate table. In general, most target loadings were higher than the cross-loadings. However, target loadings for introjected and external regulations were lower and had wider ranges than the target loadings for intrinsic and identified regulations. Because loadings on specific factors represent leftover variance not taken into account by the G_b-factor, these results suggest that controlled regulations are less specific to school subjects and more easily represented by a general factor representing across-subject aggregation in motivation.

In addition, paths connecting each motivational factor (either G_b or subject-specific motivation type) to grades in the three school subjects are presented. For intrinsic motivation, paths connecting math and English motivation to grades in corresponding school subjects were higher than those predicting achievement in non-corresponding school subjects. While the intrinsic G_b-factor was also positively correlated with grades in all school subjects, these associations were generally lower than the subject-specific prediction. While intrinsic motivation for French was not related to corresponding grades in this model, it was, however, negatively related to grades in English.

For identified regulation, a similar pattern emerged. More specifically, paths connecting this regulation in French, math, and English to grades in corresponding school subjects were higher than those observed in non-corresponding school subjects. The identified G_b-factor was not associated, however, with achievement in either subject.

For introjected regulation, all coefficients were relatively weak and non-significant. Introjected regulation for French negatively predicted grades in math and English. For external regulation, the G_b-factor negatively predicted grades in French, math, and English. Also, surprisingly, while external regulation for French negatively predicted grades in English, external regulation in English positively predicted grades in the corresponding school subject. However, non G_b-factor results obtained in introjected and external models should be interpreted with caution because of poor factor reliability.

Interestingly, these results showed good support for the hypothesis of intrinsic and identified motivation being specific to school subjects and for external regulation being a more undifferentiated and global construct. However, given the mostly non-significant results for introjected regulation, little could be said about the differentiation of this construct across school subjects when the results were analyzed from the between-subject point of view.

4. Discussion

The purpose of this study was to test motivational differentiation within and between school subjects using intrinsic, identified, introjected, and external regulations in three school subjects (French, math, and English) as well as to untangle the contribution of each type of regulation to the prediction of academic achievement in the three school subjects. First, in the within-subject differentiation perspective, we hypothesized that intrinsic and identified motivations for a given school subject would predict achievement more positively in this subject compared to introjected and external regulations. Moreover, the Gw-factor was expected to be less associated with achievement in a given subject because it was predicted to mirror motivational intensity instead of motivational quality, which has been shown to be less predictive of positive outcomes (Ratelle et al., 2007). Second, in the between- subject differentiation perspective, we expected that analyses pertaining to intrinsic and identified motivations would find stronger relations between regulations in a specific subject and achievement in the corresponding school subject than between the Gb-factor for that regulation and achievement. Conversely, in analyses pertaining to introjected and external motivations, we expected that the Gb-factor, and not the regulations in specific subjects, would better predict achievement. Below, we discuss the results regarding the two types of differentiation.

4.1. Within-subject differentiation

As many studies based on SDT demonstrate, motivational quality is important in predicting academic success (Guay, Lessard, & Dubois, 2016). Assessing school motivation should thus always distinguish among the various regulations, which have different ties to important outcomes. However, our results show that these regulations share commonality in terms of motivational intensity which, as this and previous studies show, can significantly predict educational outcomes (Ratelle et al., 2007). Our results in the within-subject perspective corroborate this idea in several ways. First, inspections of item loadings on the G_w-factors revealed that, in each school subject, the factors mirrored motivational intensity rather than motivational quality. More specifically, all item loadings on the three G_w-factors were relatively high and positive. This finding is in line with those observed in the physical activity domain (Gunnell & Gaudreau, 2015), but different from those obtained in the work context (Howard et al., 2016). More specifically, Howard et al. (2016) have shown that the G_w-factor captures motivational quality to some extent because the loadings on the G_w-factor are relatively high on intrinsic and identified motivations, but weaker on introjected and external regulations and negative on amotivation (lack of motivation; Vallerand et al., 1992). This difference between our results and those of Howard et al. (2016) might be explained by various factors (i.e., sample characteristics, wording of items in the various scales, inclusion of amotivation), including that fact that occupations are usually chosen by individuals, presumably decreasing commonality between autonomous and controlled forms of motivation. While this result could possibly be observed in education with motivation for optional school subjects, in our sample we assessed only school subjects that are mandatory in the Quebec high school curriculum. Thus, the G_w-factor for compulsory school subjects might capture motivational intensity more consistently than motivational quality (see Ratelle et al., 2007 for a similar rationale).

Second, the within-subject examination of motivation showed that the G_w-factor in French did not significantly predict achievement in any school subject, but that math and English G_w-factors yielded significant predictions of achievement in corresponding and non-corresponding school subjects. Interestingly, the latter predictions were relatively specific: the math G_w-factor was more highly correlated with achievement in math than in French or in English, and a similar pattern emerged with the English G_w-factor. These results mean that motivational intensity might be important in predicting achievement in these two subjects. However, a discrepancy in the effects of subject-specific G_w-factors (French vs. English and math) highlights interesting processes. It is possible that motivational intensity in math and English (as a second language) is important because their respective curriculums increase in complexity during the high school years. Achievement in these school subjects thus requires a constant investment of time and energy, which might be more strongly predicted by motivational intensity. This interpretation echoes recent results showing that motivational intensity could be helpful at times for academic performance (Ratelle et al., 2007). Such results challenge some postulates derived from SDT (Ryan & Deci, 2017), which usually emphasizes the positive influence of motivational quality. While motivation intensity may promote better achievement in some school subjects, it is important to keep in mind that high-intensity controlled motivation could lead to negative psychological consequences for students, namely stress, anxiety, and fear of failure (Deci, Ryan, & Guay, 2013).

Third, this set of results should be considered in light of our observations for the specific motivational components once the common variance is removed through the G_w-factor. In line with our hypotheses, intrinsic motivation for French positively predicted achievement in this school subject but not in the two other subjects. However, no significant predictions were found for identified regulation in French. A similar pattern emerged in English. Furthermore, consistent with our hypotheses and in line with SDT, introjected and external regulations negatively predicted achievement across subjects, regardless of the school subject in which they were assessed: both regulations in all subjects, except for introjected regulation in French, negatively predicted achievement in the three school subjects. The significant findings regarding introjection are particularly interesting given that most studies (see Guay et al., 2015 for a review) rarely find an association between introjection and negative outcomes. Thus, it appears that removing variance in introjected items associated with motivational intensity could uncover the “dark side” of introjection. However, as presented in the following section, these results for introjection are not quite robust, as they do not hold when introjection is analyzed by itself. On the other hand, the results obtained with external regulation are consistent with past research (see Guay et al., 2015, for a review).

Nevertheless, because in all models factor correlations were set to 0, one can wonder if there are residual factor correlations between adjacent motivation types (e.g., autonomous or controlled) which are not accounted for by the G_w-factor and that somehow distort the present results. Because this is an ESEM framework (and not CFA), instead of inflating the G-factor loadings, residual associations between specific factors can be evaluated in non-target loadings. In the within-subject ESEM bi-factor models computed in this study, cross-loadings between conceptually adjacent factors are low (i.e., very few cross-loadings reach a 0.10 value) thus suggesting that potential specific factor correlation do not cause a problem in the interpretation of the G-factor. This is due to the fact that the G-factor captures most communalities between specific factors. While much of the research using bifactor ESEM on the motivation continuum that has been done recently lead to interpretable specific factors (Howard, Gagné, Morin, & Forest, 2016; Litalien, Guay, & Morin, 2017), future research will help to determine how these models affect interpretation of the motivation continuum.

Taken together these results indicate that to better capture motivational quality, future research should remove common variance in motivation types pertaining to motivational intensity. Doing so will make individual regulations more clearly specified, such that intrinsic motivation and identified regulation will predict positive outcomes whereas introjected and external regulations will predict negative outcomes.

4.2. Between-subject differentiation

Between-subject differentiation deepens our current understanding of qualitative distinctions in school motivation by showing that intrinsic, identified, introjected, and external regulations vary in the area specificity of their predictions. While intrinsic motivation and identified regulation should be measured specifically for various school subjects to achieve better predictive power, there are no additional benefits to doing so that justify measuring introjected and external regulations toward specific school subjects. Our results corroborate this idea in several ways.

First, although the intrinsic G_b-factor is positively associated with achievement in all subjects, the specific intrinsic factors appear to be more related to achievement in their corresponding school subject, except for French, where intrinsic motivation did not predict achievement. For identified regulation, a similar pattern of school subject specificity emerged where identified motivation predicted achievement in corresponding school subjects only.

Second, when we compare results from the within and between differentiation effects for intrinsic and identified motivations, some interesting differences are noteworthy. Regardless of the school subject, both intrinsic and identified regulations are positively related to achievement; however, the relation is rather weak in a within-subject perspective, while it is stronger in a between-subject one. These differences might be explained by the fact that, for analyses in a betweensubject differentiation, identified and intrinsic regulations do not compete with each other in the prediction of achievement.

Third, when introjected regulation is analyzed at the between-subject differentiation level, all coefficients were relatively weak and nonsignificant, except for a negative prediction of English achievement by French introjection. Again, these results are different from the ones observed for within-subject differentiation, where introjected regulation for math and English were negatively correlated with achievement in all subjects. These results may indicate that the best way to capture the negative effect of introjected regulation on achievement is to remove the variance shared with all other types of motivation. When the G_b-factor is estimated among all introjected items across various school subjects, it is impossible to isolate this relevant source of variance.

Fourth, for external regulation, the G_b-factor negatively predicted grades in French, math, and English. This result is in line with recent ones by Chanal and Guay (2015), who have shown that global external regulation is associated negatively and non-differentially with achievement in various school subjects. Oddly, English achievement was also positively predicted by external regulations in English, but negatively predicted by external regulation in French. However, it is important to keep in mind that factor loadings on school-subject-specific factors for both introjected and external regulations are close to zero, which puts into question how well and clearly defined these factors are. Thus, we have to be careful when interpreting these findings.

4.3. Implications for the measurement of motivation

What are the implications of such results for the measurement of motivational constructs? Because of their specificity, there seems to be added advantages to evaluating intrinsic and identified regulations separately by school subjects, while there does not appear to be any for introjected and external regulations. In addition, the way intrinsic motivation and identified regulation specifically predict achievement in school subjects suggests that these elements could develop in relation to subject-bound processes. Conversely, the fact that the relations between introjected and external regulations and achievement are not subjectspecific suggests that these regulations could originate from general processes irrespective of school subjects.

Our results thus point toward a dual process model consistent with SDT. More specifically, SDT has a rich tradition of research on how social contexts facilitate or undermine people's autonomous/controlled motivations. In line with this theory, we speculate that intrinsic motivation and identified regulation might be more influenced by proximal relationships within a given school subject (e.g., autonomy support from the math teacher) whereas introjected and external regulations might be more influenced by proximal relationships that are not subject-bound, such as those with parents and friends. Indeed, parents and friends could prompt external and introjected regulations that will be operative across all school subjects. For example, students in a highability school might experience a great deal of pressure from their peers that could prompt external and introjected regulation across all school subjects. This dual process model for explaining the differentiation of regulation types is speculative and needs to be tested formally in future studies.

5. Limitations

The findings from this study should be interpreted in light of certain limitations. First, although we used sophisticated analyses, it is important to keep in mind that the meaning of the term "effects" remains tentative. The correlational nature of the data precludes any firm conclusion about the direction of causality among the constructs. Second, some of the effect sizes observed are relatively small. However, the magnitude of the effects observed in this study is consistent with previous research on achievement (e.g., Guay et al., 2008). Third, it was not possible to verify if the obtained sample of 1404 students was representative of the initial sample of 4000 students provided by the Quebec Ministry of Education. Specifically, the Ministry was not allowed to provide additional details on the sample characteristics. Fourth, one may wonder if this study overlooks a multilevel structure in the data where students are embedded within schools. In this study, multilevel analyses are not warranted because the number of students (purported L1 units) per school (L2) was presumably quite low. Specifically, the Quebec Ministry of Education provided us a list of 4000 students for 423 schools, which means approximately 10 students per school. Keeping in mind the actual sample of 1404 students, the number of students per school is likely much lower. Such small within-group populations reduce the precision of L2 aggregates estimation which would result in lower intra-class correlations, fewer between school effects and, thus, few advantages in carrying multilevel analyses. Statistical estimates in this study based on one-level analyses are most probably accurate and not biased by a possible multilevel structure. Furthermore, even if multilevel analyses were warranted in this study, we unfortunately do not have the required information to assign students to their school. The only information that was made available to researchers are students' coordinates (address and phone number). Therefore, this study was conducted not within schools, but rather by sending forms directly to the students and their parents.

6. Conclusion

Findings from this study introduce interesting contrasts and additions to previous ones concerning within- and between-subject differentiation (e.g., Bong, 2001). When discerning motivation types in a school subject, it appears that a Gw-factor reflecting motivation intensity could sometimes be useful in predicting achievement. Also, given that autonomous types of motivation are more differentiated between school subjects than others, namely intrinsic and identified motivations, our general recommendation would be to assess these types of motivation specifically to school subjects. However, it appears that there is no need to measure introjected and external regulation specifically. To explain such findings, we propose a dual process model for future research to test: subject-bound interpersonal contexts (i.e., teacher autonomy support) might be more important for explaining intrinsic and identified regulation, whereas other proximal relationships (e.g., peers and parents) might have large-scale influences on students' introjected and external regulations.

7. Author note

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Figure 1. Within and between-subject differentiation effects.

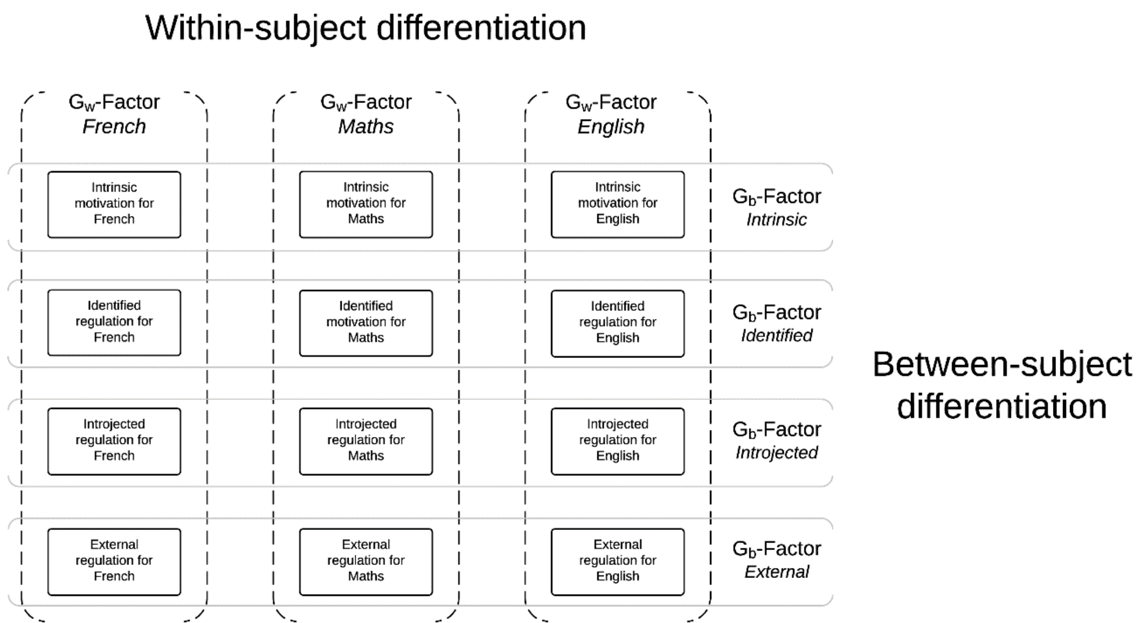

Figure 2. Example of the ESEM bi-factor model with within-subject motivationa differentiation.

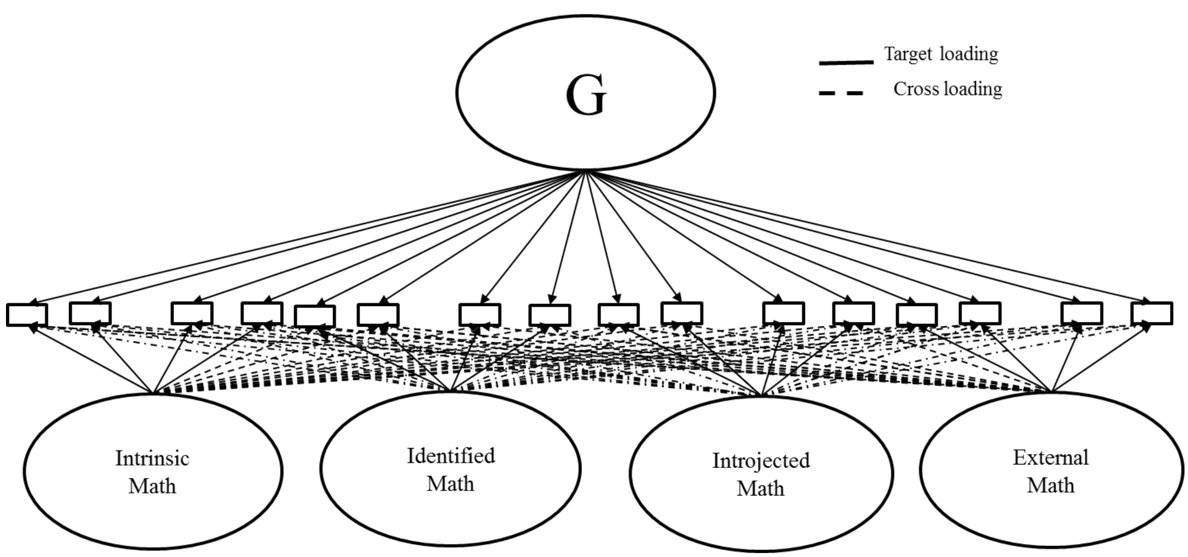

Table 1. Hypothesized relations between types of regulation, G_w-factors, G_b-factors, and achievement in French, Math, and English for the within and between school subjects differentiation effects.

	ACHIEVEMENT FRENCH	ACHIEVEMENT MATH	ACHIEVEMENT ENGLISH
		Within-subject differentiation	
French			
1. G_W-factor	+	0	0
2. Intrinsic	++	0	0
3. Identified	+	0	0
4. Introjected	-	-	-
5. External	--	--	--
Math			
6. G_w-factor	0	+	0
7. Intrinsic	0	++	0
8. Identified	0	+	0
9. Introjected	-	-	-
10. External	--	--	--
English			
11. G_w-factor	0	0	+
12. Intrinsic	0	0	++
13. Identified	0	0	+
14. Introjected	-	-	-
15. External	--	--	--
		Between-subject differentiation	
Intrinsic			
16. G_b-factor	+	+	+
17. French	++	0	0
18. Math	0	++	0
19. English	0	0	++
Identified			
20. G_b-factor	+	+	+
21. French	+	0	0
22. Math	0	+	0
23. English	0	0	+
Introjected			
24. G_b-factor	-	-	-
25. French	-	-	-
26. Math	-	-	-
27. English	-	-	-
External			
28. G_b-factor	--	--	--
29. French	--	--	--
30. Math	--	--	--
31. English	--	--	--

Note: 0= null/specific relation, + = small positive relation; ++ = moderate positive relation - = small negative relation; - - = moderate negative relation.

Table 2. Descriptive statistics.

Latent Factors and Indicators		Variable Sample Size	Means	SD	CFA Standardized Factor Loadings	u
Intrinsic Motivation						
1. Because I experience pleasure and satisfaction while learning new things in this course.	F	1404	3.30	1.250	.85	.27
	M	1403	3.56	1.277	.85	.29
	E	1402	3.53	1.244	.85	.28
2. For the pleasure I experience when I discover new things never seen before.	F	1401	3.25	1.279	.90	.18
	M	1401	3.54	1.291	.89	.20
	E	1402	3.47	1.265	.89	.21
3. For the pleasure that I experience in broadening my knowledge about subjects which appeal to me.	F	1403	3.25	1.306	.87	.24
	M	1402	3.56	1.319	.87	.24
	E	1402	3.53	1.291	.86	.27
4. Because my studies allow me to continue to learn about many things that interest me.	F	1402	3.37	1.289	.82	.34
	M	1400	3.63	1.274	.81	.34
	E	1401	3.63	1.241	.79	.38
Identified regulation						
1. Because I think that a high school education will help me better prepare for the career I have chosen.	F	1403	4.05	1.113	.86	.27
	M	1403	4.22	1.060	.87	.25
	E	1402	4.28	.973	.85	.28
2. Because eventually this course will enable me to enter the job market in a field that I like.	F	1403	4.13	1.108	.85	.27
	M	1401	4.27	1.057	.86	.26
	E	1401	4.34	.960	.84	.30
3. Because this will help me make a better choice regarding my career orientation.	F	1403	3.89	1.239	.76	.43
	M	1404	4.02	1.223	.74	.46
	E	1403	4.04	1.177	.67	.55
4. Because I believe that my high school education will improve my competence as a worker.	F	1401	4.18	1.071	.73	.47
	M	1402	4.31	.988	.71	.50
	E	1402	4.37	.940	.65	.58
Introjected regulation						
1. To prove myself that I am able to succeed in this course.	F	1401	3.72	1.278	.83	.32
	M	1400	3.82	1.271	.81	.34
	E	1401	3.77	1.263	.82	.32
2. Because of the fact that when I succeed in school I feel important.	F	1401	3.65	1.312	.79	.38
	M	1400	3.79	1.312	.79	.38
	E	1400	3.72	1.323	.79	.38
3. To show myself that I am an intelligent person.	F	1399	3.48	1.390	.75	.43
	M	1400	3.65	1.394	.75	.45
	E	1400	3.54	1.375	.74	.45
4. Because I want to show myself that I can succeed in my studies.	F	1400	3.87	1.278	.87	.24
	M	1401	3.96	1.266	.86	.26
	E	1400	3.89	1.286	.85	.28
External regulation						
1. Because I need at least a high school degree in order to find a high-paying job later on.	F	1403	3.91	1.37	.64	.59
	M	1400	3.98	1.35	.62	.61
	E	1399	3.93	1.38	.62	.62
2. In order to obtain a more prestigious job later on.	F	1402	4.24	1.046	.78	.39
	M	1399	4.34	.998	.77	.41
	E	1400	4.33	1.006	.73	.46
3. Because I want to have “the good life” later on.	F	1397	3.65	1.379	.69	.53
	M	1397	3.71	1.380	.65	.58
	E	1496	3.69	1.404	.66	.57
4. In order to have a better salary later on.	F	140	4.14	1.147	.81	.35
	M	1399	4.25	1.087	.79	.38
	E	1401	4.20	1.125	.80	.37

Note. The French (F) school subject is presented in the first row, followed respectively by math (M) and English (E).

Table 3. Latent factor correlations for within-subject measurement models (below diagonal) and between-subject measurement models (above diagonal).

	IM-F	IDEN-F	INTRO-F	EXT-F	IM-M	IDEN-M	INTRO-M	EXT-M	IM-E	IDEN-E	INTRO-E	EXT-E
IM-F	-				0.62				0.57			
IDEN-F	0.55	-				0.41				0.51		
INTRO-F	0.61	0.48	-				0.89				0.86	
EXT-F	0.13	0.35	0.29	-				0.86				0.82
IM-M					-				0.55			
IDEN-M					0.47	-				0.42		
INTRO-M					0.49	0.37	-				0.85	
EXT-M					0.14	0.42	0.28	-				0.79
IM-E									-			
IDEN-E									0.48	-		
INTRO-E									0.51	0.42	-	
EXT-E									0.17	0.48	0.31	-

Table 4. Within-subject differentiation: CFA and ESEM models tested.

	CFI	TLI	$\chi 2$	df	RMSEA	SRMR
French						
1w- CFA	.975	.970	330.825	98	.041	.032
2w- CFA Bi-Factor	.974	.964	337.514	87	.045	.047
3w- CFA Bi-Factor with grades	.975	.965	406.819	121	.041	.042
4w- ESEM	.989	.978	170.134	62	.035	.013
5w- ESEM Bi-Factor	.993	.984	112.649	50	.030	.009
6w- ESEM Bi-Factor with grades	.991	.981	187.962	83	.030	.014
Math						
7w- CFA	.972	.966	341.500	98	.042	.036
8w- CFA Bi-Factor	.973	.963	323.787	88	.044	.049
9w- CFA Bi-Factor with grades	.972	.960	422.560	121	.042	.044
10w- ESEM	.988	.978	162.111	62	.034	.014
11w- ESEM Bi-Factor	.993	.983	108.557	49	.029	.010
12w- ESEM Bi-Factor with grades	.987	.973	222.612	83	.035	.013
English						
13w- CFA	.970	.963	346.153	98	.042	.038
14w- CFA Bi-Factor	.971	.960	328.663	88	.044	.047
15w- CFA Bi-Factor with grades	.975	.957	422.161	121	.042	.043
16w- ESEM	.989	.979	152.125	62	.032	.014
17w- ESEM Bi-Factor	.993	.984	105.347	50	.028	.010
18w- ESEM Bi-Factor with grades	.989	.977	193.169	83	.031	.016

Notes. In model 11w, convergence problems were encountered. Uniquenesses of external regulation items 1 and 4, which both pertained to salary, were correlated for this model resulting in a 1 df decrease.

Table 5. Within-subject differentiation: Means for the target loadings and for the cross-loadings, SD, range, and paths predicting grades.

School Subjects	Mean Target loading	SD Target loading	ω	Ω_h/ ω_s	Range Target loading	Mean Cross-loading	SD Cross-loading	Range Cross-loading	Paths predicting grades in F	Paths predicting grades in M	Paths predicting grades in E
French – "6w"											
G	.52	.15	.93	.71	.12-.66				**.052**	.009	-.021
Intrinsic	.61	.05	.86	.47	.54-.66	-.01	.09	|.01-.20|	**.128***	.046	.023
Identified	.49	.12	.74	.34	.38-.63	.01	.08	|.01-.19|	**.082**	.027	.024
Introjected	.58	.08	.80	.45	.51-.69	.01	.07	|.02-.17|	**-.075**	-.068	-.038
External	.67	.06	.81	.69	.59-.73	.00	.06	|.01-.10|	**-.196***	-.170*	-.134*
Math – "12w"											
G	.49	.13	.91	.68	.22-.64				.268*	**.429***	.215*
Intrinsic	.63	.06	.86	.50	.56-.70	-.01	.06	|.01-.11|	-.109	**-.070**	-.139
Identified	.53	.15	.76	.40	.35-.68	.01	.05	|.00-.08|	-.235	**-.214**	-.187
Introjected	.62	.07	.81	.50	.56-.71	.01	.06	|.00-.09|	-.230*	**-.343***	-.189*
External	.64	.05	.76	.66	.59-.70	.00	.06	|.01-.10|	-.331*	**-.335***	-.230*
English – "18w"											
G	.49	.12	.91	.69	.19-.63				.109*	.089*	**.161***
Intrinsic	.65	.07	.86	.54	.56-.71	.00	.10	|.00-.21|	.022	.007	**.094***
Identified	.50	.11	.71	.38	.40-.64	.01	.08	|.00-.17|	-.019	-.001	**.039**
Introjected	.60	.05	.80	.50	.55-.67	.01	.09	|.02-.21|	-.114*	-.096*	**-.125***
External	.62	.08	.79	.62	.54-.69	.00	.06	|.01-.08|	-.248*	-.202*	**-.148***

Note. Grade predictions in corresponding school subjects are shown in bold. ω = Omega; ω_h/ω_s = Omega hierarchical/subscale; * p < .05.

Table 6. Latent factors and indicators on the G_w factors for French, math, and English school subjects.

Latent Factors and Indicators	G_w factor French	G_w-Factor Math	G_w-Factor English
INT1. Because I experience pleasure and satisfaction while learning new things in this course.	.58	.57	.51
INT2. For the pleasure I experience when I discover new things never seen before.	.62	.55	.54
INT3. For the pleasure that I experience in broadening my knowledge about subjects which appeal to me.	.58	.58	.55
INT4. Because my studies allow me to continue to learn about many things that interest me.	.60	.59	.55
Loadings mean	.60	.57	.54
IDEN1. Because I think that a high school education will help me better prepare for the career I have chosen.	.63	.60	.63
IDEN2. Because eventually this course will enable me to enter the job market in a field that I like.	.60	.55	.57
IDEN3. Because this will help me make a better choice regarding my career orientation.	.66	.55	.50
IDEN4. Because I believe that my high school education will improve my competence as a worker.	.62	.64	.50
Loadings mean	.63	.59	.55
INTRO1. To prove myself that I am able to succeed in this course.	.55	.50	.54
INTRO2. Because of the fact that when I succeed in school I feel important.	.58	.54	.55
INTRO3. To show myself that I am an intelligent person.	.55	.48	.47
INTRO4. Because I want to show myself that I can succeed in my studies.	.56	.50	.53
Loadings mean	.56	.51	.52
EXT1. Because I need at least a high school degree in order to find a high- paying job later on.	.12	.22	.31
EXT2. In order to obtain a more prestigious job later on.	.30	.41	.60
EXT3. Because I want to have “the good life” later on.	.36	.26	.19
EXT4. In order to have a better salary later on.	.43	.33	.33
Loadings mean	.30	.31	.36

Table 7. Between-subject differentiation: CFA and ESEM models tested.

	CFI	TLI	$\chi 2$	df	RMSEA	SRMR
Intrinsic						
1b- CFA	.990	.983	130.909	39	.041	.030
2b- CFA Bi-Factor	.996	.991	68.370	30	.030	.007
3b- CFA Bi-Factor with	.996	.992	103.937	54	.026	.010
4b- ESEM	.996	.987	59.602	21	.036	.006
5b- ESEM Bi-Factor	.996	.984	48.979	15	.040	.007
6b- ESEM Bi-Factor with	.997	.991	71.820	36	.027	.012
Identified						
7b- CFA	.982	.970	162.217	39	.047	.067
8b- CFA Bi-Factor	.990	.979	97.147	30	.040	.025
9b- CFA Bi-Factor with	.989	.978	154.733	54	.036	.028
10b- ESEM	.992	.976	72.866	21	.042	.021
11b- ESEM Bi-Factor	.989	.939	88.052	12	.067	.006
12b- ESEM Bi-Factor with	.995	.987	83.806	39	.029	.018
Introjected						
13b- CFA	.991	.985	116.671	39	.038	.040
14b- CFA Bi-Factor	.995	.989	73.761	30	.032	.023
15b- CFA Bi-Factor with	.915	.835	1072.316	54	.116	.023
16b- ESEM	.996	.986	60.486	21	.037	.022
17b- ESEM Bi-Factor	.999	.997	20.554	15	.016	.002
18b- ESEM Bi-Factor with	.996	.990	83.672	39	.029	.012
External						
19b- CFA	.990	.983	119.880	39	.038	.051
20b- CFA Bi-Factor	.992	.983	91.015	30	.038	.031
21b- CFA Bi-Factor with	.993	.986	129.437	54	.032	.026
22b- ESEM	.993	.978	76.196	21	.043	.030
23b- ESEM Bi-Factor	.998	.992	29.561	15	.026	.004
24b- ESEM Bi-Factor with	.996	.989	83.057	39	.028	.020

Note. In this set of models, uniquenesses between identical items across the three school subjects were correlated. However, due to convergence problems, these correlations were released for item #3 on models 12b, 17b, 18b, 23b and 24b, while correlations for item #4 were released for model 5b. In each of these models, removing correlations between an item uniquenesses resulted in a 3 df increase.

Table 8. Between-subject differentiation, Mean for the target loadings and for the cross-loadings, SD, range, and paths predicting grades

School Subjects	Mean Target loading	SD Target loading	ω	Range Target loading	Mean Cross-loading	SD Cross-loading	Range Cross-loading	Paths predicting grades F	Paths predicting grades M	Paths predicting grades E
Intrinsic – "6b"										
G	.64	.06	.95	.56-.77				**.142***	**.112***	**.122***
French	.54	.02	.82	.51-.56	.00	.07	|.01-.12|	**.056**	-.061	-.134*
Math	.55	.05	.83	.49-.59	.00	.05	|.01-.10|	-.005	**.235***	-.088
English	.59	.11	.84	.47-.72	.00	.04	|.01-.06|	-.005	-.023	**.135***
Identified – "12b"										
G	.54	.18	.92	.40-.88				**-.010**	**.014**	**.030**
French	.58	.18	.83	.35-.74	.03	.09	|.04-.12|	**.115***	.003	-.049
Math	.62	.17	.84	.42-.77	.02	.07	|.01-.10|	.015	**.165***	-.015
English	.54	.24	.79	.26-.77	.03	.11	|.03-.17|	.064	.047	**.156***
Introjected – "18b"										
G	.76	.10	.96	.66-.92				**-.018**	**-.014**	**-.007**
French	.29	.19	.58	.03-.45	.02	.15	|.01-.22|	**-.010**	-.111*	-.105*
Math	.34	.19	.55	.06-.51	.01	.13	|.02-.19|	-.008	**.037**	-.022
English	.34	.19	.63	.06-.51	.01	.13	|.03-.19|	.017	-.006	**.073**
External – "24b"										
G	.66	.17	.94	.48-.93				**-.169***	**-.130***	**-.100***
French	.31	.22	.54	.00-.52	.04	.17	|.03-.22|	**.018**	-.053	-.076*
Math	.31	.25	.53	-.03-.58	.04	.18	|.03-.24|	-.032	**.041**	-.009
English	.36	.19	.58	.09-.54	.03	.15	|.04-.22|	.014	.013	**.108***

Note. Grade predictions in corresponding school subjects are shown in **bold**. ω = Omega; ωh/ωs = Omega hierarchical/subscale; * $p < .05$.