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ORIGINAL PAPER

Empirical testing of an alternative modeling of the self-determination continuum

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Abstract

Self-determination theory (SDT) proposes various types of motivation which fall onto a continuum of self-determination. Some computational techniques allow the estimation of a global score of self-determination, with bifactor-ESEM modeling being a popular estimation method. However, this approach has shortcomings, including changing conceptual interpretation of both general and specific factors. In this study, we applied the bifactor $S-1$ modeling strategy to estimate the continuum and explore its potential contribution. By estimating all specific factors except for intrinsic motivation, this model anchors the general factor in intrinsic motivation which is prototypical of self-determination. Tested with five samples of students from elementary school to university ($N_{\text{total}} > 4000$), the bifactor $S-1$ modeling strategy was empirically supported, and its general factor yielded a stronger prediction of students' outcomes (e.g., grades, anxiety) compared to the previously advocated bifactor-ESEM model. The bifactor $S-1$ model also explains outcomes with high precision, and its conceptual concordance with SDT makes it easily interpretable.

Keywords Self-determination theory · Motivation · Bifactor $S-1$ · Exploratory structural equation modeling · Continuum · Academic motivation scale

Introduction

Motivation has important implications for individuals' daily functioning and thriving (Ryan & Deci, 2017). The central tenet of motivation theories is that motivation produces positive outcomes, independently of many contextual and individual characteristics. One central motivational theory is self-determination theory (SDT; Deci & Ryan 1985; Ryan & Deci, 2017), which relies on an organismic dialectical approach to explain how motivated behavior naturally occurs and evolves. It details the psychological nutrients (e.g., basic psychological needs) required to foster and sustain motivation. SDT distinguishes between intrinsic (IM; Deci 1971) and extrinsic motivations (EM) where IM refers to engaging in an activity because it is interesting, fun, or satisfying. In contrast, EM pertains to behaviors that are motivated by outcomes unrelated to the activity itself, which can take on various forms. Specifically, SDT proposes that motivation types convey varying levels of self-determination (i.e., the extent to which one's actions and thoughts originate from the self) that can be plotted on a continuum. This conceptualization carries two main innovations in contrast to classical theoretical frameworks on IM/EM. First, it proposes that EM is not unidimensional but rather multidimensional, divided into four regulation types, each with a specific degree of self-determination. Whereas motivational types driven by external rewards and sanctions are sometimes designated as extrinsic motivation in other theoretical approaches (e.g., Covington 2000), they are framed within SDT as a specific type of EM, namely external regulation, which is a non-self-determined type of motivation. The theory also advances that people can be extrinsically motivated through internal pressures such as shame, guilt, or pride,

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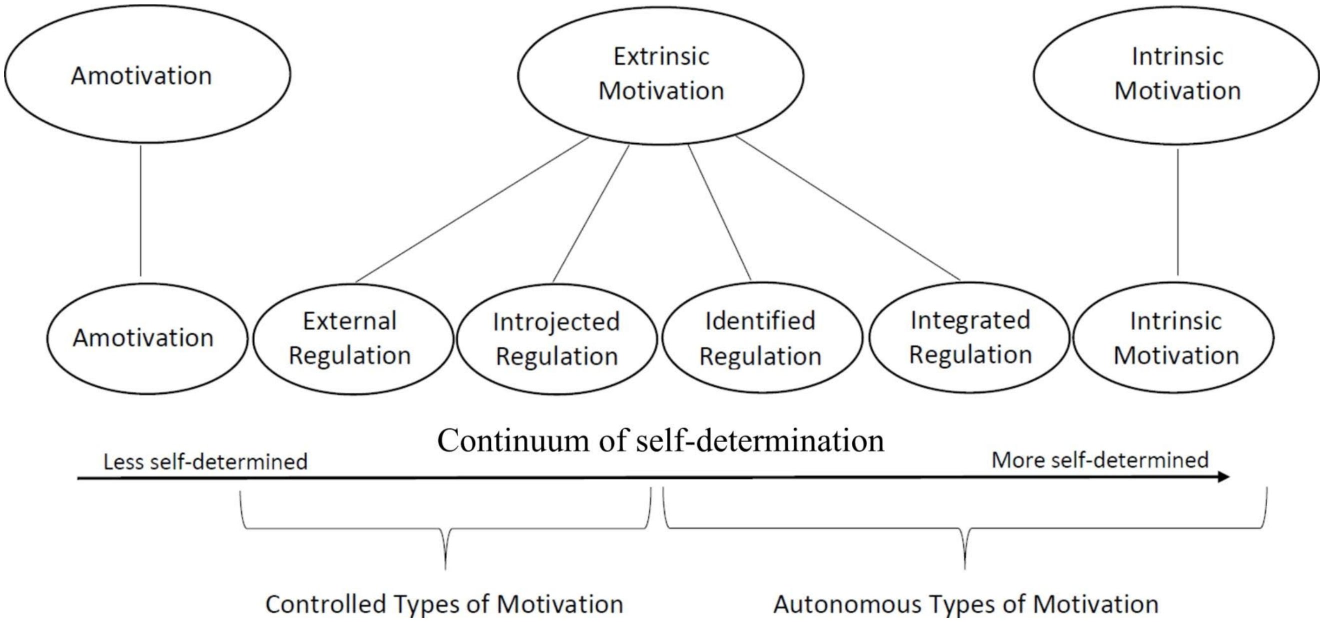

Fig. 1 *Representation of Motivation Types On the Self-Determination Continuum*. Note: Adapted from "Testing a Continuum Structure of Self-Determined Motivation: A Meta-Analysis," by J.L. Howard., M. Gagné., & J.S. Bureau, 2017, Psychological Bulletin, 143(12), p. 1347. Copyright 2017 by American Psychological Association

which is labelled introjected regulation and conveys somewhat low levels of self-determination. Importantly, SDT argues that extrinsic motives can be self-determined, such as when one engages in uninteresting tasks because they are valued and personally important (identified regulation) or because they are congruent with one's value system and self-definition (integrated regulation). Second, in addition to postulating that there are distinct types of motivation, SDT proposes that they can be ordered along a continuum that ranges from highly self-determined (intrinsic motivation) to non-self-determined (external regulation, and also amotivation, a non-motivated state; see Fig. 1).

Empirical Support for the Self-Determination Continuum

Although the idea of mapping the various motivations on a continuum has been the subject of criticism (Chemolli & Gagne, 2014), recent meta-analyses provided robust evidence regarding the existence of the self-determination continuum. Indeed, it was shown using multidimensional scaling analysis that the types of motivation proposed by SDT empirically follow a unidimensional ordering according to their intercorrelations (Howard et al., 2017). Some researchers have even suggested that the continuum may conceptually and empirically follow a semi-radex structure (Howard, Gagné, & Morin, Howard et al., 2020a, b, c), implying that each motivational type conveys information on a unidimensional spectrum of self-determination, in addition to having its own range.

Recent meta-analyses have provided support for the relevance of estimating various types of motivation (Bureau et al., 2021), both regarding unique predictive patterns of outcomes from the various motivation types as well as in terms of predictable ordering of their prediction strength along the self-determination continuum. Synthesizing decades of educational research, Howard and colleagues (2021) showed that motivation types characterized by higher levels of self-determination had stronger positive predictions of adaptive outcomes and more negative predictions of maladaptive outcomes. Indeed, intrinsic motivation and identified regulation were positively associated to adaptive outcomes (e.g., grades, effort, engagement, positive affect, self-efficacy), but only intrinsic motivation consistently negatively predicted maladaptive outcomes (e.g., negative affect, anxiety). At the other end of the continuum, amotivation showed the inverse pattern by positively predicting negative outcomes (e.g., dropout intentions, anxiety) and negatively predicting positive ones. However, the contributions of introjected and external regulations were more equivocal, the former positively predicting both adaptive and maladaptive outcomes (e.g., effort and engagement, but also anxiety and negative affect) and the latter positively predicting maladaptive outcomes related to ill-being (e.g., anxiety, low vitality). Results also showed that, on average, introjected and external regulations had smaller explanatory power when predicting outcomes, compared to intrinsic motivation, identified regulation, and amotivation. This pattern of results is also replicated in a meta-analysis focused specifically on physical education (Vasconcellos et al., 2020) as well as in the work domain, with consistent associations (positive or negative) between intrinsic motivation, identified regulation, and amotivation and turnover intentions, commitment, vitality, and exhaustion (Gagné et al., 2015). Introjected and external regulations for work also showed mixed predictive patterns in this domain. Globally, results attest to the importance of a multidimensional conceptualization of motivation and of representing types of motivation on the self-determination continuum.

Although conceptual and statistical support for the relevance of a continuum of self-determination is consistent, important questions remain: How can we best model motivational scores to capture both the unidimensional and multidimensional nature of the self-determination continuum? More specifically, how can we translate the multiple scores of motivations into usable statistical aggregates that represent both the unidimensional progression from low to high self-determination, but also the unique aspects of each motivation type?

Previous Strategies and Their Limits

In earlier research, researchers had to choose to prioritize either a unidimensional conceptualization of motivation or a multidimensional one. Some researchers favored a unidimensional scoring method because of its important advantages in terms of reducing analysis complexity and collinearity. A popular strategy was the relative autonomy index (Ryan & Connell, 1989). It involved adding together some of the motivation types proposed by SDT, with differently weighted positive and negative multipliers for each type depending on their place along the self-determination continuum. Usually, intrinsic motivation was given a strong positive weight, identified regulation was given a moderate positive weight, introjected regulation was given a moderate negative weight, and external regulation was given a strong negative weight. Sometimes, amotivation was included with a stronger negative weight (e.g., Wallhead et al., 2013). Although this procedure allowed to capture a global score of self-determination, it also entailed the problems of pooling together the error variance from each motivation type, as well as balancing motivation types according to hypothetical weights. Therefore, while this solution was adopted by many researchers within SDT, it was criticized from statistical experts based on previous work made on difference scores (Edwards, 2001; Johns, 1981).

Another strategy was to divide the continuum into two main categories, *autonomous motivation*, encompassing intrinsic motivation and identified regulation, and *controlled motivation*, encompassing introjected and external regulations (Sheldon & Elliot, 1998). Although this solution seemed practical, it deviated from the idea of an underlying unidimensional continuum. Nevertheless, using an autonomous motivation index allows combining the predictive power of intrinsic motivation and identified regulation while eliminating collinearity and is still a widespread scoring method to this day (e.g., Vasconcellos et al., 2020). As for the controlled motivation composite, while also useful, it usually shows much smaller predictive power than the autonomous motivation composite (e.g., Koestner et al., 2008).

More recently, confirmatory factor analyses (CFA) were used to specify individual factors for each type of motivation and predict outcomes from each of the motivation type individually (e.g., Gilal et al., 2020; Sebire et al., 2013). While this method has the advantage of looking at how each individual motivation type can predict outcomes, it also overlooks the importance of the unidimensional aspect of the continuum and, in doing so, introduces unnecessary multicollinearity in the prediction of outcomes (Morin et al., 2013). Higher-order CFA has been introduced to eliminate this problem but, oftentimes, it introduces additional problems. Higher-order CFAs of the self-determination continuum are usually locally unidentified at the higher-order factor level and they further restrict the association between higher-order factors and the items to a product of the association between first-order factors and items (Howard, Gagné, Van den Broeck, Howard et al., 2020a, b, c). Recently, bifactor solutions were proposed as a viable option for researchers trying to capture the level of self-determination underlying the various types of motivation. Bifactor models, in addition to specifying individual factors like one would see in traditional CFA, estimate a general factor that captures common variance shared among all indicators of the different types of motivation, without restricting the association between the general factor and each item, like in the higher-order model. Thus, bifactor solutions allow for a simultaneous estimation of unidimensional and multidimensional aspects of motivation types. In their recent analysis, Howard and colleagues (Howard, Gagné, Van den Broeck, Howard et al., 2020a, b, c) examined the various scoring methods for representing the self-determination continuum and showed that, compared to a relative autonomy index, a CFA, a higher-order CFA, and to an exploratory structural equation modeling (ESEM), the bifactor-ESEM model had the best fit indices and highest explained variance in outcomes.

Notwithstanding these positive elements, some important conceptual and empirical issues remain unresolved by the bifactor-ESEM estimation method. First, estimation of the general factor (G-factor) in bifactor models is, to a certain degree, volatile. There is no certainty regarding what conceptual information will be assigned to the G-factor and what will be assigned to the specific factors (S-factors), apart from the fact that the former will represent what is common to all items and the latter, what is uniquely common to its group of items (Morin, 2021). Therefore, interpretations of G- and S-factors must be inferred on a study-by-study basis through the commonalities and factor loadings. For instance, the meaning of general and specific factors may change among studies considering that measures of motivation vary and that some types of motivation are not always included in the analysis (e.g., amotivation, two types of external regulation, three types of intrinsic motivation). When estimating a bifactor model that did not include a measure of amotivation, Guay & Bureau (2018) established that the G-factor had factor loadings of similar strength across the various types of motivation and thus concluded that their G-factor measured the quantity of motivation rather than the degree of self-determination. These findings are in contrast with most research on the self-determination continuum using a bifactor model, which usually shows decreasing factor loadings on the G-factor from intrinsic motivation to amotivation, with the consequent conclusion that the G-factor measures a relative level of self-determination across motivation types (Tóth-Király et al., 2021).

A second issue with the bifactor model regards the meaning of S-factors. One could mistakenly assume that the S-factors represent the type of motivation measured by their respective items. This assumption does not always hold as some S-factors often have low levels of validity. For instance, past studies have obtained mean factor loadings close to 0 for certain S-factors (e.g., the S-factor for identified regulation in Gillet et al., 2018 where target loadings ranged from −0.14 to 0.16 across four models, with a mean of 0.00), which means that S-factors can sometimes capture little to no variance.

Furthermore, a G-factor estimated with a bifactor solution is orthogonal to S-factors, meaning that they are measuring distinct properties. This clashes with the conceptual underpinnings of the self-determination continuum, which conceptualizes intrinsic motivation to be the prototypical illustration for self-determination (Ryan & Deci, 2017). Simply put, although self-determination is broader and more complex than intrinsic motivation, intrinsically motivated behaviors are inexorably self-determined. Therefore, any model that estimates orthogonal factors for intrinsic motivation and self-determination raises questions about the conceptualization of either factor. All in all, the bifactor model presents conspicuous conceptual and statistical issues when applied to the self-determination continuum. Considering that the strong fit indices obtained when estimating a bifactor model are not sufficient to attest its superiority, exploring other analytical strategies that bear the strengths of the

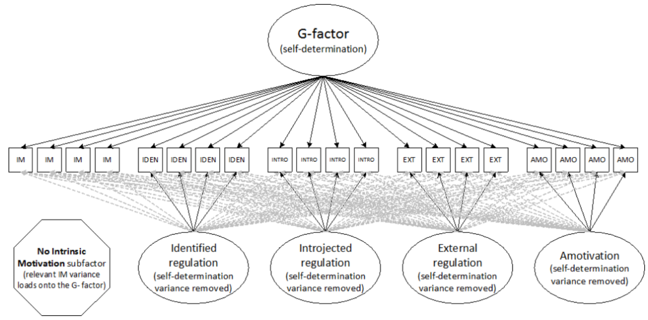

Fig. 2 *Illustration of the Bifactor S – 1 ESEM Model*. Note: IM = Intrinsic motivation; IDEN = Identified regulation; INTRO = Introjected regulation; EXT = External regulation; AMO = Amotivation

bifactor model while also overcoming some of its main limits would improve researchers' ability to capture the level of self-determination characterizing each type of motivation proposed by SDT.

Bifactor *S* – 1 as a Tailored Solution

Recently, research in the field of ADHD (Burns et al., 2019) and depression (Heinrich et al., 2020) have suggested that the bifactor *S* – 1 model (see Fig. 2) can be a tenable alternative to the more common *symmetrical* bifactor model (where one S-factor per subscale is estimated), particularly when items are expected to contribute asymmetrically to the G-factor (i.e., when S-factors are not interchangeable in terms of their relative contribution to the G-factor). The bifactor *S* – 1 may be a theoretically relevant solution to model the self-determination continuum. Since SDT postulates that intrinsically motivated behavior naturally illustrates self-determination (Ryan & Deci, 2017), it would be more coherent with the theory to anchor the G-factor estimating "self-determination" in intrinsic motivation, rather than specifying orthogonal factors for these two constructs. With a *bifactor S – 1* model, there would be no S-factor estimated from intrinsic motivation items which would only be specified by the G-factor, meaning that the G-factor would become anchored in intrinsic motivation. Conceptually, this would imply that the G-factor draws its meaning mostly from intrinsic motivation items, and in a generally decreasing fashion from other items on the continuum in accordance with their factor loading on the G-factor. In turn, this would ensure that the G-factor captures the highest possible amount of self-determination. A G-factor that more accurately conveys the level of self-determination underlying types of motivation has the potential to predict motivational outcomes with more power and precision, compared to a G-factor estimated with a symmetrical bifactor model.

Moreover, a bifactor *S* – 1 focused on intrinsic motivation would overcome the main shortcomings of symmetrical bifactor modeling of the self-determination continuum, namely the imprecise or varying meaning of each factor from one study to another. While this can happen for various reasons, the most evident one in the case of motivation pertains to the fact that studies may measure some motivational types while excluding others (e.g., amotivation). When the number of motivation types varies across studies, the meaning of the G-factor in symmetrical bifactor models may also vary across studies. With a bifactor $S - 1$ model, the self-determination factor would always be anchored in items reflecting intrinsic motivation, preventing substantial variations in the meaning of the G-factor. Finally, one important outcome of measuring a G-factor that is anchored in intrinsic motivation would be the ensuing clearer conceptual boundaries for S-factors, and perhaps reduced variations in their constitution across studies.

In summary, the bifactor $S - 1$ model has strengths that can be grouped in two major dimensions: (1) the estimation of a self-determination G-factor that is anchored in the most self-determined type of motivation, which is purported to entail a better prediction of outcomes, and (2) G- and S-factors that are more precise, and presumably more consistent across studies, as compared to those obtained from a symmetrical bifactor model (i.e., where all types of motivation are estimated by S-factors). To our knowledge, this is the first study to test a bifactor $S - 1$ model of the self-determination continuum.

The Present Study

In this research, we sought to test the benefits of estimating a bifactor $S - 1$ model to empirically represent various types of motivation along the self-determination continuum. First, to test whether a bifactor $S - 1$ model allows the estimation of a self-determination G-factor that is more consistent with SDT, we empirically compared symmetrical and $S - 1$ bifactor models from five samples in terms of model fit, factor loadings, and factor validity. Because the bifactor $S - 1$ is purported to better reflect the empirical reality of the relationship between motivation types, the model should present similar fit to the less parsimonious symmetrical bifactor model, within which it is nested. Compared to the symmetrical model, the $S - 1$ model is also expected to present factor loadings toward the self-determination G-factor that are more congruent with the theory (higher factor loadings on intrinsic motivation and decreasing loadings for the other consecutive types along the continuum), as well as factors that are better defined, showing stronger reliability estimates.

H1 Model fit indices for bifactor $S - 1$ and symmetrical bifactor models will be comparable.

H2.1 Factor loadings on the G-factor with a bifactor $S - 1$ model will more accurately represent the self-determination continuum than those obtained with a symmetrical bifactor model.

H2.2 Factor validity in the bifactor $S - 1$ model will be stronger for both the G-factor and the S-factors than factor validity in the symmetrical bifactor model.

Second, to test whether factors in a bifactor $S - 1$ model would more strongly predict important outcomes than factors in a symmetrical bifactor model, we compared effect size estimates for the prediction of three important outcomes for students: grades, anxiety symptoms, and depression symptoms. Since G-factors are usually the main predictor (sometimes used as a saved factor score; Guay et al., 2021), estimating models where the G-factor shows stronger predictive validity is advantageous. To test for the predictive power of the models in general, we compared their respective amounts of explained variance in these outcomes. Because the $S - 1$ model is nested within the symmetrical model, explained variance from the former model is not expected to surpass that from the latter. However, they should be comparable.

H3 The G-factor estimated with a bifactor $S - 1$ model will predict outcomes more strongly (as per effect size estimates of the standardized regression coefficients) than the G-factor estimated with a symmetrical bifactor model.

H4 Total variance in outcomes explained by the model will be comparable between model types.

Finally, to test whether the G- and S-factors estimated with a bifactor $S - 1$ model were more accurate in their prediction of outcomes (and thus possibly better defined) than the corresponding factors estimated with a symmetrical bifactor model, we estimated the confidence intervals in the prediction of the aforementioned outcomes for each factor of both models. A wider confidence interval is synonymous with uncertainty in the prediction of outcomes (Forbes et al., 2021), which can be caused by imprecise estimation of the factor (Marsh et al., 1998). In contrast, narrower intervals imply stronger accuracy in the prediction of outcomes.

H5 G- and S-factors in the bifactor $S - 1$ model will be more accurate in their prediction of outcomes (more restricted confidence intervals) compared to G- and S-factors in the symmetrical bifactor model.

Table 1 Dataset Descriptive Information

Published Manuscript	N	Year of data collection	M_{age}	SD_{age}	% Female	Grade Level	Outcome Assessed	
							Grades	ANX/DEP
1- Guay, Senécal, Gauthier, & Fernet (2003	839	2000	17.73	1.88	71.1	College [a]	-	Yes
2- Guay, Ratelle, Roy, & Litalien (2010)	941	2003	13.75	1.10	55.7	High school	Yes	-
3- Guay, Ratelle, Larose, Vallerand, & Vitaro (2013)	1405	2008	13.75	1.09	52.6	High school	Yes	-
4- Bureau, Gareau, Guay, & Mageau (2021)	710	2014	20.09	4.16	60.9	College [a]	-	-
5- Gilbert, Bureau, Poellhuber, Guay (2021)	1779	2019	21.59	4.93	79.0	College [b]	Yes	Yes

Note. ANX/DEP = Anxiety and depression symptoms

[a] Pre-university college

[b] University

Method

Five educational datasets were used to test the hypotheses. Table 1 provides information on each dataset (*N*, mean age, *SD* age, gender, grade level, year of data collection, and outcomes included). All data was collected in various educational institutions in the province of Quebec, Canada. All participants answered the measures in French.

Measures

Motivation Types

In all samples, motivation types were measured using the Academic Motivation Scale (AMS; Vallerand et al., 1992). This scale measures three types of intrinsic motivation (IM to know, IM to accomplish, and IM for stimulation), three types of extrinsic motivation (identified, introjected, external), and amotivation. All subscales include four items. At the secondary school level, they were answered on a 5-point Likert scale ranging from 1 (*Does not agree at all*) to 5 (*Completely agree*). At the college level, they were answered on a 7-point scale from 1 (*Does not agree at all*) to 7 (*Completely agree*). Although only two datasets included the three types of intrinsic motivation in their measure (the others measuring only intrinsic motivation to know), we followed recent insights on intrinsic motivation (Howard, Chong, et al., 2020) and eliminated redundancy by including only IM to know. Previous research suggests that types of motivation assessed by the AMS show predictable ordering in their intercorrelations, although identified and external regulations sometimes correlated more strongly together than when measured with other motivation scales (Howard et al., 2017). Notably, introjected and external regulation items in the AMS are only answered with an approach motivational orientation, no item conveyed avoidance in either regulation.

Grades

Grades were included in three of the five datasets. Two datasets (#3 and #5) featured self-reported grades while one dataset (#2) featured grades retrieved from school records. The latter included grades over many school subjects and latent aggregates were created with grades from French, math, English (second language), and physical education, which were school subjects pursued by students of all levels.

Anxiety and Depression Symptoms

One sample (#1) measured anxiety and depression with a *Psychological Distress Questionnaire* (Villeneuve et al., 1996), while another (#5) measured anxiety with the GAD-7 (General Anxiety Disorder-7; Micoulaud-Franchi et al., 2016; Spitzer et al., 2006) and depression with the PHQ-9 (Patient Health Questionnaire-9; Carballeira et al., 2007; Kroenke et al., 2001). In the *Psychological Distress Questionnaire*, participants answered whether they had experienced specific symptoms over the last four months (sample item for anxiety: "Did you feel tense or under pressure?"; sample item for depression: "Did you feel hopeless thinking about the future?". Both GAD-7 and PHQ-9 scales asked participants to indicate, over the last 14 days, if they had been bothered by a list of problems (sample item for GAD-7: Becoming easily upset or irritable; sample item for PHQ-9: Feeling down, depressed, or hopeless). All items were answered on a scale ranging from 0 (Never) to 3 (Often). In the present study, Cronbach's alpha ranged from 0.73 (sample 1) to 0.91 (sample 5) for anxiety and from 0.81 (sample 1) to 0.86 (sample 5) for depression.

Results

Analyses

For the testing of all hypotheses, two types of bifactor models were compared. The first model type was a symmetrical bifactor-ESEM model (Howard et al., 2020a, b, c). Following the ESEM framework specifications (Morin et al., 2013), this model included a G-factor defined by all available indicators from all types of motivation, as well as orthogonal S-factors for each type of motivation. All these factors were specified using target orthogonal rotation to minimize cross-loadings and ensure non-overlapping variance across factors. The second type of model, a bifactor $S-1$ model, was estimated using the same specifications as the bifactor-ESEM model, including the use of an orthogonal target rotation. However, the estimation of the S-factor for intrinsic motivation was removed. This allowed having nested models and assured comparability for a better assessment of the potential advantages of the more parsimonious bifactor $S-1$ model. Because the bifactor $S-1$ model is nested within the symmetrical bifactor-ESEM model (Hand & Lonigan, 2021), one can expect the former model to exhibit weaker fit indices and explained variance in outcomes. Examining the differences in model fit and explained variance in outcomes thus mainly serve the purpose of establishing that bifactor $S-1$ models are equally viable and similarly powerful in predicting their respective outcomes as symmetrical bifactor models. Further, comparing the strength of prediction of outcomes by the G-factor from each model will help determine if the bifactor $S-1$ model is a better solution than the symmetrical bifactor-ESEM model. To our knowledge, very few research has used a bifactor $S-1$ model within the ESEM framework (see Thöne et al., 2021 for an example). Importantly, this may speak to the novel aspect of the ESEM framework compared to CFA, rather than to potential problems in estimating a bifactor $S-1$ ESEM model.

Model Fit Comparison

On average, across the five samples, model fit statistics for all models showed close fit to the data (see Table 2). Furthermore, variations in fit indices between models were small for CFI, TLI, RMSEAs and SRMR. Following Chen's (2007) recommendation that, when sample size is adequate, CFI and TLI differences below 0.01 and RMSEA and SRMR differences below 0.015 indicate similar model fit, the present comparisons between symmetrical bifactor and bifactor $S-1$ showed that both models are equivalent. Indeed, average ΔCFI across models was 0.007, while average ΔTLI was 0.008. Similarly, average ΔRMSEA was 0.003 while average ΔSRMR was 0.003. Thus, bifactor $S-1$ models do not offer a poorer fit to the data than symmetrical bifactor models, supporting *H1*.

Factor Loading and Factor Validity Comparison

Table 2 presents the average factor loadings for each factor across all models and samples. As expected, the bifactor $S-1$ model yielded stronger factor loadings of intrinsic indicators on the G-factor than the symmetrical bifactor model (average $\Delta\beta = 0.20$). In contrast, indicators for the other types of motivation had generally weaker factor loadings on the G-factor in the $S-1$ model, compared to the symmetrical model. This can be expected since loadings on the G-factor in the $S-1$ model represent variance in items that is common to the reference motivation type (i.e., intrinsic motivation), implying that the variance in items that load on the G-factor is akin to intrinsic motivation. In comparison with the $S-1$ model, the G-factor in the symmetrical model had slightly higher factor loadings on motivation types other than intrinsic motivation, which means that it accounts for a larger proportion of variance in those items. Globally, these results support *H2.1* for the distribution of factor loadings on the G-factors of both models across motivation items.

Regarding the S-factors, the intrinsic S-factor has an average factor loading of 0.55 in the symmetrical model (and is not estimated in the $S-1$ model). The identified S-factor had an average factor loading of 0.36 in the symmetrical model and of 0.43 in the $S-1$ model, which equates to a 20% mean factor loading difference in favor of the latter model. For all other S-factors, the average factor loading differences were weak (average $\Delta M_\lambda = 0.02$), suggesting that their estimation remains quite stable across models.

Regarding factor validity, the G-factor in both models were found to be equally reliable. In the $S-1$ model, however, validity of the identified and external S-factors showed marginal superiority compared to the same factors in the symmetrical model ($M\Delta_\omega = 0.03$). Validity for introjected and amotivation S-factors was similar across model types ($M\Delta_\omega = 0.003$). Overall, *H2.2* was not empirically supported as the model factors generally showed similar reliability indices.

These results detailing model fit, average factor loadings, and factor validity for both model types cannot by themselves point to any added advantage of using a bifactor $S-1$ model compared to a symmetrical bifactor model. The comparison of models' prediction strengths for education outcomes will help determine if they yield similar results or if one model is superior.

Table 2 Results of Measurement Models for the Five Datasets

Dataset Number:	1		2		3		4		5		Average		
Model Type:	*sym.*	$S-1$	*sym.*	$S-1$	*sym.*	$S-1$	*sym.*	$S-1$	*sym.*	$S-1$	*sym.*	$S-1$	$\|\Delta\|$
Model Fit													
CFI	0.982	0.969	0.973	0.964	0.993	0.989	0.983	0.977	0.984	0.979	0.983	0.976	0.007
TLI	0.959	0.942	0.939	0.932	0.984	0.978	0.963	0.957	0.963	0.961	0.962	0.954	0.008
RMSEA	0.041	0.049	0.048	0.051	0.030	0.035	0.036	0.039	0.039	0.040	0.039	0.042	0.003
SRMR	0.014	0.018	0.016	0.019	0.009	0.013	0.014	0.018	0.011	0.014	0.013	0.016	0.003
G-factor [ω]	[0.91]	[0.91]	[0.93]	[0.92]	[0.93]	[0.92]	[0.90]	[0.90]	[0.90]	[0.89]	[0.91]	[0.91]	
λ_{mean} INT	0.61	0.81	0.66	0.81	0.59	0.85	0.53	0.78	0.70	0.85	0.62	0.82	0.20
λ_{mean} IDEN	0.53	0.44	0.61	0.54	0.62	0.50	0.49	0.42	0.53	0.46	0.56	0.47	0.09
λ_{mean} INTRO	0.46	0.40	0.61	0.58	0.56	0.50	0.55	0.47	0.14	0.12	0.47	0.41	0.08
λ_{mean} EXT	0.25	0.15	0.33	0.26	0.30	0.20	0.35	0.22	0.10	0.06	0.27	0.18	0.09
λ_{mean} AMO	−0.40	−0.39	−0.33	−0.33	-	-	−0.27	−0.29	−0.44	−0.39	−0.36	−0.35	0.01
S-factors [ω_{mean}]	[0.60]	[0.62]	[0.56]	[0.59]	[0.63]	[0.68]	[0.58]	[0.61]	[0.62]	[0.66]	[0.60]	[0.63]	
λ_{mean} INT [ω]	0.55 [0.57]	-	0.49 [0.54]	-	0.61 [0.65]	-	0.59 [0.60]	-	0.51 [0.47]	-	0.55 [0.57]	-	-
λ_{mean} IDEN [ω]	0.25 [0.36]	0.34 [0.41]	0.35 [0.46]	0.41 [0.51]	0.50 [0.57]	0.60 [0.66]	0.33 [0.40]	0.38 [0.43]	0.63 [0.43]	0.43 [0.47]	0.36 [0.44]	0.43 [0.49]	0.07
λ_{mean} INTRO [ω]	0.58 [0.64]	0.61 [0.65]	0.44 [0.48]	0.47 [0.50]	0.58 [0.62]	0.63 [0.64]	0.56 [0.61]	0.62 [0.65]	0.74 [0.74]	0.75 [0.73]	0.58 [0.62]	0.62 [0.63]	0.04
λ_{mean} EXT [ω]	0.68 [0.73]	0.70 [0.75]	0.53 [0.63]	0.57 [0.69]	0.67 [0.67]	0.69 [0.74]	0.61 [0.64]	0.66 [0.72]	0.69 [0.74]	0.69 [0.74]	0.63 [0.68]	0.66 [0.73]	0.03
λ_{mean} AMO [ω]	0.72 [0.70]	0.73 [0.68]	0.69 [0.68]	0.69 [0.66]	-	-	0.75 [0.68]	0.74 [0.64]	0.71 [0.70]	0.74 [0.71]	0.72 [0.69]	0.72 [0.67]	0.00

Note. |Δ| = Difference in absolute value; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Residuals; ω = McDonald's omega (factor validity); INT = Intrinsic motivation; IDEN = Identified regulation; INTRO = Introjected regulation; EXT = External regulation; AMO = Amotivation; *sym.* = Symmetrical bifactor-ESEM; $S-1$ = Bifactor $S-1$ ESEM

Predictive Strength Comparison

Grades

Three datasets (#2, #3, and #5) included a measure of grades, allowing to compare the predictive strength of both bifactor models. Results are presented in Table 3. Across all models, the average prediction (β) of grades by the G-factor was 0.14 for the symmetrical bifactor model and 0.21 for the bifactor $S - 1$ model, demonstrating that the G-factor of the latter model was on average 46% more effective[1] in predicting grades than the G-factor of the former model. In contrast, the average predictive strength of the intrinsic S-factor in the symmetrical model, which was not specified in the $S - 1$ model, was 0.16. Other S-factors showed small variations in their prediction of grades ($\Delta_\beta \leq 0.03$). Regarding the amount of explained variance in student grades (R^2), only slight differences were observed between models, going from 0.112 in the symmetrical bifactor models to 0.108 in the bifactor $S - 1$ model, a difference of 0.004 (or 0.4%) explained variance ($\Delta R^2 = 0.004$). Considering that the $S - 1$ model is nested in the symmetrical model, this result shows that although the $S - 1$ model is more parsimonious, it is about equally powerful in its general predictive strength of student achievement as the symmetrical model, with a larger prediction attributed to the G-factor.

We further compared the prediction accuracy of both bifactor models by contrasting 95% confidence intervals (CI) around their regression coefficients for the prediction of grades by G- and S-factors. Regarding the G-factors, the 95% CI was, on average, reduced by 39% for the $S - 1$ model compared to the symmetrical model. The S-factors also had narrower 95% CI in the $S - 1$ model, with average decreases of 31%, 19%, 11%, and 18% for the prediction of grades by identified, introjected, and external regulations, and amotivation respectively. Hence, using an $S - 1$ bifactor model substantially reduced CI around regression coefficients, especially for the G-factor.

Considering that relying on factor scores is a common practice when working with bifactor models (e.g., for establishing profiles; Gillet et al., 2020; Tóth-Király et al., 2021), it is important to demonstrate that the enhanced prediction from the G-factor of the $S - 1$ model also applies to this type of indicators. Stronger prediction of grades from the G-factor of the $S - 1$ model, compared to the G-factor of the symmetrical model, was maintained if a factor score saved from estimated models was used to predict grades (Table 3). Across the three samples of students, the factor score saved from the bifactor $S - 1$ model was 31% more effective in predicting grades (*r* from 0.14 to 0.19) than the factor score saved from the symmetrical bifactor model.

Anxiety and Depression Symptoms

Two datasets (#1 and #5) measured anxiety and depression symptoms (see Table 3). On average, the prediction of anxiety and depression by the G-factor of the symmetrical bifactor model was 0.09 and −0.21, respectively. Regarding the prediction from the G-factor of the bifactor $S - 1$ model, it was 0.12 and −0.24 for anxiety and depression, respectively. These results show that the G-factor from the latter model was more effective in predicting anxiety (37% stronger prediction on average) and depression (17% stronger prediction on average) than the G-factor estimated from the former model. Specific factors showed minor increases or decreases in their prediction of anxiety and depression, but these variations were all very small ($\Delta_\beta \leq 0.01$). Again, the amount of explained variance (R^2) across all models only varied slightly between types of bifactor model, going from 0.082 (anxiety) and 0.165 (depression) in the symmetrical bifactor model to 0.080 (anxiety) and 0.160 (depression) in the bifactor $S - 1$ model ($\Delta R^2_{anxiety} = 0.002$; $\Delta R^2_{depression} = 0.005$). These results show that both types of bifactor models have comparable predictive strength, but that the G-factor from the $S - 1$ model shows stronger point estimates compared to the symmetrical model.

We further compared the prediction accuracy of the two models by comparing the 95% CI of regression coefficients for the prediction of anxiety and depression from G- and Sfactors. Results show that the differences in 95% CI where even more pronounced with these outcomes than with grades. Regarding the G-factors, the 95% CI of the anxiety/depression predictions were, on average, reduced by just over 50% with the $S - 1$ model, compared to the symmetrical model. For anxiety, this entailed a statistically significant (and stronger) prediction in one dataset using the G-factor from the $S - 1$ model, while this prediction was not statistically significant with the G-factor from the symmetrical model in that same dataset. S-factors also had narrower 95% CI across all factors in the $S - 1$ model, with average decreases ranging from 10 to 41%.

As with grades, additional predictive models using factor scores to predict anxiety and depression symptoms were estimated. The factors scores saved from bifactor $S - 1$ models still showed slightly superior prediction over those saved from symmetrical bifactor models (Table 3). Respectively, the point estimate of the correlation between anxiety and the factor score saved from an $S - 1$ model and anxiety was on

[1] This percentage was obtained by averaging, across all studies that measured grades, the ratios for which the numerator was the beta of the prediction of grades from the G-factor of the $S - 1$ model as and the denominator was the beta of the prediction of grades from the G-factor of the symmetrical model. Hence, a ratio of 1.1 would mean a 10% stronger prediction.

Table 3 Predictive Model Results

Dataset Number:	1		2		3		5		Average			
Model Type:	*sym.*	*S* – 1	*sym.*	*S* – 1	*sym.*	*S* – 1	*sym.*	*S* – 1	*sym.*	95% CI	*S* – 1	95% CI
Grades (R^2)			(0.188)	(0.179)	(0.083)	(0.081)	(0.064)	(0.063)	(0.112)		(0.108)	
G-factor			0.15	0.24	0.12	0.18	0.15	0.21	0.14	0.02 – 0.26	0.21	0.14 – 0.28
S-Intrinsic			0.21	-	0.14	-	0.14	-	0.16	0.03 – 0.30	-	-
S-Identified			0.09	0.04	0.07	0.07	−0.01	−0.05	0.05	−0.09 – 0.19	0.02	−0.08 – 0.11
S-Introjected			−0.11	−0.18	−0.09	−0.10	−0.01	−0.02	−0.07	−0.17 – 0.03	−0.10	−0.18 – −0.02
S-External			−0.08	−0.13	−0.19	−0.19	−0.06	−0.06	−0.11	−0.20 – −0.02	−0.13	−0.21 – −0.05
S-Amotivation			−0.31	−0.27	-	-	−0.14	−0.12	−0.22	−0.32 – −0.13	−0.19	−0.27 – −0.12
Factor score (saved from G)			0.15	0.19	0.11	0.17	0.17	0.20	0.14	-	0.19	-
Anxiety (R^2)	(0.077)	(0.072)					(0.086)	(0.088)	(0.082)		(0.080)	
G-factor	−0.09	−0.12					−0.10	−0.13	−0.09	−0.30 – 0.12	−0.10	−0.19 – −0.05
S-Intrinsic	−0.08	-					−0.08	-	−0.08	−0.34 – 0.18	-	-
S-Identified	0.04	0.03					0.05	0.07	0.05	−0.18 – 0.27	0.05	−0.05 – 0.15
S-Introjected	0.16	0.15					0.18	0.19	0.17	0.08 – 0.26	0.17	0.09 – 0.24
S-External	0.12	0.12					0.08	0.08	0.10	0.02 – 0.18	0.10	0.02 – 0.17
S-Amotivation	0.14	0.14					0.18	0.17	0.16	0.03 – 0.29	0.15	0.08 – 0.23
Factor score (saved from G)	−0.07	−0.10					−0.10	−0.12	−0.08	-	−0.11	-
Depression (R^2)	(0.159)	(0.149)					(0.170)	(0.170)	(0.165)		(0.160)	
G-factor	−0.25	−0.28					−0.17	−0.20	−0.21	−0.35 – −0.06	−0.24	−0.31 – −0.17
S-Intrinsic	−0.13	-					−0.09	-	−0.11	−0.27 – 0.05	-	-
S-Identified	0.06	0.03					0.02	0.05	0.04	−0.12 – 0.21	0.04	−0.07 – 0.15
S-Introjected	0.14	0.13					0.17	0.17	0.16	0.06 – 0.25	0.15	0.08 – 0.22
S-External	0.11	0.09					0.11	0.11	0.11	0.03 – 0.19	0.10	0.03 – 0.17
S-Amotivation	0.21	0.21					0.30	0.29	0.26	0.16 – 0.35	0.25	0.18 – 0.33
Factor score (saved from G)	−0.21	−0.25					−0.17	−0.18	−0.19	-	−0.21	-

Note. The data collection from Model 4 included neither grades nor anxiety/depression symptoms. All numbers are standardized β. R^2 = Explained variance in outcome; *sym.* = Symmetrical bifactor-ESEM; *S* – 1 = Bifactor *S* – 1 ESEM; 95% CI = Total width of the 95% confidence interval average 29% stronger than the point estimate of the correlation between anxiety and the factor score saved from a symmetrical model (r from −0.08 to −0.11). For depression, the point estimate of the correlation for the factor scores saved from a bifactor $S-1$ model was 11% more effective than those saved from a symmetrical bifactor model (r from −0.19 to −0.21).

Discussion

Howard and colleagues (2020) have shown that the symmetrical bifactor-ESEM model was the best scoring or estimation method for an empirical representation of the self-determination continuum, with the strongest fit indices and greater amount of explained variance compared to other methods. In this research, we tested the bifactor $S-1$ ESEM model as an alternative strategy to the symmetrical bifactor-ESEM model in which the general factor was anchored in intrinsic motivation, the most self-determined type of motivation, thereby allowing for a precise conceptual specification of all factors.

Model Specification

As expected, comparative analysis of both models first showed that they were largely equivalent in terms of model fit. This implies that both models represent the data well, and that both can be considered potentially valid representations of the self-determination continuum. In terms of factor loadings and factor validity, the G-factor in the $S-1$ model was more weighted on intrinsic motivation and showed decreasing loadings for items of subsequent motivation types along the self-determination continuum, partly supporting our first hypothesis. The G-factor in the symmetrical model generally showed a similar pattern, except for the third dataset in which the average loading for identified regulation items were stronger than the average loading for intrinsic items. Furthermore, factor validity in both model types was similar for the G-factor, suggesting that the two strategies for modeling the general factor capture roughly equivalent amount of variance among all items, although its distribution varies. With the symmetrical model, the distribution of factor loadings on the G-factor across items of the self-determination continuum was spread more evenly between the various motivation types. Regarding the S-factors, they were on average slightly less reliable in the symmetrical model compared to the $S-1$ model, albeit this difference was small.

Globally, although both models fitted the data well, generally respected the ordering of motivation types with regards to the item loadings on the G-factor, and resulted in reliable G-factors, the higher loadings for the intrinsic motivation items on the G-factor in the $S-1$ model may be the key to a better-defined G-factor that achieves better prediction of relevant outcomes.

Predictive Power

While both types of bifactor models were comparable in terms of amount of variance explained in each outcome, the bifactor $S-1$ model is second to none in terms of strength of prediction of grades, anxiety, and depression by the G-factor. On average, this meant an increased prediction strength of student outcomes when comparing G-factors. We note that the absolute difference between the point estimates of the predictions were small in general (average difference of 0.047). However, the fact that both models are nested and that the G-factor from the more parsimonious $S-1$ model is a stronger predictor of outcomes illustrates that the way the variance is pooled into the G-factor in the $S-1$ bifactor model is more relevant for outcome prediction than the way it is pooled for that factor in the symmetrical bifactor model. Notably, modeling the self-determination continuum with an $S-1$ model instead of a symmetrical model resulted in a considerable reduction in the width of the confidence intervals of the prediction of grades, anxiety, and depression symptoms. For the G-factors, this entailed an average reduction in the width of the 95% CI in outcome prediction of 48.4%. This increased precision in prediction is important as studies modeling the self-determination continuum with an $S-1$ model are less likely to yield Type 1 error (i.e., incorrectly infer that the G-factor does not predict important outcomes). The stronger prediction accuracy also occurred with S-factors, which showed a reduction in the width of the 95% CI in outcome prediction by these factors. These results illustrate that G- and S-factors estimated with an $S-1$ bifactor model are better at predicting outcomes, possibly because they are defined with clearer conceptual boundaries. It may also be that they are less prone to capturing irrelevant sources of variance compared to the symmetrical bifactor model. Indeed, because the G-factor is anchored in intrinsic motivation, it should not capture undesirable variance measured in the self-determination continuum that is not specifically shared by intrinsic motivation items.

What Is the Meaning of the General and Specific Factors?

The meaning of factors in bifactor models is a debated issue, especially in the case of asymmetrical contribution to the G-factor. Proponents of the model posit that the G-factor captures “variance shared among all indicators” (Morin, 2021, Hierarchically-Ordered Constructs section), while S-factors capture “the variance shared among all indicators forming a subscale beyond that explained by the G-factor” (Morin, 2021, Hierarchically-Ordered Constructs section). In models where one can expect items to have a relatively similar contribution to the G-factor, such as with psychological need satisfaction (Garn, 2018), the information mapped on by the G-factor is straightforward (e.g., overall need satisfaction), and so is the information kept in the S-factors (e.g., competence satisfaction beyond overall need satisfaction), even when they are poorly defined. However, applied to the estimation of the self-determination continuum, S-factor definitions can be somewhat vague because many items along the continuum have little common variance, meaning that they will largely vary in their respective contribution to the G-factor (some highly positive, some medium positive, some low positive or null, some negative). With a symmetrical bifactor model, common variance is extracted to create an empirically driven G-factor that maximizes overall shared variance. While this representation is valuable, it comes with drawbacks. First, the actual meaning of the G-factor in the symmetrical model must be confirmed or inferred on a study-by-study basis through the inspection of factor loadings to the G-factor, and it can show notable variations in meaning depending on the motivation types included in the analysis (Heinrich et al., 2021). Second, an overall representation also means that the G-factor may capture other sources of irrelevant common variance (e.g., acquiescence, response style).

The $S-1$ model solves these issues by first anchoring the G-factor in intrinsic motivation indicators, “a prototypical example of autonomous behavior” (Ryan & Deci, 2017, p.117) and thus of self-determination. Then, other items load on the G-factor based on their shared meaning with intrinsic motivation. Within a motivation type, the combined G-factor loadings represent the extent to which that motivation type conveys self-determination. This contribution is naturally very strong for intrinsic motivation and fades as one progresses down the continuum toward amotivation (where the prediction becomes negative).

In addition, S-factors also have a clear meaning in the $S-1$ model type. Indeed, since these factors are all orthogonal to the self-determination G-factor, their meaning can be interpreted as what is common to their indicators but is unrelated to self-determination. As a result, S-factors can be interpreted as the purely non-self-determined facet of these extrinsic motivations. For amotivation, it is rather the variance attributed to indifference or apathy, purged from its “active disinterest” aspect, which loads negatively on the G-factor. These interpretations show that a model that estimates a G-factor with clearer conceptual boundaries also allows for more conceptual clarity on the S-factors.

Next Steps

The main takeaways from this research are twofold. First, a G-factor derived from a bifactor $S-1$ model of the self-determination continuum is more powerful in outcome prediction—and its prediction has a reduced scope of uncertainty around it—than a G-factor derived from a symmetrical bifactor model. Researchers looking for more conceptual accuracy in their estimation of the self-determination continuum would benefit from using a bifactor $S-1$ estimation, especially if they aim to predict key outcomes using the G-factor (whether latent or with factor scores). Second, a bifactor $S-1$ model also allows for a better use of the S-factors, as their interpretation is not dependent on factor loadings. Hence, they always pertain to variance in a motivation type that does not relate to intrinsic motivation. Furthermore, factors would show more conceptual stability, as the meaning of the G-factor is less likely to fluctuate from one study to another compared to when using a symmetrical bifactor model. This, however, remains a question to be empirically tested. Because all the items present in the model are important to determine what variance in intrinsic motivation will be specifically included in the G-factor, some shift in the meaning of the G-factor could also be expected with a bifactor $S-1$ model.

All in all, using a bifactor $S-1$ model allows to make predictions regarding the added advantage of various motivation types over a global level of self-determination. Hence, not only will these estimations be more accurate, but they are also likely to be more comparable across studies. Importantly, motivational researchers sometimes include or exclude various motivation types such as amotivation (Guay & Bureau, 2018), material/social external regulation (Gagné et al., 2015), approach or avoidance types of introjected regulation (Assor et al., 2009) and types of intrinsic motivation (Carbonneau et al., 2012). Testing the robustness of the model with such variations remains to be done. To maximize the stability and benefits of the bifactor $S-1$ model, the G-factor should always be anchored in intrinsic motivation to be concordant with SDT assumptions. To this effect we recommend including only one type of intrinsic motivation even when more are available (preferably IM to know or IM to accomplish, as they both show similar contribution to the prediction of outcomes; Howard, Chong, et al., 2020). If necessary, other intrinsic motivation facets can be estimated within the model as S-factors.

Is the Bifactor *S* – 1 Model Better for All Applications?

While there are compelling advantages for a bifactor *S* – 1 model applied to the self-determination continuum, this model is not the be-all and end-all of bifactor modeling. In some situations, it might bring few to no advantages over the symmetrical bifactor model. For example, when various dimensions of a construct are expected to have similar contributions to the G-factor, and when the theory does not explicitly state that one factor is prototypical in representing the G-factor (both of which are not the case with the self-determination continuum), then the *S* – 1 bifactor model brings no conceptual advantage. Recent argumentation on the subject is clear that the symmetrical bifactor model is, in general, a robust and coherent model for many measurement situations (Morin, 2021). Although a pertinent use of the bifactor *S* – 1 model seems to be very contextualized, our results show that its use for modeling the self-determination continuum has consistent and compelling advantages that should not be overlooked.

Conclusions

When first introduced, the self-determination continuum brought forward distinctive features. On the one hand, it detailed a plurality of multifaceted components that each carries qualitative information to how individuals are motivated. On the other hand, it presented all these facets as elements of varying motivational strength along a continuum of self-determination. The bifactor *S* – 1 model is a convenient way of modeling the self-determination continuum to capture those distinctive features with conceptual clarity (i.e., a clear meaning for each factor), enabling a prediction of relevant outcomes with the best accuracy (lowest confidence intervals) and strength (highest regression coefficients).

Declarations

The data that support the findings of this study are available on request from the corresponding author.

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References

Assor, A., Vansteenkiste, M., & Kaplan, A. (2009). Identified versus introjected approach and introjected avoidance motivations in school and in sports: The limited benefits of self-worth strivings. *Journal of Educational Psychology*, *101*(2), 482–497. http://ovidsp.ovid.com/ovidweb.cgi?T=JS &CSC=Y&NEWS=N&PAGE=fulltext&D=ovftj&AN=00004760-200905000-00019

Bureau, J. S., Gareau, A., Guay, F., & Mageau, G. A. (2022). Investigating how autonomy-supportive teaching moderates the relation between student honesty and premeditated cheating. *British Journal of Educational Psychology, 92,* 175–193. https://doi.org/10.1111/bjep.12444

Bureau, J. S., Howard, J. L., Chong, J. X. Y., & Guay, F. (2021). Pathways to student motivation: A meta-analysis of antecedents of autonomous and controlled motivations. *Review of Educational Research*, 003465432110424. https://doi.org/10.3102/00346543211042426

Burns, G. L., Geiser, C., Servera, M., Becker, S. P., & Beauchaine, T. P. (2019). Application of the Bifactor S – 1 Model to Multisource Ratings of ADHD/ODD Symptoms: an Appropriate Bifactor Model for Symptom Ratings. *Journal of Abnormal Child Psychology 2019*, *48:7*(7), 881–894. https://doi.org/10.1007/S10802-019-00608-4. *48*

Carballeira, Y., Dumont, P., Borgacci, S., Rentsch, D., de Tonnac, N., Archinard, M., & Andreoli, A. (2007). Criterion validity of the French version of Patient Health Questionnaire (PHQ) in a hospital department of internal medicine. *Psychology and Psychotherapy: Theory Research and Practice*, *80*(1), 69–77. https://doi.org/10.1348/147608306X103641

Carbonneau, N., Vallerand, R. J., & Lafrenière, M. A. K. (2012). Toward a tripartite model of intrinsic motivation. *Journal of Personality*. https://doi.org/10.1111/j.1467-6494.2011.00757.x

Chemolli, E., & Gagne, M. (2014). Evidence against the continuum structure underlying motivation measures derived from self-determination theory. *Psychological Assessment*, *26*(2), 575–585. http://ovidsp.ovid.com/ovidweb.cgi?T=JS &CSC=Y&NEWS=N&PAGE=fulltext&D=ovftp&AN=00012030-201406000-00020

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling*, *14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Covington, M. V. (2000). Intrinsic versus extrinsic motivation in schools: A reconciliation. *9(1), 22–25.*https://doi-Org.Acces.Bibl.Ulaval.ca/10.1111/1467-8721.00052. https://doi.org/10.1111/1467-8721.00052

Deci, E. L. (1971). Effects of externally mediated rewards on intrinsic motivation. *Journal of Personality and Social Psychology*, *18*(1), 105–115. https://doi.org/10.1037/H0030644

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Plenum

Edwards, J. R. (2001). Ten difference score myths: *Https://Doi.Org/10.1177/109442810143005*, *4*(3), 265–287. https://doi.org/10.1177/109442810143005

Forbes, M. K., Greene, A. L., Levin-Aspenson, H. F., Watts, A. L., Hallquist, M., Lahey, B. B., Markon, K. E., Patrick, C. J., Tackett, J. L., Waldman, I. D., Wright, A. G. C., Caspi, A., Ivanova, M., Kotov, R., Samuel, D. B., Eaton, N. R., & Krueger, R. F. (2021). Three recommendations based on a comparison of the reliability and validity of the predominant models used in research on the empirical structure of psychopathology. *Journal of Abnormal Psychology*, *130*(3), 297–317. https://doi.org/10.1037/ABN0000533

Gagné, M., Forest, J., Vansteenkiste, M., Crevier-Braud, L., van den Broeck, A., Aspeli, A. K., Bellerose, J., Benabou, C., Chemolli, E., Güntert, S. T., Halvari, H., Indiyastuti, D. L., Johnson, P. A., Molstad, M. H., Naudin, M., Ndao, A., Olafsen, A. H., Roussel, P., Wang, Z., & Westbye, C. (2015). The Multidimensional Work Motivation Scale: Validation evidence in seven languages and nine countries. *European Journal of Work and Organizational Psychology*, *24*(2), 178–196. https://doi.org/10.1080/1359432X.2013.877892

Garn, A. C. (2018). Basic psychological need satisfaction toward learning: A longitudinal test of mediation using bifactor exploratory structural equation modeling. *Journal of Educational Psychology*, *111*(2), 354. https://doi.org/10.1037/EDU0000283

Gilal, F. G., Chandani, K., Gilal, R. G., Gilal, N. G., Gilal, W. G., & Channa, N. A. (2020). Towards a new model for green consumer behaviour: A self-determination theory perspective. *Sustainable Development*, *28*(4), 711–722. https://doi.org/10.1002/SD.2021

Gilbert, W., Bureau, J. S., Poellhuber, B., & Guay, F. (2021). Predicting college students' psychological distress through basic psychological need-relevant practices by teachers, peers, and the academic program. *Motivation and Emotion, 45,* 436–455. https://doi.org/10.1007/s11031-021-09892-4

Gillet, N., Morin, A. J. S., Huart, I., Odry, D., Chevalier, S., Coillot, H., & Fouquereau, E. (2018). Self-determination trajectories during police officers' vocational training program: A growth mixture analysis. *Journal of Vocational Behavior*, *109*, 27–43. https://doi.org/10.1016/J.JVB.2018.09.005

Gillet, N., Morin, A. J. S., Ndiaye, A., Colombat, P., & Fouquereau, E. (2020). A test of work motivation profile similarity across four distinct samples of employees. *Journal of Occupational and Organizational Psychology*, *93*(4), 988–1030. https://doi.org/10.1111/JOOP.12322

Guay, F., Senécal, C., Gauthier, L., & Fernet, C. (2003). Predicting career indecision: A self-determination theory perspective. Journal of counseling psychology, 50, 165–177. https://doi-org.acces.bibl.ulaval.ca/10.1037/0022-0167.50.2.165

Guay, F., Ratelle, C. F., Roy, A., & Litalien, D. (2010). Academic self-concept, autonomous academic motivation, and academic achievement: Mediating and additive effects. Learning and Individual Differences, 20, 644–653. https://doi.org/10.1016/j.lindif.2010.08.001

Guay, F., Ratelle, C., Larose, S., Vallerand, R. J., & Vitaro, F. (2013). The number of autonomy-supportive relationships: Are more relationships better for motivation, perceived competence, and achievement?. *Contemporary Educational Psychology, 38,* 375–382. https://doi.org/10.1016/j.cedpsych.2013.07.005

Guay, F., & Bureau, J. S. (2018). Motivation at school: Differentiation between and within school subjects matters in the prediction of academic achievement. *Contemporary Educational Psychology*, *54*. https://doi.org/10.1016/j.cedpsych.2018.05.004

Guay, F., Morin, A. J. S., Litalien, D., Howard, J. L., & Gilbert, W. (2021). Trajectories of self-determined motivation during the secondary school: A growth mixture analysis. *Journal of Educational Psychology*, *113*(2), 390–410. https://doi.org/10.1037/EDU0000482

Hand, E. D., & Lonigan, C. J. (2021). Examining the Relations between Preschooler's Externalizing Behaviors and Academic Performance Using an S-1 Bifactor Model. *Research on Child and Adolescent Psychopathology*, 1–13. https://doi.org/10.1007/S10802-021-00861-6/TABLES/3

Heinrich, M., Zagorscak, P., Eid, M., & Knaevelsrud, C. (2020). Giving G a Meaning: An application of the bifactor-(S-1) approach to realize a more symptom-oriented modeling of the Beck Depression Inventory–II. *Assessment*, *27*(7), 1429–1447. https://doi.org/10.1177/1073191118803738

Heinrich, M., Geiser, C., Zagorscak, P., Burns, G. L., Bohn, J., Becker, S. P., Eid, M., Beauchaine, T. P., & Knaevelsrud, C. (2021). On the Meaning of the " P Factor" in Symmetrical Bifactor Models of Psychopathology: Recommendations for Future Research From the Bifactor-(S – 1) Perspective. *Assessment*, 107319112110602. https://doi.org/10.1177/10731911211060298

Howard, J. L., Gagné, M., & Bureau, J. S. (2017). Testing a continuum structure of self-determined motivation: A meta-analysis. *Psychological Bulletin*, *143*(12), https://doi.org/10.1037/bul0000125

Howard, J. L., Chong, J. X. Y., & Bureau, J. S. (2020a). The tripartite model of intrinsic motivation in education: A 30-year retrospective and meta-analysis. Journal of Personality, 88(6), 1268–1285. https://doi.org/10.1111/jopy.12570

Howard, J. L., Gagné, M., & Morin, A. J. S. (2020b). Putting the pieces together: reviewing the structural conceptualization of motivation within SDT. Motivation and Emotion, 44, 846–861. https://doi.org/10.1007/s11031-020-09838-2

Howard, J. L., Gagné, M., Van den Broeck, A., Guay, F., Chatzisarantis, N., Ntoumanis, N., & Pelletier, L. G. (2020c). A review and empirical comparison of motivation scoring methods: An application to self-determination theory. Motivation and Emotion 2020c, 44:4(4), 534–548. https://doi.org/10.1007/S11031-020-09831-9. 44

Howard, J. L., Bureau, J. S., Guay, F., Chong, J. X. Y., & Ryan, R. M. (2021). Student motivation and associated outcomes: A meta-analysis from self-determination theory. *Perspectives on Psychological Science*. https://doi.org/10.1177/1745691620966789

Johns, G. (1981). Difference score measures of organizational behavior variables: A critique. *Organizational Behavior and Human Performance*, *27*(3), 443–463. https://doi.org/10.1016/0030-5073(81)90033-7

Koestner, R., Otis, N., Powers, T. A., Pelletier, L. G., & Gagnon, H. (2008). Autonomous motivation, controlled motivation, and goal progress. *Journal of Personality*, *76*(5), 1201–1230. https://doi.org/10.1111/J.1467-6494.2008.00519.X

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9. *Journal of General Internal Medicine*, *16*(9), 606–613. https://doi.org/10.1046/J.1525-1497.2001.016009606.X

Marsh, H. W., Hau, K. T., Balla, J. R., & Grayson, D. (1998). Is more ever too much? The number of indicators per factor in confirmatory factor analysis. 33(2), 181–220. http://Dx.Doi.Org.Acces.Bibl.Ulaval.ca/10.1207/S15327906mbr3302_1. https://doi.org/10.1207/S15327906MBR3302_1

Micoulaud-Franchi, J. A., Lagarde, S., Barkate, G., Dufournet, B., Besancon, C., Trébuchon-Da Fonseca, A., Gavaret, M., Bartolomei, F., Bonini, F., & McGonigal, A. (2016). Rapid detection of generalized anxiety disorder and major depression in epilepsy: Validation of the GAD-7 as a complementary tool to the NDDI-E in a French sample. *Epilepsy & Behavior*, *57*, 211–216. https://doi.org/10.1016/J.YEBEH.2016.02.015

Morin, A. J. S., Marsh, H. W., & Nagengast, B. (2013). Exploratory structural equation modeling. In G. R. Hancock, & R. O. Mueller (Eds.), *Structural equation modeling: A second course* (2nd ed., pp. 395–436). Information Age Publishing, Inc

Morin, A. J. S. (2021). Exploratory structural equation modeling. In R. H. Hoyle (Ed.), *Handbook of Structural Equation Modeling* (2nd editio). Guilford

Ryan, R. M., & Connell, J. P. (1989). Perceived locus of causality and internalization: Examining reasons for acting in two domains. *Journal of Personality and Social Psychology*, *57*(5), 749–761. https://doi.org/10.1037/0022-3514.57.5.749

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. The Gilford Press

Sebire, S. J., Jago, R., Fox, K. R., Edwards, M. J., & Thompson, J. L. (2013). Testing a self-determination theory model of children's physical activity motivation: a cross-sectional study. *International Journal of Behavioral Nutrition and Physical Activity 2013 10:1*, *10*(1), 1–9. https://doi.org/10.1186/1479-5868-10-111

Sheldon, K. M., & Elliot, A. J. (1998). Not all personal goals are personal: Comparing autonomous and controlled reasons for goals as predictors of effort and attainment. *Personality and Social Psychology Bulletin*, *24*(5), 546–557. https://doi.org/10.1177/0146167298245010

Spitzer, R. L., Kroenke, K., Williams, J. B. W., & Löwe, B. (2006). A Brief Measure for Assessing Generalized Anxiety Disorder: The GAD-7. *Archives of Internal Medicine*, *166*(10), 1092–1097. https://doi.org/10.1001/ARCHINTE.166.10.1092

Thöne, A. K., Junghänel, M., Görtz-Dorten, A., Dose, C., Hautmann, C., Jendreizik, L. T., Treier, A. K., Vetter, P., von Wirth, E., Banaschewski, T., Becker, K., Brandeis, D., Dürrwächter, U., Geissler, J., Hebebrand, J., Hohmann, S., Holtmann, M., Huss, M., Jans, T., & Döpfner, M. (2021). Disentangling symptoms of externalizing disorders in children using multiple measures and informants. *Psychological Assessment*. https://doi.org/10.1037/PAS0001053

Tóth-Király, I., Morin, A. J. S., Bőthe, B., Rigó, A., & Orosz, G. (2021). Toward an Improved Understanding of Work Motivation Profiles. *Applied Psychology*, *70*(3), 986–1017. https://doi.org/10.1111/APPS.12256

Vallerand, R. J., Pelletier, L. G., Blais, M. R., Briere, N. M., Senecal, C., & Vallieres, E. F. (1992). The academic motivation scale: A measure of intrinsic, extrinsic, and amotivation in education. *Educational and Psychological Measurement*, *52*(4), 1003–1017. https://doi.org/10.1177/0013164492052004025

Vasconcellos, D., Parker, P. D., Hilland, T., Cinelli, R., Owen, K. B., Kapsal, N., Antczak, D., Lee, J., Ntoumanis, N., Ryan, R. M., & Lonsdale, C. (2020). Self-determination theory applied to physical education: A systematic review and meta-analysis. *Journal of Educational Psychology*, *112*(7), 1444. https://doi.org/10.1037/edu0000420

Villeneuve, P., Valois, P., Frenette, E., & Sévigny, S. (1996). Nonparametric analyses of the psychological distress questionnaire of Santé-Québec [Analyses d'items non-paramétriques du questionnaire de détresse psychologique de l'enquête Santé Québec]. *Communication Présentée Au XIXe Congrès Annuel de La SQRP. Université Du Québec à Trois-Rivières*

Wallhead, T., Garn, A. C., Vidoni, C., & Youngberg, C. (2013). Game Play Participation of Amotivated Students During Sport Education. *Journal of Teaching in Physical Education*, *32*(2), 149–165. https://doi.org/10.1123/JTPE.32.2.149