The Radex Structure of Motivation

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ABSTRACT

Self-determination theory is a multi-dimensional approach to human motivation which proposes that motivation is driven by a range of classifiably distinct regulation styles. However these different regulations are also considered to fall along a continuum of self-determination which strongly implies that only a single factor (the degree of self-regulation present) is important. It is currently not clear in the theory how motivation can be considered both a multi-dimensional and single-dimensional construct. The current set of studies explore the structure of motivation through a range of advanced statistical methodologies and meta-analysis. Specifically, Chapter 2 explores the possibility of specifying a continuum of self-determination alongside the independently specified regulation factors in Bifactor Exploratory Structural Equation Modeling (B-ESEM). Results indicate the importance of a continuum, but also demonstrate the importance of individual regulation factors in addition to this continuum. Chapter 3 applies Latent Profile Analysis (LPA) to two samples of employees from Belgium and Canada in order to examine how combinations of motivation are experienced from a more naturalistic form of analysis (i.e. person-centered analysis). Results support a continuum interpretation. Finally, Chapter 4 presents a meta-analytic investigation of the simplex-like pattern of regulations, before also applying multidimensional scaling (MDS) to 486 independent samples from across five major life domains. The simplex-like pattern was confirmed meta-analytically and MDS graphically represents this continuum. However, as with Chapter 2, MDS indicates that a more complex two-dimensional representation of motivation may also be valid and represent meaningful elements of the structure of motivation. In summary, results of this dissertation support a radex structure of motivation in which regulations are predictably ordered by degree of self-determination (but not structured as a continuum) while also maintaining their unique qualities as distinct factors.
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This thesis has been substantially accomplished during enrolment in the degree.

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This thesis contains work that has been published and/or prepared for publication.

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Chapter 1

Dissertation Introduction

One of the perennial, yet under-developed questions in motivational psychology over the last 30 years has been the debate around whether a single motivational force drives all behavior or whether there are multiple forms of motivation each with distinctive characteristics. Self-Determination Theory (SDT; Deci & Ryan, 1985) has blossomed over these years and is a leading theory in the multiple motivations camp. SDT specifies several regulatory mindsets which guide individual behavior based upon how self-determined or volitional the behavior is. This is important in SDT as it is proposed that each of these regulations will produce different outcomes in terms of well-being, task performance, and commitment to a course of action (Cerasoli, Nicklin, & Ford, 2014; Gagne et al., 2015; Ng, Ntoumanis, Thogersen-Ntoumani, Deci, Ryan, Duda, & Williams, 2012). However, upon closer inspection of the theory, confusion arises as to the nature of the regulations being proposed as they are often said to fall along a continuum of self-determination. This implies that the regulations are not in fact distinct factors but merely points along a continuum, leading to the position that motivation can be measured through a single measure of quantity. This seemingly contradicts the defining proposition of SDT, which states that we each hold various distinguishable types of motivation which have important implications for our behavior. This confusion has raised further questions concerning whether motivation is best described as a single entity characterized only through the quantity of motivation present, or whether the unique qualities of different regulations are also important predictors of behavior. This dissertation will attempt to clarify this distinction between quantity and quality of motivation within SDT and in doing so empirically test the structure of motivation. The aim of this dissertation is to establish a theoretical structure of motivation which, in turn will enable future research to
investigate further analytical issues such as optimal operationalization procedures. **Self-Determination Theory**

SDT differentiates between the goal or outcome and the regulatory process driving behavior towards that goal (Deci & Ryan, 2000). That is, SDT describe *reasons why* activities are pursued through the specification of multiple regulatory processes, known as regulations. In addition to the regulations, it also describes the process through which these regulatory processes are driven, that is, through satisfaction of basic psychological needs. Specifically, SDT posits that the pursuit of desired goals will result in a certain degree of basic need satisfaction, which will then determine the type of regulation an individual experiences. The type of regulation driving behavior is then a telling predictor of how successful goal striving will be. Self-determination theory specifies three basic psychological needs – autonomy, competence, and relatedness – which are essential in understanding why chosen goals are valued by an individual, and the experiential process an individual undergoes during goal pursuit behaviors (Deci & Ryan, 2000). As will be discussed in a subsequent section, needs are essential to SDT as they drive the internalization process, that is, the process through which initially controlled behaviors become more autonomously controlled (Deci & Ryan, 2000). As a result, the satisfaction of basic need determines the type of regulation an individual experiences when pursuing motivated behavior. These types of regulation, each with unique characteristics but orderable by the degree of internalization, or self-determination, as detailed below.

Intrinsic motivation describes purely self-determined motivation. An individual driven by intrinsic motivation enjoys, or finds the behavior interesting in and of itself. This type of motivation does not require any external reinforcement, and may even be diminished by such forces as they may adjust the individual’s focus from the inherent
interest of the behavior towards external coercive forces (Deci, Koestner, & Ryan, 1999; 2001). Instead, promoting and maintaining this type of self-driven motivation requires only the satisfaction of the three basic psychological needs, and leads to outcomes such as vitality, proactivity, and effort, as well as reduced emotional exhaustion (Gagne et al., 2015). The remaining regulations are often classified as extrinsic motivation, as they are influenced to some degree by external forces beyond an individual’s own interest.

External regulation is the least internalized form of regulation in which behavior is coerced by the promise (or threat) of external rewards (or punishments). These coercive factors can be either material (e.g. financial) or social (gaining others approval; Gagne et al., 2015). Individuals acting under this type of regulation do not find the behavior interesting or enjoyable in the least, but will perform in order to attain (or avoid) the associated rewards (or punishments). While this form of regulation is all too commonly used, especially in workplaces, but also in many other domains such as parenting and education, the results of such forms of motivation are mixed. In general this regulation type will lead to performance of the target behavior, but much evidence has suggested that such a regulatory focus will not lead to any extended participation in the behavior (Deci, Koestner, & Ryan, 1999), and is likely to have a detrimental impact on the individual’s well-being (Deci & Ryan, 2000; Gagne & Deci. 2005). For example, in a meta-analysis by Ng and colleagues (2012) it was found that external regulation was positively associated with depression, anxiety, and negative affect, and negatively related to vitality and quality of life. Cerasoli, Nicklin, and Ford, (2014) provide an excellent comparison of the effects of external regulation and intrinsic motivation in which it was found that while both external regulation and intrinsic motivation were predictive of quantity of work undertaken, only intrinsic motivation was related to quality of work completed. In summary, external regulation may lead individuals to engage in the target
behavior (as long as the reward or the punishment is in effect), but due to their lack of interest and engagement, they will exert only the minimum required effort and likely suffer poor well-being in addition.

Introjected regulation represents behavior which is pursued in order to avoid negative self-related feelings (e.g., guilt, shame), or to gain positive self-related feelings (e.g., pride). This is still considered a relatively controlled type of regulation often described as partially internalized. The contingent rewards associated with introjected regulation are self-administered through self-esteem related thoughts and emotions (Ryan & Deci, 2000). For example, after attaining a goal driven by introjected regulation, an individual is likely to feel proud of their accomplishment. Alternatively, a sportsperson who performs poorly is like to experience feelings of shame or guilt for not living up to the expectations of the coach or teammates, which exemplifies the more negative side of introjected regulation. While not receiving any external reward or even encouragement, these individual will be somewhat driven to accomplish even undesirable tasks in order to achieve this stage of elevated self-esteem. This type of regulation is more likely to be sustained over time but is ultimately not considered a stable form of regulation as behavior remains dependent of contingent consequences, albeit self-administered ones, with further behavior unlikely when dissociated from the self-esteem based outcomes (Koestner, Losier, Vallerand, & Carducci, 1996). The dual nature of introjected regulation is demonstrated clearly in the health domain by meta-analytic findings linking introjection with negative outcomes such as depression and anxiety, as well as positive factors such as engagement in physical education and maintaining a healthy diet (Ng et al., 2012).

Identified regulation is a more highly internalized form of extrinsic motivation commonly specified in SDT. Identified regulation is characterized by recognition of the
value inherent in the behavior. Individuals experiencing identified regulation find meaning in the behavior and actively pursue it, rather than relying on coercive forces as characterized by introjected and external regulations. Due to this internal, positive, and growth oriented approach to motivated behavior, identified regulation is considered to be an autonomous form of motivation. However this is distinct from intrinsic motivation as the behavior itself is not enjoyed, it is the outcome that is valued. Identified regulation has proven to be a strong predictor of variables such as vitality, and positive affect (Ng et al., 2012), as well as participation in voluntary voting behavior (Koestner, Losier, Vallerand, & Carducci, 1996), and has even been shown to be a more effective predictor of positive results than even intrinsic motivation (Koestner, Losier, Vallerand, & Carducci, 1996; Ng et al., 2012). Behavior driven by identified regulation is likely to be maintained over time (Burton, Lydon, D’alessandro, & Koestner, 2006), and specifically may result in greater short term participation in exercise, for example, whereas intrinsic regulation may lead to exercise being sustained over a longer duration (Teixeira, Carraça, Markland, Silva, & Ryan, 2012). Both intrinsic motivation and identified regulation are likely to be sustained longer than less autonomous regulations (i.e. introjected and external) as the reasons for action are likely deeper and less fickle than external or internal coercive rewards which are central to external and introjected regulations respectively (Teixeira et al., 2012).

Integrated regulation is considered to be more internalized than identified regulation and represents instances in which the meaning of target behaviors is integrated into the individual’s sense of self, and is congruent with personal values, interests, and beliefs (Deci, Ryan & Guay, 2013; Ryan & Deci, 2000). For example, through childhood every child learns values and perspectives from their family and context which often persist into adulthood, whether it be a concern for the environment, dedication to particular hobbies, or something as simple as a tendency to keep ones house tidy. All of
these instances fall into the category of integrated regulation, in which individuals have assimilated these beliefs and reasons for behaving into their sense of self, or self-identity. It is distinguishable from identified regulation in that behaviors driven by identified regulation are instrumental in achieving a perceived meaningful outcome (e.g. environmental sustainability), whereas behaviors driven by integrated regulation are not instrumental but are themselves accepted parts of an individual’s identity. In other words, while not enjoyable or particularly meaningful, I like to keep my house clean because that is what I am and what I do. Integrated regulation has been associated with positive outcomes across domains such as athlete flow, job satisfaction and commitment, and negatively with factors such as athlete burnout, employee strain, and employee turnover (Lonsdale, Hodge, & Rose, 2008; Tremblay, Blanchard, Taylor, Pelletier, & Villeneuve, 2009).

Amotivation is often depicted along the continuum of self-determination, although as will be discussed further in a subsequent section, many disagree with this as amotivation is by definition a lack of motivation. Amotivation is defined as a lack of intention to enact behavior, as opposed to either intrinsic or extrinsic motivation, which are all instances of intentional behavior (Ryan & Deci, 2000). Predictably, amotivation is uniformly associated with poor performance (e.g. reduced performance, proactivity, and job effort; Gagne et al., 2015) and well-being (depression, anxiety, reduced positive affect and quality of life; Ng et al., 2012), across life domain.

Other instances of less commonly used regulations include three subscales of intrinsic motivation as measured in the Academic Motivation Scale and the Sports Motivation Scale (Vallerand et al., 1989; Vallerand, Pelletier, Blais, Briere, Senecal, & Vallieres, 1992). Intrinsic motivation to know represents the inherent satisfaction and enjoyment of learning and trying to understand something new (Vallerand et al., 1992).
Intrinsic motivation towards accomplishment is characterized by the pleasure of trying to accomplish something challenging or creating something, while intrinsic motivation to experience stimulation is said to motivate behaviors which involve inherent enjoyment, aesthetic pleasure, or other sensory excitement (Vallerand et al., 1992). While some studies have separated these subscales psychometrically, and provided some evidence towards differential predication (Guay et al., 2015; Pelletier et al., 1995; 2013), these regulations are always very highly correlated (Vallerand et al., 1992) and as such are not operationalized in the vast majority of SDT research.

A range of scales are available across many life domains including work, education, sport, exercise, and health (as described in detail in Chapter 4). Measures generally ask participants why they enact behaviors in the specific domain (e.g. I put effort into my work because...), with subscales representing the reasons above listed reasons (e.g. My work is enjoyable; I would feel guilty if I didn’t; etc.). These scales generally include four subscales (intrinsic, identified, introjected, and external regulations), although amotivation is also commonly distinguishable when included (e.g. Gagné et al., 2015; Markland & Tobin, 2004; Lonsdale, Hodge, & Rose, 2008). While some scales also include integrated regulation and/or intrinsic motivation subscales (Pelletier, Fortier, Vallerand, Tuson, Brière, & Blais, 1995; Vallerand, Pelletier, Blais, Briere, Senécal, & Vallieres, 1992), these are consistently too highly correlated strongly with theoretically adjacent regulations and consequently not widely used.

Using these scales, the regulations are operationalized in a number of ways across studies. One way is through the construction of latent factors representing each of the regulations (i.e. intrinsic, identified, introjected, etc.), through CFA (see Gagné et al., 2010; 2015; Tremblay et al., 2009). These factor scores are then be used in further structural equation modeling or alternate procedures. Alternatively, various means of
forming composite scores are also practiced, with the Relative Autonomy Index the most common (Grolnick & Ryan, 1987). While specifics of this approach will be discussed later, it is in essence a single score created through the weighted aggregation of regulation subscales. Finally, some researchers form composite scores representing autonomous and controlled motivations through higher-order factor analysis (De Cooman, Stynen, Van den Broeck, Sels, & De Witte, 2013; Gagne et al., 2010). These usually consist of autonomous motivation being an aggregate of intrinsic motivation and identified regulations (and integrated if available), whereas external motivation consists of introjected and external regulation (as well as amotivation when measured).

While the regulations are commonly described in terms of their relative position along a continuum, ranging from least self-determined (e.g. amotivation or external regulation), to most self-determined with intrinsic motivation, they each incorporate unique characteristics. These unique characteristics, tacitly accepted in all SDT scales, specify a multidimensional representation of motivation in the form of regulations, which has been supported by each validation study of these scales (e.g. Gagne et al., 2015; Pelletier et al., 1995; Vallerand et al., 1992). Why should regulations be distinguishable if they differ only as a function of self-determination? This is seemingly a fundamental contradiction in the theory as regulations cannot be defined by unique characteristics if they are proposed to fall along a single continuum. In the case of a continuum, the only axis on which the regulations would be free to vary would be degree of self-determination. Despite constant reference to this continuum structure in SDT (Deci & Ryan, 1985; Deci & Ryan, 2000; Gagne & Deci, 2005), the very definition of the regulations, in which unique properties beyond the mere degree of self-determination are specified, brings into question this proposition and highlights the contradiction.

The Continuum of Self-Determination
The theory maintains that a continuum of self-determination underlies the regulations proposed by SDT (Ryan & Connell, 1989). It suggests that through a process of internalization, similar to the assimilation processes described in the parenting domain (Grusec & Goodnow, 1994), a person can move from more controlled types of motivation (e.g., external regulation) to more autonomous forms (introjected, identified, and intrinsic). This process of internalization describing how beliefs, values, and actions are assimilated into an individual’s sense of self from any range of initially external sources (Ryan, 1995). The driving force behind this process, according to SDT, is the satisfaction of three basic psychological needs of autonomy, competence, and relatedness (Deci & Ryan, 1985; 2000). Autonomy is described as a sense of volition in determining future actions, whereas competence is a perception of mastery and influence on one’s surrounding environment (Deci & Ryan, 1985). Relatedness is a sense of belonging and connection with other individuals (Deci & Ryan, 1985). When individuals enact a behavior, they will internalize the worth of such a behavior depending on the level of need satisfaction afforded by the context in which the behavior is enacted. When individual’s needs are satisfied, they will experience more internalized forms of regulation, and thereby increase the likelihood of reenacting the behavior in the future. This process has been demonstrated meta-analytically with evidence linking need satisfaction most strongly with intrinsic motivation, and most negatively to amotivation (Van den Broeck, Ferris, Chang, & Rosen, 2016). Indeed, these results show clearly for each of the three needs that greater satisfaction leads to more autonomous regulations. This process very neatly describes how, for example, two individuals can join a sporting team for the first time, and form very different motivations towards future participation in the sport depending on how competent, autonomous, and related they felt during initial exposure.
Importantly, SDT is not a developmental theory which requires progression through the less self-determined regulations in order to experience more internalized motivation (Deci & Ryan, 1985). Instead, depending on the degree of need satisfaction experienced, individuals will skip to whichever regulation best reflects their need satisfaction, regardless of the regulations’ proposed placement along a “continuum.” This means individuals can form highly autonomous motivation to pursue new behaviors without first experiencing external pressures to complete the behavior associated with external regulation. Likewise, an employee beginning employment solely for the purpose of earning a living may instantly transition from external regulation to identified regulation as they come to develop new meaning in their job, potentially leading to an individual having multiple reasons to enact a behavior.

While intuitively appealing, this structure of regulations and the internalization mechanism through which individuals move between these motivations suffers from a confusion of terms. This problem can best be seen in the following example. The proposition that motivation runs along a continuum of self-determination leads a reader to think of motivation as a single force varying in degree or quantity, whereas the specification and measurement of individual regulations forces the reader to imagine separate continua for each of the regulations (Chemolli & Gagne, 2014). In this second instance, regulations are portrayed as separate constructs in which individuals are free to score high or low on each. How can these regulations, all of which have their own continuum along which to score, also fit onto a single continuum of self-determination? In sum this issue raises the unanswered question of, is motivation one continuum or many?

Such a problem has arisen in other fields of research over the last century and has resulted in development of Guttman’s Radex Theory (Guttman, 1954). Guttman’s work
differentiates between three possible structures variables can assume – a simplex, a circumplex, and a radex. Beginning with the most simple, a simplex is a set of variables which are of the same kind and are arranged in a simple order of complexity. This is what is meant by the colloquial use of the term continuum. Variables within a simplex structure measure the same construct, but at greater or lesser degrees. For example, a mathematics exam designed to measure numerical ability would contain simple items to differentiate between those who did not study and those who studied a little. It would also contain more complex items to differentiate between those who studied a little and those who truly mastered the content. As such, this test of numerical ability would form a simplex as it measures one single type of construct (numerical ability), through the use of variables (questions) differing in degree of complexity (Figure 1). A simplex is a single dimensional space, and an individual can only reside at one point along such a structure (e.g. a student cannot simultaneously score high and low on a numerical ability exam).

Figure 1. A simplex of numerical ability

| N₁ | N₂ | N₃ | N₄ | N₅ | N₆ |

Note: N₁-N₆ represent items on a numerical ability test ordered by increasing difficulty.

A circumplex arises when two simplexes are combined to form a two dimensional space. This structure is widely used in psychology, most notably in the areas of values (Schwartz values circumplex; Schwartz, 1992) and emotions (Russell, 1979). Such structures represent two different types of variable – one measured along an X-axis and the other along a Y-axis. Each of these function as simplexes, but when the two are combined form a circumplex. To describe Russell’s (1979) circumplex of emotions, individuals can score their emotions on two dimensions – pleasantness and intensity. In this circumplex all emotions are definable by the degree to which the individual experiences them as either pleasant (e.g. happy and content) or unpleasant (angry and
bored). The second dimension describes intensity of felt emotions and thereby distinguishes happiness (higher intensity) from contentedness (lower intensity), and anger (high intensity) from boredom (low intensity). While each of these dimensions can be described individually as continua, when examined together they form a circumplex. From this example it is easy to see how differences in *kind* and *degree* can coexist yet remain separable.

Figure 2. *A hypothetical circumplex of emotions*

Finally Guttman proposes a radex, abbreviated from “a radial expansion of complexity” to describe a structure in which multiple simplexes are arranged around a bi-dimensional space, similar to a circumplex. A radex diverges from a circumplex in several notable ways. Firstly, whereas a circumplex can model only two (or feasibly three; Lövheim, 2012) simplexes, a radex is capable of incorporating any number of constructs differing in kind. Secondly, unlike a circumplex in which variables can be places on any axis without altering the interpretation, a radex makes most sense when ordering is specified among the different types of variables. For example, in a radex
bordering variables are more closely associated in theory than non-bordering variables, allowing theoretical distances between concepts to be interpreted. In the previously mentioned education example with numerical ability, if students were to take further testing, say a literary exam, a general problem solving test, and a test of music ability, the structure could now be described by a radex (Figure 3). In this hypothetical example it would be expected that literary ability would be more aligned with problem solving and musical ability tests than with numerical ability. The proximity and ordering of these tests, each of which forms its own simplex, is meaningful and carries information about the theoretical distance between each of the tests. This meaningful ordering of constructs is the defining property of a radex structure.

**Figure 3. A hypothetical radex structure of intelligence facets**

Note: $L_{1-4}$ represent items on the literary exam, $P_{1-4}$ are items on a general problem solving exam, $N_{1-4}$ are items on a numerical ability exam, $M_{1-4}$ are items on a musical ability test.

A radex structure such as this allows variables of categorically different kinds to be arranged in a predictable pattern. It allows test takers to score however they may along a separate simplex (i.e. continuum) for each type of variable without discounting the possibility that some of these variables will be more closely related than others, and may indeed form a very stable ordering. Stated simply, a radex allows for a full range of difference in degree (quantity) and kind (quality).
Despite increasing debate around the structure of motivation in SDT (e.g., Chatzisarantis, Hagger, Biddle, Smith, & Wang 2003; Chemolli & Gagne, 2014), research has largely avoided this approach, settling instead for pure Classical Test Theory procedures such as exploratory and confirmatory factor analysis (EFA and CFA) in order to establish structure. The result of this has been the development of many SDT motivation scales across a range of domains, all of which find multiple distinguishable types of regulation, but likewise persist in finding that regulations do display a predictable ordering (e.g., Chatzisarantis et al., 2003; Guay, Morin, Litalien, Valois, & Vallerand, 2015). This has understandably caused much confusion and has led to various scale scoring practices reflecting this confusion. The following will focus on the three most commonly promoted and applied scoring practices, namely the Relative Autonomy Index (RAI; Grolnick & Ryan, 1987), dichotomization of motivation into autonomous and controlled factors, and the estimation of all individual regulations.

Ryan and Connell (1989) were the first to propose the continuum hypothesis in SDT by arguing that regulations were ordered in a simplex pattern. As explained above, a simplex precludes the presence of differences in kind. This prevents the possibility that regulations possess unique individual characteristics which could justify them being separated categorically from one another (see Chemolli & Gagne, 2014 for a more thorough description). This simplex assumption is testable in SDT by looking at whether theoretically closer regulations correlate more highly than theoretically more distant regulations. Such a pattern would suggest the presence of a continuum of self-determination. For example, intrinsic motivation correlates more positively with identified regulation than it does with introjected regulation. This reasoning was used to justify the use of the RAI (Grolnick & Ryan, 1987), which has subsequently been called into question (Chemolli & Gagné, 2014; Judge, Bono, Erez, & Locke, 2005; Koestner &
Losier, 2002). While many variations of the RAI exist, it consists of assigning weights to subscale measures of regulation according to their placement on the hypothesized continuum and combining them to form a composite score describing a person’s relative autonomous motivation, as depicted in the following formula:

$$RAI = 2(\text{intrinsic}) + 1(\text{identified}) - 1(\text{introjection}) - 2(\text{external})$$

Some of the disagreements about the RAI include theoretical concerns including that introjection is not clearly autonomous or controlling (Deci & Ryan, 2000; Ng, 2012), that the use of the RAI contravenes the distinguishing factor of SDT which is its multidimensional conceptualization of motivation. More statistical and practical concerns have also been voiced including that the RAI is a difference scores and therefore lacks reliability (Edwards, 2001; Johns, 1981), that such a simplification results in information loss which has shown to be important (Bono & Judge, 2003; Edwards, 2001), and that the weights assigned to each regulation are arbitrary (Chemolli & Gagne, 2014; Howard et al., 2016a).

Additionally it is worth noting that the weights assigned to regulations do not necessarily represent associations with outcomes correctly. For example, a weighting of -2 associated with external regulation indicates that this factor will predict outcomes twice as strongly as introjected regulation, which is weighted at -1. Likewise, according to this logic, intrinsic motivation and external regulation should be equally as powerful predictors of outcomes, although in different directions. The examination of any research paper indicates that these values are not so easily defined, and to date no research has validated these weightings.
Furthermore, the logic of the RAI disregards the proposed multidimensional structure of motivation which distinguishes SDT from many other theories of motivation. This approach suggests that motivation can be described satisfactorily by the *quantity* of self-determined motivation alone. When researchers maintain each of the regulations as distinct variables in their research, they are recognizing that each regulation has distinct characteristics or qualities and are therefore assuming that *quality* of motivation is more informative than a single measure of quantity. This approach seems much more in line with the theory in which it is frequently stated that people driven by the higher quality regulations (i.e. more autonomous regulations) outperform those driven by lower quality (more controlled) regulations on a wide range of variables from multiple domains (Cerasoli et al., 2014; Gagne et al., 2015; Ng et al. 2012).

Objections have also been raised about the use of composite scores such as the autonomous/controlled dichotomy, particularly because this simplification can result in information loss (Bono & Judge, 2003; Edwards, 2001). Scales in SDT research invariably contain subscales measuring a range of regulations, which clearly indicates that these factors have not only been endorsed based on theoretical grounds, but have also withstood rigorous psychometric validation. Yet despite the effort made to distinguish these types of motivation, it is often considered best practice to largely ignore these subscales and combine them in such a way as to create, for example, two factors for controlled and autonomous motivation. This higher order factor structure has been tested many times and has shown reasonable factorial validity (Gagné, Forest, Gilbert, Aube, Morin, & Malorni, 2010; Gagné et al., 2015). However, measurement and covariate models rarely if ever indicate this to be a preferable approach as opposed to using individual sub-scale scores, beyond being more practical when testing hypotheses rather than having to deal with four to six variables. Additional concerns have been raised
concerning the point at which controlled and autonomous motivation are divided, with arguments made that even this point is somewhat arbitrary as introjection is often more highly correlated with identified rather than external regulation (see chapter 2).

The alternative consists of operationalizing each subscale individually and examining relations between each of these and the desired covariates. This is the most comprehensive approach, but is often not feasible due to the complication of examining 4-6 variables simultaneously in hypothesis testing models. While measurement modelling suggests this full operationalization of subscales is the optimal approach to take and undoubtedly makes fullest use of the information gathered by specifying specific relationships between motivations and covariates (Marsh, Morin, Parker, & Kaur, 2014), it also raises concerns about multicollinearity (Asparouhov et al., 2015). Specifically, due to the relatively high correlations between many conceptually adjacent factors, when separated out into categorically distinct factors they will display reduced predictive capabilities (Marsh, Morin, Parker, & Kaur, 2014). A more practical matter also prevents full operationalization as it seems that all too often the restrictions of space, time, and scope placed upon researchers means that many opt for composite and difference scores. In order to counteract this lack of parsimony, researchers have been known to use only a selection of regulations – primarily more autonomous forms. This in itself raises issues concerning information which may be lost though the exclusion of other regulations, including the consideration that they could interact if they are indeed different dimensions. If regulations are indeed separate variables with unique characteristics, then this approach of selectively using regulations disregards information supposedly pertinent, according to SDT. In essence this approach follows the same assumption as a composite score approach such as the RAI as it suggests that the relationships between
the remaining regulations and covariates will be predictable based on the results from the selected regulations’ relationships.

Each of these approaches to measurement makes contradicting assumptions about the presence of a continuum, and yet very little attention has been paid to directly examining these assumptions. For example, the use of difference scores such as the RAI assumes the presence of a continuum and infers that differences in kind between regulations are unimportant and can be ignored. Likewise, dichotomization into autonomous and controlled motivations still assumes a continuum ordering but contrives a distinction between introjected and identified regulations which warrants one to be classified as controlling while the other autonomously motivated, essentially conceding the presence of two continua (i.e. one continuum representing controlled motivation, and a second distinct continuum representing autonomous motivation). Distinct operationalizations for each regulation, on the other hand, assumes that each additional regulation subscale contributes something beyond the degree of self-determination as represented by a continuum. If this is the case, the linear dependency between regulations (i.e. the continuum) is inconsequential as individual regulations are capable of not only representing the degree of self-determination, but additional unique characteristics inherent in each subscale, thereby identifying more detailed relationships between regulations and covariates than either of the two more simple methods mentioned above.

In order to clarify this issue and identify more optimal methods for using SDT motivation in research, this dissertation aims to test whether the assumptions of a continuum hold under a range of empirical tests. We begin by identifying previous efforts to test the continuum assumptions, before presenting original research and the implication of this research in context. The following is an exhaustive list of methods previously used to inform the continuum debate and as such will be addressed individually.
1. Examination of the Simplex Structure of Regulations in Correlation Matrices

One of the leading arguments for the continuum perspective is the presence of a simplex structure observable between regulation correlations. This simplex pattern requires higher correlations between more theoretically proximal regulations and weaker correlations between more distal regulations. To cite the authors who introduced this concept to SDT:

“The simplex concept is derived from Guttman’s (1954) radex theory, which describes ordered relations between correlated variables. In a simplex, variables are ordered in terms of complexity or conceptual similarity, such that those deemed more similar correlate more highly than those that are hypothetically more discrepant” (Ryan & Connell, 1989, p. 750).

In a correlation matrix this means that the highest correlations will be present along the diagonal with a tapering effect such that correlations become lower (or turn negative) the further they are from the diagonal. In essence this pattern tests whether the regulations are in the correct order relative to each other. While this is useful knowledge in itself, no guidelines exist to indicate how closely each of the regulations should be to one another, or whether they should be spaced equidistantly.

Since its initial implementation, this “test” has become the ubiquitous test by which the continuum structure of motivation has been assessed. This step is most common among scale validation studies, which use this hypothesized structure as evidence for a well-constructed scale (Guay, Vallerand, & Blanchard, 2000; Lonsdale, Hodge, Rose, 2008; Markland, & Tobin, 2004), or for researchers justifying the use of composite scores such as the RAI (Grolnick & Ryan, 1987). However, as previously noted, these ad hoc and “eyeball” analyses are suited to roughly establishing an order of regulations, but do not provide strong enough evidence to justify the use of composite
scores and difference scores such as the RAI due to the potential variation within this broad structure. In sum, despite the centrality of the simplex structure to the argument for a continuum structure of motivation, relatively little research has been dedicated to it. Instead it remains a central, but largely untested assumption within the theory.

In an attempt to assess the fit of the simplex structure a bit more rigorously, Ryan and Connell (1989) proposed an adjacency index. This process consisted of assigning an adjacency index to the between-regulation correlations according to how theoretically close they are on a continuum, (for example the correlation between external and introjected is designated a value of 3, external and identified is designated a value of 2, and external and intrinsic is designated 1). These weighted correlations are then used in regression to explain variance in squared correlations. More specifically, Ryan and Connell (1989, pp. 752-753) describe this method as follows:

“To evaluate this pattern for congruency with our simplexlike or ordered correlation model, we devised the following statistical tool. First, we assigned an adjacency index to the correlations between reason categories according to how close the reason categories are along a continuum of autonomy, as follows:

\[ r_{e, ij} = 3, \quad r_{e, id} = 2, \quad r_{e, in} = 1, \quad r_{ij, id} = 3, \quad r_{ij, in} = 2, \quad \text{and} \quad r_{id, in} = 3 \]

Then we computed the amount of variance accounted for by this adjacency index in the obtained squared correlations among the reason categories. Squared correlations were used in order to restore interval scale properties to this data so as to meet the assumptions of a correlational test.”
In this study, the authors found support for a simplex structure through this method. However, this method has not been widely used since this inception, and has been criticized strongly as lacking sensitivity as being highly insensitive even when clear divergences from the simplex structure are evident in the correlation tables (Chemolli and Gagne, 2014; Fernet Senécal, Guay, Marsh, & Dowson, 2008; Guay Vallerand, & Blanchard, 2000).

2. Confirmatory Path Analysis between Motivation Regulations

Alternate approaches to testing for the simplex structure come in the form of path analysis models using composite scores for the regulation subscales. Some authors adapted this idea to test for the linear dependencies between regulations (Li, 1999; Li & Harmer 1996). This approach consists of creating a path model in which paths are only permitted between adjacent regulations while the others are set to zero (e.g. amotivation -> external -> introjected -> identified -> intrinsic). Being a model based approach, unlike the adjacency indices approach proposed by Ryan and Connell, this method allows for confirmatory model testing in the way of fit statistics and modification indices. Results of the study by Li and Harmer (1996) largely supported the presence of a simplex structure, although several significant indirect effects were also found indicating that the structure of these variables may not be entirely explained by linear dependencies. Specifically, significant effects were observed between external regulation and intrinsic motivation in males, and amotivation and intrinsic motivation in females. In the scale validation of the Exercise Motivation Scale (Li, 1999), the simplex structure was again supported through this method.

Chatzisarantis, Hagger, Biddle, Smith, and Wang (2003) conducted a meta-analysis correcting for sampling error and measurement error of 21 published articles in which the perceived locus of causality scale (PLOC; Ryan & Connell, 1989) was used to
measure motivation. The study used the same path analysis procedure proposed by Li and Harmer (1996) on corrected correlation matrices in order to test if the pathways between any two regulation subscales were completely mediated by theoretically more proximal subscales. Results of this study found support for the continuum of motivation running from external regulation to introjected and identified regulation, but concluded that the extreme ends of the scale including intrinsic motivation and amotivation did not fall along this same continuum of self-determination. These results indicate a potentially more nuanced conceptualization of the SDT continuum, although this point has not been taken up in the intervening years. While interesting, this study by Chatzisarantis et al. is restricted to a relatively small sample of studies utilizing one specific scale. Given the widespread use of SDT’s conceptualization of motivation across a wide range of life domains and the development and use of many motivation scales adapted to these life domains, the time is ripe to examine the consistency of the simplex structure of motivation over a range of scales and domains in order to establish with greater certainty the stability of the continuum underlying SDT motivation, which is one of the goals of this dissertation.

While the path analytic studies tend to find support for the simplex structure, this approach suffers from a significant problem, namely, that it has been shown to be insensitive to even very large divergences from a simplex structure (Rogosa & Willett, 1985). As such, more sensitive tests have been employed, including Rasch analysis (Rasch, 1960).

3. Rasch Analysis

Given that previous attempts to quantitatively support the simplex ordering of regulations, which would indicate the presence of a continuum of motivation, have not been settled, Chemolli and Gagné (2014) sought to apply even more specific analyses to
this question. Chemolli and Gagné (2014) tested the simplex structure of motivation using data derived from the Academic Motivation Scale (AMS; Vallerand et al., 1992) and the Multidimensional Work Motivation Scale (MWMS; Gagne et al., 2015) through the application of Rasch analysis (Rasch, 1960). Rasch analysis is a special case of item response theory (Lord, 1980), which essentially specifies that all items should fall along a single dimension measuring the target construct (in this case, motivation). Items that fall further from this line are therefore measuring additional factors beyond the main Rasch dimension (motivation), and thereby indicate multidimensionality. This highly specific test of a simplex structure did not find support for a single-dimensional representation of SDT motivation in either the AMS or the MWMS (Chemolli & Gagne, 2014). It was concluded that the heuristic of a continuum underlying motivation is not necessary, and likely hindering the progression of academic research by encouraging composite and difference scores as replacements for the full range of categorical motivation types. The authors indicated that rather than motivation being arranged along a single simplex, motivation is multi-dimensional, and requires multiple continua in order to adequately represent the construct, thereby supporting the need for separable subscales representing each individual regulation.

4. Factor analysis

Every motivation scale based on SDT uses subscales that measure different regulations established on research using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). These measurement models are important as they present a statistically testable representation of motivation as a multidimensional construct, and almost invariably find support for this conceptualization (Gagne et al., 2015; Li, 1999; Lonsdale, Hodge, & Rose, 2008; Mullan, Markland, & Ingledelew, 1997; Pelletier et al., 1995; Pelletier, Rocchi, Vallerand, Deci, & Ryan, 2013; Ryan & Connell,
These measurement models are, in and of themselves, a test of the continuum as it suggests that the most optimal representation of data collected on these scales is a multidimensional one, and not a single factor representing combined self-determination. For example, many scale validation studies have tested alternate factor structures such as a single factor solution and occasionally 2-3 factor solutions (usually representing autonomous and controlled factors). However, as reported by Gagne et al. (2015) and Lonsdale, Hodge, and Rose (2008), these studies consistently reject the simplified 1-factor structures in preference for the hypothesized multidimensional solutions (in both cases 6-factor solutions). Likewise, Li (1999) even found support for an 8-factor solution including three separate subscales of intrinsic motivation over the more simplistic 1- and 3-factor solutions in the validation of the Exercise Motivation Scale. Such results demonstrate that factor analytic procedures will consistently support the multi-dimensional nature of motivation, and thereby undermine the continuum argument.

Despite the belief that motivation should be multidimensional and strong factor analytic and psychometric evidence supporting this, statements about a continuum underlying motivation are persistent in published research and are frequently invoked to support the use of simplistic measures such as composite scores combining regulations and the RAI.

5. Other Measurement Modeling Tests

In addition to providing a factor structure for motivation scales, measurement models contain much more information that can be used to provide evidence for or against a continuum of self-determined motivation. These tests primarily rely on relatively new and advanced statistical measurement models such as exploratory structural equation modeling (ESEM) and bifactor modeling.
a. **ESEM and the Examination of Cross-loadings.** Exploratory structural equation modeling is a recent development in factor analysis which combines elements from EFA, CFA, and SEM in a single analysis (Asparouhov & Muthen, 2009; Marsh et al., 2014; Morin et al., 2013). It is a versatile tool that can be used in an exploratory manner, but is equally as suited to confirming a hypothesized factor structure through the application of target rotation (Asparouhov & Muthen, 2009; Marsh et al., 2014; Morin et al., 2016). The benefit of ESEM over CFA lies in the estimation of all cross-loadings, which may well represent construct relevant influence of the latent factors on indicators (Morin et al., 2016), and as such has been shown to produce less inflated inter-factor correlations than traditional CFA (Asparouhov & Muthen, 2009; Marsh, Ludtke, Nagengast, Morin, & Von Davier, 2013; Morin et al., 2016). Given this, results from such an analysis would provide more reliable information concerning the previously mentioned simplex pattern, as ESEM has shown to give more accurate and less inflated estimates of between factor correlations than CFA.

Guay, Morin, Litalien, Valois, and Vallerand (2015) applied ESEM to two samples totaling over 5000 college and high school student responses to the AMS (Vallerand et al., 1992). As predicted, results from ESEM analyses provided greater discriminant validity between regulations than CFA and thereby was deemed to be better suited to interpret the simplex structure. Findings from sample 1 failed to replicate the simplex structure, whereas sample 2 did support the ordering of motivation subscales. As noted by Guay et al., partial support for the simplex pattern is somewhat common among research utilizing the AMS, and may also apply to other domains and scales.

Another procedure for examining the presence of the continuum becomes available in ESEM analyses through the estimation of all cross-loadings. It is expected that for any given specific factor (such as introjection), cross-loadings should be higher
for more theoretically adjacent factor items (such as identified and external regulations), and lower for more distal factor (such as amotivation and intrinsic motivation). Due to the newness of ESEM, only one study to date has examined this pattern of cross-loadings. Guay and colleagues (2015) found that while cross-loadings in general were very low, often less than .1, there was some evidence that items were more likely to load positively on theoretically adjacent factors and negatively on more distant factors. There were, however, many violations of this pattern, particularly between intrinsic motivation sub-scales (i.e. intrinsic motivation to know, to experience stimulation, and to accomplish). In sum, it appears that scale construction of validated SDT scales is sufficiently well conducted such that factors are relatively distinct and cross-loadings are unanimously low, meaning this test provides only minor evidence in favor of a continuum ordering of SDT motivation regardless of the theoretical distance between items.

b. A General Factor Representing the Continuum. Bifactor modeling captures the shared variance between all measurement items in a general factor, in conjunction with other first order factors. In other words, items are specified to be informed by their respective subscales as in standard CFA, while also loading onto a general (G-) factor (Reise, 2012). In the current context, such a G-factor is proposed to represent the continuum of SDT or overall quantity of self-determined motivation, in addition to the commonly specified regulation factors (i.e. external, introjected, etc.). This approach to examination of common variance within items is preferable to higher-order factor analysis because of the often times unreasonable proportionality constraints imposed by higher-order procedures. Specifically, in a higher order model, items are related to the higher-order G-factor only through the first order regulation factors, essentially specifying a fully mediated relationship (McAbee, Oswald, & Connelly, 2014). While these proportionality constraints do result in greater parsimony, they are unlikely to hold
in many research settings (Reise, 2012; Yung, Thissen, & McLeod, 1999), and do not necessarily make strong theoretical sense (Gignac, 2016). Bifactor modeling offers a more direct and flexible manner of representing common variance between items which has shown to be more capable of recovering true higher-order factor structures than hierarchical factor analysis (Jennrich & Bentler, 2011).

Evidence for a continuum structure of motivation requires two criteria to be met with bifactor modeling. First, if the general factor has strong item loadings but individual regulations do not, then this would support the continuum hypothesis. If alternatively the specific regulation factors possess strong items loading and the general factor does not, then this would be evidence against the continuum. A well-fitting model in which a general factor can be specified alongside the individual regulations suggests that motivation contains important quantity and quality characteristics. In other words, it would suggest that while regulations are ordered along a continuum-like structure characterized by the general amount of self-determined motivation, the characteristics of individual regulations are still identifiable and therefore likely important. Second, the pattern of item loadings on the general factor matter. If this general factor represents the continuum of self-determined motivation, then this direct representation of the continuum should display a pattern of item factor loadings such that items at one end of the continuum are strongly negative and items at the other end are strongly positive. A smooth increasing of factor loadings from negative to positive would indicate that in total the items are indeed measuring the full length of the continuum and doing so rather comprehensively.

To date only a single study can be found which explores SDT motivation through bifactor modeling (Gunnell & Gaudreau, 2014). In this exploratory bifactor analysis, it was found that a distinguishable general factor could be specified in addition to the
specific regulation factors of the revised Behavioral Regulation in Exercise Questionnaire (BREQ-2), although it did not appear to represent the self-determination continuum. This is because, in regards to the second criterion concerning the pattern of factor loadings on the general factor, item loadings on all specific regulation factors as well as the general factor were always positive. Even amotivation items loaded positively on the general factor (mean item loading = .34). Instead, if a continuum of self-determination were present it would be expected that amotivation items would load on the general factor in the opposite direction to intrinsic factors. As such, this study did not support the continuum hypothesis.

As amotivation represents an absence of self-determined motivation, its items should fall at one extreme end of the continuum with high negative loadings on the G-factor. Highly externalized reasons for behaving, such as external regulation items are proposed to be next along the continuum and should load less negatively than amotivation items on the general factor. While the weight assigned to external regulation in the RAI calculation is negative (Grolnick & Ryan, 1987), there is no well supported reason why these item loadings on a g-factor should necessarily be negative. Instead, it is perhaps more theoretically justifiable if external regulation items display item loadings close to zero, as external regulation is considered to be externally controlled and therefore lack self-determination altogether. Introjected regulation items will be next and, according to the theory which commonly classifies introjection as a controlled regulation, are also proposed to load mildly negatively on the G-factor (Grolnick & Ryan, 1987), although less so than external regulation items. This issue has caused some concern over recent years introjection is commonly found to sometimes associate positively with outcomes, indicating that it may be closer to identified regulation than to external regulation (Gagne et al., 2015; Pelletier et al., 2013), while at other times being predictive of negative
outcomes such as depression and anxiety (Ng et al., 2012). This raises concerns over the
very common practice of classifying introjection as a negative or controlled form of
motivation as will be covered in further detail in a proceeding section concerning the
viability of composite scores such as the Relative Autonomy Index (RAI).

Identified regulation items are then proposed to load positively on the general
factor and represent the first agreed upon positive items. Integrated regulation items
would be theorized to fall next along the continuum and therefore should show higher
positive item factor loadings on the G-factor than identified regulation items. However,
due to the aforementioned difficulties in distinguishing between identified, integrated, and
intrinsic factors, integrated regulation has not been included in any test of the continuum
to date, and unfortunately could not be included in the present research either. Intrinsic
motivation items are proposed to lie at the other most extreme end of the continuum
(opposite to amotivation), with high positive factor loadings. While the single bifactor
model to date does not support this pattern (Gunnell & Gaudreau, 2014), replication with
a larger sample and in different domains is necessary to inform this area of the debate.

c. Covariates of General and Specific Factors. In addition to establishing
whether a general factor representing the continuum of self-determined regulation is
possible, bifactor analyses can also demonstrate the relative strength of the continuum in
predicting outcomes compared to specific regulation factors. Firstly, a bifactor model
could be estimated and the factor scores for the general factor (i.e. the continuum) and
specific factors (representing each regulation) could then be associated with covariates.
This simultaneous estimation of a continuum and regulation factors would be telling as it
would determine the proportion of predictive power associated with each. If the general
factor is found capable of predicting the vast majority of variance in outcomes, then this
would call into question the usefulness of individual regulations and support the
continuum hypothesis. Alternatively, if the regulations explain more variance than the general factor, then this would be strong evidence against the continuum. This would be a very powerful test of the continuum hypothesis because it demonstrates the practical impact of conceptualizing motivation either multidimensionally or along a single dimension of self-determined motivation. For example, if the individual regulations explain even a relatively small proportion of an outcome (e.g. employee well-being or performance), then this more complicated representation of motivation may indeed be preferable to the more parsimonious single-factor representation. The only study to conduct these analyses to date found that a general factor, described as general motivation, was the strongest predictor of time 1 physical activity, and the only significant predictor of physical activity and goal progress at time 2 (Gunnell & Gaudreau, 2014). However, identified and intrinsic regulations were also found to predict time 1 physical activity. These results from the exercise domain indicate that a general factor may be more important in predicting outcomes, but that individual regulations still retain some predictive power which may be of practical importance.

6. Motivation Profiles

An alternate way to examine motivation and the continuum is through the construction of motivational profiles. A motivation profile represents commonly occurring combinations of regulations. For example it may be very common for some employees in a workplace to experience very high levels of external regulation (working for money) combined with lower levels of intrinsic motivation (working for fun), while for other employees it may be that they experience high levels of both external regulation and intrinsic motivation. These combinations of regulations, extended to include the regulations in between, would represent a profile. An additional consideration to note here is the fact that none of the previously mentioned approaches (e.g. RAI,
autonomous/controlled composites) allow for interaction effects between regulations. Individuals will unanimously be able to give multiple reasons behind any specific behavior, and this is demonstrated in any self-report measure in which participants report varying degrees of each regulation. However, if regulations do indeed represent unique characteristics beyond a single dimension of the self-determination continuum, then interaction effects are possible, and indeed likely to be present. Given the relatively large number of regulations specified by SDT, traditional interaction tests (i.e. moderation), are impractical to capture the full array of possible interactions. The profile approach, also known as a person-centered approach, captures these complex interactions through the delineation of natural groupings.

It is through this technique that we can examine if, for example, employees high in external and low in intrinsic motivation are better or worse employees that those who display high levels of intrinsic and low levels of external regulation. While both of these profiles would possess roughly equal quantities or levels of overall motivation, outcomes associated with each of these profiles may be very different due to the different overall quality of motivation within a profile. This type of examination is also suited to answering questions about what happens when external regulation is added to high levels of intrinsic motivation or identified regulation. Will it make the employee more motivated to work while maintaining their autonomous focus or will it lead to less optimal outcomes as the controlling nature of external regulation plays an influence? Realistically, these are questions not answerable by variable-centered analyses such as multiple regression and SEM due to the complexity of 5-way interaction effects and the significant multicollinearity issues which would be present in such analyses.

Profile analysis of motivation will be important in elucidating the continuum debate through the demonstration of how regulation combinations are experienced and
reported by individuals. Specifically, through examination of the distribution of regulations among the most commonly endorsed profiles, researchers can draw some inferences about the presence of a continuum underlying motivation. Assuming the continuum does indeed exist and all regulations are in fact measuring the same underlying facet, then profiles should all follow smooth unimodal curve with a single high point, with some endorsement of adjacent regulations, and less endorsement of more distal regulations.

Alternatively, if there is no continuum of self-determined motivation, then individuals should be free to endorse regulations in a more sporadic manner. It should then be common for profiles to display, for example, high levels of both identified and external regulations towards work, but not experience high levels of introjected regulation. Assuming no continuum, so long as the work context facilitates identified regulation and promotes external regulations but also takes steps to reduce feelings of obligation associated with introjected regulation, then there is no reason this profile cannot exist. Under the assumption of a continuum, this profile will not occur as an individual whose primary motivator is identified regulation will expect to have somewhat high levels of introjected regulation and lower levels of external regulation due to the connectedness inherent in the continuum underlying the regulations.

After surveying the published literature examining motivation through person-centered analysis, it can been seen that the majority of studies, regardless of domain, do indeed produce profiles with unimodal curves as would be predicted if regulations were ordered along a continuum. Out of the twelve studies found, five of these perfectly replicated the smooth curve indicative of ordered constructs (Graves, Cullen, Lester, Ruderman, & Gentry, 2015; Liu, Wang, Tan, Koh, & Ee 2009; Matsumoto, & Takenaka, 2003; Moreno-Murcia, Gimeno, Hernández, Pedreño, & Marín, 2013; Ntoumanis, 2002).
A further three studies found the same pattern across most profiles but also reported slight discrepancies in a single profile (Boiche, Sarrazin, Grouzet, Pelletier, & Chanal, 2008; Moran, Diefendorff, Kim, & Liu, 2012; Ullrich-French, Cox, 2009). These discrepancies were on the whole very minor and involved one out-of-place regulation in a single profile. These results are very feasibly attributable to small sample sizes. For example, the offending profile reported by Moran, Diefendorff, Kim, and Liu (2012) contained only 37 people (from a sample size of 226). Interestingly, discrepancies from the predicted smooth and unimodal pattern were noticeable mostly between sub-scales of intrinsic regulation and integrated regulation. This is less surprising given that these factors are notoriously hard to distinguish and consistently display extremely high correlations with identified and intrinsic factors.

Four final studies were found in which multiple violations of the unimodal curve assumption were reported (McNeill & Wang, 2005; Ratelle, Guay, Vallerand, Larose, & Senecal, 2007; in de Wal, den Brok, Hooijer, Martens, & van den Beemt, 2014; Yli-Piipari, Watt, Jaakkola, Liukkonen, & Nurmi, 2009). As with the previously mentioned profiles, the majority of issues concerning divergence from the smooth unimodal curve were present primarily around the highly correlated intrinsic and identified factors, and more often than not consisted of very small sample sizes (e.g. 23 people in the offending cluster reported by McNeil & Wang, 2005). Given that two of these studies incorporated very small total samples to derive the profiles (e.g. n = 121 & 174 for McNeill & Wang, 2005 and Yli-Piipari et al., 2009 respectively), these profiles may not be stable or reproducible, and therefore somewhat undermine the conclusions which can be drawn from these studies.

In summary, research in this area generally supports the notion of a continuum structure among the regulations as profiles on the whole tend to follow unimodal curves,
indicating a predictable ordering of these variables. However, enough violations of this smooth curve assumption have been noted, specifically the larger studies by Ratelle et al., (2007) and in de Wal et al., (2014), to leave this issue disputable. In order to clarify this issue, further research would benefit from using the full range of regulations, latent profile analysis instead of cluster analysis, and sufficiently large samples to increase the probability of finding reproducible profiles.

7. Multidimensional Scaling

Multidimensional scaling (MDS) is an alternative method to factor analysis designed to depict important structures and relationships present between variables in multi-dimensional space (Jaworska & Chupetlovska-Anastasova, 2009), rather than through item loadings and latent constructs. However, it must be noted that MDS is a predominantly exploratory approach and does not allow for strong conclusions to be drawn (Giguère, 2006). Specifically this technique is valuable in the investigation of a self-determination continuum for two reasons. Firstly it can be used to compare between single- and multi-dimensional representations of motivation statistically and produce estimates of how much of the structure each dimension is capable of explaining. Secondly, it graphically represents the relative position of each regulation factor which allows for interpretation of how evenly these factors are spaced. If motivation were truly a continuum it would be expected that a single-dimensional representation would be the best fit to the data, and this when displayed graphically should show regulations to be evenly distributed across the continuum. Alternatively, the presence of additional dimensions would indicate a more complex multi-faceted interpretation of motivation is more warranted.

To date there is only a single forthcoming study in which this technique is applied (Sheldon, Osin, Gordeeva, Suchkov, & Sychev, in press). Across the four samples
included in this study, it was found that between 38-71% of variance in the structure of regulations was accountable due to the continuum of self-determination (i.e. the first dimension). However, a two-dimensional model also fitted equally as well. When presented graphically this two-dimensional solution demonstrated a clear semi-circle shape, indicating that a more complex interpretation may be necessary than a single-dimensional continuum. This semi-circle resembles an inverted “U” with amotivation at one lower end of the U and intrinsic motivation at the other end, with external, introjected, and identified regulations roughly following this inverted “U” curve between these points. This issue will be addressed more thoroughly in this dissertation (Chapter 4), through the application of this method through meta-analysis.

8. Theoretical arguments

In addition to statistical tests conducted to evaluate the tenability of the continuum hypothesis, logical arguments concerning the continuum remain to be examined and resolved. For example a logical inconsistency arises with the continuum argument when we consider that the SDT continuum is said not to be developmental – meaning a person does not have to progress from external to introjected and so forth, but can instead adopt any regulation at any point in time. As introduced above, this ability to switch between regulations without progressing through the continuum is indicative of categorically distinct groupings and theoretically precludes the presence of a continuum as it does not fit with the initial simplex argument put forth by Guttman (1954). A commonly cited metaphor evoked to demonstrate this argument is that of a thermometer (e.g., Chemolli & Gagne, 2014). A thermometer reading 100° implies that this temperature subsumes all of the properties of the lower temperatures. In other words, the mercury must travel through 20°, 50°, and past 80° in order to reach 100°. Endorsement of a higher score necessitates that all lower scores have also been surpassed. The non-developmental nature of
motivation according to SDT states that this progression does not occur, which inadvertently signals the absence of a true continuum.

It is also hard to envision how high levels on a particular regulation would progress into low levels on the next more self-determined regulation as would be supposed by a continuum structure. For example, do very high levels of external regulation reach a point where the person then realizes that they are in fact driven by low levels of introjected regulation and not external regulation anymore? Alternatively if someone begins to lose intrinsic interest in an activity, do they then invariably fall into a situation of high identified regulation in which the activity takes on very high levels of meaningfulness? The change in regulation instead seems to reflect a change in the quality of a person’s motivation more than in its quantity.

Another point which requires addressing is the fact that a continuum does not allow a person to score on more than one point on the continuum when responding to the scales considered in this thesis. In other words, if the regulations do indeed form a continuum then it should not be possible for an individual to experience more than one type of regulation within a domain. The fact that people unanimously report experiencing all regulations to some degree, as demonstrated clearly in person-centered studies, undermines the continuum position somewhat as it indicates that people are not experiencing motivation as a single force on which they perceive themselves as either high or low, but instead suggests that people intuitively believe they have multiple reasons for behaving. This is roughly analogous to a thermometer reading high and low temperatures at the same time. Clearly a true continuum does not work this way.

However, the fact that people report multiple motivating forces may be the result of how researchers measure motivation. In particular the issue of whether people actually experience more than one type of motivation at any given time is something that has not
been studied. Instead, most measures of motivation are questionnaires which ask participants to rate on a 5- or 7-point scale the degree to which each motivation influences their effort in that particular domain (e.g., work) in general. This approach is far too insensitive to address the issue of whether these reported regulatory processes are occurring simultaneously or one at a time from moment to moment.

However, those who support the distinctness of regulations accept the assumption that at any given point in time an individual will endorse all regulations to some extent and all regulations will influence subsequent behavior. This is analogous to having multiple instruments reading entirely separable phenomenon at the same time. For example while the thermometer is still measuring temperature, there is now an instrument measuring humidity, as well as another measuring wind speed, etc. The weather conditions are now measured by several different instruments which will each report a single score at any given point in time, and collectively can be said to measure the current weather. This is the mindset evoked in measurement modeling such as CFA, in which factors are specified as distinct, but correlated, concepts.

**Overview of Dissertation**

This dissertation presents three studies that use different statistical techniques to examine the continuum hypothesis. Chapter 2 presents a study which demonstrates support for a continuum of self-determined motivation by comparing CFA, ESEM, bifactor-CFA and bifactor-ESEM using data derived from the MWMS (Gagne et al., 2015). Support for the continuum hypothesis was examined through examination of fit indices for these different models, examination of factor loadings on specific and general factors, and through the examination of cross-loadings found with ESEM. In addition, the contribution of specific versus general factors to explaining variance in important
motivation covariates was examined to ascertain the importance of quantity versus quality of motivation. This study will be the first to directly test the relative importance of regulations after taking into account a self-determination continuum by directly modeling all of these factors in bifactor ESEM, and associating these with relevant covariates.

Chapter 3 presents a study which demonstrates support for a continuum of motivation through the use of latent profile analysis using two samples from different countries of workers who completed the MWMS (Gagne et al., 2015). This study is better suited to addressing questions of the continuum than previous person-centered work because it uses the full range of regulations which gives a higher definition perspective of the unimodal continuum pattern, it applies the more advanced and naturalistic technique of latent profile analysis, and replicates across two relatively large samples from two countries. In addition, profiles are related to known antecedents and outcomes of work motivation, providing new knowledge about how regulations interact together.

Chapter 4 presents a meta-analysis designed to test the simplex assumption across four main domains and thirteen commonly applied motivation scales. This extensive meta-analysis, comprising 486 samples, demonstrates just how stable the simplex structure is, and highlights facets within the theory which do not conform to the continuum hypothesis, providing recommendations for scoring methods, such as the RAI. Furthermore this study incorporates multi-dimensional scaling which clearly displays the distance perceived by participants between each regulation. Not only does this analysis compare the structural fit of single- versus multi-dimensional representations of motivation, it also graphically represents the continuum. A discussion of support for and against the existence of a continuum of self-determined motivation follows in Chapter 5, before recommendations on how best to use the conceptualization of motivation derived from self-determination theory are offered.
Chapter 2
Using Bifactor-Exploratory Structural Equation Modeling to Test for a Continuum Structure of Motivation

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Abstract

This paper explores the nature of workplace motivation by testing the continuum structure of motivation proposed by self-determination theory (SDT) through the application of relatively new and advanced methodological techniques. Specifically we demonstrate the usefulness of the overarching bifactor exploratory structural equation modeling (B-ESEM) framework in organizational psychology and discuss implications of such models over more traditional confirmatory factor analyses. This framework is applied to responses obtained from 1124 Canadian employees who completed a multidimensional measure of workplace motivation. The results support a continuum of self-regulation but furthermore indicate the importance of accounting for both quality of motivation in addition to its global quantity. Indeed, the results showed that specific types of motivation explained variance in covariates over and above the variance already explained by the global quantity of self-determination. The current study further demonstrates the limitation of the commonly used relative autonomy index and offers alternate conceptualizations of human motivation.

Keywords: work motivation, self-determination theory, continuum, bifactor exploratory structural equation modeling (B-ESEM)
Modern psychological science is progressing to a level of theoretical complexity which necessitates the use of equally sophisticated methodological and statistical tools. This observation calls for substantive-methodological synergy (Marsh & Hau, 2007). Substantive-methodological synergies are joint ventures in which methodological advances are applied to substantively important areas of research in order to help provide more precise, or refined, answers to complex research questions. The current paper is anchored into such a substantive-methodological synergy framework and aims to: (1) Test the continuum structure of motivation proposed by self-determination theory (SDT; Deci & Ryan, 1985), and (2) demonstrate the usefulness of the overarching bifactor exploratory structural equation modeling (B-ESEM) framework in organizational psychology. We start this paper by reviewing key substantive issues related to the SDT continuum hypothesis of motivation, and then present in greater details the bifactor-ESEM psychometric framework.

Substantive Issues: The Continuum Structure of Motivation

Self-Determination Theory of Human Motivation

SDT (Deci & Ryan, 1985, 2000; Ryan & Deci, 2000) proposes that individuals experience autonomous motivation when their reasons for engaging in behaviors are volitional, and experience controlled motivation when their reasons for engaging in the behaviors are pressured either internally or externally. Each of these two forms of motivation can be characterized by different types of motivation, expected to form a continuum. At one extreme, the most autonomous form of motivation is intrinsic motivation. Intrinsic motivation occurs when individuals derive a sense of enjoyment and satisfaction from the enactment of the behavior itself. At the other extreme, the most controlled form of motivation is external regulation, which occurs when individuals engage in an activity for purely instrumental reasons, such as to obtain rewards or avoid
punishment. Between these extremes, introjected regulation happens when a person engages in behavior to reduce negative self-related feelings (e.g., shame, guilt), or to experience positive self-related feelings (e.g., pride), and identified regulation occurs when the outcome of the behavior is personally meaningful. Introjected regulation can be exemplified by employees who work late to maximize their performance and feel better about themselves, whereas identified regulation would be exemplified by employees who stay late to finish work that they perceive to be important to the organization.

In the work domain, external regulation can be further subdivided according to whether the source of the external pressure to enact the target behavior is material or social (Gagné et al., 2015). External material regulation stems from tangible rewards and punishments, such as monetary benefits and job security. In contrast, external social regulation is related to social rewards and punishments, such as approval and criticism from others. Although not initially covered in SDT, others have noted that it is also important to assess amotivation (Pelletier, Fortier, Vallerand, Tuson, Brière, & Blais, 1995; Vallerand, Pelletier, Blais, Brière, Senécal, & Vallières, 1993), referring to an absence of willingness to exert effort, in order to cover scenarios where people have no reason or willingness to put any effort into an activity. Indeed, early SDT-based motivation instruments were limited in that they implicitly assumed that everyone would have some reason to embark on a targeted course of action, failing to explicitly assess lack of motivation. In the current study, we rely on the Multidimensional Work Motivation Scale (MWMS; Gagné et al., 2015), a newly developed scale designed to measure these distinct types of motivation in the work domain. Previous CFA has supported the multidimensional structure of the MWMS in seven different languages (Gagné et al., 2015). Here, we use a subsample from Gagné et al. (2015) and use bifactor-ESEM to test SDT's hypothesis that motivation types follow an underlying continuum.
Motivation Types on a Continuum

A key aspect of SDT’s conceptualization of motivation is that motivation types are ordered along a continuum depicting the degree of relative autonomy, or self-determination (Ryan & Deci, 2000). SDT suggests that the qualitatively different motivation types also differ quantitatively along a single continuum of self-determination. The continuum hypothesis has typically been examined through an inspection of the correlations between the motivation types (Ryan & Connell, 1989; see Guay, Morin, Litalien, Valois, & Vallerand, 2015 for a review in the education domain). For instance, Ryan and Connell (1989) tested whether the correlations between motivation types followed a simplex structure. The simplex structure refers to a correlation pattern showing that adjacent motivation types correlate more strongly and positively with one another than more distal motivation types (which should correlate negatively). For example, intrinsic motivation should correlate more strongly with identified regulation than with introjected or external regulations. Although amotivation has not traditionally been taken into account in tests of the SDT continuum, a case has been made for this factor to fall at the lowest point of the continuum (Cox, Ullrich-French, Madonia, & Witty, 2011; Guay, Ratelle, Roy, & Litalien, 2010; Stevenson & Lochbaum, 2008).

Some past research has supported the continuum hypothesis (e.g., Li, 1999; Li & Harmer, 1996; Ryan & Connell, 1989), while other research has not, especially when using more advanced statistical techniques (e.g., Chemolli & Gagné, 2014; Guay et al., 2015; Wininguer, 2007). For example, Chemolli and Gagné (2014) argued that if the continuum hypothesis truly represented the structure of motivation, CFA should support the adequacy of a single factor model, and loadings on this single factor would range from negative for the least self-determined forms of motivation to positive for the most self-determined forms of motivations. They used Rasch analysis, a stringent statistical test
specifically developed to evaluate continuum structures (Rasch, 1960), to test whether there was a continuum structure underlying the items of the MWMS and the Academic Motivation Scale (Vallerand et al., 1992), and found no support for it. These results concur with past research that has consistently supported multidimensional models over unidimensional ones (e.g., Gagné et al., 2010, 2015; Li, 1999; Mallett, Kawabata, Newcombe, Otero-Forero, & Jackson, 2007).

A different test of this hypothesis was conducted by Guay et al. (2015), who investigated the continuum assumption of SDT using exploratory structural equation modeling (ESEM). Guay et al. (2015) further noted that in ESEM, the SDT continuum could be expressed in two distinct and complementary manners. In line with previous studies, the continuum hypothesis would be supported by the observation of the expected simplex pattern at the level of factor correlations. Because ESEM tends to result in more exact estimates of these factor correlations (see the methodological section below), the simplex pattern could be expected to be clearer using ESEM than CFA. Moreover, support for the continuum hypothesis could also come from the observation of larger cross-loadings between adjacent subscales than between more theoretically distal subscales. Testing these propositions with the Academic Motivation Scale (Vallerand et al., 1992), Guay et al. (2015) found that the data fit the ESEM representation better than the CFA model, and that factor correlations were more in line with the expected SDT continuum with ESEM than with CFA. However, even though the simplex pattern was cleaner with ESEM, the results still showed many digressions, and did not fully replicate across samples. Results also revealed cross-loadings somewhat in line with the SDT continuum (i.e., stronger between adjacent factors), though they remained generally small. Overall, these results partially supported the continuum hypothesis (for a similar ESEM representation of doctoral students’ academic motivation, see Litalien, Guay, &
In the present study, we extend these previous studies by combining into a single bifactor-ESEM framework the tests conducted separately by Chemolli and Gagné (2014) and Guay et al. (2015) to a new measure of work motivation (Gagné et al., 2015).

**Methodological Issues: Introduction to Bifactor-ESEM**

CFA has become the ubiquitous test of factor structures in psychological measurement. Measures which fail to meet designated goodness-of-fit standards are deemed of little worth in the eyes of researchers and reviewers alike. Despite this, psychological scales which consistently meet these rather arbitrary benchmarks are few. This has caused many to question the necessity of the Independent Cluster Model (ICM) constraints inherent in CFA, in which cross-loadings between items and non-target factors are assumed to be exactly zero. Undoubtedly, CFA has had a positive influence on psychological measurement by encouraging researchers to develop more a priori, precise, and parsimonious models (e.g., Morin, Marsh, & Nagengast, 2013). Through its integration into the Structural Equation Modeling (SEM) framework, CFA has provided ways to test how the data fits with a priori expectations, to systematically investigate the degree to which a measurement or predictive model is invariant across meaningful subgroups of participants, and to assess relations between constructs corrected for measurement errors. These developments have been so substantial that CFA has completely superseded traditional Exploratory Factor Analyses (EFA) for all but the most preliminary tests of factor structure.

Over and above the intuitive appeal of clearly defined concepts, measured by a small number of items perfectly designed to assess a single construct, has come a recent recognition that the ideals pursued through a CFA approach are often impossible to achieve in applied research (e.g., Marsh et al., 2009, 2010). Nowadays, many researchers recognize that the ICM constraints inherent in CFA are oftentimes not appropriate given
the nature of the data (for a review, see Marsh, Morin, Parker, & Kaur, 2014).

Specifically, the fallible and imperfect nature of typical psychometric indicators which typically can be expected to tap into more than one source of true score variance calls into question the usefulness of CFA (e.g., Morin, Arens, & Marsh, 2016a). As noted by Morin et al. (2016a), indicators are rarely, if ever, perfectly and uniquely related to a single construct, and will almost always display some degree of construct-relevant association with non-target factors assessing conceptually-related (such as interrelated motivation types, see Guay et al., 2015; Litalien et al., 2015) or hierarchically-ordered constructs (such as when motivation types are expected to assess an overarching motivation continuum, see Chemolli & Gagné, 2014).

**CFA versus ESEM**

Relying on an EFA measurement model allowing for the estimation of cross-loadings is typically required as a test of construct-relevant multidimensionality related to the assessment of conceptually related constructs (Morin et al., 2016a; Morin, Arens, Tran, & Caci, 2016b). However, EFA has often been criticized for being data driven and “exploratory” in nature (e.g., Kahn, 2006; Preacher & MacCallum, 2003). This implies an approach in which multiple models are compared and the model producing the best correspondence to the data (based on a variety of criteria) is retained for further use. In contrast, CFA is generally assumed to be theory-driven and models are assessed in and of themselves using a variety of goodness-of-fit indices. This view has led to the erroneous assumption that EFA is a data-driven procedure unsuited to confirmatory studies. According to Morin et al. (2013: 396):

“This perception is reinforced by the erroneous semantically-based assumption that EFA is strictly an exploratory method that should only be used when the researcher has no a priori assumption regarding factor structure and that confirmatory methods are...
better in studies based on a priori hypotheses regarding factor structure. This assumption still serves to camouflage the fact that the critical difference between EFA and CFA is that all cross-loadings are freely estimated in EFA. Due to this free estimation of all cross-loadings, EFA is clearly more naturally suited to exploration than CFA. However, statistically, nothing precludes the use of EFA for confirmatory purposes, except perhaps the fact that most of the advances associated with CFA/SEM were not, until recently, available with EFA.”

The recent development of ESEM (Asparouhov & Muthén, 2009; Marsh et al., 2014; Morin et al., 2013) provides a promising way to circumvent restrictive ICM assumptions. ESEM provides an overarching framework allowing for the combination of CFA, EFA, and SEM into a single model. ESEM thus incorporates the benefits from each technique into a single analytic framework where factors defined according to ICM assumptions can cohabitate with EFA factors incorporating cross-loadings.

A frequent misunderstanding about EFA/ESEM is that the inclusion of cross-loadings is likely to change, or taint, the meaning of the latent factors that are estimated. This flawed criticism neglects the fact that EFA/ESEM corresponds to a reflective measurement model where the factors are assumed to influence the items, rather than the opposite. A perhaps more critical issue is whether the factor itself is adequately captured, from a psychometric perspective, as being primarily reflected in its a priori indicators. Indeed, whenever results show large and hard to explain cross-loadings suggesting that some specific factors are mainly reflected in unexpected items rather than in their a priori items, then alternatives models should be explored. As noted by Morin et al. (2016a: 135-136):

“Small cross-loadings should be seen as reflecting the influence of the factor on the construct-relevant part of the indicators, rather than the indicators having an impact...
on the nature of the factor itself. It should be kept in mind that this interpretation applies to relatively small cross-loadings that are in line with theoretical expectations, whereas any model showing large and unexplainable cross-loadings or cross-loadings larger than target loadings should be re-examined.”

Forcing cross-loadings to be exactly zero involves ignoring some potentially true influence of a factor (such as stress) on indicators presenting some residual association with these factors (such as insomnia) over and above their association with their main a priori factor (such as burnout). In fact, even when large cross-loadings suggest a problem in the model, forcing them to be zero simply hides sources of misspecification that will in turn be expressed as model misfit – leading to an examination of model modification indices to locate the source of misfit. An advantage of EFA/ESEM is that it allows for the simultaneous consideration of all cross-loadings in a single step, whereas modification indices are calculated based on the inclusion of a single cross-loading at a time (Morin & Maïano, 2011).

It could be argued that ignoring these associations between items and non-target constructs simply results in reduced goodness-of-fit indices and that typical interpretation guidelines for goodness-of-fit indices are just too stringent for complex measurement models (e.g., Marsh, Hau, & Wen, 2004). However, a clear demonstration that cross-loadings do not taint the meaning of the latent factors comes from simulation studies showing that EFA/ESEM tends to provide more exact estimates of true population values for factor correlations when cross-loadings (even small ones) are present in the population model, and to remain unbiased when the population model corresponds to ICM-CFA (Asparouhov & Muthén, 2009; Marsh, Lüdtke, Nagengast, Morin, & Von Davier, 2013; Morin et al., 2016a; Sass & Schmitt, 2010; Schmitt & Sass, 2011; for a more extensive discussion, see Asparouhov, Muthén, & Morin, 2015). In turn, biased CFA estimates of
factor correlations likely affect the discriminant validity of the factors by creating artificial multicollinearity in subsequent analyses where these factors are used in prediction.

Another legitimate concern about EFA/ESEM is the issue of rotational indeterminacy, meaning that the parameter estimates from any EFA/ESEM model will vary as a function of the rotation procedure that is retained (e.g., Morin & Maïano, 2011; Sass & Schmitt, 2010; Schmitt & Sass, 2011). More precisely, EFA/ESEM models based on different rotations procedures – designed to reduce either cross-loadings or factor correlations to various degrees – will converge on alternative solutions that have equivalent covariance implications (i.e., data fitting different models equivalently). In practice, alternative forms of oblique rotations tend to provide nearly identical, or at least equivalent in terms of substantive interpretations, solutions as demonstrated in simulation studies by Sass and Schmitt (2010); and Schmitt and Sass (2011), and real data examples by Morin and Maïano (2011) and Morin et al. (2013). However, users should remain aware of this issue and, whenever they decide to use empirical (atheoretical) rotation procedures, should always conduct at least a preliminary exploration of alternative rotations to verify the stability of results. Recent recommendations suggest that this issue can be solved in confirmatory applications of EFA/ESEM relying on target rotation whereby the rotation is guided by a priori expectations regarding the expected factor structure (Marsh et al., 2014; Morin et al., 2016a). The development of target rotation (in which all cross-loadings are freely estimated but “targeted” to be as close to zero as possible) makes it possible to use a fully confirmatory approach to the specification of EFA/ESEM factors (Asparouhov & Muthén, 2009; Browne, 2001). The most common use of ESEM so far has been the testing of theoretically established models in which the number and content of specified latent factors was a priori defined (Marsh et al., 2014).
**Bifactor-ESEM**

As noted above, a second source of construct relevant multidimensionality is related to the assessment of hierarchically-ordered constructs (such as an overarching motivation continuum). This possibility has typically been investigated using higher-order factor models, which directly test the hypothesis that the various factors can combine into one or many higher-order factors. However, higher-order factor models rely on highly restrictive implicit assumptions that may not hold in practice and may explain why they often fail to meet minimal requirements of adequate fit (Gignac, 2008; Morin et al., 2016a; Reise, 2012). More precisely, higher-order models assume that the association between items and the higher-order factor is fully mediated by the first-order factors (McAbee, Oswald, & Connelly, 2014), so that the higher-order factor does not in itself explain any unique variance over and above that already explained by the first-order factors. For this reason, the first-order factors in a higher-order model reflect a combination of the variance explained by the higher-order factor and of the variance uniquely attributable to each first-order factor (Morin et al., 2016b). More importantly, because the relation between the higher-order factor and the item is mediated through the first-order factor, this relation is captured by the product of the loading of the item on a first-order factor, and the loading of this first-order factor on the higher-order factor: A constant for all items associated with a single first-order factor. Similarly, the relations between the items and the disturbances of the first-order factors (reflecting the variance uniquely attributable to the first-order factor) is also indirect, and reflected by the product of the loadings of the items on their first-order factor with a constant for all items associated with a single first-order factor. Because of this characteristic, the ratio of variance attributed to the global factor versus uniquely attributed to the first-order factor is constant for all items associated with a single first-order factor (Gignac, 2008; Morin et
An alternative, and far more flexible, way to examine whether the presence of a single global SDT factor underlying answers to motivation questionnaires involves the use of a bifactor representation, in which all items are used to define their respective motivation subscales while also being used to directly define a global SDT motivation factor that represents the continuum (Reise, 2012). Bifactor models have existed for decades (Holzinger & Swineford, 1937), and are well known in research on intelligence (Gignac, 2008) or personality (McAbee, Oswald, & Connelly, 2014). In comparison to higher-order models, bifactor models present none of these redundancies or restrictions, and provide a way to explicitly separate the variance attributable to specific factors from the variance attributable to the global general factor, while allowing for the estimation of direct relations between the items and both the specific and global factors. More precisely, bifactor models assume that the covariance among a set of \( n \) items can be explained by a set of \( f \) orthogonal factors including one Global (G) factor and \( f-1 \) Specific (S) factors. In bifactor-CFA models, each item is used to define the G-factor and one of the S-factors. Bifactor models thus partition covariance into a G-factor underlying all items, and \( f-1 \) S-factors corresponding to the covariance not explained by the G-factor. This clean partitioning is made possible by the orthogonality of the factors, which forces all of the variance shared among all items to be absorbed into the G-factor, and the S-factors to represent what is shared among a specific subset of items but not the others.

Interestingly, higher-order models form restricted nested versions of bifactor models. While the above mentioned proportionality constraints implicit in higher-order models introduce some parsimony to the model, they are unlikely to hold in most research settings (Reise, 2012; Yung, Thissen, & McLeod, 1999) or to make sense theoretically (Gignac, 2016), thus positioning bifactor models as the more robust modeling procedure.
Jennrich and Bentler (2011) showed that while bifactor models were able to properly recover true higher-order factor structures, higher-order factor models could not always properly recover true bifactor structures. Bifactor models should thus be preferred over higher-order models unless strong theoretical reasons are present to support the need to model the relations between the indicators and the global factors as indirect, and the presence of the implicit proportionality constraints (for a more extensive discussion of these issues, see Gignac, 2016).

Whenever a single instrument is expected to incorporate both conceptually-adjacent constructs and hierarchically-ordered constructs, it becomes important to rely on a model that allows for the incorporation of both cross-loadings (i.e., EFA) and global factors (i.e. bifactor). Indeed, research has shown that unmodeled cross-loadings tend to result in inflated estimates of the global factor in bifactor-CFA, and that an unmodeled global factor tends to result in inflated cross-loadings in EFA (e.g., Morin et al., 2016a; Murray & Johnson, 2013). Recent development of bifactor target rotation for EFA makes it possible to incorporate bifactor modeling to the ESEM framework (Reise, 2012; Reise, Moore, & Maydeu-Olivares, 2011). The resulting bifactor-ESEM method offers the most detailed and flexible models possible, more so than either EFA or CFA/SEM alone, and can now be implemented while relying on a confirmatory bifactor target rotation approach (Morin et al., 2016a, 2016b).

The Present Study

In the present study, we conducted an integrated test of SDT’s continuum hypothesis of motivation combining the perspectives of: (1) Guay et al. (2015; also see Litalien et al., 2015), which showed that taking into account sources of construct-relevant psychometric multidimensionality related to the assessment of conceptually-related constructs was necessary to obtain a clearer representation of the continuum structure of
motivation; and (2) Chemolli and Gagné (2014), who argued that the strongest evidence in favor of the SDT continuum hypothesis should come from the demonstration that all motivation items contribute to the assessment of a single overarching self-determination factor (i.e., from the observation of another source of construct-relevant psychometric multidimensionality related to the assessment of hierarchically-ordered constructs). To do so, we rely on the bifactor-ESEM framework proposed by Morin et al. (2016a, 2016b), which allows for the simultaneous consideration of these two perspectives into a single model.

The bifactor component of this framework directly tests whether the items measuring the different types of motivation load onto a single factor with loadings ranging from negative to positive according to the expected position of the items along the SDT continuum (aligned with Chemolli and Gagné’s perspective), while allowing the estimation of specific factors for each motivation type. Essentially, should this hypothesis be supported, this global factor is expected to provide a global estimate of the overall quantity of self-determined motivation characterizing individual employees, whereas the resulting specific factors would reflect the more specific quality, or flavor, of employees’ motivational profiles. More precisely, because of the inherent orthogonality of bifactor models, employees’ overall amount (quantity) of self-determined motivation will be reflected in the G-factor, whereas the specific features (quality) of employees’ motivational profiles left unexplained by this global amount of self-determination will be reflected in the S-factors (e.g., pleasure, guilt, pressure). The ESEM component of this framework allows us to incorporate the presence of a second layer of continuity in motivation ratings expressed through the estimation of cross-loadings between motivation factors (e.g., Morin et al., 2016a), as advocated by Guay et al. (2015).

Thus, based on current theory suggesting the existence of an overarching
continuum of motivation (Chemolli & Gagné, 2014) and research suggesting the importance of controlling for cross-loadings between motivation factors in order to obtain a proper depiction of the underlying structure of motivation measures (Guay et al., 2015; Litalien et al., 2015), we expect the bifactor-ESEM model to provide the most adequate representation of employees’ answers to the MWMS (Gagné et al., 2015). However, following Morin et al. (2016a, 2016b) recommendations regarding the application of the bifactor-ESEM framework for the identification of the sources of construct-relevant multidimensionality present in complex psychometric measures, as well as basic principles of model testing (e.g., Bollen, 1989), we contrast this a priori bifactor-ESEM representation with more parsimonious alternative models including either none (CFA) or only-one (ESEM, Bifactor-CFA) of these likely sources of multidimensionality. These four alternative models are presented in Figure 1.

To establish the criterion-related validity of the resulting global (G) and specific (S) motivation factors, we also test the extent to which they are related to a series of covariates that occupy a core position in SDT theorization both generically (i.e., the satisfaction of the needs for autonomy, competence and relatedness) and in the work context (i.e., employees levels of affective and continuance commitment to the organization). SDT proposes that the satisfaction of basic psychological needs for autonomy (a sense of volition), competence (the experience of mastery) and relatedness (feeling connected to others) should promote autonomous over controlled types of motivation (Deci & Ryan, 2000; Gagné & Deci, 2005). Research has found strong support for this proposition both in general and organizational psychology (Deci & Ryan, 2000, 2008; Gagné et al., 2015).
Figure 1: Simplified representations of specified models

Note. ICM-CFA: Independent cluster model- confirmatory factor analysis; ESEM: Exploratory structural equation modelling.
Past research has also found rather robust relations between different types of motivation and distinct commitment mindsets (Gagné, Chemolli, Forest, & Koestner, 2008; Gagné et al., 2015). In particular, affective organizational commitment (emotional attachment to, and identification with the organization; Meyer, Allen, & Smith, 1997) has been positively related to autonomous (identified and intrinsic) motivation (Gagné et al., 2008), while continuance commitment (staying in the organization because of the perceived cost of leaving and lack of alternatives; Meyer et al., 1997) has been positively related to external regulation and negatively related to more internalized regulations (Battistelli, Galletta, Portoghese, & Vandenberghe, 2013; Gagné, Chemolli, Forest, & Koestner, 2008; Vandenberghe & Panaccio, 2012).

In order to more precisely assess the criterion-related validity of the motivational factors, we also systematically contrast models in which only the G-factor (i.e., reflecting the overall quantity of self-determined motivation) is allowed to predict the covariates, with models in which the S-factors (i.e., reflecting the specific quality of motivation) are also allowed to predict the covariates. These comparisons systematically test the added value (in terms of percentage of explained variance in the covariates) that is afforded by the simultaneous consideration of both motivation quantity and quality.

**Method**

**Participants and Procedure**

This study used archival data collected between 2008 and 2012 that has been previously used to validate the MWMS (Gagné et al., 2015). The current sample includes 1124 full time Canadian employees from a range of organizations and industries. Content of the surveys varied within data sets in terms of covariates and demographics, but all
participants completed the same 19 items forming the MWMS. Employees completed confidential surveys voluntarily on an online platform or in paper format on their work premises. Additional details are provided in Gagné et al. (2015).

Measures

The MWMS (Gagné et al., 2015) includes 19 items assessing six distinct motivation types. Each item is a response to the stem, “Why do you or would you put efforts into your current job?” along a 1 (not at all) to 7 (completely) point Likert scale. Example items include, “I don’t know why I’m doing this job, it’s pointless work” (Amotivation; α = .78 in the current study), “To get others’ approval (e.g., supervisor, colleagues, family, clients...)” (External regulation social; α = .77), “Because others will reward me financially only if I put enough effort in my job (e.g., employer, supervisor...)” (External regulation material; α = .63), “Because otherwise I will feel ashamed of myself” (Introjected regulation; α = .71), “Because putting efforts in this job aligns with my personal values” (Identified regulation; α = .80), and “Because the work I do is interesting” (Intrinsic motivation; α = .90). Validation evidence for the MWMS based on the current data set has already demonstrated adequate fit for a six-factor ICM-CFA structure (invariant across French and English languages), acceptable scale score reliability (Cronbach’s α ranged from .70-.90 for all subscales), and supported the convergent and discriminant validity of the scales (Gagné et al., 2015).

Need satisfaction was measured using an early version of the work-related Basic Needs Satisfaction Scale (Van den Broeck, Vansteenkiste, Witte, Soenens, & Lens, 2010). This instrument assesses the satisfaction of the three basic needs for: (a) autonomy (3 items, α = .81, e.g., “I feel like I can be myself at my job”); (b) competence (3 items, α = .85, e.g.,
“I really master my tasks at my job”), and (c) relatedness (4 items, \( \alpha = .82 \), e.g., “At work I feel part of a group”) on a 1 (totally disagree) to 5 (totally agree) Likert scale.

Affective commitment to the organization was measured using Meyer, Allen, and Smith’s (1993) organizational commitment measure (6 items, \( \alpha = .84 \), e.g., “This organization has a great deal of personal meaning to me”). Continuance commitment to the organization was measured by Stinglhamber, Bentein, and Vandenberghe’s (2002) French adaptation of Meyer et al.’s (1993) measure to ensure a complete coverage of both high-sacrifice (i.e., cost of leaving) and low-alternative (i.e., Lack of alternatives) facets (6 items, \( \alpha = .70 \), e.g., “I consider my job opportunities as too limited to consider leaving the organization”). All items were rated on a 1 (totally disagree) to 7 (totally agree) Likert scale.

**Estimation and Specification**

All models were estimated using Mplus 7.3 (Muthén & Muthén, 2014) robust Maximum Likelihood (MLR) estimator. CFA models were specified according to ICM assumptions, with items allowed to load onto their a priori motivation factor, and all cross-loadings constrained to be exactly zero. ESEM was specified using target rotation: Item loadings on their a priori motivation factors were freely estimated, and all cross-loadings were also freely estimated but “targeted” to be as close to 0 as possible. Bifactor-CFA (B-CFA) models were specified as orthogonal, with each item specified as loading on the SDT G-factor as well as on their a priori S-factors corresponding to the six distinct motivation types. Finally, bifactor-ESEM (B-ESEM) was estimated using bifactor target rotation: All items were used to define the SDT G-factor, while the 6 S-factors were defined using the same pattern of target and non-target loadings and cross-loadings as in the ESEM solution.

The current models correspond to typical bifactor specifications where all items are used to
define the G-factor, and one S-factor in line with theoretical expectations that all items reflect motivation types organized according to the expected continuum structure of motivation reflected in the G-factor.\textsuperscript{1} We note however that hybrid models, such as models including more than one G-factor (e.g., Caci, Morin, & Tran, 2015), or models where only a subset of items are used to define the G-factor (e.g., Brunner, Lüdtke, & Trautwein, 2008), are also possible when theoretical expectations suggest that these might be more appropriate.

Covariates were then integrated to the final retained measurement model, allowing estimation of relations between the motivation factors and the covariates. In a first model, only the G-factor was allowed to covary using the ESEM-within-CFA method described by Morin et al. (2013, 2016a) which allows for the estimation of relations between only a subset of B-ESEM factors (i.e., here only the G-factor) and covariates. This model simulates the common approach used in SDT of using a single motivation score (\textit{quantity}; i.e., the relative autonomy index; Fernet, Gagné, & Austin, 2010; Grolnick & Ryan, 1987; Markland & Ingledew, 2007; Pelletier, Seguin-Levesque, & Legault, 2002), which ignores the relative impact of different types (or \textit{qualities}) of motivation. In a second model (relying on a regular B-ESEM representation), both the G-factor and the S-factors were allowed to predict scores on all covariates. These two models were contrasted to one another on the basis of goodness of fit information, but also based on standardized regression coefficients and model-based estimates of the percentage of explained variance (R\textsuperscript{2}) in the covariates afforded by the model.

**Model Comparisons**

Because of the known oversensitivity of the chi-square test of exact fit to sample size and minor model misspecifications (e.g., Marsh, Hau, & Grayson, 2005), model fit was
assessed using commonly used goodness-of-fit indices and information criteria: the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA) with its confidence interval, the Akaike Information Criteria (AIC), the Constant AIC (CAIC), the Bayesian Information Criteria (BIC), and the sample-size adjusted BIC (ABIC). According to typical interpretation guidelines (e.g., Hu & Bentler, 1999; Marsh, Hau, & Wen, 2004; Marsh et al., 2005), values greater than .90 and .95 for the CFI and TLI respectively support adequate and excellent fit of the data to the model while values smaller than .08 or .06 for the RMSEA support acceptable and excellent fit. When comparing models, changes in RMSEA, CFI and TLI greater than .01 were deemed significant as established by Cheung and Rensyold (2002), and Chen (2007). Although they cannot be used to assess the global fit of a single model, the information criteria (AIC, CAIC, BIC, ABIC) are particularly useful in the comparison of alternative models, with lower values supporting a better fitting model. These guidelines have so far been established for CFA, and have also been used in previous applications of ESEM (e.g., Marsh et al., 2009, 2014; Morin et al., 2013, 2016a). However, because ESEM includes many more parameters than ICM-CFA, due to the free estimation of cross-loadings, it has been suggested that indicators including a correction for parsimony (i.e., TLI, RMSEA, AIC, CAIC, BIC, ABIC) will be critical to the assessment of model fit in an ESEM context (Marsh et al., 2009, 2010, 2014; Morin et al., 2013, 2016a).

It is important to keep in mind that these remain rough guidelines for descriptive model evaluation, which also needs to take into account the even more important information coming from parameters estimates, statistical conformity and theoretical meaningfulness (Marsh et al., 2004, 2005). Indeed, each of these models is able to absorb unmodelled sources
of construct-relevant multidimensionality (e.g., Asparouhov et al., 2015; Morin et al., 2016a; Murray, & Johnson, 2013). For this reason, a close examination of parameter estimates and theoretical conformity is necessary to select the best alternative among a series of models as simple goodness-of-fit-assessment is often insufficient to differentiate among models that often provide similar levels of fit to the data (Marsh et al., 2011; Morin et al., 2016a). Morin et al. (2016a, 2016b) suggest to start with a comparison of CFA and ESEM solutions. In this comparison, as long as the factors remain well-defined by strong target factor loadings, the key issue is related to the factor correlations. Statistical evidence that ESEM tends to provide more exact estimates of true factor correlations (Asparouhov et al., 2015) suggests that ESEM should be retained whenever the results show a discrepant pattern of factor correlations. Otherwise, the CFA model should be preferred based on parsimony. Then, the second comparison involves contrasting the retained model with its bifactor counterpart (B-CFA or B-ESEM). Here, the key elements favoring a bifactor representation are the observation of a G-factor that is well-defined by strong factor loadings, and the observation of reduced cross-loadings in B-ESEM compared to ESEM.

**Results**

**Measurement Models**

Table 1 presents the goodness-of-fit indices and information criteria associated with each of the estimated models. The ICM-CFA demonstrated marginally adequate fit, whereas the B-CFA did not. In contrast, the ESEM solution provided an excellent representation to the data according to all indices, and provided a better representation than the ICM-CFA solution based on lower scores on the information criteria and substantial improvement on the goodness-of-fit indices ($\Delta$$\text{CFI} = +.05$; $\Delta$$\text{TLI} = +.06$; $\Delta$$\text{RMSEA} = -.02$). Furthermore, the
90% confidence intervals for the RMSEA showed no overlap between the CFA and ESEM solutions, indicating a high degree of differentiation between competing models. Finally, although the B-ESEM solution provided an excellent representation of the data, it displayed only marginal improvement relative to the ESEM solution according to goodness-of-fit indices ($\Delta$CFI < .01; $\Delta$TLI = +.01; $\Delta$RMSEA = -.01), overlapping confidence intervals for the RMSEA, almost identical values for the information criteria, but resulted in a non-significant chi square value suggesting that it is the only model providing exact fit to the data. However, no analysis should be conducted in disconnection from theory, expectations, and a detailed examination of parameter estimates (Marsh et al., 2014; Morin et al., 2016a).

Table 1: *Goodness of fit statistics and information criteria*

<table>
<thead>
<tr>
<th>Model</th>
<th>$\chi^2$</th>
<th>df</th>
<th>RMSEA (90% CI)</th>
<th>CFI</th>
<th>TLI</th>
<th>AIC</th>
<th>BIC</th>
<th>CAIC</th>
<th>ABIC</th>
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</thead>
<tbody>
<tr>
<td>ICM-CFA</td>
<td>513*</td>
<td>137</td>
<td>.05 (.05 - .06)</td>
<td>.94</td>
<td>.92</td>
<td>73958</td>
<td>74320</td>
<td>74392</td>
<td>74091</td>
</tr>
<tr>
<td>ESEM</td>
<td>128*</td>
<td>72</td>
<td>.03 (.02 - .03)</td>
<td>.99</td>
<td>.98</td>
<td>73608</td>
<td>74296</td>
<td>74433</td>
<td>73861</td>
</tr>
<tr>
<td>Bifactor-CFA</td>
<td>834*</td>
<td>133</td>
<td>.07 (.06 - .7)</td>
<td>.88</td>
<td>.85</td>
<td>74332</td>
<td>74714</td>
<td>74790</td>
<td>74472</td>
</tr>
<tr>
<td>Bifactor-ESEM</td>
<td>75</td>
<td>59</td>
<td>.02 (.00 - .03)</td>
<td>1.00</td>
<td>.99</td>
<td>73574</td>
<td>74328</td>
<td>74478</td>
<td>73851</td>
</tr>
</tbody>
</table>

*Note.* ICM = Independent cluster model; CFA = Confirmatory factor analysis; ESEM = Exploratory structural equation modeling; df = Degrees of freedom; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; CI = confidence interval; AIC = Akaike information criterion; CAIC = Constant AIC; BIC = Bayesian information criterion; ABIC = Sample size adjusted BIC; * $p < .01$.

Because the data did not fit the B-CFA model to even a minimally acceptable standard, and following Morin et al. (2016a, 2016b) recommendations, we first turn to a comparison of ICM-CFA and ESEM, before moving on to the B-ESEM solution. Before doing so however, it is worth noting that on the strict basis of goodness-of-fit assessment showing the superiority of the ESEM and B-ESEM solutions when compared to the ICM-CFA and B-CFA solutions, cross-loadings are clearly to be expected in the solution. Because of this, factor correlations are expected to be higher in the ICM-CFA model compared to the ESEM models as this is the only way through which these cross-loadings can be expressed.
Because the B-CFA model is orthogonal however, the only way for these omitted cross-loadings to be expressed is through an inflated estimate of the factor loadings of items on the G-factor (Morin et al., 2016a), which is unlikely to be a sufficient to compensate for this source of misfit should the cross-loadings reflect another source of multidimensionality than the presence of an underlying global construct. This likely explains why the fit of the B-CFA model was lower and less adequate than that of the ICM-CFA.

Parameter estimates for ICM-CFA and ESEM are reported in Tables 2 (correlations) and 3 (factor loadings, cross-loadings and uniquenesses). Looking first at the loadings and cross-loadings, the overall size of the factor loadings of the items on their target factors remained similar in the ICM-CFA ($\lambda = .50$ to .90; $M = .69$) and ESEM ($\lambda = .37$ to .93; $M = .65$) solutions, showing well-defined factors corresponding to a priori expectations. In the ESEM solution, target factor loadings systematically remained higher than cross-loadings, which generally remained very small ($|\lambda| = 0$ to .37 $M = .02$). In fact, only two cross-loadings were higher than .30: Item 1 of identified regulation (“Because I personally consider it important to put effort into this job”) cross-loaded on the introjected regulation factor at .37, and introjected item 2 (“Because it makes me feel proud of myself”) on the identified factor at .31. Closer inspection suggested no pattern of larger cross-loadings between adjacent factors and smaller or more negative cross-loadings between more distant factors, providing weak support for the continuum hypothesis at the cross-loadings level.
Table 2: Standardized factor correlations for the ICM-CFA (above the diagonal) and ESEM (below the diagonal) solutions

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
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<td>.46**</td>
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<td>.44**</td>
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<td>.53**</td>
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<td>.18**</td>
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</tr>
<tr>
<td>Item 3</td>
<td>- .47**</td>
<td></td>
<td>- .41**</td>
<td></td>
<td>- .17**</td>
<td>.14**</td>
</tr>
</tbody>
</table>

Note: * p < .05, ** p < .01

Table 3: Standardized factor loadings (λ) and uniquenesses (δ) for ICM-CFA and ESEM

<table>
<thead>
<tr>
<th>Items</th>
<th>ICM-CFA solution</th>
<th>ESEM solution</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>λ</td>
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<td>Item 2</td>
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<td>Item 3</td>
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<tr>
<td>Item 3</td>
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<td>3. Introjected</td>
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<td>Item 2</td>
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<td>4. External-social</td>
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<td>.72</td>
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<td>Item 2</td>
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<td>5. External-material</td>
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<tr>
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<td>.55</td>
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<td>6. Amotivation</td>
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<tr>
<td>Item 3</td>
<td>.71</td>
<td>.50</td>
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As expected, factor correlations proved to be slightly lower in ESEM ($r = -.47$ to .77, $|M| = .31$) than ICM-CFA ($r = -.48$ to .81, $|M| = .37$).\(^2\) The overall pattern of those correlations, however, was not changed by the decision to rely on an ICM-CFA or ESEM solution. A closer examination of these correlations reveals that they match the continuum hypothesis relatively well, being stronger between conceptually closer factors than between conceptually distant factors. Additionally, the amotivation factor appears to represent one end of the hypothesized continuum, showing generally negative correlations with more autonomous forms of motivations (intrinsic and identified), a smaller correlation with introjected regulation, and positive correlations with the social and material forms of external regulation (with a slightly larger correlation for the material factor than for the social factor).

Looking at the B-ESEM solution, we already noted that it represented the data quite well, and provided an exact fit to the data. It is interesting to note that typical (i.e. orthogonal) representations of bifactor models attempt to synthetize the covariance (i.e., correlations) among factors through the estimation of a single G-factor, and to keep in mind that the ESEM correlations generally supported the continuum hypothesis. As such, a key advantage of the bifactor-ESEM model in comparison to the ESEM model, in addition to its exact fit to the data, is that it provides a single directly interpretable self-determination G-factor. Interestingly, results from the bifactor-ESEM solution (see Table 4) revealed a well-defined G-factor representing general self-determination. This G-factor follows the idea of a continuum underlying motivation: The loadings on the G-factor were high and positive for the items associated with the autonomous motivation S-factors ($\lambda = .71$ to .75 for intrinsic motivation, and .56 to .79 for identified regulation), moderate for the items associated with introjected regulation ($\lambda = .26$ to .61), lower for the items associated with external regulation-
social ($\lambda = .02$ to .21), small or negative for the items associated with the external regulation-material S-factor ($\lambda = -.07$ to .25), and negative for the items associated with amotivation ($\lambda = -.35$ to -.30).

Table 4: Standardized factor loadings ($\lambda$) and uniquenesses ($\delta$) for bifactor-CFA and bifactor-ESEM

<table>
<thead>
<tr>
<th>Items</th>
<th>Bifactor-CFA</th>
<th>G- Factor ((\lambda))</th>
<th>S- Factor ((\lambda))</th>
<th>G- Factor ((\lambda))</th>
<th>S- Factor ((\lambda))</th>
<th>S- Factor ((\lambda))</th>
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Further examination of this solution reveals reasonably low cross-loadings, remaining lower than target loadings (|\(\lambda| < .01$ to .33; M = .08), and reasonably well-defined S-factors (\(\lambda = .26$ to .78; M = .50), with very few noteworthy exceptions. Importantly, the cross loadings tended to be smaller in the bifactor-ESEM solution than in the ESEM solution,
suggesting that part of the ESEM cross-loadings reflected the presence of the unmodelled G-factor. It is also interesting to note that the S-factors located at the ends of the continuum (amotivation, external-social regulation, external-material regulation, and intrinsic motivation; \( \lambda = .41 \) to \( .78 \); \( M = .57 \)) retained substantial specificity once the covariance attributed to the self-determination G-factor was taken into account. Conversely, the S-factors located toward the midpoint of the continuum (identified and introjected regulation; \( \lambda = .26 \) to \( .55 \); \( M = .38 \)) retained less specificity once the general self-determination factor is taken into account. Based on the evidence presented thus far, both in terms of exact fit to the data but most importantly theoretical conformity of the parameter estimates, the final retained model is the bifactor-ESEM model. In practical terms, this model also provides a way to simultaneously take into account all motivation factors (motivation quality), together with a global estimate of the quantity of self-determined motivation into a single predictive model, and to do so without having to rely on a psychometrically suboptimal RAI.

**Predictive Models**

From the final retained bifactor-ESEM solution, SEM analyses were used to assess the criterion-related validity of the various motivation factors. More precisely, these models were used to compare the added value of the specific motivation facets (representing the specific quality of employees’ motivational profiles) over and above the G-factor (representing overall quantity of self-determined motivation) in terms of percentages of explained variance in the various covariates considered. This comparison was achieved by contrasting a model in which only the G-factor was allowed to predict scores on the covariates, with a model in which both the G- and S-factors were allowed to predict scores on the covariates. As shown in Table 5, when considered as the sole predictor of covariates,
the self-determination G-factor was significantly associated, as expected, with higher scores on the affective commitment mindset (explaining 38% of its variance), as well as on the satisfaction of the needs for autonomy ($R^2 = 15\%$), competence ($R^2 = 1\%$), and relatedness ($R^2 = 15\%$). It was not significantly associated with continuance commitment.

These relations were all maintained in the next model where the S-factors were also allowed to relate to the covariates. This more complete model resulted in visible increases in explained variance in the various covariates: (a) from 38% to 42% for affective commitment; (b) from 0% to 14% for continuance commitment; (c) from 15% to 26% for the satisfaction of the need for autonomy; (d) from 1% to 5% for the satisfaction of the need for competence; (e) from 15% to 25% for the satisfaction of the need for relatedness. These increases in percentages of explained variance are also accompanied by increases in goodness-of-fit (complete model: $CFI = .99$; $TLI = .98$; $RMSEA = .02$; restricted model where only the G-factor relates to the covariates; $CFI = .98$; $TLI = .98$; $RMSEA = .03$).

Interestingly, relations observed between the S-factors and the covariates appear to be partly in line with our expectations, showing that continuance commitment was mainly, and positively, associated with levels of amotivation and external-social regulation. Contrary to our expectations, continuance commitment and external-material regulation were not significantly related. In contrast, and fully in line with our expectations, affective commitment was significantly, and negatively, associated with levels of amotivation, external-material regulation, and introjected regulation, but positively associated with identified and intrinsic motivation, as well as with the G-factor. However, we also noted an unexpected positive relation between affective commitment and external-social regulation.

With regards to basic need satisfaction, the results are also essentially in line with our
expectations that all three needs would be positively related to more autonomous forms of motivation. Indeed, significant positive relations between the satisfaction of the needs for autonomy and relatedness and motivation factors were limited to intrinsic motivation and to the G-factor, whereas they were strictly limited to the G-factor for the needs for competence. Moreover, relations between satisfaction of the needs for autonomy and relatedness were significant and negative with amotivation, introjection, and even identified regulation.

Table 5: Relations with covariates: Standardized coefficients

<table>
<thead>
<tr>
<th>Covariates</th>
<th>Quantity only</th>
<th>Quantity and Quality</th>
<th>G-Factor</th>
<th>R²</th>
<th>Amot.</th>
<th>Ext-Mat.</th>
<th>Ext-Soc.</th>
<th>Introd.</th>
<th>Ident.</th>
<th>Intrinsic</th>
<th>G-Factor</th>
<th>R²</th>
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<td>-.11 (&lt;.01)</td>
<td>.10</td>
<td>-.14</td>
<td>.20</td>
<td>.17</td>
<td>.55</td>
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<tr>
<td>Continuance Commitment</td>
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<td>.15 (.01)</td>
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<td>-.09</td>
<td>-.02</td>
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<td>Competence</td>
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<td>.07 (.01)</td>
<td>-.09</td>
<td>.06</td>
<td>-.11</td>
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<td>-.19 (&lt;.01)</td>
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Discussion

The present study had the dual objective of testing SDT’s continuum hypothesis of motivation (Deci & Ryan, 1985) using ratings obtained on the Multidimensional Work Motivation Scale (Gagné et al., 2015), while demonstrating the usefulness of the bifactor-ESEM framework for management research. Support for the continuum hypothesis of motivation has been at best inconsistent in previous research (Chemolli & Gagné, 2014; Gagné et al., 2015; Guay et al., 2015; Litalien et al., 2015; Mallett et al., 2007). In particular, recent studies relying on more systematic tests of this hypothesis using ESEM (Guay et al.,
2015; Litalien et al., 2015) and Rasch analysis (Chemolli & Gagné, 2014) respectively showed weak or no support for the continuum hypothesis. In the current study, we relied on a newly developed overarching bifactor-ESEM framework, which combines the logic of previous analyses conducted by Guay et al. (2015; Litalien et al., 2015) and Chemolli and Gagné (2014) to conduct a more comprehensive test of the SDT continuum hypothesis.

Using this framework, the SDT continuum could be expressed in three different manners. First, SDT’s continuum can be evidenced by the observation of ICM-CFA or ESEM factor correlations corresponding to the expected simplex pattern, showing larger correlations between conceptually adjacent motivation factors, and smaller or negative correlations between conceptually distant factors (Guay et al., 2015; Litalien et al., 2015). In the current study, the ICM-CFA/ESEM correlations provided support for SDT’s continuum hypothesis, showing stronger correlations between conceptually adjacent factors, and smaller or negative between more conceptually distal factors. Second, the SDT’s continuum can be evidenced by the observation of ESEM or B-ESEM cross-loadings that are larger and positive between conceptually adjacent motivation factors, and smaller or negative between conceptually distant factors (Guay et al., 2015; Litalien et al., 2015). In the current study, the results did not support this proposition as cross-loadings were uniformly small and evidenced no clear pattern of loading more highly on theoretically closer specific factors. Third, the strongest evidence in favor of SDT’s continuum hypothesis could come from the observation that the G-factor estimated as part of the B-CFA or B-ESEM solutions is characterized by a pattern of target loadings from the items associated with the motivation types corresponding to the continuum assumptions of SDT (e.g., Chemolli & Gagné, 2014). In the current study, the G-factor loadings were largely in line with the presence of an underlying continuum of
motivation. Given that the bifactor-ESEM model was retained for final interpretation, these results support the notion that motivation types follow an underlying continuum.

However, although our results provide strong evidence that motivation types follow a continuum structure globally aligned with SDT hypothesis, the observed continuum structure is not completely in agreement with SDT assumptions that that external and introjected regulations should load negatively on a continuum factor. Such a factor structure would represent what has been described in SDT as “relative self-determination” (Grolnick & Ryan, 1987). Instead, the introjection subscale loaded positively on the G-factor and the external regulation subscales loaded weakly but positively. As such, the factor loadings on the G-factor rather seem to represent a general quantity of self-determination (rather than relative self-determination), as they ranged from strongly positive for autonomous motivation items, slightly positive for introjected items, non-significant for external regulation items, to moderately negative for amotivation items. The pattern of factor loadings on the S-factors also suggested that while the subscales may be ordered in a predictable fashion, each still provided relevant unique information. As such, although our results support the presence of a continuum structure of motivation as proposed by SDT, they also suggest a need to revise the exact nature of this theoretical continuum, pending replication of the present results.

Turning now to the methodological contribution of this research, the results revealed that the data fit the ESEM representation better than the ICM-CFA model. This suggests that even the small cross-loadings present in the current data were enough to cause significant model misspecification. These cross-loadings are not surprising given the conceptually fine distinction between motivation types. Accounting for conceptual relatedness between the motivation types resulted in a significantly better fitting model, but also in more precise
estimates of the factor correlations (Marsh et al., 2013; Morin et al., 2016a, 2016b; Sass & Schmitt, 2010; Schmitt & Sass, 2011).

The estimated factor correlations were slightly lower in the ESEM solution than in the ICM-CFA solution. While not directly relevant to this study where the final retained model was a bifactor-ESEM model, this discrepancy in correlation estimates could have significant implications if these latent factors were used in prediction. Indeed, relying on ICM-CFA would introduce unnecessary multicollinearity (Asparouhov et al., 2015), which may explain why there are few published studies that use all of the separate motivation subscales in predictive regression or SEM models. Instead, many SDT studies typically rely on a single relative autonomy index (RAI; Grolnick & Ryan, 1987) or on two higher-order factors of autonomous and controlled motivation (e.g., Gillet, Gagné, Sauvagère, & Fouquereau, 2013).

The data did not fit the bifactor-CFA model as well as the other models. This was most likely the result of suppressing cross-loadings, which has been shown in past research to be problematic (Morin et al., 2016a, 2016b), especially for measures of conceptually close constructs such as motivation types (Guay et al., 2015). Given the orthogonality of this solution, these cross-loadings could only be expressed through an inflation of the loadings on the G-factor. Thus, the relatively poor fit of the B-CFA solution, and the superior fit of the B-ESEM solution, supports the idea that these cross-loadings are needed to reflect the presence of conceptually related constructs that could not entirely be captured by an overarching global factor. Indeed, the bifactor-ESEM displayed excellent fit, and revealed a pattern of factor loadings on the G-factor that supports the presence of a continuum structure.

Importantly, a key practical and theoretical advantage of the B-ESEM model is that it
provided an explicit expression of the expected self-determination continuum (rather than implicitly assuming its existence through an eyeballing of factor correlations). More precisely, the B-ESEM solution has the advantage of providing a directly interpretable latent estimate of overall self-determined motivation, and of allowing explicit tests of whether the S-factors (reflecting the residual variance attributable to qualitatively different motivation types over and above the global self-determined motivation factor) contribute to the prediction of meaningful outcomes over and above this global self-determined motivation factor. Pending replication of the current results, this advantage clearly suggests that this method should be given careful attention in future research in which the objective is to assess relations between self-determined motivation and various predictors, covariates, and outcomes.

Through the incorporation of covariates into the final retained B-ESEM model, the current study has uniquely been able to test the criterion-related validity of the G- and S-factors, and examine the degree to which the global quantity of self-determined motivation and the more specific qualities of motivation over and above this global factor explained variability in the covariates. Our results clearly showed the added value of considering these specific motivation facets over and above the global quantity of self-determined motivation. Specifically, across all covariates, the results showed that the complete model consistently resulted in a higher proportion of explained variance in the covariates when compared to the model in which only the G-factor was allowed to associate with covariates.

Furthermore, the simplified quantity-only model failed to recognize key directional differences between the various forms of regulations. When examining the relations between motivation and affective commitment for example, amotivation, external-material, and
introjected regulations all displayed negative relations with affective commitment, whereas external-social regulation did not. This result is important as it suggests that the regulations proposed by SDT are not always associated with covariates in a manner that directly and linearly follows their expected position on the continuum but rather (once the global quantity of self-determination is taken into account), are qualitatively different from one another to the extent of presenting differentiated patterns of relations with covariates. Similarly, when examining continuance commitment, which was not related to the G-factor, the quantity only model contributed to hide valuable information, such as a positive relation with external-social regulation and a negative association with amotivation. It appeared that quantity of self-determined motivation had essentially no association with continuance commitment whereas qualities specific to external-social and amotivation were significantly associated with this covariate. These examples demonstrate the importance of recognizing and modeling both quantity and qualities of motivation in not only explaining more variance in covariates, but also in creating a more detailed picture of the relations between covariates and motivation.

The results, when considered together, suggest that though there is evidence for a continuum structure underlying the types of motivation, important information would be lost if we were to assume that all motivation types can be summarized within a single (latent or manifest) score reflecting a self-determination continuum, such as the RAI. More precisely, it is critical to note that although the current results support “a” continuum of self-regulation, they do not represent “the” classical representation of the SDT continuum hypothesis (see above discussion), and clearly do not support the way this hypothesis has been used to justify the use of difference scores to combine all motivation types into a single RAI (Grolnick &
Ryan, 1987, see Chemolli and Gagné, 2014, for an in-depth discussion of the RAI. More precisely, the RAI is typically calculated by subtracting scores on the external and introjected regulation subscales from the scores on the identified and intrinsic motivation subscales to obtain a single indicator of self-regulation (Grolnick & Ryan, 1987). When amotivation is included, it is also given a negative weight. Results from this study clearly show that this mode of calculation is flawed given that very few loadings on the G-factors are negative, with the sole exception of those involving amotivation. Instead, it appears that in order to fully utilize the richness of information inherent within SDT, it is important to take into account both the quantity of self-determination and the specific effects of individual regulations.

The resulting bifactor-ESEM structure provides an alternative approach that allows for the simultaneous consideration of the global quantity of self-determined motivation, together with all qualitative variations along the SDT continuum in a single model not tainted by multicollinearity. These findings have important implications for self-determination theory in explicitly showing that individual regulations do provide valuable information both in terms of increasing the amount of variance accounted for by the models, but also in providing more theoretical precision regarding the nature of the observed relations with key covariates. Two recommendations emerge out of these results. First, the continuum hypothesis could be revised to focus on the global “quantity of self-determined motivation” rather than on “relative autonomy”. Second, researchers using self-determination theory should not ignore quality over quantity in motivation research, as both aspects were shown to have complementary predictive power and are themselves meaningful factors. Bifactor-ESEM models provide researchers with the means to take into account both quality and
quantity of self-determined motivation. In the current study, both the general and specific factors were used as both were theoretically pertinent to the hypotheses under examination. The decision to contrast predictive models including only the G-factor to predictive models including both the G- and S- factors aimed to illustrate the loss of information related to the reliance on a simplified “quantity-only” representation of human motivation. Still, it should be kept in mind that bifactor models are essentially designed to represent theoretically meaningful G- and S-factors estimated from the same set of items whenever there are reasons to expect the presence of construct-relevant multidimensionality due to the presence of hierarchically-ordered constructs. As such, it is part of the inherent theoretical logic of bifactor models that all factors need to be incorporated in further predictive models. In contrast, alternative models are available whenever there is a need to control for theoretically meaningless, or construct irrelevant, sources of multidimensionality in a measure, such as models incorporating correlated method factors (Eid, 2000), or models incorporating a global factor aiming to control for shared responses tendencies in the estimation of meaningful correlated factors (Podsakoff, MacKenzie, & Podsakoff, 2003).

Limitations and Directions for Future Research

The present study is not without limitations. First, though our sample was large, it was limited to Canadian employees, and to a handful of different work settings. As such, future research should aim to replicate the current study to samples including more job types, work conditions, and cultures. Chemolli and Gagné (2014) noted through a semi-systematic review of the literature covering different life domains (including work, sport, and education) that the pattern of correlations between the motivation subscales appears to be more variable across studies than self-determination theory predicts. This variability may be due to
different scales being used to assess motivation, but also possibly moderated by contextual factors, such as life domain (e.g., work, sport, education) and work conditions. Meta-analytic examination of these correlations across domains would help elucidate this issue. Similarly, although not directly relevant to organizational research, it is also critical, from the perspective of SDT, to see whether the present results replicate across different levels of analyses (e.g., state versus domain; Vallerand, 1997), life periods, contexts, and activities (Guay et al., 2015; Pelletier Rocchi, Vallerand, Deci, & Ryan, 2013; Vallerand et al., 1992).

Another potential direction for future research will be the introduction of Bayesian models in which prior knowledge of cross-loadings could be directly specified and incorporated to the estimated models (Asparouhov & Muthén, 2009). This method provides a way to achieve a balance between accounting for the most influential cross-loadings while at the same time retaining greater parsimony in areas where knowledge has advanced enough to afford a priori predictions regarding the nature of these most significant cross-loadings. In these contexts, it is important to note that a key advantage of Bayesian methods is that the use of model priors does not completely constrain the estimation of the model, thus allowing for unexpected cross-loadings to be incorporated (Asparouhov & Muthén, 2009). While promising, this approach will require more research into identifying expectable cross-loadings and is not without limitations (e.g., no clear goodness-of-fit information, approximate invariance constraints). For a comprehensive coverage of ESEM versus Bayesian SEM models, we refer readers to Gucciardi and Zyphur (2016). However it is important to reinforce that, irrespective of parsimony, current evidence suggests that there is no risk to adopting an ESEM parameterization of the data even when no cross-loadings are present in the population model (Asparouhov, Muthen & Morin, 2015).
Conclusion

Methodologically, this study demonstrated the use of the relatively new bifactor-ESEM framework for organizational researchers by showing how it can help to provide a more precise test of SDT’s continuum hypothesis. Substantively, our results inform the value of postulating a continuum structure underlying the motivation types on both theoretical and practical grounds. There has been mixed support for a continuum structure, as past research has mostly used insensitive tests of the continuum structure (see Chemolli and Gagné, 2014). Recent research, including the current study, have used more stringent techniques to test this assumption with mixed results (Chemolli & Gagné, 2014; Guay et al., 2015; Litalien et al., 2015). The current study provided clearer support for a continuum structure of motivation, though this continuum is not completely in line with the way it is postulated in SDT. However, criterion-related tests revealed that relying solely on a single latent motivation construct results in the loss of critical information specific to each motivation type.

In practice, the continuum hypothesis has led researchers to use the RAI. Not only is this formulaic motivational construct not supported by the factor structure obtained in the current study, nor by results of previous research (e.g., Chemolli & Gagné, 2014), but the results show that relying on a single construct representing quantity of self-determined motivation is insufficient to fully explain motivational covariates. Rather, our results demonstrate the added value of considering quality of motivation through the motivation subscales even when accounting for quantity of self-determined motivation. Such omission could potentially have grave consequences for evidence-based decisions taken in workplaces to motivate the workforce. In this context, a key advantage of the bifactor model comes from its orthogonality, providing a way to simultaneously consider all motivation facets without
encountering potentially severe problems of multicollinearity. In SDT research conducted so far, it has typically been impossible to simultaneously consider all types of motivations in a single model, possibly due to the presence of substantial multicollinearity among motivation subscales that is likely to remain even when using an ESEM approach due to the lack of control for the global quantity of self-determination underlying ratings to all motivation items. The bifactor-ESEM approach thus provides a more comprehensive approach to testing the critical assumptions of SDT regarding the role of self-determination and motivation types than has been available so far in the literature.
Endnote

1 Higher-order CFA and ESEM models were also estimated for comparison purposes, but excluded from further analysis due to a lack of theoretical and empirical support. In conformity with our expectations, fit statistics for these models proved to be significantly lower than for bifactor alternatives: (a) higher-order CFA: $\chi^2 = 1003$, $df = 146$, $p \leq .01$; RMSEA = .07; CFI = .86; TLI = .83; AIC = 74522; BIC = 74839; CAIC = 74902; ABIC = 74639; $\Delta \chi^2$ relative to B-CFA: $\Delta \chi^2 = 159$, $\Delta df = 13$, $p \leq .01$; (b) higher-order ESEM: $\chi^2 = 320$, $df = 81$, $p \leq .01$; RMSEA = .05; CFI = .96; TLI = .92; AIC = 73817; BIC = 74460; CAIC = 74588; ABIC = 74053; $\Delta \chi^2$ relative to B-ESEM: $\Delta \chi^2 = 236$, $\Delta df = 22$, $p \leq .01$.

2 Correlations between the external-material and external-social factors ($r = .74$ in ICM-CFA and .68 in ESEM), and between the identified regulation and intrinsic motivation factors ($r = .78$ in ICM-CFA, and .77 in ESEM) were high and not substantially deflated in ESEM. However, alternative models in which these factors were collapsed into a single factor did systematically result in a substantial decrease in model fit. Thus, when the external social and material factors were collapsed into a single factor, the goodness-of-fit showed a substantial decrease for both ICM-CFA ($\Delta TLI = -.02$, $\Delta RMSEA = -.01$) and ESEM ($\Delta TLI = -.02$, $\Delta RMSEA = -.01$). Likewise, when identified and intrinsic regulations were merged into a single factor, the goodness-of-fit again showed a substantial decrease for ICM-CFA ($\Delta TLI = -.07$, $\Delta RMSEA = -.02$) and ESEM ($\Delta TLI = -.02$, $\Delta RMSEA = -.01$).
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Chapter 3

Motivation Profiles at Work: A Self-Determination Theory Approach

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Abstract

Self-determination theory proposes that individuals experience distinct types of motivation to varying degrees. While it is well documented that these types of motivation differentially predict outcomes, very little attention has been paid to how they interact within individuals. The current study addresses the simultaneous occurrence of multiple motivation types within individual workers by adopting a person-centered approach on two samples of employees from different countries (n = 723 & 286). Four very similar motivation profiles were found across samples, representing balanced motivation, amotivated, autonomously regulated and highly motivated employees. In Sample 1, governmental employees presented a greater likelihood of membership in the least desirable amotivated profile. In Sample 2, autonomously and highly motivated profiles showed superior work performance and higher levels of wellbeing, while the amotivated profile fared the worst. The presence of external regulation in a profile appears unimportant when combined with autonomous forms of motivation, and detrimental to outcomes in the absence of autonomous forms of motivation. These results support the hypothesis that autonomous forms of motivation are far more important in promoting positive workplace outcomes than more controlling forms.

Keywords: Motivation, self-determination theory, profiles, latent profile analysis.
Motivation, generally defined as the energy, direction and persistence of behavior (Pinder, 1998), is an inherently complex concept as evidenced by the variety of approaches to its conceptualization and measurement. Self-determination Theory (SDT; Deci & Ryan, 1985) offers a well-supported conceptualization which proposes that motivation is best represented by conceptually distinct, yet complementary, types of behavioral regulations experienced by individuals to varying degrees. While it is now well documented that these types of regulation differentially predict outcomes (e.g., Koestner & Losier, 2002), very little attention has been paid to how they interact within individuals. The current study addresses the simultaneous occurrence of multiple behavioral regulations within individual workers by adopting a person-centered approach to work motivation. While variable-centered analyses, which have dominated the field so far, have been extremely useful in their own right, the complexity of interactions between numerous types of motivation cannot easily be examined using traditional regression techniques, which become almost impossible to interpret when more than three interacting variables are simultaneously considered. No such limit exists when person-centered analyses are used to assess how configurations of motivation factors are organized within individuals.

This shift to a person-centered strategy is more than just a shift in methods. It involves a fundamentally different way of thinking about motivation which may affect the design of interventions (Zyphur, 2009). When conceptualizing types of motivation as variables, we are not thinking about a whole person, but about one of the many components that make up a person’s motivational profile. Resulting interventions are designed to increase one type of motivation (e.g., intrinsic) without taking into consideration how the intervention will impact the other types of motivation (e.g., extrinsic). Such an omission may well make
interventions less effective. In contrast, the person-centered approach takes into account the interplay between a person’s motives, and consequently may lead to interventions aiming to influence the person’s whole motivational profile. This is likely to produce better tailored and cost efficient interventions for particular subpopulations of employees (Morin & Marsh, 2015). In practice, this approach would make SDT more compatible with how people in positions of authority, such as managers, actually think about the motivation of their employees (Morin, Morizot, Boudrias, & Madore, 2011; Zyphur, 2009).

As reviewed below, a few attempts have been made to conceptualize work motivation profiles. The present study, however, does so more comprehensively by: (a) including all types of regulation proposed by SDT (unlike Van den Broeck, Lens, De Witte, & Van Coillie, 2013), (b) using two large heterogeneous samples of workers from two countries (unlike Graves, Cullen, Lester, Ruderman, & Gentry, 2015) and, (c) utilizing the latest advances in latent profile analysis (unlike Moran, Diefendorff, Kim, & Liu, 2013 and Van den Broeck et al., 2013). As such it represents an incremental advancement in this area of research and potentially provides a more accurate representation of the types of profiles that are likely to be found in the work domain. Furthermore, it extends previous research by demonstrating how the relative frequency of the profiles differs across job categories (white collar, blue collar, governmental), and the relation between the profiles and a variety of outcomes, including in-role and extra-role performance, engagement, burnout, and job satisfaction.

**Self-Determination Theory**

SDT conceptualizes motivation as multiple distinguishable facets, each representing a different form of behavioral regulation, and assumed to follow a continuum of self-
determination (Deci & Ryan, 1985; Gagné & Deci, 2005). At one extreme, intrinsic motivation occurs when an individual participates in an activity for the enjoyment inherent in the activity itself, while at the other extreme extrinsic motivation occurs when behaviors are enacted for an instrumental reason. SDT proposes that extrinsic motivation can be internalized to become autonomously regulated. Identified regulation, an internalized form of extrinsic motivation, occurs when an individual elects to act because the behavior or the outcome of the behavior is of personal significance. Identified regulation and intrinsic motivation, are autonomous forms of motivation, while the next two regulations are controlled forms motivation. Introjected regulation, an internalized yet controlled form of extrinsic motivation, occurs when behaviors are undertaken in order to avoid negative self-feelings such as shame, or to attain positive self-feelings such as pride. External regulation, a non-internalized form of extrinsic motivation lying at the lower end of the continuum, occurs when behaviors are undertaken for externally derived rewards or punishments. The most current conceptualization of workplace motivation suggests that external regulation is best described through two components, external-social, and external-material (Gagné et al., 2015). External-social regulation is characterized by the desire to gain approval or respect from others, or to avoid criticism, whereas external-material regulation focuses on material rewards, and the avoidance of losing one’s job.

Finally, amotivation is the absence of any desire to exert effort. Amotivation has been defined as a state in which individuals do not associate a behavior with subsequent outcomes, and as such, behaviors are executed for reasons unknown or not executed at all (Deci & Ryan, 1985). Accordingly, amotivated individuals are likely to feel detached from their actions, or may feel a lack of control over their present situation or behavior, and will
therefore invest little time or energy towards such behaviors. This state was shown to be associated with a wide range of negative workplace outcomes including lower vitality, job satisfaction, affective commitment, adaptivity, proactivity, and job effort, as well as greater emotional exhaustion, burnout, and turnover intention (Gagné et al., 2015; Tremblay, Blanchard, Taylor, Pelletier, & Villeneuve, 2009). Thus, given that people are still enacting work behaviors despite their lack of motivation, and considering the notable negative consequences associated with amotivated behavior, it is our contention that amotivation is an important feature of the self-determination continuum to consider.

In addition to the empirical evidence demonstrating the negative influence of amotivation on performance and wellbeing, on a more theoretical point, a complete depiction of the continuum of motivation should not only include a variety of motives for engaging in specific behaviors (ranging from the intrinsic pleasure to external constraints) but also the complete lack of motive to engage in these behaviors (which forms the opposite pole of the self-determination continuum). This representation of the SDT continuum has been recently supported in the work area by a recent study by Howard, Gagné, Morin and Forest (2016), in which it was found that amotivation is located along the same continuum as the behavioral regulations, with no evidence of discontinuity.

While there is ongoing debate concerning the presence of this continuum beyond a mere heuristic tool (Chemolli & Gagné 2014), this research will examine whether the pattern of regulations expected from this continuum hypothesis is present in employee profiles. Specifically, support for the continuum hypothesis would be demonstrated if profiles follow a smooth increase/decrease in the level of the different regulations as a function of their position on the continuum. Alternatively, weak support would be found through the presence
of profiles in which people experience similar levels of regulations assumed to be located at opposite poles of the continuum (e.g., intrinsic and external regulations; Grolnick & Ryan, 1987).

So far, substantial research has examined how these regulations relate to various antecedents and outcomes. Results generally demonstrate that intrinsic motivation and identified regulation yield more positive outcomes, such as productivity and retention, than introjected and external regulations (Gagné, 2014; Gagné & Deci, 2005), though some research has found differences in the effects of intrinsic versus identified regulation, and in the effects of introjected versus external regulation (Gagné et al., 2015; Koestner & Losier, 2002). This approach does not take into account the multidimensional nature of motivation, and the fact that workers may simultaneously endorse multiple reasons for doing their job. Moreover, this research does not shed light on how distinct motivational regulations interact in predicting outcomes. What happens when employees are motivated for both autonomous and controlled reasons, compared to employees who are only motivated for autonomous reasons? For instance, is it more important to have a high level of overall motivation or is the proportion of autonomous to controlled motivation more influential? How do amotivated employees compare to employees presenting controlled motivation? How combinations of specific regulations relate to key outcomes also remains unknown, and essentially unexplored because of the heavy reliance on variable-centered methods. Indeed, the complexity of interactions required to fully describe motivation (i.e., involving six interacting types of motivation) calls for the adoption of a person-centered approach. In response, the aims of this study are to establish which motivational profiles are most likely to emerge in the work domain and to examine predictors and outcomes of profile membership.
Motivational Profiles

Few studies have applied a person-centered approach to motivation research across domains (education, sport, work, etc.). Most have used cluster analysis, a method which has been criticized (e.g., Meyer & Morin, 2016; Morin et al., 2011; Vermunt & Magidson, 2002) as being too sensitive to the clustering algorithm and measurement scales, as lacking clear guidelines for the selection of an optimal number of profiles, and as relying on rigid assumptions that do not always hold with real-life data (i.e., exact assignment of employees to a single profile, conditional independence, equality of the indicators’ variances across clusters). Furthermore, cluster analytic studies have often relied on small samples of dubious generalizability (Boiché, Sarrazin, Grouzet, Pelletier, & Chanel, 2008; Gillet, Berjot, & Paty, 2009; Gillet, Berjot, Vallerand, Amoura, & Rosnet, 2012; Gillet, Vallerand, & Paty, 2013; Gillet, Vallerand, & Rosnet, 2009; McNeill & Wang, 2005).

Motivational profiling has also largely been limited by the dichotomization of motivation into the broad categories of autonomous and controlled regulations. This dichotomization is a commonly used practice that simplifies the profiles and makes them easier to estimate, but that also reduces the richness of potential findings and may hide potentially important configurations. Nonetheless, among studies using this dichotomization in the educational domain, the observed profiles of academic motivation have been relatively well replicated, and generally revealed profiles characterized by high autonomous/low controlled motivation (HA/LC), high autonomous/high controlled motivation (HA/HC), low autonomous/high controlled motivation (LA/HC), and low autonomous/low controlled motivation (LA/LC; Hayenga & Corpus, 2010; Liu, Wang, Tan, Koh, & Ee, 2009; Ratelle, Guay, Vallerand, Larose, & Senècal, 2007; Vansteenkiste, Sierens, Soenens, Luyck, & Lens,
Results from the sport domain often replicate these profiles with slight variations (e.g. HA/HC, Moderate Autonomy/LC, HA/MC, MA/HC; Gillet, Vallerand, & Rosnet, 2009; Gillet, Vallerand, & Paty, 2013).

Given the heavy reliance on financial compensation in the work domain, motivational profiles are likely to differ from those identified in the educational and sport domains, especially when focusing on a more comprehensive coverage of all types of regulations. This particularity of the work domain makes it important to look at external and introjected regulations as separate constructs. To our knowledge, only three studies have examined motivational profiles at work (Graves, Cullen, Lester, Ruderman, & Gentry, 2015; Moran et al., 2012; Van den Broeck et al., 2013). Van den Broeck et al. (2013) applied cluster analysis to three samples of employees, collapsing the regulations into a controlled-autonomous dichotomy, leading to the identification of the same set of four profiles identified in the education and sport area. In contrast, Moran et al. (2012) applied cluster analysis to the full range of behavioral regulations. Through this more complete representation, these authors identified five clusters, most of which differed from those identified in the education and sport domain: One presenting a moderate levels of motivation across regulation types, one presenting high levels of motivation across regulation types (corresponding to the HA/HC profile), one representing low levels of autonomy (low levels of identified and intrinsic motivation) and moderate levels on the other forms of regulation, one presenting a more self-determined profile (high on introjected, identified and intrinsic motivation), and one presenting moderate levels on most regulations except for a low level of introjection. Finally, Graves et al. (2015) identified six latent profiles in a small sample of managers. These profiles presented similar configurations of motivation (i.e., highest on intrinsic and
identified regulation, followed by introjected, and lowest on external regulation) but different overall levels, so that one was higher on autonomous than controlled forms of motivation, while another was low on all forms of regulations. However, this study relied on a relatively small sample of managers, and provided insufficient information regarding model specification to allow other researchers to replicate their results or to objectively assess the adequacy of the analyses.

This relative lack of research in the work domain, the dichotomization of regulations into controlled or autonomous categories, and the reliance on cluster analyses performed on small samples clearly represent significant limitations of research in this area. In contrast, the present study applied latent profile analyses (LPA) to the full range of behavioral regulations as they occur in a work context using large heterogeneous samples of employees from two countries (Canada and Belgium) in order to derive a common set of work motivation profiles. Employees completed the recently validated Multidimensional Work Motivation Scale (Gagné et al., 2015), which has been shown to have several advantageous features (e.g., improved psychometric properties, greater content coverage in terms of motivation types) compared to traditional measures of work motivation (e.g., Gagné et al., 2010).

In contrast to cluster analyses, LPA is a far more flexible model-based approach to classification (Muthén, 2002). Being model-based, LPA allows for the estimation of alternative models in which the restrictive assumptions of cluster analyses can be relaxed. Importantly, LPA aims to find the smallest number of profiles that can describe associations among a set of continuous variables, relying on a formal set of objective criteria to guide the identification of the optimal number of latent profiles in the data. These profiles are called latent because they are prototypical in nature, which means that rather than forcing each
employee to correspond to a single profile, all participants are allocated a probability of membership in all profiles based on their degree of similarity with each prototypical latent profile.

Due to the scarcity of research on motivational profiles in the work domain, especially of studies considering the full array of motivation types, it is difficult to specify hypotheses about the nature and number of expected profiles. Given that previous research has typically found four to six profiles, it was expected that a relatively small number of profiles (4-6) would be identified, and would represent not only different levels of overall motivation, but also different shapes, reflecting distinct combinations of regulation types. Based on previous research, it was also anticipated that a profile dominated by autonomous forms of regulation, a profile dominated by controlled forms of regulation, and at least one profile containing both autonomous and controlled forms of regulation would be identified. While the emergence of different profiles remains possible, in particular across the two samples considered here, the current study aimed to introduce a broad typology of meaningful profiles common to most workplaces. However, latent profile analyses suffer from the same limitations as variable-centered analyses in terms of generalizability and in providing a meaningful representation of the data (i.e., construct validity). In particular it has been previously argued that the only way to really support a substantive interpretation of latent profiles is to embark on a process of construct validation to demonstrate that the identified profiles either meaningfully relate to covariates (predictors, or outcomes), or can reliably be replicated across samples (Marsh, Lüdtke, Trautwein, & Morin, 2009; Morin, Morizot, et al., 2011; Muthén, 2003). To address this issue, we tested whether the identified set of profiles generalized across two Western countries. Furthermore, we assessed the extent
Predictors of Motivation Profiles

To date little research has examined determinants of employees’ motivation profiles. Among this limited research, Moran et al. (2012) showed that membership into more autonomously motivated profiles could be predicted by greater levels of satisfaction of the needs for competence, autonomy, and relatedness, while Graves et al. (2015) showed that members of the more autonomously motivated profiles tended to occupy hierarchically higher positions and to report receiving higher levels of supervisor support. These results are consistent with SDT, which proposes that the satisfaction of these needs and exposure to work-related context that support their satisfaction, are key determinants of autonomous motivation (Deci & Ryan, 1985; Gagné & Deci, 2005). As such, it is also to be expected that job categories allowing for greater levels of need satisfaction may result in a greater proportion of employees corresponding to predominantly autonomously-driven profiles (i.e., higher in intrinsic motivation and identified regulation). In particular, research shows that workplace characteristics that influence need satisfaction, such as job design, participative leadership, and organic (vs. bureaucratic) structures, tend to be associated with significantly higher levels of autonomous motivation (De Cooman et al., 2013; Gillet, Gagné, Sauvagère, & Fouquereau, 2012). By this reasoning, it was expected that manufacturing and other blue-collar industries often characterized by less skill variety, autonomy, more directive leadership, and hourly wages, would be less likely to satisfy these needs. For this reason, we expected motivational profiles characterized by lower levels of autonomous motivation and higher levels of controlled motivation to be more frequent among employees working in
these sectors. In contrast, white-collar employees from the technology sector should be more likely to experience task variety and participative leadership, which would likely facilitate need satisfaction (Blais, Brière, Lachance, Riddle, & Vallerand, 1993; Gagné et al., 2010; Gagné, Senécal & Koestner, 1997). Thus, we expected motivational profiles characterized by higher levels of autonomous motivation and lower levels of controlled motivation to be more frequent among these employees. Finally, white-collar governmental employees should be more likely to experience highly bureaucratic job structures, which may stifle motivation, making it more likely for these employees to correspond to profiles characterized by lower levels of both autonomous and controlled motivation. This study incorporated blue-collar manufacturing, white-collar technological, and white-collar governmental job categories as predictors of profile membership to test these hypotheses.

**Consequences of Motivation Profiles**

Past research has found that profiles characterized by high levels of autonomous motivation seem to yield better performance outcomes. However, it is less clear how controlled types of motivation relate to performance. So far, most research conducted regarding the outcomes of motivational profiles have been conducted in the educational area. This research has shown that the HA/LC profile tends to be associated with higher levels of academic achievement, as well as lower levels of procrastination, openness to cheating, and school dropout than the HA/HC profile (Hayenga & Corpus, 2010; Ratelle et al., 2007; Vansteenkiste et al., 2009). In contrast, the LA/LC and LA/HC profiles both yielded lower levels of academic achievement and higher levels of procrastination, but did not differ from one another, indicating that the presence of controlled motivation had negligible effects on performance (Vansteenkiste et al., 2009). However, additional results suggested that
controlled motivation may actually detract from optimal performance, measured by grade point average and self-perceived skill acquisition, even when autonomous motivation is also present (Hayenga & Corpus, 2010; Liu, Wang, Tan, Koh, & Ee, 2009). It thus appears that profile composition, or the ratio of autonomous to controlled motivation, may represent a stronger predictor of performance outcomes than the simple overall “quantity” of motivation that characterizes a specific profile.

However, in the work domain, researchers have theorized that some levels of introjected and external regulation may prove beneficial in predicting positive outcomes (Boiché et al., 2008; Moran et al., 2012; Van den Broeck et al., 2013). A meta-analysis also found that while intrinsic motivation was more strongly related to the quality of the work completed, external regulation was more strongly associated with the quantity of work completed (Cerasoli, Nicklin, & Ford, 2014). Likewise, work pressure, theorized to foster external regulation, was positively related to the quantity of work effort and engagement (De Cooman et al., 2013; Van den Broeck, De Cuyper, De Witte, & Vansteenkiste, 2010). The one profile study in the work domain that has examined performance showed that the HA/LC and HA/HC profiles yielded comparable levels of self-reported in-role performance, and higher levels than those observed in the LA/HC and LA/LC profiles (Moran et al., 2012).

As suggested above, the quality and quantity of performance may be promoted through different motivational profiles (Cerasoli et al., 2014). Similarly, required (in-role) and discretionary (extra-role) performance may also be differentially affected by motivational profiles (Gagné et al., 2015). For instance, we might expect that profiles characterized by high levels of autonomous types of motivation would yield greater levels of in-role and extra-role performance, while profiles presenting high levels of controlled types
of motivation would only yield greater levels of in-role performance. The question is whether controlled types of motivation will stifle extra-role performance, as has been suggested in some variable-centered research (Battistelli, Galletta, Portoghese, & Vandenberghe, 2013).

Past research also found that profiles characterized by high levels of autonomous motivation yield better wellbeing outcomes (Van den Broeck et al., 2013). In this situation, unlike what is observed in the prediction of performance, controlled motivation does not seem to have any advantage in promoting wellbeing – it even seems to decrease it. In the educational domain, the HA/LC profile was found to be associated with lower levels of school-related anxiety than the HA/HC profile, while the LA/LC and LA/HC profiles were associated with the highest levels of school anxiety (Vansteenkiste et al., 2009). In the work domain, Van den Broeck et al. (2013) and Graves et al. (2015) both found that HA-HC and HA-LC profiles reported the greatest (and equal) levels of job satisfaction. However, strain was lower in the HA-LC than in the HA-HC profile; followed by the LA-LC profile. Employees from the LA-HC profile reported the highest levels of work-related strain. The present study expands on these studies by the inclusion of work engagement (vigor, dedication, and absorption; Schaufeli & Bakker, 2003) and burnout (emotional exhaustion, cynicism, and personal inefficacy; Maslach, Schaufeli, & Leiter, 2001) as potential outcomes of employees’ motivational profiles.

Method

Participants and Procedure

This study incorporated two samples of data collected between 2008 and 2013. Sample 1 consisted of 723 Canadian employees recruited within three different industry sectors: 105 from the technological sector, 319 from the government sector and 299 from the
manufacturing sector (Mean age = 44.30; Female = 15.8% [54.1% gender info missing]). The subsample of 105 white collar technology sector employees was previously used in the MMWS validation study (Gagné et al., 2015). These employees completed surveys containing the original English (n = 178) or French (n = 545) versions of the MWMS. Sample 2 consisted of 286 Belgian employees (Mean age = 41.66 years; Female = 57.7%; Mean Tenure = 9.39 years) who completed Dutch versions of the outcome measures, in addition to the Dutch MWMS. In both countries, a variety of organizations were approached with the possibility to participate in this study of work motivation. These organizations were selected mainly through a process of convenience based on lead investigators contacts and proximity. Employees from the organization who agreed to participate had the possibility to complete confidential surveys on an online platform or in paper format on their work premises. Participation was voluntary.

Measures

A variable specifying job category (e.g., blue collar manufacturing, white collar technology, white collar governmental) was available only for Sample 1 (n = 723) and was subsequently dummy-coded in two complementary variables to reflect white collar technology sector employees (1; n = 105) versus others (0) and governmental employees (1; n = 319) versus others (0).

The MWMS (Gagné et al., 2015) includes 19 items assessing six distinct motivation types. Each item is an answer to the question “Why do you or would you put effort into your current job?” along a 1 (not at all) to 7 (completely) point Likert scale. Sample items include, “I don’t know why I’m doing this job, it’s pointless work” (Amotivation; Cronbach’s α = .74 & .87 in samples 1 and 2 respectively), “Because others will reward me financially only if I
put enough effort in my job (e.g., employer, supervisor...)” (External regulation material; α = .60 & .70), “To get others’ approval (e.g., supervisor, colleagues, family, clients...)” (External regulation social; α = .78 & .76), “Because otherwise I will feel ashamed of myself” (Introjected regulation; α = .69 & .71), “Because putting efforts in this job aligns with my personal values” (Identified regulation; α = .78 & .67), and “Because the work I do is interesting” (Intrinsic motivation; α = .90 & .88). Validation evidence for the MWMS has demonstrated a good fit for a six-factor structure, equivalence of the underlying measurement model across the English, French and Dutch linguistic versions used in the present study, acceptable scale score reliability (α from .70-.90 for all subscales), and supported the convergent and discriminant validity of scales (Gagné et al., 2015).

The outcomes variables were available only in Sample 2. In-role performance was measured by seven self-reported items taken from Abramis (1994). Items were rated on a 1 (really bad) to 5 (really good) Likert scale with each item based on the question stem of, “In the last (seven days/week you worked), how well were you…” Items included, “doing your best work,” and “showing initiative in your work” (α = .85). Extra-role performance was measured by 9 items from Morrison (1994), with each item rated 1 (totally disagree) to 5 (totally agree) along a Likert scale (α = .81; e.g., “I help in the training of new colleagues” and “I take active part in meetings of the organization”). Job Satisfaction was measured through 14 items taken from De Witte, Hooge, Vandoorne, and Glorieux (2001). Items were rated on a 5-point scale (1, totally dissatisfied to 5, totally satisfied) in response to questions such as, “How satisfied are you in general with your work?” (α = .89). Engagement was measured using 15 items from the Utrech Work Engagement Scale (UWES, Schaufeli & Bakker, 2003) on a 1 (very rarely) to 6 (always) Likert scale. Subscales for vigor (5 items,
e.g., “When I get up in the morning, I feel like going to work”), dedication (5 items, e.g., “I am enthusiastic about my job”), absorption (5 items, e.g., “When I am working, I forget everything else around me”) were combined into an overall measure of work engagement for the sake of parsimony ($\alpha = .95$). Finally, burnout was measured on a 6-point scale using the Schaufeli and van Dierendonck (1993) adaptation of the Maslach Burnout Inventory. Two subscales of emotional exhaustion (5 items; e.g., “working all day is a heavy burden for me”) and cynicism (4 items; e.g., “I doubt the usefulness of my work”) were included and combined in the current analyses ($\alpha = .93$), and scored from 1 (very rarely) to 6 (always).

**Analyses**

**Preliminary Measurement Models**

Preliminary measurement models were estimated in both samples using the robust maximum likelihood estimator (MLR) available in Mplus 7.3 (Muthén & Muthén, 2014), in conjunction with Full Information Maximum Likelihood (FIML) estimation to deal with the very low level of missing data present this data set (0% to 2.8% per item; $M = 1.1\%$). In each sample, we contrasted a classical confirmatory factor analytic (CFA) model, in which each of the six MWMS factors was defined on the basis of it’s a priori items, with no cross-loading allowed between items and non-target factors, with an exploratory structural equation modeling (ESEM; Asparouhov & Muthén, 2009; Morin, Marsh, & Nagengast, 2013), which was defined in the same manner as the CFA model while allowing for the free estimation of cross-loadings between items and non-target factors. These ESEM models were specified using a confirmatory approach using target rotation (Asparouhov & Muthén, 2009), which allows for the pre-specification of target loadings in a confirmatory manner, while cross-loadings are targeted to be as close to zero as possible. Recent studies conducted on
motivational data show the advantages of using an ESEM measurement model (Guay, Morin, Litalien, Valois & Vallerand, 2015; Litalien, Guay, & Morin, 2015) in terms of obtaining reduced estimates of factor correlations more in line with theoretical expectations. This decision is also based on the results from simulation studies (Asparouhov & Muthén, 2009; Sass & Schmitt, 2010; Schmitt & Sass, 2011) and studies of simulated data (Marsh, Lüdtke, Nagengast, Morin, & Von Davier, 2013; Morin, Arens, & Marsh, 2015) showing that forcing cross-loadings (even as small as .100, Marsh et al., 2013) present in the population model to be exactly zero (as in CFA) forces these cross-loadings to be absorbed through an inflation of the factor correlations. In contrast, these same studies show that the free estimation of cross-loadings, even when none are present in the population model, still provides unbiased estimates of the factor correlations (also see Asparouhov, Muthén, & Morin, 2015; Morin, Arens et al., 2015). Thus, Asparouhov et al. (2015, p. 1564) note that:

“Overall, these studies clearly show that the inclusion of cross-loadings is neither logically flawed nor logically incorrect but rather empirically supported by statistical research. Going back to the flawed argument that cross-loadings “taint” the nature of the constructs, these results rather show that it is the exclusion of these cross-loadings that modifies the meaning of the constructs.”

Given the known oversensitivity of the chi-square test of exact fit ($\chi^2$) to sample size and minor model misspecifications (e.g., Marsh, Hau, & Grayson, 2005), we relied on goodness-of-fit indices to describe the fit of these models (Hu & Bentler, 1999): (a) the comparative fit index (CFI), (b) the root mean square error of approximation (RMSEA) and its
90% confidence interval (CI); (c) the standardized root mean square residual (SRMR). Values greater than .90 and .95 for the CFI respectively indicate adequate and excellent model fit, while values smaller than .08 or .06 for the RMSEA and SRMR respectively support acceptable and excellent model fit. In both samples, these results revealed the clear superiority of the ESEM measurement model [(Sample 1: $\chi^2 = 124.575$, df = 72, $p < .001$; CFI = .986; RMSEA = .032; CI = .022 to .041; SRMR = .016); (Sample 2: $\chi^2 = 161.020$, df = 72, $p < .001$; CFI = .955; RMSEA = .066; CI = .052 to .079; SRMR = .020)], when compared to the CFA model [(Sample 1: $\chi^2 = 421.443$, df = 137, $p < .001$; CFI = .924; RMSEA = .054; CI = .048 to .059; SRMR = .058); (Sample 2: $\chi^2 = 401.719$, df = 137, $p < .001$ CFI = .866; RMSEA = .082; CI = .073 to .092; SRMR = .070)]. This conclusion was supported by an assessment of the parameter estimates obtained from both models, which revealed generally well-defined factors, and reduced factor correlations in the ESEM [(Sample 1: $|r| = .015$ to .761; $M_{|r|} = .281$); (Sample 2: $|r| = .026$ to .446; $M_{|r|} = .234$)], when compared to CFA model [(Sample 1: $|r| = .057$ to .836; $M_{|r|} = .366$); (Sample 2: $|r| = .021$ to .844; $M_{|r|} = .401$)].

LPA were conducted using factor scores (specified to have a mean of 0 and a standard deviation of 1) from the retained ESEM measurement models (e.g., Kam, Morin, Meyer, & Topolnytsky, 2016; Morin & Marsh, 2015). In comparison with scale scores, factors scores have the advantage of providing a partial control for measurement errors by giving more weight to items presenting lower levels of measurement errors (Kam, Morin, Meyer & Topolnytsky, 2016; Morin & Marsh, 2015; Skrondal & Laake, 2001). Correlations and estimates of scale score reliability for all variables (including these factor scores) used in the present study are reported in Table 1.
### Table 1. Correlations and Scale Score Reliability (α) Estimates for the Variables Used in the Present Study

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<td>1. Amotivation</td>
<td>-</td>
<td>0.137*</td>
<td>0.190*</td>
<td>-0.200*</td>
<td>-0.396*</td>
<td>-0.401*</td>
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<td>2. Ext-Material</td>
<td>0.107</td>
<td>-</td>
<td>0.465*</td>
<td>0.324*</td>
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<td>3. Ext-Social</td>
<td>0.79*</td>
<td>0.304*</td>
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<td>0.297*</td>
<td>0.015</td>
<td>-0.095*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Introjected</td>
<td>-0.039</td>
<td>0.200*</td>
<td>0.218*</td>
<td>-</td>
<td>0.357*</td>
<td>0.246*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Identified</td>
<td>-0.133</td>
<td>0.108</td>
<td>0.345*</td>
<td>0.441*</td>
<td>-</td>
<td>0.761*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Intrinsic</td>
<td>-0.361*</td>
<td>0.209*</td>
<td>-0.026</td>
<td>0.399*</td>
<td>0.446*</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. In-role Performance</td>
<td>-0.161*</td>
<td>-0.084</td>
<td>-0.029</td>
<td>0.222*</td>
<td>0.247*</td>
<td>0.252*</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Extra-role Performance</td>
<td>-0.054</td>
<td>-0.133*</td>
<td>-0.059</td>
<td>0.207*</td>
<td>0.247*</td>
<td>0.264*</td>
<td>0.329*</td>
<td>-</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>9. Engagement</td>
<td>-0.453*</td>
<td>0.035</td>
<td>-0.142*</td>
<td>0.265*</td>
<td>0.374*</td>
<td>0.660*</td>
<td>0.345*</td>
<td>0.359*</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10. Burnout</td>
<td>0.426*</td>
<td>0.029</td>
<td>-0.175*</td>
<td>-0.185*</td>
<td>-0.287*</td>
<td>-0.456*</td>
<td>-0.292*</td>
<td>-0.165*</td>
<td>-0.438*</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>11. Job Satisfaction</td>
<td>-0.506*</td>
<td>0.021</td>
<td>-0.175*</td>
<td>0.240*</td>
<td>0.331*</td>
<td>0.612*</td>
<td>0.234*</td>
<td>0.220*</td>
<td>0.646*</td>
<td>-0.500*</td>
<td></td>
</tr>
</tbody>
</table>

α (Sample 1)  
Mean: 0.741  
SD: 0.931

α (Sample 2)  
Mean: 0.886  
SD: 0.856

Note: *p < .05. Sample 1 is above diagonal. Sample 2 is below diagonal. External-M = External-Material Regulation; External-S = External-Social Regulation. Scores are all factor scores from preliminary models with a mean of 0 and standard deviation of 1.
Latent Profile Analyses

Based on our expectation that 4 to 6 latent profiles would be identified, models including 1 to 8 profiles were estimated in each sample using the robust Maximum Likelihood (MLR) estimator available in Mplus. The means and variances of the six motivation factors were freely estimated in all profiles (Morin, Maiano et al., 2011; Peugh & Fan, 2013), using 7,000 random sets of start values, 300 iterations for each random start, and the 200 best solutions retained for final stage optimization (Hipp & Bauer, 2006). All models converged on well replicated solutions.

In order to determine the optimal number of profiles in each sample, it is important to consider the substantive meaning and theoretical conformity of the profiles (Marsh et al., 2009; Muthén, 2003), the statistical adequacy of the solution, and a variety of statistical indicators. Among these statistical indicators, we report the Akaike Information Criterion (AIC), the Bayesian information criterion (BIC), the Consistent AIC (CAIC), the sample-adjusted BIC (ABIC), the adjusted version of the Lo, Mendell, and Rubin likelihood ratio test (LMR), and the Bootstrap Likelihood Ratio Test (BLRT). The entropy was also examined, and indicates the precision with which the cases are classified into the profiles (on a 0 to 1 scale). However, the entropy should not be used in itself to determine the optimal number of profiles (Lubke & Muthén, 2007; Peugh & Fan, 2012, 2013, 2015; Tein, Coxe, & Cham, 2013).

Extensive simulation research has looked at the performance of these various indicators to help in selecting the optimal number of latent profiles in the data in the context of latent profile analyses and other forms of person-centered mixture models. Overall, these studies converge in supporting the efficacy of the CAIC, the BIC, the ABIC, and the BLRT.
in choosing the model which best recovers the sample’s true parameters (e.g., Henson, Reise, & Kim, 2007; McLachlan & Peel, 2000; Morgan, 2015; Nylund, Asparouhov, & Muthén, 2007; Peugh & Fan, 2012, 2013, 2015; Tein et al., 2013; Tofighi & Enders, 2008; Tolvanen, 2007; Yang, 2006). In particular, a recent simulation study (Diallo, Morin, & Lu, 2016) suggest that the BIC and CAIC should be privileged under conditions of high entropy (e.g., ≥ .800), whereas the ABIC and BLRT appear to perform better in conditions of low entropy (e.g., ≤ .500). In contrast, the bulk of current research evidence suggests that, like the entropy, the AIC and LMR/ALMR should not be used in the class enumeration process (e.g., Diallo et al., 2016; Henson et al., 2007; Nylund et al., 2007; Peugh & Fan, 2013; Tofighi & Enders, 2007; Yang, 2006). In the current study, these indicators are thus simply reported to ensure a thorough disclosure of results, but will not be used to select the optimal number of profiles. A lower value on the AIC, CAIC, BIC and ABIC suggests a better-fitting model. Both the LMR and BLRT compare a $k$-profile model with a $k-1$-profile model. A significant $p$ value indicates that the $k-1$-profile model should be rejected in favor of a $k$-profile model. However, since these tests are all variations of tests of statistical significance, the class enumeration procedure can still be heavily influenced by sample size (Marsh et al., 2009). That is these indicators frequently keep on improving with the addition of latent profiles to the model without reaching a minimum. In these cases, information criteria should be graphically presented through “elbow plots” illustrating the gains associated with additional profiles (Morin, Maïano, et al., 2011; Morin & Marsh, 2015; Petras & Masyn, 2010). In these plots, the point after which the slope flattens suggests the optimal number of profiles that should be examined, together with adjacent solutions including one more and one less profile, for theoretical conformity and statistical adequacy.
Latent Profile Analyses with Predictors and Outcomes

Starting from the final LPA solution retained for Sample 1, we then proceeded to tests of the relations between the two dummy variables created to reflect job categories and the probability of membership into the profiles. These two variables were included to the final model through a multinomial logistic regression. In multinomial logistic regressions, each predictor has \( k-1 \) (with \( k \) being the number of profiles) complementary effects for each possible pairwise comparison of profiles. The regression coefficients reflect the increase, for each unit increase in the predictor (with dummy variables this reflects the difference between the job category coded 1 and the remaining job categories), that can be expected in the log-odds of the outcome (i.e., the probability of membership in one profile versus another). For simplicity, we report odds ratios (OR), reflecting the change in likelihood of membership in a target profile versus a comparison profile associated with the target job category. For example, an OR of 3 suggests that employees from the target job category are three-times more likely than others to be member of the target profile (versus the comparison profile).

Then, starting from the final LPA solution retained for Sample 2, we tested the relations between profile membership and the multiple outcome variables available in this sample (performance, extra-role behaviors, job satisfaction, engagement, and burnout), through the direct inclusion of these outcomes in the model as additional profile indicators (Morin & Wang, 2016). The MODEL CONSTRAINT command of Mplus was used to systematically test mean-level differences across all specific pairs of profiles (using the multivariate delta method; e.g., Raykov & Marcoulides, 2004).

Results

The fit indices for the alternative solutions estimated separately in both samples are
reported in Table 2. For both samples, the CAIC, BIC, ABIC, and BLRT kept on improving with the addition of latent profiles. However, we also note that the entropy values are quite high (≥ .800) for all of the estimated models in both samples. Following Diallo et al.’s (2016) recommendations, this suggests that the decision of how many profiles to retain should mainly focus on the BIC and CAIC. Because these indicators failed to reach a minimum, we relied on a graphical representation of these information criteria (Morin, Maïano, et al., 2011; Morin & Marsh, 2015; Petras & Masyn, 2010). These plots are reported in Figure 1, and show that the decreases in values of most information criteria reached a plateau around 4 profiles in both samples 1 and 2. Examination of the 4-profile solutions and of the adjacent 3- and 5-profile solutions showed that all solutions were fully proper statistically in both samples. This examination also revealed that adding a fourth profile always resulted in the addition of a well-defined qualitatively distinct and theoretically meaningful profile to the solution, whereas adding a fifth profile resulted in the arbitrary division of one of the existing profile into smaller profiles differing only quantitatively from one another. As this additional small profile did not add anything meaningful in theoretical terms (i.e., it has the same meaning as already present profiles), the more parsimonious 4-profile solution was thus retained for each sample, in line with the conclusion suggested by the statistical indicators. This solution provides a reasonable level of classification accuracy, with an entropy value of .861 in Sample 1 and .886 in Sample 2. Classification probabilities are presented in Table 3. These results clearly demonstrate the high level of classification accuracy of these solutions, with average posterior probabilities of class membership in the dominant profile varying from .887 to .950 in Sample 1 and from .923 to .980 in Sample 2, with low cross-probabilities (varying from ≤.001 to .073 in Sample 1 and from <.001 to .042 in Sample 2).
Table 2. *Class Enumeration*

<table>
<thead>
<tr>
<th>Sample</th>
<th>Log Likelihood</th>
<th>#fp</th>
<th>scaling</th>
<th>AIC</th>
<th>CAIC</th>
<th>BIC</th>
<th>ABIC</th>
<th>Entropy</th>
<th>LMR</th>
<th>BLRT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample 1 (n = 723)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Profile</td>
<td>-5746.162</td>
<td>12</td>
<td>1.163</td>
<td>11516.324</td>
<td>11583.325</td>
<td>11571.325</td>
<td>11533.222</td>
<td>Na</td>
<td>Na</td>
<td>Na</td>
</tr>
<tr>
<td>2 Profiles</td>
<td>-5054.193</td>
<td>25</td>
<td>1.020</td>
<td>10158.385</td>
<td>10297.971</td>
<td>10272.971</td>
<td>10193.588</td>
<td>0.816</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>3 Profiles</td>
<td>-4808.461</td>
<td>38</td>
<td>1.135</td>
<td>9692.922</td>
<td>9905.092</td>
<td>9867.092</td>
<td>9746.431</td>
<td>0.840</td>
<td>0.002</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>4 Profiles</td>
<td>-4611.800</td>
<td>51</td>
<td>1.196</td>
<td>9325.600</td>
<td>9610.354</td>
<td>9559.354</td>
<td>9397.414</td>
<td>0.861</td>
<td>0.086</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>5 Profiles</td>
<td>-4491.730</td>
<td>64</td>
<td>1.118</td>
<td>9111.461</td>
<td>9468.799</td>
<td>9404.799</td>
<td>9201.581</td>
<td>0.851</td>
<td>0.018</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>6 Profiles</td>
<td>-4384.863</td>
<td>77</td>
<td>1.093</td>
<td>8923.726</td>
<td>9353.648</td>
<td>9276.648</td>
<td>9032.151</td>
<td>0.867</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>7 Profiles</td>
<td>-4291.002</td>
<td>90</td>
<td>1.044</td>
<td>8762.005</td>
<td>9264.512</td>
<td>9174.512</td>
<td>8888.735</td>
<td>0.861</td>
<td>0.002</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>8 Profiles</td>
<td>-4226.600</td>
<td>103</td>
<td>1.099</td>
<td>8659.200</td>
<td>9234.291</td>
<td>9131.291</td>
<td>8804.236</td>
<td>0.853</td>
<td>0.162</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Sample 2 (n = 286)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Profile</td>
<td>-2281.653</td>
<td>12</td>
<td>2.0090</td>
<td>4587.305</td>
<td>4643.177</td>
<td>4631.177</td>
<td>4593.124</td>
<td>Na</td>
<td>Na</td>
<td>Na</td>
</tr>
<tr>
<td>2 Profiles</td>
<td>-1714.199</td>
<td>25</td>
<td>0.9661</td>
<td>3478.397</td>
<td>3594.797</td>
<td>3569.797</td>
<td>3490.520</td>
<td>0.930</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>3 Profiles</td>
<td>-1589.459</td>
<td>38</td>
<td>0.9764</td>
<td>3254.917</td>
<td>3431.845</td>
<td>3393.845</td>
<td>3273.344</td>
<td>0.897</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>4 Profiles</td>
<td>-1473.405</td>
<td>51</td>
<td>1.1226</td>
<td>3048.810</td>
<td>3286.266</td>
<td>3235.266</td>
<td>3073.540</td>
<td>0.886</td>
<td>0.023</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>5 Profiles</td>
<td>-1416.272</td>
<td>64</td>
<td>1.0316</td>
<td>2960.545</td>
<td>3258.528</td>
<td>3194.528</td>
<td>2991.579</td>
<td>0.890</td>
<td>0.012</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>6 Profiles</td>
<td>-1380.270</td>
<td>77</td>
<td>1.0258</td>
<td>2914.539</td>
<td>3273.051</td>
<td>3196.051</td>
<td>2951.877</td>
<td>0.906</td>
<td>0.033</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>7 Profiles</td>
<td>-1347.972</td>
<td>90</td>
<td>1.0299</td>
<td>2875.944</td>
<td>3294.983</td>
<td>3204.983</td>
<td>2919.585</td>
<td>0.917</td>
<td>0.232</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>8 Profiles</td>
<td>-1315.187</td>
<td>103</td>
<td>1.0627</td>
<td>2836.373</td>
<td>3315.940</td>
<td>3212.940</td>
<td>2886.319</td>
<td>0.911</td>
<td>0.227</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

Note: #fp = Number of free parameters; AIC = Akaike information criterion; CAIC = Constant AIC; BIC = Bayesian information criterion; ABIC = Sample size adjusted BIC; LMR = p value associated with the adjusted Lo-Mendell-Rubin likelihood ratio test; BLRT = p value associated with the bootstrap likelihood ratio test.
Figure 1. Elbow Plot for the Information Criteria in Sample 1 (left) and 2 (right).

Table 3. 
Posterior Classification Probabilities for the Most Likely Latent Profile Membership (Row) by Latent Profile (Column).

<table>
<thead>
<tr>
<th></th>
<th>Amotivated (P.1)</th>
<th>Moderately Autonomous (P.2)</th>
<th>Highly Motivated (P.3)</th>
<th>Balanced (P.4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sample 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amotivated (P.1)</td>
<td>0.902</td>
<td>0.001</td>
<td>0.001</td>
<td>0.096</td>
</tr>
<tr>
<td>Moderately Autonomous (P.2)</td>
<td>0.003</td>
<td>0.976</td>
<td>0.014</td>
<td>0.007</td>
</tr>
<tr>
<td>Highly Motivated (P.3)</td>
<td>0.000</td>
<td>0.008</td>
<td>0.938</td>
<td>0.054</td>
</tr>
<tr>
<td>Balanced (P.4)</td>
<td>0.041</td>
<td>0.010</td>
<td>0.032</td>
<td>0.917</td>
</tr>
<tr>
<td><strong>Sample 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amotivated (P.1)</td>
<td>0.942</td>
<td>0.004</td>
<td>0.000</td>
<td>0.054</td>
</tr>
<tr>
<td>Moderately Autonomous (P.2)</td>
<td>0.000</td>
<td>0.925</td>
<td>0.034</td>
<td>0.041</td>
</tr>
<tr>
<td>Highly Motivated (P.3)</td>
<td>0.000</td>
<td>0.031</td>
<td>0.941</td>
<td>0.028</td>
</tr>
<tr>
<td>Balanced (P.4)</td>
<td>0.007</td>
<td>0.023</td>
<td>0.021</td>
<td>0.949</td>
</tr>
</tbody>
</table>

Note. P: Profile.

The retained 4-profile solutions are represented in Figure 2 for Sample 1, and Figure 3 for Sample 2 (with exact numerical results reported in Table 4). These figures makes it rapidly obvious that the profile structure is remarkably similar across samples, providing clear support to the generalizability of the profiles. For both samples, Profile 1 characterized
amotivated employees (corresponding to 27.6% of the employees in Sample 1 and 13.1% in Sample 2) presenting very high levels of amotivation and average to low levels on all other motivation factors. For this profile, it is noteworthy that levels of motivation decrease as a direct function of their relative degree of self-determination as proposed by SDT. Profile 2 (11.5% in Sample 1; 27.8% in Sample 2) characterizes employees presenting very low levels of social and material forms of external regulations, low levels of amotivation and introjection, and average or slightly above average levels of identified regulation and intrinsic motivation. This moderately autonomous profile thus also appears to follow the continuum structure of self-regulation proposed by SDT in that it presents a single dominant regulation type with levels of other regulations tapering off as they become more theoretically distant. Profile 3 characterizes highly motivated employees (25.6% in Sample 1; 22% in Sample 2) presenting a relatively low level of amotivation and moderate to high levels on the other types of regulations which increase as a direct function of their relative degree of self-regulation according to SDT. This profile clearly presents the highest levels on the more autonomous forms of motivation (identified regulation and intrinsic motivation) out of all profiles identified in both Samples. This highly autonomous profile thus also appears to follow the continuum structure of self-regulation proposed by SDT. Finally, Profile 4 characterizes employees presenting average levels of all regulations although the results obtained in sample 2 suggest that this profile may also show a tendency to have slightly above average levels of external regulation, and slightly below average levels of autonomous forms of regulation. This profile, which also follows the self-regulation continuum proposed by SDT, thus appears to describe employees with balanced motivation (35.3% in Sample 1; 37.1.0% in Sample 2).
Figure 2. Sample 1 Profiles (n = 723)

Note. Indicators are estimated from factor scores with mean of 0 and a standard deviation of 1.

Figure 3. Sample 2 Profiles (n = 286)

Note. Indicators are estimated from factor scores with mean of 0 and a standard deviation of 1.
Table 4
Mean Levels of Motivation in the Retained Latent Profile Models.

<table>
<thead>
<tr>
<th></th>
<th>Amotivated (P.1)</th>
<th>Moderately Autonomous (P.2)</th>
<th>Highly Motivated (P.3)</th>
<th>Balanced (P.4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Variance</td>
<td>Mean</td>
<td>Variance</td>
</tr>
<tr>
<td>Sample 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amotivation</td>
<td>1.025</td>
<td>1.169</td>
<td>-0.554</td>
<td>0.019</td>
</tr>
<tr>
<td>External-M</td>
<td>0.053</td>
<td>0.841</td>
<td>-1.075</td>
<td>0.112</td>
</tr>
<tr>
<td>External-S</td>
<td>0.242</td>
<td>0.786</td>
<td>-1.308</td>
<td>0.006</td>
</tr>
<tr>
<td>Introjected</td>
<td>-0.331</td>
<td>0.764</td>
<td>-0.467</td>
<td>0.761</td>
</tr>
<tr>
<td>Identified</td>
<td>-0.840</td>
<td>1.005</td>
<td>0.143</td>
<td>0.498</td>
</tr>
<tr>
<td>Intrinsic</td>
<td>-0.867</td>
<td>1.009</td>
<td>0.288</td>
<td>0.54</td>
</tr>
<tr>
<td>Sample 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amotivation</td>
<td>1.679</td>
<td>4.131</td>
<td>-0.338</td>
<td>0.002</td>
</tr>
<tr>
<td>External-M</td>
<td>-0.050</td>
<td>1.152</td>
<td>-0.675</td>
<td>0.193</td>
</tr>
<tr>
<td>External-S</td>
<td>0.292</td>
<td>0.624</td>
<td>-0.805</td>
<td>0.260</td>
</tr>
<tr>
<td>Introjected</td>
<td>-0.335</td>
<td>1.301</td>
<td>-0.236</td>
<td>0.510</td>
</tr>
<tr>
<td>Identified</td>
<td>-0.597</td>
<td>1.352</td>
<td>-0.034</td>
<td>0.611</td>
</tr>
<tr>
<td>Intrinsic</td>
<td>-1.450</td>
<td>0.974</td>
<td>0.437</td>
<td>0.267</td>
</tr>
</tbody>
</table>

Note. P: Profile; External-M = External-Material Regulation; External-S = External-Social Regulation; Indicators are estimated from factor scores with mean of 0 and a standard deviation of 1.

Predictors of Profile Membership

Results from the multinominal logistic regression examining relations between job category and profile membership in Sample 1 are reported in Table 5. Given that both dummy predictors were simultaneously considered, the blue-collar employees were used as the comparison group, with the effects of the first dummy predictor representing differences between white-collar technology sector employees and all other employees, and the second representing differences between white-collar governmental employees and all other employees. These results show that white-collar technology employees presented a lower likelihood of membership in the moderately autonomously motivated profile (Profile 2) than in all other profiles when compared to employees from other job categories. In contrast, white-collar governmental employees presented a greater likelihood of membership into the least desirable amotivated profile (Profile 1) than in all other profiles when compared to all
other employees. These employees were also less likely to be in the moderately autonomously motivated (Profile 2) or highly motivated (Profile 3) profiles than in the balanced profile (Profile 4).

Table 5. Results from Multinominal Logistic Regression Evaluating Relations between Job Type and Latent Profile Membership (Sample 1)

<table>
<thead>
<tr>
<th>Job Category</th>
<th>Profile 1 vs. 2</th>
<th>Profile 1 vs. 3</th>
<th>Profile 1 vs. 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>White Collar</td>
<td>Coefficient (SE) OR</td>
<td>Coefficient (SE) OR</td>
<td>Coefficient (SE) OR</td>
</tr>
<tr>
<td>Government</td>
<td>1.118 (0.413)** 3.059**</td>
<td>-0.320 (0.429) 0.726</td>
<td>0.235 (0.397) 1.265</td>
</tr>
<tr>
<td>White Collar</td>
<td>Coefficient (SE)</td>
<td>Coefficient (SE)</td>
<td>Coefficient (SE)</td>
</tr>
<tr>
<td>Government</td>
<td>1.544 (0.397)** 4.683**</td>
<td>1.557 (0.303)** 4.745**</td>
<td>0.803 (0.363)* 2.232*</td>
</tr>
</tbody>
</table>

Profile 2 vs. 3

<table>
<thead>
<tr>
<th>Job Category</th>
<th>Profile 2 vs. 4</th>
<th>Profile 3 vs. 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>White Collar</td>
<td>Coefficient (SE) OR</td>
<td>Coefficient (SE) OR</td>
</tr>
<tr>
<td>Government</td>
<td>-1.438 (0.485)** 0.237**</td>
<td>-0.883 (0.407)* 0.413*</td>
</tr>
<tr>
<td>White Collar</td>
<td>Coefficient (SE)</td>
<td>Coefficient (SE)</td>
</tr>
<tr>
<td>Government</td>
<td>0.014 (0.351) 1.014</td>
<td>-0.740 (0.351)* 0.477*</td>
</tr>
<tr>
<td>Government</td>
<td>-0.754 (0.267)** 0.470**</td>
<td></td>
</tr>
</tbody>
</table>

Note. *p <.05. **p <.01; OR = Odds Ratio; SE = Standard error of the coefficient

Outcomes of Profile Membership

Outcomes variables were added to the final 4-profile solution retained for Sample 2. Mean levels of each outcome across the four profiles are graphically depicted in Figure 4, while the exact mean levels of the outcomes and the statistical significance for each pairwise comparison of outcome levels across profiles are reported in Table 6. Most of these comparisons are statistically significant, with only a few exceptions, supporting the predictive validity of the extracted latent profiles. Starting with performance, the results show that levels of both in-role and extra-role performance are highest in both the highly motivated profile (Profile 3) and the moderately autonomous profile (Profile 2), and lowest among both the amotivated (Profile 1) and balanced (Profile 4) profiles, which could not be distinguished from one another. Levels of job satisfaction and engagement significantly differed in a similar manner across profiles, being highest among the highly motivated profile (Profile 3) and the moderately autonomous profile (Profile 2), followed by the balanced profile (Profile 4), and lowest among the amotivated profile (Profile 1). Finally, levels of burnout were
highest in the *balanced* profile (Profile 4), followed by the *amotivated* profile (Profile 1), and then by both the *highly motivated* (Profile 3) and *moderately autonomous* (Profile 2) profiles, which could not be distinguished from one another.¹

![Graph showing outcomes associated with profile membership](image)

**Figure 4. Outcomes Associated with Profile Membership**

*Note.* Indicators are estimated from factor scores with mean of 0 and a standard deviation of 1.

¹ Upon request from a reviewer, all analyses were replicated while controlling for gender. These additional models converged on results substantively identical to those reported here. Additional details are available upon request from the corresponding author.
Table 6. *Outcome Means and Pairwise Comparisons between Profiles (Sample 2)*

<table>
<thead>
<tr>
<th></th>
<th>Amotivated (P.1)</th>
<th>Moderately Autonomous (P.2)</th>
<th>Highly Motivated (P.3)</th>
<th>Balanced (P.4)</th>
<th>1 vs 2</th>
<th>1 vs 3</th>
<th>1 vs 4</th>
<th>2 vs 3</th>
<th>2 vs 4</th>
<th>3 vs 4</th>
<th>Summary of comparisons</th>
</tr>
</thead>
<tbody>
<tr>
<td>In-Role Performance</td>
<td>-0.408</td>
<td>0.267</td>
<td>0.400</td>
<td>-0.249</td>
<td>-0.675**</td>
<td>-0.808**</td>
<td>-0.159</td>
<td>-0.133</td>
<td>0.516**</td>
<td>0.650**</td>
<td>1 = 4 &lt; 2 = 3</td>
</tr>
<tr>
<td>Extra-Role Performance</td>
<td>-0.202</td>
<td>0.319</td>
<td>0.496</td>
<td>-0.408</td>
<td>-0.521**</td>
<td>-0.697**</td>
<td>0.206</td>
<td>-0.177</td>
<td>0.727**</td>
<td>0.904**</td>
<td>1 = 4 &lt; 2 = 3</td>
</tr>
<tr>
<td>Job Satisfaction</td>
<td>-1.544</td>
<td>0.505</td>
<td>0.646</td>
<td>-0.138</td>
<td>-2.049**</td>
<td>-2.190**</td>
<td>-1.406**</td>
<td>-0.140</td>
<td>0.643**</td>
<td>0.784**</td>
<td>1 &lt; 4 &lt; 2 = 3</td>
</tr>
<tr>
<td>Engagement</td>
<td>-1.283</td>
<td>0.538</td>
<td>0.684</td>
<td>-0.271</td>
<td>-1.821**</td>
<td>-1.967**</td>
<td>-1.012**</td>
<td>-0.146</td>
<td>0.809**</td>
<td>0.955**</td>
<td>1 &lt; 4 &lt; 2 = 3</td>
</tr>
<tr>
<td>Burnout</td>
<td>1.257</td>
<td>-0.372</td>
<td>-0.423</td>
<td>0.030</td>
<td>1.629**</td>
<td>1.681**</td>
<td>-1.228**</td>
<td>0.051</td>
<td>-0.401**</td>
<td>-0.453**</td>
<td>2 = 3 &lt; 4 &lt; 1</td>
</tr>
</tbody>
</table>

Note. *p < .05; **p < .01; Indicators are estimated from factor scores with mean of 0 and a standard deviation of 1.
Discussion

This study aimed to extend motivation theory and research through the identification of profiles of employees based on the simultaneous consideration of the six forms of behavioral regulation assumed to form the underlying continuum of self-determination proposed by SDT (Deci & Ryan, 1985). The current study provides an incremental contribution to the literature, finding four motivation profiles in the work domain that replicated across two reasonably large and heterogeneous samples of employees from two different countries. Prior research has generally been plagued by the reliance on small samples, the use of cluster analyses, and the arbitrary dichotomization of behavioral regulations into two broad categories of autonomous and controlled regulations (Graves et al., 2015; Moran et al., 2012; Van den Broeck et al., 2013). In contrast, this study relied on two large samples of employees from Canada and Belgium from across multiple industries and job categories. Additionally, unlike much of the past person-centered research, the current study used state of the art analyses to not only identify an optimal number of profiles, but also to include antecedents and outcome variables in a statistically more advanced and rigorous manner than previously possible. A final key contribution of this study lies in the demonstration of the value of considering the whole range of behavioral regulations in the estimation of motivation profiles, as opposed to dichotomizing motivation into autonomous and controlled composite variables. In particular, the nature of the profiles observed in the present study, which generalized across samples, supported the underlying continuum structure of motivation proposed by SDT (Deci & Ryan, 1985). In sum, the comprehensive sampling and analyses employed in the current research lend support to the robustness and reliability of the detected profiles.
In line with prior research conducted in the education, sport, and work domains, our results revealed four latent profiles, which were replicated across the two samples. Particularly important is the observation that these profiles revealed qualitative and quantitative differences in employees’ experiences of work motivation. These profiles showed that not only do employees experience varying amounts of overall motivation or self-determination, they also tend to experience different types of motivation. Additionally, our results revealed that the relative likelihood of membership into these profiles differed as a function of job type, and that it was associated with a variety of work-related performance and wellbeing outcomes. Meyer, Morin, and Vandenbergh (2015) recently noted that the value of person-centered analyses in the work domain depends not only on their ability to identify subgroups of employees differing from one another meaningfully on a set of variables, but also on the ability to demonstrate that these subgroups emerge regularly across samples, can be predicted in a meaningful manner, and are relevant to the prediction of work outcomes. As they met all of these criteria, our results can be considered highly meaningful.

As anticipated, we found a profile containing predominantly autonomous forms of regulation, a balanced profile containing roughly equal levels of all regulations, and at least one profile containing both autonomous and controlled forms of regulation. External regulation seemed to stand on its own in these profiles, whereas introjected regulation seemed to cluster more closely with autonomous forms of regulation, showing the importance of considering regulations at this level instead of aggregating them into global controlled and autonomous variables. For instance, the highly motivated profile was characterized by high levels of intrinsic motivation, identified regulation, and introjected regulation, and slightly above average levels of external regulation. Looking at the positive
performance and wellbeing outcomes associated with this profile, it appears to be one of the most desirable profiles. Our results further revealed that white-collar technology sector employees are somewhat more disposed to correspond to this profile compared to the moderately autonomous profile. However, these white-collar workers were equally as likely to correspond to the amotivated and balanced profiles as to the highly motivated profile. This suggests that job characteristics known to be more prevalent in the white-collar technology sector, such as the more frequent use of participative management, enriched job designs and tasks variety, and even profit-sharing schemes, may result in situations where employee either have their basic psychological needs met and therefore experience autonomous forms of motivation (Blais et al., 1993; Gagné et al., 1997, 2010; Gagné & Forest, 2008), or alternatively experience amotivation or external pressure to perform – a kind of polarizing effect in which these practices either work well or fail badly.

The moderately autonomous profile was characterized by low levels of external and introjected regulations, and above average levels of identified regulation and intrinsic motivation. This profile is similar to the highly motivated profile in its shape, but not in the overall level of motivation. This profile also presented above average levels of performance and wellbeing, performing as well as the highly motivated profile. This indicates that while the overall quantity of motivation may play some role in influencing work outcomes, the shape of the profile appears to have more important outcome implications. Specifically, as long as a profile is dominated by autonomous rather than controlled forms of regulation, individuals will display above average levels of performance and wellbeing. This finding suggests that increasing all motivation types may not improve performance or wellbeing. Rather, it appears more important to increase identified regulation and intrinsic motivation,
while ensuring that they remain higher than external regulation.

The moderately autonomous profile becomes even more interesting when compared to the balanced profile, given that both are characterized by similar amounts of overall motivation. However, while the moderately autonomous profile is dominated by autonomous motivation, the balanced profile is generally average across all regulations. Such a comparison allows for a clear examination of the relative importance of shape effects while holding reasonably constant the overall quantity of motivation. The results showed that the moderately autonomous profile was far more desirable than the balanced profile, which was associated with significantly lower levels on all indicators of performance and wellbeing. Thus, motivation profiles dominated by an emphasis on meaning and interest appear to lead to higher performance and wellbeing, compared to the balanced or amotivated profiles, regardless of overall amount of motivation. These results comparing the highly autonomous and moderately autonomous profiles, as well as the moderately autonomous and balanced profiles, are important. Indeed, these comparisons suggest that, far from being an effective motivator (Cerasoli et al., 2014; Gerhart & Fang, 2015), an emphasis on social and material rewards may have a negative impact on performance when it is not accompanied by a comparable emphasis on meaning, interest and pleasure (Gagné & Deci, 2005). Worse, this negative impact may be accompanied by an equally negative impact on wellbeing, making it doubly difficult for these employees to increase their performance in the long term (e.g., Ryan, Deci, & Grolnick, 1995). Interestingly, the previously discussed results regarding the fact that the moderately autonomous and highly motivated profiles are associated with similarly desirable outcomes suggest that high levels of autonomous regulations appear to protect employees from the effects of high levels of more controlled forms of regulations.
Finally, the amotivated profile characterizes employees for whom work is neither motivated by meaning, guilt, enjoyment, or rewards but are rather mainly *amotivated*, suggesting they may possibly feel “trapped” in their position due to high perceived sacrifices associated with leaving (i.e., continuance commitment; Morin, Meyer, McInerney, Marsh, & Ganotice, 2015). In line with our expectations, white collar governmental employees, who tend to be exposed to more rigid bureaucratic structures, presented a significantly greater likelihood of membership into this profile (De Cooman et al., 2013; Gillet et al., 2013), followed by membership in the *balanced* profile, strongly suggesting that characteristics of this job are highly detrimental to autonomous motivation. Also in line with our expectations, employees from this *amotivated* profile presented the lowest levels of wellbeing out of all profiles, and levels of performance that were undistinguishable from those observed in the *balanced* profile. This profile appeared to be the least desirable.

It is interesting to note that the amotivated and highly motivated profiles both follow the expected continuum structure so closely that it could be argued that for these profiles a single factor representing global self-determined motivation (e.g., Howard, Gagné, Morin, & Forest, 2016) could be sufficient to describe these employees satisfactorily. Alternately, for the moderately autonomous and balanced profiles where the profiles do not follow the continuum structure as perfectly, it appears necessary to take into account qualitative distinctions between the various motivation subscales in order to obtain a complete picture of employees’ work motivation.

In regards to previous person-centered research on work motivation, the current results provide an incremental contribution to the literature by replicating, in part, the profiles found by Graves et al. (2015), and expanding greatly on the cluster analytic results of Van
den Broeck et al. (2013) and Moran et al. (2012). All of these studies succeeded in identifying the most extreme profiles, including a highly motivated profile characterized by above average levels of all types of motivation, and an amotivated profile characterized by below average levels on most types of motivation. The *moderately autonomous* profile identified in the current study also largely replicates the self-determined profile found by Graves et al. (2015) in a sample of managers. The *balanced* profile, which shows a slight tendency towards an external focus, is a more novel finding of the current study. Not only has this profile allowed for a highly insightful comparison between two profiles characterized by similar global amounts of motivation but different shapes, but it suggests that some employees draw motivation from multiple sources equally but do not seem to thrive in their workplace as a result of it.

Finally, the current study provides evidence of generalizability of the reported profiles. Like with variable-centered research, the confidence with which person-centered results can be used to guide practice depends on replicability and the convergence of results obtained from a variety of samples. Through multiple samples and studies, it becomes possible to identify a set of core profiles which are commonly occurring in most work contexts, and more peripheral profiles which may arise due to specific workplace circumstances or in specific subgroups of employees (Solinger, Van Olffen, Roe & Hofmans, 2013). The current study offers a set of four core profiles which, interestingly, replicate some of the profiles found by Graves et al., (2015). This suggests that the subset of replicated profiles are more likely to reflect core profiles of employee motivation, whereas the additional profiles reported by Graves et al. may be more peripheral, arising specifically in manager sub-populations.
In sum, our results incrementally add to previous research by examining work motivation profiles in the most rigorous manner available to date (i.e., through the incorporation of all regulation types into state-of-the-art LPA) with reasonably large and heterogeneous samples of employees from two countries. Additionally we provide initial evidence which demonstrates that profile membership varies as a function of job category with white-collar technology sector employees less likely to be in the moderately autonomously motivated profile, while government employees are more likely to be amotivated in their work. Lastly our results show that profile membership has meaningful implications for a wide range of work outcomes with profile characterized by predominantly autonomous forms of motivation being associated with more positive performance and wellbeing outcomes.

Limitations and Directions for Future Research

Though the current study presents several advantages over previous research, it also presents notable limitations. As with all cross-sectional research it is impossible to reach clear conclusions regarding the directionality of the associations between the observed motivational profiles and the so-called outcome variables on the basis of a single study. The possibility thus remain that the observed associations follow reversed or even reciprocal relations as performance and wellbeing may themselves act as predictor of employee motivation profiles. However, lending confidence to the current interpretations, prior longitudinal research has supported the idea of directional relationships through which motivation levels predict later levels of performance and wellbeing (e.g., Baker, 2003; Dysvik & Kuvaas, 2013). Still, future research is needed to clarify this issue, and particularly to investigate possible reciprocal relations among these constructs (e.g., Morin, Meyer,
Bélanger, Boudrias, Gagné, & Parker, 2016). Longitudinal studies will also be needed to examine the development and temporal stability of motivation profiles. It would be most useful to know how, and under which conditions, the different profiles found in the present study develop and evolve over time, considering both organizational newcomers (Bauer & Erdogan, 2014) as well as employees at later career stages (Gould & Hawkins, 1978). Like the present study, future person-centered research should also strive to favor LPA over more traditional cluster analyses for reasons covered comprehensively elsewhere (Meyer & Morin, 2016; Morin et al., 2011; Vermunt & Magidson, 2002). In particular, LPA tends to rely on far less stringent assumptions, which can be relaxed as needed, relative to cluster analyses, as well as a lower level of reactivity to measurement scales and clustering algorithm.

Furthermore, LPA allows for the direct incorporation of covariates into the model, without the need to rely on suboptimal two-step strategies. Finally, research would also benefit from devoting attention to the effects of specific modifiable organizational design factors, such as organizational structure, job design, leadership style, and compensation systems, on membership into specific motivational profiles. While our results suggest a clear relation between job categories and membership into specific profiles, a finer grained analysis of the mechanisms involved in these relations would have important practical relevance to the design of specific interventions to improve employee motivation. In this regard, it would be particularly useful to know how organizational changes, such as job design changes and compensation system changes, are able to predict changes in profile membership that would affect transitions from one profile to another.
**Practical Implications**

In person-centered research, evidence for generalizability is built from an accumulation of studies, from which it becomes possible to identify a core set of profiles emerging with regularity, together with more peripheral profiles emerging irregularly under specific conditions (Solinger, Van Olffen, Roe & Hofmans, 2013). The fact that the profiles identified in this study are in line with theoretical expectations and emerged consistently across two independent samples of employees recruited in two countries supports their generalizability. Though additional research is needed, we can suggest organizations can use these four profiles to think about how employees falling into these profiles can be best managed. For example, knowing that the *balanced* profile has lower than average performance, probably because of a lack of meaning and enjoyment, organizations could try to provide meaning (e.g., through task significance; Grant, 2008) and stimulation (e.g., through job redesign; Hackman & Oldham, 1975) to employees. Specifically, employers may find that while a job has inherent meaningfulness and intrinsically enjoyable factors, employee motivation, and therefore performance, remains below expectations. Results from this study indicate that this may occur when external motivators are equally influential as more autonomous factors (such as is the case in the *balanced* profile). In these conditions, reducing the external focus and promoting more autonomously-driven reasons could be enough to nudge employees away from the *balanced* profile, with its largely below average outcomes, and into the *moderately autonomous* profile. Such a small adjustment could lead to employees being driven predominately by autonomous factors and subsequently performing more successfully and experiencing greater wellbeing. As such, knowing that autonomous motivation is relatively more important than external regulations in promoting
performance and wellbeing, organizations may wish to focus more on meaning and enjoyment than on rewards and punishments.

The drawback of the variable-centered approach is that it often leads to thinking about an intervention that will improve a variable (e.g., intrinsic motivation) without taking into consideration what it may do to other forms of motivation (e.g., introjection). Conversely, the person-centered approach allows managers to consider employees as whole entities, rather than focusing narrowly on isolated individual characteristics. This approach recognizes the complexity of human motivation and behavior, and as such may provide a more complete and integrated description of this reality.

Our results could also prove particularly useful in informing the long-standing debate on the impact of incentives on work motivation. Gerhart and Fang (2015; also see Cerasoli et al., 2014) recently argued that controlled types of motivation may yield positive outcomes and that these motivation types could be promoted through the use of monetary incentives. Results of the current study suggest a relatively weak association between external material regulation and performance, and offer no support for the proposition that external rewards are successful in increasing performance when accompanied by autonomous forms of motivation. Similar conclusions have been put forward in previous person-centered research by Van den Broeck et al. (2013) and Moran et al., (2012), who also found more positive outcomes associated with more autonomously driven profiles than profiles driven by controlled regulations even when accounting for differing levels of global motivation.

In regards to the outcomes considered in this study, it is clear that organizations should attempt to promote profiles characterized by relatively higher levels of autonomous than external forms of regulations, through meaning making and the stimulation of people’s
interests for the work they do. It seems that as long as organizations can achieve this, they do not need to focus so much on promoting external regulation through material and social rewards or punishments. Our results thus indicate that it is not worth promoting controlled forms of motivation in addition to promoting autonomous forms of motivation, as has been argued by Gerhart and Fang (2015). Furthermore, the outcomes associated with the externally regulated profile suggest that there is an important risk associated with focusing on the promotion of external forms of regulations. As such, it appears that organizations would benefit more from a focus on nurturing more autonomous forms of motivation through increases in job meaningfulness, interest, and autonomy, than from a focus on social and material rewards.
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Chapter 4

Testing a Simplex Structure of Self-Determined Motivation: A Meta-Analysis

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Abstract

Self-determination theory proposes a multidimensional representation of motivation comprised of several factors said to fall along a continuum of relative autonomy. The current meta-analysis examined the relationships between these motivation factors in order to demonstrate how reliably they conformed to a predictable simplex-like pattern. Based on a sample of \( k = 486 \) data samples representing over 205,000 participants who completed one of thirteen validated motivation scales, the results largely supported a simplex-like structure of motivation, though not in line with weights used for the relative autonomy index. Further examination of heterogeneity indicated that while regulations were predictably ordered across domains and scales, the exact distance between subscales varied across samples in a way that was not explainable by a set of moderators. Results did not support the inclusion of integrated regulation or the three subscales of intrinsic motivation (i.e. intrinsic motivation to know, to experience stimulation, and to achieve) due to excessively high inter-factor correlations and overlapping confidence intervals. Recommendations for scale refinements and the scoring of motivation are provided.

Keywords: self-determination theory, simplex, continuum, meta-analysis
Self-determination theory (SDT; Deci & Ryan, 1985; 2008) is a general theory of human motivation that is widely used across many sub-disciplines of psychology, including educational psychology (e.g., Reeve, 2002), exercise psychology (e.g. Teixeira, Carraça, Markland, Silva, & Ryan, 2012), and work psychology (e.g. Gagné & Deci, 2005). It has developed to become one of the most highly cited motivation theories with some fundamental SDT texts being cited nearly 30,000 times (e.g., Deci & Ryan, 1985; Ryan & Deci, 2000) Given the extent of its use, it is useful to review how its basic premises hold up to empirical scrutiny. One such premise is that human motivation can be operationalized along multiple dimensions related to the source of one’s motivation and that these dimensions can be meaningfully ordered along a quasi-simplex structure, also referred to as a continuum. This assumption has been tested, over the years, using a variety of methods that have more or less supported this premise. However, no meta-analytic tests have ever been undertaken to examine the tenability of the quasi-simplex assumption, and the present study set out to undertake such a test.

Given that the continuum assumption underlying the different types of motivation in SDT has given rise to scoring practices that rely completely on this assumption, it is important to put this assumption to the test. Through meta-analysis, we investigated whether the quasi-simplex pattern of correlations between the types of motivation holds up and whether this pattern is homogeneous across samples. We also looked for possible moderators to explain any heterogeneity found across the samples. Knowing whether the quasi-simplex pattern holds up and whether it is homogeneous allows us to ascertain whether popular scoring practices, such as the relative autonomy index (RAI; Grolnick & Ryan, 1987), are valid representations of motivation or not.
We first describe the conceptualization of human motivation proposed by SDT. We thereafter describe the continuum hypothesis and the quasi-simplex pattern before reviewing evidence accumulated so far for and against this hypothesis. We then present the results of a meta-analysis of the correlation patterns between the types of motivation, using 486 samples from over five life domains, and offer an interpretation of how results support or do not support the continuum hypothesis. We end with recommendations for the scoring of motivation scores when using scales developed using SDT’s conceptualization of motivation.

Motivation According to Self-Determination Theory

Self-determination theory proposes a multidimensional theory of motivation which developed out of the idea that intrinsic and extrinsic reasons for behaving will lead to differential performance and well-being outcomes for individuals (Deci & Ryan, 1985). While intrinsic motivation defines behaviors enacted for their own sake, extrinsic motivation is defined as doing something for an instrumental reason that can be divided further, based on degree of internalization. Internalization is the process through which individuals assimilate external social norms into personally supported beliefs (Deci & Ryan, 2000). For example, children assimilate many of their parents’ values as their own as they are constantly exposed to such values in their home environment. Likewise, external motivating forces can be internalized, resulting in categorically different types of motivation, referred to as regulations in SDT.

External regulation is characterized by behaviors in which a person chooses to act in order to gain a social or material reward or avoid punishment from an external source such as a manager or parent and is therefore not internalized. Depending on how deeply someone has internalized their reasons for behaving, they can experience a range of other more
autonomous, but still classifiably controlled forms of regulation. Introjected regulation describes a situation in which a person acts out of personal feelings of guilt, shame, or pride, and is considered a partially internalized controlled form of motivation (Ryan & Deci, 2000). A sportsperson who aims to excel in their sport based upon a desire to feel pride or avoid the shame of poor performance is demonstrating behavior driven by introjected regulation. Identified regulation describes engaging in behaviors seen as personally meaningful, such as volunteers who spend time working in an animal shelter to improve animal welfare. While the work is often times not enjoyable in itself (e.g., cleaning kennels), the volunteers see their behavior as meaningful and in line with personal values and beliefs, making this form of motivation more autonomously driven. Integrated regulation characterizes a person whose engagement in a behavior is perceived as part of their self-identity. That is, the behavior is not only seen as meaningful but as part of who the person is, making it even more autonomously driven. A nurse, for example, may not only see the importance of their job in helping others, but also have integrated the profession of nurse into their sense of self strongly enough to motivate participation in uninteresting and not inherently rewarding tasks. Finally, intrinsic motivation is the most autonomous form of motivation and is characterized by behaviors engaged out of interest and enjoyment inherent in the activity. Examples of this may include musicians or athletes who play just for the enjoyment of the behavior itself.

The first scale developed to measure these distinct regulation types was the Self-Regulation Questionnaire developed by Ryan and Connell (SRQ; 1989). This initial scale measured three basic regulations (i.e. external, introjected, and identified), as well as intrinsic motivation, and has since been adapted and used throughout many domains including sport, exercise, work, education, and health. Subsequent research has strongly supported the
existence of these distinct types of motivation through the validation of several measures intended for use in specific life domains, such as the Academic Motivation Scale (AMS; Vallerand et al., 1992), the Multidimensional Work Motivation Scale (MWMS; Gagné et al., 2015), the Behavioral Regulation in Exercise Questionnaire, and the Behavioral Regulation in Sport Questionnaire (BREQ and BRSQ respectively; Mullan, Markland, & Ingledew, 1997; Lonsdale, Hodge, & Rose, 2008).

In addition to these factor structures being repeatedly validated across multiple domains, countries, and languages (e.g., Gagné et al., 2015; Pelletier et al., 1995; Vallerand et al., 1992), the distinction between regulations has practical significance as well. Indeed, reviews of motivation research across different life domains clearly demonstrate that intrinsic motivation and identified regulation yield superior behavioral (e.g., persistence, performance) and well-being (e.g., vitality, positive affect) outcomes than external and introjected regulations (Gagné & Deci, 2005; Ng et al., 2012; Teixeira, Carraça, Markland, Silva, & Ryan, 2012).

Some caveats in these validations however include the fact that many measures of motivation do not include integrated regulation, as it has proven challenging to create a subscale that is distinguishable from identified regulation and intrinsic motivation (e.g., Gagné et al., 2015). In addition, the widely used Academic Motivation Scale (Vallerand et al., 1992) and the Sports Motivation Scale (Pelletier et al., 1995) draw finer distinctions by including three types of intrinsic motivation including intrinsic motivation to know, intrinsic motivation to experience, and intrinsic motivation to accomplish. Amotivation is another area of inconsistency with the majority of scales including an amotivation subscale (e.g. MWMS, BREQ-2, SMS, and AMS) and others omitting it (e.g. BREQ and the Motivation at Work...
Regardless of these differences, all of these scales claim to follow a simplex-like ordering of subscales, as is required by the continuum assumption of motivation within SDT.

**The Continuum Assumption**

Despite empirical evidence for the distinctness of different types of motivation, the theory also hypothesizes that a continuum of self-determination underlies the regulations (Ryan & Connell, 1989). It suggests that through a process of internalization, a person can move from more controlled types of motivation (e.g., external regulation) to more autonomous forms (introjected, identified, integrated, and intrinsic) as a function of the degree to which the person feels their three basic psychological needs of autonomy, competence, and relatedness are fulfilled (Deci & Ryan, 2000).

Ryan and Connell (1989) were the first to propose the continuum hypothesis in SDT by arguing that regulations were ordered in a quasi-simplex pattern. A simplex model is a predictable ordering of factors differing by quantity or degree (Guttman, 1954). A simplex precludes the presence of differences in kind. Relative to a theorized continuum of motivation, a simplex pattern would be characterized by adjacent regulations having high correlations between them and non-adjacent regulations having smaller correlations between them. Ryan and Connell (1989) devised a method to test for conformity of the correlation matrix between motivation types to a simplex pattern. Their adjacency index derived a measure of the variance accounted for by a predicted pattern of correlations against an actual one. However, Chemolli and Gagné (2014) tested this method against correlation matrices from different samples that obviously showed different levels of conformity to a quasi-simplex pattern, and found that in each case the adjacency supported the continuum
hypothesis. In other words, they showed that the adjacency index was not a sensitive test of the quasi-simplex pattern.

Li and Harmer (1996; Li, 1999) took the idea of an adjacency index further and tested the linear dependency of regulations using path analysis, which relies on the assumption that associations from one regulation to another are mediated by regulations in between. Results largely supported a simplex interpretation, although indirect effects were also found between external regulation and intrinsic motivation in males, and amotivation and intrinsic motivation in females. Chatzisarantis, Hagger, Biddle, Smith, and Wang (2003) found concurring results in a meta-analytic investigation of this same linear dependency in sport and exercise samples, and further suggested that amotivation and even intrinsic motivation should not be considered part of the continuum. However, it has also been demonstrated that covariance structure analyses such as these are highly insensitive and will likely fail to identify even extreme violations of a simplex structure (Rogosa & Willett, 1985).

Chemolli and Gagné (2014) subsequently set out to test the continuum assumption using a statistical test that was developed expressly for this purpose: Rasch analysis (Rasch, 1960). They used this analytic method on samples using two well-validated and highly used motivation scales in the work and education domains, and found no support for a continuum of self-determination, instead supporting a multidimensional representation of motivation. However, through the application of bifactor exploratory structural equation modeling, Howard, Gagné, Morin, and Forest (2016a) succeeded at simultaneously identifying each of the subscales representing the different types of motivation and a general factor that could represent a continuum underlying all the items across the subscales. Such a model constitutes
evidence for a continuum of self-determination. Moreover, it showed that both the specific and the general factors explained variance in a range of covariates.

A far less rigorous but more common test of the continuum assumption consists simply of observing the expected trend of large to small order of regulation correlations in a correlation matrix. For example, Guay, Morin, Litalien, Valois, and Vallerand (2015) conducted Exploratory Structural Equation Modelling (ESEM) on two samples totaling over 5000 college and high school student responses to the Academic Motivation Scale (AMS; Vallerand et al., 1992). They found that while one sample (Sample 2) did indeed display the expected pattern of correlations, the other sample (Sample 1) did not conform perfectly.

In light of the disparate conclusions drawn from various studies using various analytical methods and the growing doubt concerning the viability of the continuum assumption, we set out to meta-analyze all available correlation matrices derived from research using well-validated SDT-based motivation scales. This meta-analysis is important because it helps inform the debate about whether (1) there is a continuum of self-determination underlying the different types of motivation proposed in SDT and (2) whether the use of the relative autonomy index (RAI; Grolnick & Ryan, 1987) is appropriate.

While many variations of the RAI exist, it generally consists of assigning weights to subscale scores of each regulation according to their placement on the hypothesized continuum and combining them to form a composite score describing a person’s overall motivation, as depicted in the following formula:

\[
RAI = 2(\text{intrinsic}) + 1(\text{identified}) - 1(\text{introjection}) - 2(\text{external})
\]
The RAI has been called into question numerous times in the last two decades and for various reasons. Some have argued that using a single score masks important effects unique to certain types of motivation (Judge, Bono, Erez, & Locke, 2005; Koestner & Losier, 2002). Others have argued that the RAI is a difference score (Chemolli & Gagné, 2014), which have been criticized on numerous grounds, including that they are unreliable and that they can mask the real source of effects (Edwards, 2001; Johns, 1981; Zuckerman, Gagné, Nafshi, Knee, & Kieffer, 2002).

More recently, it has also been suggested that the weights assigned to the different forms of motivation do not accurately represent the nature of all regulations. Specifically, the negative loading assigned to introjected regulation is questionable as this regulation theoretically contains both positive (e.g. pride) and more negative (e.g. shame) elements (see Gagné et al., 2015). Recent bifactor modeling supports the positive influence of introjected regulation as the factor loadings of introjection items on the general factor representing the continuum were positive and therefore not necessarily representing a negative motivational force, as the RAI weightings indicate (Howard et al., 2016a). The highly negative weighting assigned to external regulation may also be inappropriate as the RAI positions external regulation as a negative force equal in strength to intrinsic motivation, but in the opposite direction. Findings from Howard et al., (2016a) suggest that external regulation should instead be considered a relatively neutral source of self-determination, rather than a strongly negative one, as they obtained non-significant factor loadings for external regulation items on the general factor. For this reason, they recommended against using the RAI, which seems to weigh the motivation types inappropriately.
Overview of the Meta-Analysis

Despite claims that the correlation pattern between types of motivation should follow a simplex pattern, and a tacit acceptance of this assumption by researchers, it has never been verified whether this pattern is consistent across measures, domains, and contexts. The general statements concerning the continuum structure of regulations within SDT canon does not specify whether it should be expected to replicate exactly across domains, or give insight into how SDT scales should be designed in order to correctly represent this rather important facet of motivation measurement. A meta-analytic examination of inter-regulation correlations across domains and scales verified the generalizability of this simplex pattern and investigated possible factors responsible for heterogeneity of correlations. This meta-analysis aimed to achieve two main objectives. First, to test the degree to which a simplex is present and stable across domains, measures, and contexts.

It is possible that life domains, a contextual variable in which an activity is undertaken (e.g., work, study, sport, exercise), could change the strength of relations between the different types of motivation. For example, in the work domain, external regulation (motivation through rewards) may be more closely linked to intrinsic motivation, given that workers need to earn a living, compared to the sport domain, where rewards may have a more antagonistic relation to intrinsic motivation (i.e., turning play into work). We also considered that the scale used to measure motivation within and across life domains may not all be created equal, giving rise to differences in correlation matrices. Items to measure the same motivational construct differ across life domains to reflect the context, possibly giving rise to differences in correlations between subscales. Because of the wide range of studies included in this meta-analysis, only a limited number of moderating variables were
applicable and usable, namely age, gender, language, status as student, school level (where appropriate), and publication status.

The second objective was to identify and rectify areas in which theory and practice disagree, specifically with regards to: (a) the theoretical distance between regulations and appropriate weights to represent this should aggregation scoring methods be used; (b) the necessity of integrated regulation, which has proven to be difficult to distinguish from identified regulation and intrinsic motivation (e.g., Gagné et al., 2015); (c) the appropriateness of amotivation as part of a continuum of self-determination (Chatzisarantis et al., 2003); (d) the necessity and appropriateness of having three types of intrinsic motivation; and (e) the degree to which introjection should be considered as a controlled form of motivation, as opposed to autonomous.

Given that SDT is a highly used theory across many domains, it is not surprising to find a range of more or less well-validated motivation scales being used across different life domains, such as education, work, sport, and exercise. The current meta-analysis is concerned only with motivation scales that have been developed thoughtfully to represent the breadth of motives within a life domain and sufficiently tested for their reliability and validity, instead of haphazardly created for a single study. This led to the inclusion of 13 scales for consideration in the meta-analysis. The first selected scale was the original Self-Regulation Questionnaire (SRQ; Ryan & Connell, 1989; also known as the Perceived Locus of Causality scale; Goudas, Biddle, & Fox, 1994), which was the scale first developed to examine children’s motivation towards school work. The 18 items representing external, introjected, identified and intrinsic regulations, being easily adaptable, have been used to measure motivation in other domains. For example the SRQ is commonly adapted to the
health domain to examine behaviors such as weight loss (Gorin, Powers, Koestner, Wing, & Raynor, 2014), eating disorders (van der Kaap-Deeder et al., 2014), and alcohol consumption (Hagger et al., 2012). Other examples of domains this scale has been adapted to include friendship motivation (Okada, 2007; Soenens, Vansteenkiste, & Niemiec, 2009), and support for charitable causes (Gutberg, 2013). The Situation Motivation Scale (SIMS; Guay, Vallerand, & Blanchard, 2010) is another domain non-specific scale which has been validated but was excluded from the current study due to its lack of domain specificity and primary application to experimental research.

In the domain of work there exist four validated and commonly used scales. The first was developed by Blais and colleagues (1993) in French and contains 31 items measuring external, introjected, and identified regulation, as well as intrinsic motivation. The majority of studies using this scale either did not provide correlations between subscales (n = 44) or were published in French and therefore not captured in the search criteria. As such, we were able to obtain an insufficient number of samples (n = 2) to include it in any meaningful way in the current meta-analysis. The Work Extrinsic and Intrinsic Motivation Scale (WEIMS; Tremblay, Blanchard, Taylor, Pelletier, & Villeneuve, 2009) was adapted from Blais et al. (1993) to include questions assessing amotivation and integrated regulation, while the Motivation at Work Scale (Gagné et al., 2010) was adapted from Blais et al. to improve the subscales’ psychometric properties for the four core regulations (i.e. external, introjection, identified, and intrinsic motivation). Most recently, the Multidimensional Work Motivation Scale (Gagné et al., 2015) was created with all new items to deal with psychometric issues with the previous three scales. It includes subscales to measure two facets of external
regulation by distinguishing between material and social rewards and punishments. Though it includes amotivation, it does not include integrated regulation.

The domain of sport has seen the development of two scales which have been updated over time - the Sports Motivation Scale (SMS; Pelletier et al., 1995) and the Behavioral Regulation in Sport Questionnaire (BRSQ; Lonsdale, Hodge, & Rose, 2008). Subsequently a SMS-6 (Mallett, Kawabata, Newcombe, Otero-Forero, & Jackson, 2007) and SMS-II (Pelletier, Rocchi, Vallerand, Deci, & Ryan, 2013) have been developed and validated based on the original SMS. The SMS-6 is notable as it expands the original SMS to include items to measure integrated regulation. The most recent iteration of this scale development process is the SMS-II which, compared to the SMS which originally contained three subscales describing intrinsic motivation, revised this structure to contain only a single factor representing intrinsic motivation.

Likewise, in the domain of exercise two scales have predominated - the Exercise Motivation Scale (EMS; Li, 1999), and the Behavioral Regulation in Exercise Questionnaire (BREQ; Mullan, Markland, & Ingledeuw, 1997). Subsequent variations of the BREQ include the BREQ-2 (Markland & Tobin, 2004) and BREQ-3 (also known as the BREQ-2revised; Wilson, Rodgers, Loitz, & Scime, 2006), which include amotivation and integrated regulation subscales respectively.

Within the education domain, the Academic Motivation Scale (AMS; Vallerand et al., 1992; adapted from the French EMS; Vallerand, Blais, Brière, & Pelletier, 1989) is the only validated and commonly used measure. In addition to the three core regulation (external, introjected, and identified), the AMS also includes an amotivation subscale, as well as three
types of intrinsic motivation – intrinsic motivation to know, intrinsic motivation to achieve, and intrinsic motivation to experience stimulation.

**Method**

**Inclusion Criteria**

In order to be included in the present research, studies had to meet the following criteria: (1) they examined motivation in primary quantitative research using one of the 13 scales mentioned above (or an adaptation of; SRQ, WEIMS, MAWS, MWMS, SMS, SMS-6, SMS-II, BRSQ, EMS, BREQ, BREQ-2, BREQ-3, and AMS); (2) they provided data for correlations between at least two subscales (those that appeared to measure multiple subscales but did not use or report required statistics were contacted for further information); (3) scales which had been significantly altered from the validated version for any reason were excluded (e.g. for use in different domains; Gutberg, 2013; Okada, 2007; Soenens, Vansteenkiste, & Niemiec, 2009); and (4) the report of results was published in English, though the scale may have been used in another language. The inclusion criteria resulted in a final database of 486 independent samples from 374 published and 88 unpublished articles, and a total of 4111 correlation coefficients from over 205,000 participants (ranging from 11-4554 participants, mean \( n = 427.64 \)). A full list of articles included in this meta-analysis is included in the online supplementary section.

**Literature Search**
Literature search procedures are depicted in Figure 1. We employed multiple search strategies in order to identify all relevant data pertaining to correlations between SDT motivation subscales. Data must have been available between 1989 and October 2016 to be included in this study. All published and non-published data were sought after, including dissertations. The primary method was a forward search beginning with scale validation articles and attainment of studies citing these works through the use of Web of Science and Google Scholar databases. This search yielded 9,233 articles and dissertations. Secondly, the EBSCO and PsychINFO databases were searched for scale names (e.g. *Sports Motivation Scales*, *SMS*, *Multidimensional Work Motivation Scale*, *MWMS*, etc.). At this point duplicates were removed. The first and third authors then examined each of the remaining articles to eliminate those which had cited the scale validation articles but not used the scale in quantitative research. These two steps resulted in the removal of 8473 articles. Of the remaining 763 articles, many did not provide correlation tables or other information pertinent to this study (k = 478). Accordingly we attempted to contact all of these authors requesting the missing information from specific articles, resulting in emails to 311 authors. A reminder was sent to those who had not replied one month after first contact. A final attempt to contact these authors was made three month after initial contact. A number of authors were not contactable after exhaustive searches for valid email addresses (n = 10). This email protocol also served as a means to contact authors and research groups active in respective SDT fields, inquiring about any unpublished or soon to be published data sets. We received replies from 106 authors (34.08%), of which 33 either indicated that the data had been lost or deleted, or declined to participate due to time restraints involved with retrieving archived data. A further 16 authors expressed interest in participating but failed to provide data after several months.
and multiple reminders. The remaining 57 authors provided an additional 96 samples (63 from published articles, 33 from unpublished sources).

Figure 1. *Flow diagram of literature search procedures*

- **Identification of Studies**
  - Identified through forward search (articles = 9,233)
  - Secondary database search for scale names (articles = 18,415)
  - 26,365 duplicates removed (articles = 1,283)
  - Removal of 514 non-quantitative studies (articles = 769)
  - Studies presenting quantitative SDT research with targeted scales (articles = 769)
  - Insufficient data (articles = 478)
  - 311 authors contacted
  - 205 authors not contactable
  - Data lost (articles = 49)
  - 57 authors provided data for 63 articles (k = 96)
  - Rejected as data had been included already (k = 6)

- **Included**
  - 488 samples included in meta-analysis
Coding

A coding spreadsheet was developed and agreed upon by all the authors. The following information was to be included in the coding procedure; study identification (authors names, year of publication, journal published in, published/unpublished, cross sectional/longitudinal, sample size), motivation variable information (scale used, alpha coefficient), correlations between regulation subscales, and demographic information (domain of research, country, language, student/employee/other, level of school [university/secondary/primary], mean age, percent of males in sample). Samples were coded primarily by the first author, with the third author providing checks by randomly coding approximately 10% of articles independently. Intercoder agreement rates were high, ranging from 95-100% for all above listed data categories. Disagreements were discussed between the first and third authors and all were resolved through closer re-examination of articles.

Meta-Analytic Procedures

Aggregate effect sizes were calculated using the Comprehensive Meta-Analysis software (CMA, Version 3.3.070; Borenstein, Hedges, Higgins, & Rothstein, 2011). Random-effects models were used throughout which assume that between-study variance is attributable to either study artifacts or to moderating factors. This method is strongly recommended over the more restrictive fixed-effects model which assumes that variance is solely due to sampling error, which is untenable in all but a few instances (Borenstein, Hedges, & Rothstein, 2007; Hunter & Schmidt, 2000; Schmidt & Hunter, 2014).

Each raw correlation was corrected for reliability and weighted by sample size. When alpha coefficients were not obtainable, mean reliability scores were imputed. Confidence intervals, Cochran’s Q and I² statistics, as well as T and T² statistics are reported to describe
homogeneity (see Table 1). The T statistic is an estimation of the standard deviation of effect sizes for the population, whereas $T^2$ is the associated variance. The $I^2$ statistic describes the percentage of the variability in the effect estimate that results from true heterogeneity, or moderating effects, rather than artifacts such as sampling error or chance (Higgins & Thompson, 2002; Higgins, Thompson, Deeks, & Altman, 2003). We predominantly relied on the $I^2$ statistic rather than Cochran’s Q because the Q statistic and associated chi-square tests depend upon sample size and will return highly significant results in very large samples even when very little variation actually exists (Rosenthal & DiMatteo, 2001). Given the rather extensive size of this meta-analysis, with up to 461 samples and 205,000 individual data points being included in some analyses, Q and chi-squared statistics are likely to overestimate the degree of true heterogeneity present (i.e. accountable by moderators). In contrast, the $I^2$ statistic is a transformation of Cochran’s Q statistic that accounts for sample size, and is therefore less influenced by sample size or number of samples analyzed (Higgins & Thompson, 2002; Higgins et al., 2003).

In order to test for possible moderators that may explain heterogeneity (e.g., scale, domain, demographic variables), meta-regression was applied to the continuous moderators of age and percentage of males in the sample, while standard subgroup moderation analyses were applied to categorical variables. The degree of variance explained by moderators was assessed primarily based on $I^2$ with greater than 75% representing considerable heterogeneity, 50% representing moderate heterogeneity, 25% suggesting low levels of heterogeneity (Higgins et al., 2003; Higgins & Green, 2011).

Publication bias is likely not a concern in the current meta-analysis as recent work has suggested that the file draw problem does not produce an inflation bias in meta-analytically
derived correlations as is commonly believed (Dalton, Aguinis, Dalton, Bosco, & Pierce, 2012). This is due to the fact that studies are not favored for publication based on significant inter-factor correlations, as they may be for studies focusing on difference tests. Nonetheless, moderation analysis was performed in order to compare published and unpublished subsamples. Funnel plots and the traditional fail-safe N statistic (Rosenthal, 1979) are available on request.

Finally, metric multi-dimensional scaling (MDS) was applied to the resulting correlation table in order to further explore the dimensionality of the continuum. Specifically, this test is designed to identify the number of dimensions (or axis on a graph) by which the data are best represented. Such a test is also ideal for depicting graphically how similar or distant various regulations are in two (or three) dimensional space. In essence, this is an alternative method to factor analysis designed to depict important relationships and non-obvious structures in an economical manner (Jaworska & Chupetlovska-Anastasova, 2009). However, it must be noted that MDS is a predominantly exploratory approach and does not allow for strong conclusions to be drawn (Giguère, 2006). These analyses were conducted in SPSS (version 22). Initial configuration was set to simplex ordering, with a maximum of 100 iterations permitted to reach a suitable solution (stress convergence at .0001, minimum stress .0001). An initial analysis was run in which 5 dimensions were specified in order to examine the associated scree plot representing the degree of stress. Lower values of stress indicate a well-fitting model such that .00 represents perfect fit, .025 is considered excellent, .05 is good fit, .10 is a fair fitting model, and >.20 is considered poor fit (Kruskal, 1964). Allowing for additional dimensions will almost always result in lower stress values, but simultaneously adds complexity to the interpretation. As such, the optimal number of
dimensions should be determined by examination of the degree of reduced stress against parsimony. The dispersion accounted for (DAF) statistic is a measure of the variance accounted for in the current model.
Table 1. *Meta-analytic Summary Statistics*

<table>
<thead>
<tr>
<th></th>
<th>95% CI</th>
<th></th>
<th></th>
<th>Q</th>
<th>F²</th>
<th>T</th>
<th>T²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>k</td>
<td>n</td>
<td>r</td>
<td>Lower</td>
<td>Upper</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intrinsic</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Integrated</td>
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<td>26420</td>
<td>.818</td>
<td>.756</td>
<td>.865</td>
<td>14623.80*</td>
<td>.994</td>
</tr>
<tr>
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<td>384</td>
<td>168252</td>
<td>.854</td>
<td>.826</td>
<td>.878</td>
<td>152514.40*</td>
<td>.998</td>
</tr>
<tr>
<td>Introjected</td>
<td>372</td>
<td>166341</td>
<td>.313</td>
<td>.278</td>
<td>.347</td>
<td>22761.80*</td>
<td>.984</td>
</tr>
<tr>
<td>External</td>
<td>386</td>
<td>181923</td>
<td>-.093</td>
<td>-.131</td>
<td>-.055</td>
<td>25484.57*</td>
<td>.985</td>
</tr>
<tr>
<td>Amotivation</td>
<td>247</td>
<td>108352</td>
<td>-.477</td>
<td>-.511</td>
<td>-.442</td>
<td>13161.90*</td>
<td>.981</td>
</tr>
<tr>
<td>Identified</td>
<td>98</td>
<td>28030</td>
<td>.913</td>
<td>.876</td>
<td>.940</td>
<td>24519.48*</td>
<td>.996</td>
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<tr>
<td>Introjected</td>
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<td>30200</td>
<td>.516</td>
<td>.425</td>
<td>.597</td>
<td>10430.70*</td>
<td>.991</td>
</tr>
<tr>
<td>External</td>
<td>97</td>
<td>29924</td>
<td>.128</td>
<td>.033</td>
<td>.220</td>
<td>6528.04*</td>
<td>.985</td>
</tr>
<tr>
<td>Amotivation</td>
<td>76</td>
<td>23414</td>
<td>-.248</td>
<td>-.298</td>
<td>-.197</td>
<td>1244.29*</td>
<td>.940</td>
</tr>
<tr>
<td>Identified</td>
<td>447</td>
<td>194718</td>
<td>.603</td>
<td>.573</td>
<td>.632</td>
<td>47845.70*</td>
<td>.991</td>
</tr>
<tr>
<td>External</td>
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<td>202138</td>
<td>.173</td>
<td>.106</td>
<td>.239</td>
<td>112638.20*</td>
<td>.996</td>
</tr>
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<td>-.431</td>
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<td>25674.08*</td>
<td>.988</td>
</tr>
<tr>
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<td>.600</td>
<td>.565</td>
<td>.634</td>
<td>69013.60*</td>
<td>.993</td>
</tr>
<tr>
<td>External</td>
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<td>.987</td>
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<td>.448</td>
<td>.570</td>
<td>72033.34*</td>
<td>.996</td>
</tr>
</tbody>
</table>

Note: *p < .001, k = number of independent samples, n = number of participants, r = Meta-analytic correlation coefficient after corrections, 95% CI = upper and lower confidence intervals around corrected correlation coefficient (r), Q = Cochran’s Q used to examine hypothesis that all studies examine the same effect, F² = percentage of variance in the corrected population sample not explained by chance, T = standard deviation of effect sizes for the population, T² = variance of T.
Results

Effect sizes, confidence intervals, variance and homogeneity statistics are presented in Table 1. A composite correlation matrix was calculated from 4111 correlations, as shown in Table 2. The current meta-analytic comparison between published and unpublished works are highly similar (see Table 3) with confidence intervals between the two groups overlapping regularly. Accordingly, publication bias was not considered to be present. Inspection of confidence intervals (see Table 1) indicates that the correlation ranges remained within a relatively small range of values and were generally non-overlapping (with exception to integrated regulation). Overall, the correlation matrix generally conforms to a quasi-simplex pattern, as correlations between conceptually adjacent regulations are higher than correlations between non-adjacent regulations, becoming negative at the extremes. However, it is worth noting that correlations between the “autonomous” types of regulations (identified, integrated, and intrinsic) are much higher than those between the other adjacent regulations. For example the correlations between identified, integrated, and intrinsic range from .818 - .913, whereas correlations between adjacent “controlled” pairs range from .510 - .603. The non-equidistant dispersion of regulations has implications for scoring systems such as the RAI which assume and specifies equal distances between regulations. However, further analysis of the sources of heterogeneity, through the $I^2$ statistic, found true heterogeneity ranging from 98.13%-99.75% across the correlation matrix, indicating that correlations varied significantly across samples. These indicators of homogeneity support a simplex-like structure but suggests the values will vary dependent on moderators. Moreover, introjected regulation is as positively related to autonomous forms of regulations as it is with external regulation. These results as a whole do not support the weighting system used for the RAI.
Table 2. Meta-analytic correlation matrix of SDT regulations

<table>
<thead>
<tr>
<th></th>
<th>Intrinsic</th>
<th>Integrated</th>
<th>Identified</th>
<th>Introjected</th>
<th>External</th>
<th>Amotivation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intrinsic</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Integrated</td>
<td>.818 (.84)</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Identified</td>
<td>.853 (384)</td>
<td>.913 (98)</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Introjected</td>
<td>.313 (372)</td>
<td>.516 (99)</td>
<td>.603 (447)</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>External</td>
<td>-.093 (386)</td>
<td>.128 (97)</td>
<td>.173 (460)</td>
<td>.564 (449)</td>
<td>-</td>
<td></td>
</tr>
<tr>
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<td>-.370 (300)</td>
<td>.113 (299)</td>
<td>.510 (313)</td>
<td>-</td>
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</tbody>
</table>

*Note: Number of samples in parentheses.*

Table 3. Correlation matrices of published and unpublished regulation data

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<th>Published</th>
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<tr>
<td></td>
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<td>Integrated</td>
</tr>
<tr>
<td>Intrinsic</td>
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<td>.845-.899</td>
</tr>
<tr>
<td>Integrated</td>
<td>.844 (58)</td>
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</tr>
<tr>
<td>Identified</td>
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<td>.922 (69)</td>
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<tr>
<td>Introjected</td>
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<td>.508 (68)</td>
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<tr>
<td>External</td>
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<td>Amotivation</td>
<td>-.484 (200)</td>
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<table>
<thead>
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<th>Identified</th>
<th>Introjected</th>
<th>External</th>
<th>Amotivation</th>
</tr>
</thead>
<tbody>
<tr>
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<td>.323-.413</td>
<td>-.115-.076</td>
<td>-.515-.376</td>
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</tr>
<tr>
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<tr>
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<td>.887 (28)</td>
<td>.552-.701</td>
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<tr>
<td>Introjected</td>
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<td>.632 (85)</td>
<td>.491-.620</td>
<td>.046-.238</td>
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</tr>
<tr>
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<td>.224 (88)</td>
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<td>-.297 (45)</td>
<td>.143 (43)</td>
<td>.338 (47)</td>
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</tr>
</tbody>
</table>

*Note: Correlation coefficients (and k) below diagonal. 95% confidence intervals above diagonal. Unpublished coefficients include dissertations.*

Continuous and categorical moderator variables were examined next in an attempt to explain the heterogeneity of correlations and arrive at acceptably non-variant correlation matrices which can confidently be generalized to other similar populations.

The first set of moderators considered were age and gender. Results of meta-regression in which correlations were independently regressed onto continuous age and gender variables (i.e. proportion of males in sample) generally indicated that age and gender could not explain the variance in the correlations (statistics are available upon request).

The majority of these results were not significant and did not significantly reduce the
percentage of variance accounted for by moderators ($I^2$), indicating that age and gender did not explain the heterogeneity in the correlation matrix.

The second set of moderator variables tested for were domain effects. Five domains were identified as containing sufficient samples to provide reliable results (work, exercise, sport, physical education, and education). These correlations matrices are presented in Table 4. As presented above the diagonal, the $I^2$ statistic is consistently high (between 94.65% and 99.85% of variance not explained) for correlations estimated from more than a few samples. Cursory comparison of these matrices by domain suggest that the structure of correlations does vary somewhat between domains (both in magnitude, and occasionally in direction), although caution is still warranted in interpreting these results as significant heterogeneity remains unexplained (see Figure 2 for a graphical display of relations between regulations across domains). In short, life domain did not sufficiently explain the heterogeneity in the correlation matrix or affect the overall structure of the matrix.
Table 4. Correlation Matrices of major SDT domains

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<th>Work</th>
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<th>Introjected</th>
<th>External</th>
<th>Amotivation</th>
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<tr>
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<tr>
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<tr>
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<tr>
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<td>99.53 (0)</td>
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<tr>
<td>Identified</td>
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<td>.91 (41)</td>
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<td>.71 (114)</td>
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<td>82.371 (0)</td>
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<td>0.00 (.48)</td>
<td>4.18 (.31)</td>
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<td>98.480 (0)</td>
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<td>.63 (29)</td>
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<td>-.51 (14)</td>
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<td>94.65 (0)</td>
<td>97.57 (0)</td>
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<td>.99.66 (0)</td>
<td>97.38 (0)</td>
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<td>93.60(0)</td>
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<tr>
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<td>-.07 (158)</td>
<td>.43 (156)</td>
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</tr>
<tr>
<td>Amotivation</td>
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<td>-.31 (26)</td>
<td>-.52 (100)</td>
<td>.01 (101)</td>
<td>.55 (102)</td>
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<th>Physical Education</th>
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<th>Identified</th>
<th>Introjected</th>
<th>External</th>
<th>Amotivation</th>
</tr>
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<td>98.91 (0)</td>
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</tr>
<tr>
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<td>0.00 (.47)</td>
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</tr>
<tr>
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<td>.62 (2)</td>
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<td>99.44 (0)</td>
<td>99.20 (0)</td>
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</tr>
<tr>
<td>Introjected</td>
<td>.34 (32)</td>
<td>.25 (2)</td>
<td>.55 (43)</td>
<td>99.52 (0)</td>
<td>98.10 (0)</td>
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<td>-.09 (2)</td>
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<tr>
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<td>-.41 (2)</td>
<td>-.50 (34)</td>
<td>.05 (33)</td>
<td>.72 (33)</td>
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</tbody>
</table>

Note: Correlations (k) are below the diagonal. $p^2$ and (p value of Chi-squared test associated with Q) statistics are presented above the diagonal. Intrinsic subscales are not presented here but are available in the appendix.
The next moderating factor examined was the specific scale used, while still controlling for domain. Analyses were run for the 13 measures of motivation included in this meta-analysis, with correlation matrices for the most commonly used scales presented in Table 5 (matrices for all scales are presented in the online supplementary section). Number of samples for each correlation ranged from 1 to 83 and were particularly low for the WEIMS (k = 4-6) and the SMS-II scales (k = 1-2). While statistical power is not an issue as the meta-analysis does not focus on statistical significance, it should be kept in mind that results based on small samples such as these scales are less rigorous estimates.

Note: Y-axis represents correlation coefficients between regulations. Each graph represents relationships for a different regulation with the first depicting intrinsic motivation, the second integrated regulation, etc.
of the population than analyses containing more studies (Valentine, Pigott, & Rothstein, 2010). Alternatively, the Self-Regulation Questionnaire (SRQ; Ryan & Connell, 1989; Goudas et al., 1994) has been commonly applied over multiple domains, particularly the sport, physical education, and education domains, and as such results are presented for use of this scale separately within each of these domains. Results indicate again that significant amounts of heterogeneity remains unexplained within these subsamples, with exception to groups containing very few samples. Therefore, it appears that the scale used does not sufficiently explain the heterogeneity in correlation matrices.

In order to examine the influence of nationality, this moderator was applied at the first stage of moderation (when not controlling for domain or scale). A sufficient number of samples were available for 7 countries (k ranging from approximately 10 to 69, as presented in the appendix,). The proportion of unexplained variance was uniformly greater than 92.61%, indicating that the country in which data were gathered did not explain the heterogeneity found in the correlation matrix.

A final round of moderation analyses were conducted in order to account for participant characteristics, that is, whether participants were students, employees, or non-specified (Table 6). The student subsample was examined further by dividing students into groups representing elementary school, secondary school, college, and university level students. While the pattern of regulations varied slightly over the different subgroups, 95% confidence intervals overlapped in all, bar a couple of comparisons (detailed results are available in the online supplementary section). Additionally, the $I^2$ statistic remains significant indicating that this subgroup analysis did not explain the heterogeneity found in the correlation matrix.
### Table 5. Correlation matrices and $I^2$ for major scales from each domain

<table>
<thead>
<tr>
<th>MWMS (Work)</th>
<th>Intrinsic</th>
<th>Integrated</th>
<th>Identified</th>
<th>Introjected</th>
<th>External</th>
<th>Amotivation</th>
</tr>
</thead>
<tbody>
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<td>97.60 (0)</td>
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<td>74.18 (0)</td>
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<tr>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
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<td>-</td>
<td>98.28 (0)</td>
<td>82.07 (0)</td>
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</tr>
<tr>
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<td>.66 (40)</td>
<td>-</td>
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<td>78.08 (0)</td>
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<td>-.40 (14)</td>
<td>-.17 (14)</td>
<td>.27 (18)</td>
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</table>

<table>
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<th>Integrated</th>
<th>Identified</th>
<th>Introjected</th>
<th>External</th>
<th>Amotivation</th>
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<tbody>
<tr>
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<td>99.02 (0)</td>
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<td>-</td>
<td>-</td>
<td>-</td>
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<td>96.99 (0)</td>
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<td>.53 (9)</td>
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<th>Amotivation</th>
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<td>Integrated</td>
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<td>99.27 (0)</td>
<td>96.74 (0)</td>
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<tr>
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<td>98.82 (0)</td>
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<tr>
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<td></td>
</tr>
<tr>
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<tr>
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<td>-.14 (23)</td>
<td>.59 (23)</td>
<td>.83 (22)</td>
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</tr>
</tbody>
</table>

*Note:* Correlations (k) are below the diagonal. $I^2$ and (p value of Chi-squared test associated with Q) statistics are presented above the diagonal. The AMS results do not include three subscales of intrinsic regulation (these are reported in the online Supplementary section).
Table 6. Correlation matrices for student, employee, or other groups

<table>
<thead>
<tr>
<th></th>
<th>Intrinsic</th>
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<tr>
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<td>.53 (134)</td>
<td>99.49 (0)</td>
<td>98.70 (0)</td>
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<tr>
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<tr>
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<td>.01 (43)</td>
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<td></td>
</tr>
<tr>
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Employees

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<th>External</th>
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<td></td>
</tr>
<tr>
<td>Introjected</td>
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<td>.68 (10)</td>
<td>.15 (75)</td>
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<td>.42 (30)</td>
<td>.12 (29)</td>
<td>.36 (32)</td>
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</tr>
<tr>
<td>Amotivation</td>
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<td>-.02 (6)</td>
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<td>.12 (29)</td>
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Students

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<td>Intrinsic</td>
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<td>.63 (189)</td>
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<td>98.86 (0)</td>
<td></td>
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<tr>
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<td>.48 (31)</td>
<td>.17 (195)</td>
<td>.63 (188)</td>
<td>99.74 (0)</td>
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<td>.13 (31)</td>
<td>.45 (136)</td>
<td>.08 (132)</td>
<td>.55 (135)</td>
<td></td>
</tr>
<tr>
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<td>-.45 (136)</td>
<td>.08 (132)</td>
<td>.55 (135)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Correlations (k) are below the diagonal. $I^2$ and (p value of Chi-squared test associated with Q) statistics are presented above the diagonal.

Multidimensional scaling

Multidimensional scaling was applied to the complete meta-analytically derived correlation matrix in order to further test the continuum hypothesis (which would imply a single dimension) and measure the distance between regulations statistically. The first step involved generation of a scree plot of the stress (a measure of model fit) of an increasing amount of dimensions. A distinct plateau in the graph was observed at three dimensions, indicating that any more dimensions would be superfluous. However as is often the case, this observational analysis is not conclusive as it is unclear whether two, or
even one dimension would be sufficient to represent the data. As such, analyses were run separately specifying 1-3 dimensions to attain individual fit statistics. The 3-dimensional solution was clearly not optimal as it exhibited not only greater stress (i.e. model misfit) but also greater complexity than either 1- or 2-dimensional solutions. The 1-dimensional model displayed excellent fit statistics (Normalized Stress = .00246; Stress-I = .04963; DAF = .99754) and explained 99.75% of variance in the model. The data fit the 2-dimensional model even better (Normalized Stress = .00125; Stress-I = .03535; DAF = .99875), but only explained .071% more of the variance in the structure. Accordingly, it appears that the 1-dimensional model should be retained for reason of parsimony, although the 2-dimensional model may still have important implications. Figures 3 and 4 display graphical representations of the distance between motivation regulations for 1- and 2-dimesnional solutions.

Figure 3. Graphical representation of the single dimensional results of MDS

Note: Interval markers have no inherent meaning beyond demonstrating relative distance between factors.

Figure 4. Graphical representation of two dimensional results of MDS.

Note: Interval markers have no inherent meaning beyond demonstrating relative distance between factors.
In general results of these MDS analyses support the simplex-ordering of regulation. The unidimensional solution shows that the regulations are quite equidistant, except for integration, which is very close to identification. However, the bi-dimensional solution shows something closer to a semi-radex structure, as suggested previously by Chemolli and Gagné (2014). This process was also repeated for a separate meta-analytically derived correlation matrix including only studies which used the three subscales of intrinsic motivation (see Figures 5 and 6). This analysis not only highlights the theoretical closeness of these three intrinsic motivation subscales, but also their problematic overlap with identified and integrated regulation.

Figure 5. Graphical representation of 1-dimensional results of MDS for data containing intrinsic motivation subscales

Note: In order from left to right: Stimulate, Know, Identified, Accomplish, Integrated, Introjected, External, Amotivation. Interval markers have no inherent meaning beyond demonstrating relative distance between factors.

Figure 6. Graphical representation of 2-dimensional results of MDS for data containing intrinsic motivation subscales

Note: Interval markers have no inherent meaning beyond demonstrating relative distance between factors.
Discussion

Based on a meta-analysis from 486 samples with over 205,000 data points derived from the use of 13 different motivation scales, the continuum hypothesis proposed in self-determination theory to describe the multidimensional structure of motivation was tested. Results largely support the presence of a simplex-like ordering of motivation. Though heterogeneity was found, confidence intervals around meta-analytically derived estimates of between regulation correlations were for the most part non-overlapping. External, introjected, identified regulation as well as amotivation were consistently separated and non-overlapping which suggests that studies with large enough samples sizes should be able to distinguish these factors. Intrinsic, integrated, and identified on the other hand were highly correlated for almost all domains and scales, and indeed confidence intervals of integrated regulation almost always overlapped with neighboring regulations, suggesting a lack of differentiation.

With the exception of integrated regulation, these results support a simplex pattern across domains and scales which, along with largely non-overlapping confidence intervals, provides some evidence towards the continuum hypothesis. Chance dictates that occasionally the simplex pattern will be violated, but that these are relatively unlikely occurrences and are not, in and of themselves, strong evidence against the continuum.

However, tests of heterogeneity established that very few homogeneous subpopulations were discernable, meaning that point estimates between regulation correlations are likely to vary. This holds true even when accounting for nationality, age, and gender of participants, as well as target domain and even scale used. This heterogeneity indicates that the relative distance between regulations will possibly vary depending on contextual factors, many of which were not taken into consideration in the current meta-analysis. The present results are consistent with the meta-analysis conducted
by Chatzisarantis and colleagues (2003) examining the linear dependency between regulations in the physical education domain utilizing the SRQ, which likewise could not identify homogeneous correlation matrices. Chatzisarantis et al. (2003) suggested this may even be because these relationships are innately heterogeneous, although they do not rule out the possibility of additional moderators emerging with large samples. This heterogeneity, whether inherent in the structure or caused by contextual factors, is likely responsible for the occasional transgressions of the simplex structure noted in multiple studies (e.g. Guay et al., 2015).

The second notable implication of this heterogeneity is that the regulations are not stationary, easy to quantify points along a continuum, but instead represent ranges. This has significant implications for operationalizations which rely on single composite scores such as the Relative Autonomy Index (RAI; Grolnick & Ryan, 1987), as it suggests that weights will be rough approximations of the distances between regulations. Keeping in mind that the RAI is a difference score which entails statistical shortcomings, our results do not specifically invalidate the idea of RAI-type weightings as the simplex-like pattern is still present. It does, however raise concerns about the validity of the weights used in such scoring practices, as designated weightings do not reflect the true distancing of regulations. As previously noted, even when accounting for scale and domain, significant heterogeneity remained in the correlation tables produced by this meta-analysis, which ultimately indicates that tools such as the RAI, even when disregarding their other potential flaws (Chemolli & Gagné, 2014), are bound to low precision and reliability as weightings will vary to some degree with each data set.

Additional moderation analyses examining differences between students, employees, and non-specified participants, and between different types of students indicates that only very small difference may be noticeable in the structure of regulations
(tables are presented in the online supplementary section). However, these are in general not significant as point estimates and 95% confidence intervals overlapped between these groups in a vast majority of cases. The finding that students respond similarly to these scales is consistent with the above stated meta-regression analysis of age, and indicates that the structure of these scales is invariant across age.

In sum, examination of the meta-analytically derived correlation matrix and associated confidence intervals suggests that the general simplex-like ordering of regulations is indeed present and invariant across a range of important dimensions such as domain, scale, nationality, age, and gender. However, the exact distance between regulations is variable, dependent upon domain and scale to some extent, but also due to contextual factors not captured in this study, or even heterogeneity inherent in the constructs themselves.

Moving to the exploratory multidimensional scaling results, it appears that the first dimension is by far the most important factor in explaining the structure underlying these regulation factors. The dimensions in multidimensional scaling are assumed to explain the perceived similarity between scales, albeit in an exploratory manner. As presented in Figure 3, when displayed in this manner the continuum of self-determination is clearly evident, with exception to the extremely close proximity between identified and integrated regulations. Factors are relatively equidistant along this dimension, again with the exception of integrated regulation, and the somewhat closer proximity of intrinsic motivation to identified regulation. Furthermore, the data fit this model excellently (Higgins & Green, 2011) and explain more than 99% of the variance in this structure. This analysis indicates that participants perceive these factors in a manner consistent with the continuum hypothesis as the ordering is precisely as would be expected under these assumptions, with integrated regulation providing the exception.
The addition of a second dimension does improve model fit and increases the proportion of variance explained, but these improvements are very small (ΔStress = .00121, ΔDAF = .00121%). It is unclear what this second dimension represents. However, this second dimension may have practical and theoretical implications for identified and integrated regulation as it suggests that while they occupy the same space on a single dimensional continuum of self-determination, they are somewhat different on this second dimension. This second dimension may explain why integrated regulations is at times distinguishable from identified regulation in classical test theory approaches to measurement modelling such as CFA scale validation procedures. A recent study by Sheldon, Osin, Gordeeva, Suchkov, and Sychev (in press) conducted MDS on a newly developed scale and found near identical results to the current meta-MDS results, again indicating that a second dimension may indeed be present. They argue that the second dimension may represent the degree of effort or self-control individuals need to exert for each type of motivation, which is particularly interesting when examining the large distance between external regulation and amotivation on this second factor. While theoretically adjacent in terms of self-determination, these two types of motivation are likely to result in very different behaviors with external regulation (which is highest in this second factor) more likely to lead to behavior enactment, and amotivation (which is lowest in this second dimension) relatively unlikely to lead to any behavior.

The finding that a single dimension representing the self-determination continuum explains the structure between correlations is largely consistent with previous work by Howard et al. (2016a) which found, when applying bifactor exploratory structural equation modeling, that a general factor representing the continuum was capable of accounting for the majority of variance in covariates. However, the individual regulations were found to explain additional unique and significant variance in covariates, which may
feasibly be a direct result of the second dimension modeled in the current study. This second dimension, while relatively minor, may differentiate regulations enough to make it appear as though each individual regulation has unique characteristics beyond its degree of self-determination. It is currently unclear whether this second dimension is theoretically important in SDT, has practical implications or merely represents noise in the measures.

These findings are also consistent with results from the linear dependency approach to continuum testing. Through the calculation of adjacency indices (Ryan & Connell, 1989) or linear dependencies models (Li & Harmer, 1996), these studies have consistently found and argued for a linear dependency between regulations. In other words, regulations were found to relate strongly with theoretically neighboring regulations and were not significantly associated directly with more distant regulations, as would be predicted by the presence of a continuum. While these types of tests are known to lack sensitivity (Chemolli & Gagné, 2014; Rogosa & Willett, 1985), alternate approaches, such as Rasch Analysis, may be too conservative and restrictive as it forces the data to fit a single dimension. Indeed, Rasch analysis shows poor fit when more than one dimension underlies the data. Given that results from the current MDS and results obtained by Howard et al. (2016a) demonstrated good fit for more than one dimension, it is not surprising that Chemolli and Gagné (2014) obtained poor fit for the Rasch analyses, which indicated a five factor solution for the MWMS, and a two factor solution for the AMS.

Recommendations

The current study provides clearer results concerning the necessity of several individual regulations. Firstly, results of this meta-analysis suggest that integrated regulation has no clear or unique place along the self-determination continuum. Highly
self-determined regulations are already somewhat crowded by relatively high correlations between intrinsic motivation and identified regulation which in itself may be an issue worth addressing in subsequent scale development projects. The addition of an integrated regulation factor, as is common in domains such as sport and exercise, merely crowds this conceptual space further and is almost indistinguishable from identified regulation, as clearly demonstrated in Figures 3 and 4. This is not only a theoretical issue but will have implications for research incorporating this factor as these extremely high correlations with identified and intrinsic motivation will lead to multicollinearity. Not only will this suppress associations with covariates for these closely aligned factors, but can also potentially change the meaning of these factors when entered into analyses simultaneously. As such, it is recommended that research does not use integrated regulation subscales. Additionally, scale developers should either avoid measuring this factor or at the very least examine the factor structure through more telling Item Response Theory (IRT) procedures rather than relying solely on CFA procedures (Reise, Ainsworth, & Haviland, 2005).

An additional issue to front when considering the overcrowding of the highly self-determined area of the continuum is the appropriateness of intrinsic motivation subscales as specified in the Sport Motivation Scale (SMS; Pelletier et al., 1995) and the Academic Motivation Scale (AMS; Vallerand et al., 1992). Correlations between the subscales of intrinsic motivation to accomplish, to know, and to experience stimulation ranged from .86-.96 which represents extremely high similarity and in itself calls into question whether these are in fact separable constructs. As with the high degree of similarity between identified and integrated regulations, these subscales will likely face issues of multicollinearity and result in difficulty in interpreting results. Furthermore, when multidimensional scaling is applied to these factors it is evident that they occupy a very
similar space along the self-determination continuum (Figure 5), adding more factors to a space already occupied and informed by identified regulation. This issue has been addressed to some degree with subsequent revisions of the SMS (e.g. SMS-6 & SMS-II) excluding these intrinsic subscales in favor of a general intrinsic motivation factor. Based on the results of this meta-analysis, it is recommended that intrinsic subscales are not used in research.

This meta-analysis also informs the debate concerning whether amotivation should be considered along the continuum of self-determination as it is by definition a lack of motivation (Chatzisarantis et al., 2003). The current results suggest that amotivation is well placed along the continuum as evidenced by its rather equidistant spacing along the single dimension solution produced through multidimensional scaling (See Figure 3). Indeed it appears to provide a negative counterpoint to intrinsic motivation (i.e. equally as negative as intrinsic motivation is positive).

Examination of the two-dimensional model (Figure 4) does however indicate that, along the second dimension, amotivation is quite distant from its conceptual neighbor, extrinsic regulation. This is an interesting finding and may be responsible for some findings which support the removal of amotivation from the SDT continuum (Chatzisarantis et al., 2003). However, it is unclear whether this theoretical distance from external regulation is grounds for excluding amotivation or alternatively a unique characteristic and therefore an argument for its inclusion. Additional support for amotivation can be found in studies applying person centered analyses (Howard, Gagné, Morin, and Van den Broeck, 2016b) which found that between 13-27% of employees experience a motivation profile predominantly characterized by amotivation. This suggests that many people do indeed experience amotivation to the exclusion of other SDT regulations, and therefore is a useful construct in describing these people. As such, it
is currently recommended that amotivation be included in SDT research as it appears to fit the simplex-like ordering of regulations well, and may be an important individual factor when the second dimension, resembling effort, found here and by Sheldon et al. (in press) is considered. However, this conclusion is not definitive and further research and theorizing is strongly recommended.

Finally, the current study questions the practice of considering introjected regulation as a controlled (as opposed to autonomous) form of motivation. This issue is particularly salient in studies which dichotomize the range of regulations into autonomous and controlled factors. While such practices produce adequate factorial validity (Gagné et al., 2010), the current study suggests that introjected regulation is not a strongly external factor, but instead is relatively equidistant from both external and identified regulations, and almost a center-point along the continuum of self-determination. When examining the empirical literature, examples predominantly link introjection with positive outcomes such as affective commitment, job effort, proactivity, and vitality (Gagné et al., 2015; Pelletier et al., 2013), or do not find significant relationships (Gagné et al., 2015). However in some cases introjection is also associated with negative effects such as depression and anxiety (Ng et al., 2012). This is seemingly inconsistent with a predominantly “controlling” type of regulation. Instead, this pattern is exactly what would be predicted by a factor lying in the center of a continuum and which is measured by both positive and negative elements (e.g. shame and pride, and both approach and avoidance oriented questions; Gagné et al., 2015). The implies that any “controlled motivation” factor which is extracted from combining external and introjected regulation will, in addition to suffering from lower reliability (Gagné et al., 2015), only contain information common to both regulations. It will therefore neglect a rather large segment of introjection, specifically the more positive elements of it. As a result, construct relevant
information is lost in this process which will likely reduce the effect size of further analyses, and of course will result in a theoretically incomplete factor.

**Limitations and Future Directions**

This meta-analysis, despite being based on a large number of samples, has a few limitations that are important to take into consideration. First, heterogeneity could not be explained by the moderators considered. While this is unfortunate as it prohibits specification of what exactly the correlations should look like for any given population, it is also a testament to the degree of variability in these matrices. Future studies specific to domains would be better suited to answering this question as the scope of the current study and the nature of many of the included samples precluded to take into consideration domain specific moderators (e.g., classroom or work characteristics), which are likely to play a significant role in moderating the relationships between regulations.

Second, a number of existing samples were not included in the meta-analysis as authors were not contactable or able to provide the necessary information after rather comprehensive attempts to elicit such information, making the results of the meta-analysis not completely representative of all the SDT-based research done to date on human motivation. While the achieved sample size was larger than in most meta-analyses, and was sufficient to test most of the questions we sought to address, more studies may have enabled further moderation analyses with the possibility of identifying non-variant correlation matrices for subpopulations. Through Bayesian updating, these studies as well as newly collected data could be incorporated into the current set as a mean of expanding this project and keeping the information up to date (Schmidt & Raju, 2007).

Third, while this study sought primarily to examine the pattern of correlations between motivational regulations, future research could resolve the issue of how best to
operationalization motivation through the incorporation of antecedent and outcome variables. This would allow for the direct comparison of different operationalization (e.g. RAI vs. dichotomization vs. individual regulations) and more clearly describe differences in the amount of variance each approach is capable of explaining. Such a meta-analysis would be more manageable within domains, or even for individual scales.

**Practical and Theoretical Implications**

The current study allows for more informed recommendations to be made concerning the appropriateness of different operationalizations of motivation. The Relative Autonomy Index (RAI; Grolnick & Ryan, 1987), despite its popularity, has been criticized as an overly simplistic representation of an otherwise complex set of motivational regulations (Chemolli & Gagné, 2014). However, the current study, finding rather strong evidence for a continuum of self-determination, supports the idea of a single dimensional measure of motivation. Considering a single dimension accounts for more than 99% of the structure of regulations in MDS, it may make sense that scoring methods used in research reflect this. This approach would also increase parsimony of SDT based research models and allow for more straightforward integration with other constructs and theories. However, this raises two issues within SDT. Firstly, a single factor representation of motivation disregards the proposed multidimensional structure which distinguishes SDT from many other theories of motivation. Why should researchers create rather long scales to capture each of the regulations and apply them to research if a single factor representing the degree of self-determination would achieve the same goal?

Furthermore, the RAI is perhaps not the ideal method of representing a single factor of self-determined motivation as the creation of such an index still inherits statistical problems associated with difference scores, such as poor reliability (Edwards, 2001; Johns, 1981). Moreover, current weights used to calculate the RAI do not
necessarily reflect the correlations found between the regulations in the current meta-analysis, nor do they reflect factor loadings found on the general factor in Howard et al. (2016a). A more suitable solution might be to apply bifactor-exploratory structural equation modeling in order to derive a factor which represents the similarity present in each and every item in a more statistically rigorous method than applied by the RAI (see Howard et al., 2016a). This is an area that would benefit from greater exploration as very few studies have operationalized motivation in this manner and it is still uncertain if such a process would predict outcomes as successfully as other methods.

A second common method of operationalizing SDT motivation is through the dichotomization of regulations into autonomous and controlled factors, with autonomous motivation representing a combination of intrinsic motivation and identified regulation, whereas controlled regulation is commonly a composite of introjected and external regulations. This method tries to strike a balance between the perceived overly simplistic single dimensional representation approach and the unwieldy practice of specifying all regulations individually. While this higher order factor structure has been tested many times and has shown reasonable factorial validity (Gagné et al., 2010; Ryan & Connell, 1989), concerns have been raised regarding the point at which controlled and autonomous motivation are divided. Following the interpretation of the current findings, this approach is not recommended on empirical grounds as introjection is not necessarily a controlled form of regulation, but seems to be a mix of self-determination and control. Likewise, on statistical grounds this approach is also not encouraged because grouping introjection with external regulation through either direct first order specification of autonomous/controlled factors, or through higher-order factor analysis will ignore the more positive elements of introjection. This is because any factor created to represent introjection and external regulation will only represent the elements these two factors
have in common, which of course will be the more controlling elements. Systematically ignoring the more autonomous elements of the introjected factor will result in a part of the continuum not being measured, and therefore does not make fullest use of available data.

The final common approach to operationalizing SDT motivation is specification and use of all regulations individually (e.g. intrinsic, identified, introjected, and external), as is displayed in every validated scale creation or validation article. While this is considered the most comprehensive approach, the current meta-analysis calls into question the degree to which the regulations have unique qualities beyond what can be accounted for by a continuum. Instead it suggests that these unique characteristics may not be highly influential features in the structure of SDT motivation, after accounting for the continuum structure. While the current results suggest these unique features do not play a central role in structuring these regulations, further research needs to be conducted to establish the influence these unique characteristics have on outcomes. This may be a case of small and statistically insignificant structuring playing a significant role when applied to practice. Recent research by Howard et al, (2016a) indicates that this may be the case, finding that even after accounting for a general factor representing the continuum, individual regulations are still identifiable through factor analysis, and are indeed related to covariates in the predicted manner. However, this issue remains unresolved and would benefit from more rigorous investigation including predictive models from across domain and incorporating a greater range of outcomes.

This approach also raises concerns about multicollinearity and parsimony (Asparouhov, Muthén, & Morin, 2015). Multicollinearity will be present to some degree whenever factors correlate, but becomes particularly troubling as correlations approach unity. This is notable here as integrated regulation is consistently shown to correlate with
identified regulation extremely highly (often > .90). This results in not only reduced power of prediction in subsequent analyses, but also plays a role in altering the meaning of these factors (Marsh, Morin, Parker, & Kaur, 2014). Likewise, the correlations between integrated and intrinsic motivation, as well as identified regulation and intrinsic motivation, are higher than desirable (generally between .80-.90) which is another systematic source of multicollinearity. The issue of parsimony is another concern which has led many researchers to adopt the more simplistic approaches. Modeling all of the regulations individually is not always feasible, particularly with smaller sample sizes or models for which motivation is perhaps not the central construct of interest. Despite concerns about multicollinearity and the unwieldy nature of such a complex operationalization, this approach has proven to be powerful in past research and should not currently be discounted as a feasible procedure through which to apply SDT motivation in research. However, the predictive power of the unique facets of individual regulations should be further tested after controlling for the continuum.

A final method to scoring motivation is the person-centered approach (e.g. latent profile analysis; Howard et al. 2016b). This method may prove important as it largely circumvents the entire debate concerning how best to operationalize motivation and instead recognizes that individuals report some degree of all types of motivation and observes different groups of individuals who experience similar profiles of motivation. Such an approach provides a more naturalistic perspective of how motivations coexist and are experienced by individuals (see Howard et al., 2016b; Ratelle, Guay, Vallerand, Larose, & Senécal, 2007, for an examples on work and educational motivation respectively). Profile analyses such as these also avoid issues concerning multicollinearity.
Future research could also focus on the viability and performance of a scale designed to represent solely the continuum of self-determined motivation as a better single factor measure of motivation as compared to the RAI. Such a scale would have the benefit of being shorter to administer and easier to incorporate into predictive models due to its simplicity. Creation of such a scale would ideally incorporate practices from Item Response Theory (IRT) such as difficulty analysis in order to ensure that all parts of the continuum are being targeted by the minimum number of items (e.g. Jenkins-Guarnieri, Vaughan, & Wright 2015; Reise, Ainsworth, & Haviland, 2005).

Conclusion

A meta-analysis of data from different life domains using motivation scales based on self-determination theory’s multidimensional conceptualization of motivation revealed support for a simplex-like ordering between regulations. However, the size and direction of the correlations do not support the use of the Relative Autonomy Index, which has also been criticized on statistical grounds. Moreover, multi-dimensional scaling demonstrated the possibility of smaller but potentially important second dimension, which should be explored through further research. It is recommended that researchers utilize the full array of discernable regulations whenever possible, although a single factor representation is also viable so long as steps are taken to account for the statistical problems associated with the RAI. Furthermore, it is highly recommended that integrated regulation not be used as it overlaps far too much with identified regulation and intrinsic motivation. Likewise, the use of the three intrinsic motivation subscales should generally be avoided as these also demonstrate consistently high correlations and occupy much the same space on the continuum. Amotivation, on the other hand, appears to occupy a space on the continuum not covered by the other regulations, and therefore might be worth retaining, though more research is needed to determine its unique contribution. Finally, the
positioning of introjected regulation as a “controlled” regulation, as opposed to an autonomous form, is perhaps not appropriate as it appears introjection occupies the center point of the continuum and is neither clearly or entirely autonomous nor controlling in nature.
References


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Chapter 5

Dissertation Discussion

The aim of this research was to explore support for two competing and somewhat contradictory assumptions inherent in SDT, specifically, whether motivation follows a uni-dimensional continuum structure, or whether it is in fact comprised of several categorically distinguishable concepts. Evidence from the three studies presented herein does not present decisive evidence towards either the hypothesis that motivation is a continuum, or that it is comprised of multiple categorically distinct regulation types. Instead, the conclusion to be drawn from the combined evidence of these studies, as well as previous research, is that the structure of motivation, as conceptualized in self-determination theory, resembles a radex (Guttman, 1954). That is, motivation varies by both degree and kind simultaneously. While regulations are ordered predictably in a simplex-like manner representing the degree of self-determination present, each individual regulation remains a separable construct with unique characteristics upon which individuals are free to score either high or low. However, a true radex forms a complete circle with each segment theoretically close to its neighboring concepts, and a binary opposite to the concept directly opposing it in the circle. This structure does not perfectly describe the regulations because only intrinsic motivation and amotivation could be considered opposing constructs. For example, introjected regulation is closely associated with both external and identified regulation, and is not directly in opposition to either intrinsic motivation or amotivation, meaning there is no binary opposite for this factor. Likewise, intrinsic motivation and amotivation are highly divergent concepts and should not be adjacent factors in a circular radex structure. Instead they should be on opposing sides. As such, it is proposed that SDT motivation forms a half-radex in which
intrinsic motivation and amotivation are opposing forces, while the remaining regulations are ordered between the two, as displayed in figure 4.

Figure 4: The Half-radex of Self-determination

Note: $A_{1.5}$ represent a continuum of Amotivation items, $E_{1.5}$ External items, $I_{1.5}$ Introjected items, $I_{d1.5}$ Identified items, $I_{n1.5}$ Intrinsic motivation.

**Evidence for a Half-radex**

The study presented in Chapter 2 applied advanced measurement modelling techniques to specify a factor representing the continuum of self-determination in addition to specific regulation factors. Through Bifactor Exploratory Structural Equation Modelling (BESEM) the continuum structure of work motivation was directly specified as a general factor in addition to the individual regulations. It should be noted that in this measurement model, all factors remain relatively well specified, with factor loadings generally above acceptable standards. This result appears to support the presence of a continuum through the specification of a general factor which is comprised of strong factor loadings ranging from negative to positive in a relatively smooth pattern, as would be expected in the presence of a continuum. However, the ability to distinguish specific
factors modeling the individual regulations still has theoretical, and potentially practical, implications as this suggests that the construct of SDT motivation is more than a simple continuum. These factors indeed provide evidence that each of these regulations is defined by unique characteristics, beyond what can be accounted for by degree of self-determination alone. However, the relative strength of factor-loadings on the general factor, as compared to regulation factors (S-factors), does indicates that the simplex-like ordering may be more influential than the individual characteristics of each regulation. Such findings fit well within a radex structure in that, while ordered in a predictable continuum-like fashion, each regulation remains a distinguishable construct with unique characteristics.

These factors were then associated with covariates in order to compare the predictive capabilities of each of these factors. The general factor representing the continuum was the strongest predictor of most outcomes, but the addition of individual regulations to the model demonstrated that these specific factors were responsible for an increase in the total variance accounted for beyond the general factor. The results also demonstrated the potential problem of a single factor approach to motivation measurement and of excluding the unique characteristics of individual regulations. Specifically, in the prediction of continuance commitment, the only significant predictors are individual regulations, and not the general self-determination factor. This is important as it suggests that the elements of these factors, which make them distinctive and unique, are capable of predicting outcomes, even beyond the amount of self-determination inherent in these factors. These results strongly support the principle that SDT motivation is multi-dimensional, and not merely a function of degree of self-determination.

In sum, this study provides evidence that regulations are indeed aligned in a continuum-like structure as evidenced by a well specified general factor which clearly
represents the degree of self-determination inherent in the motivation constructs, but also that individual regulations are identifiable and important, even beyond this continuum factor. The results support the notion that motivation is best described by both quantity of self-determined motivation and quality of individual regulations. Such a structure incorporating both degree and kind is consistent with a radex structure.

The study presented in Chapter 3 applied a person-centered approach to construct profiles of employee motivation. While the results may be applicable to more applied areas of research, they also shed light on the theoretical structure of SDT motivation. Results from two samples recruited from different organizations across different countries yielded four rather consistent work motivation profiles. Interestingly, all of these profiles can be characterized by one more strongly endorsed regulation and scores for theoretically adjacent regulations declining as they become more distant from the lead regulating factor. In other words, profiles are all characterized by unimodal curves. This piece of evidence would support the presence of a continuum ordering of regulations as it would be highly unlikely (even impossible) for individuals to experience simultaneously both high and low degrees of self-determination. Instead results indicate that for any given work behavior or work context, individuals will be driven primarily by a single form of regulation, as would be consistent with that individual being placed at a single point along a continuum. However, individuals are evidently not placed on a single point along a continuum of self-determination as they unanimously report experience multiple types of regulation to some degree. Relatively flat, or equal, motivation profiles such as Profile 4 in each of the samples of Study 2 are particularly detrimental to the continuum hypothesis, as these suggest that individuals hold multiple reasons for behaving simultaneously. If motivation were a true continuum, the only possible reason for enacting a behavior would be that it is more self-determined than other options, and
therefore individuals could not endorse multiple points along the continuum. This sentiment is echoed in radex theory (Guttman, 1954) where it is stated that items ordered by a simplex, “which differ only on a single complexity factor,” and in which endorsement of more complex items also requires endorsement of less complex items (Guttman, 1954). This is not what was observed. Instead, people appear to hold multiple motivating reasons for enacting behavior (such as those represented by Profile 4 in each sample) which strongly suggests that people distinguish each of the regulations as different constructs, thereby indicating that motivation is likely to be multi-dimensional in structure. In summary, as with the results of Study 1, these seemingly ambiguous and even contradictory results are in fact exactly what would be expected if motivation were arranged in a radex structure, which allows for scores on multiple regulation sub-scales, while maintaining a predictable continuum-like order of regulations.

Finally, the meta-analysis presented in Chapter 4 tested the simplex structure of regulations across multiple domains and multiple validated scales. While this study was extensive in scope, the implications for the continuum are simple. The simplex pattern was generally present across 486 independent samples from across five main domains and 13 widely used and validated scales. While the validity of integrated regulation was brought into further question, the general results support the continuum-like ordering of regulations in terms of self-determination. The congruity of this pattern between domains and across scales indicates that the structure of motivation is relatively stable, although the exact conceptual distance between each regulation is ambiguous (as evidenced by the presence of heterogeneity within correlation matrices).

Additional post-hoc multi-dimensional scaling analyses indicated that a single dimension is the most important in explaining the structure of motivation and explains a vast majority of the variance of structure between regulations. While the addition of a
second dimension does increase the model’s fit and increases the variance explained, this increase is extremely small. However, the increase in fit is important as it indicates that multi-dimensional conceptualizations of motivation are not invalid. At this stage it is not entirely clear how this second dimension of motivation should be interpreted. The leading proposal in this very recent area of thought is that in addition to the degree of self-determination, motivation may also be classifiable by the degree of effort required in enactment of the behavior (Sheldon et al., in press). For example, someone who experiences strong external regulation due to the association of external monetary rewards is likely to enact the reinforced behavior but will perceive it as a highly effortful situation. Alternatively, someone who is intrinsically motivated (and therefore low on the second dimension found in study 3), will not feel as though such a behavior is effortful at all. Such an interpretation is congruent with the literature on ego depletion (Muraven, Rosman, & Gagne, 2007; Ryan & Deci, 2008) which generally finds that externally motivated behaviors are more depleting than more autonomously driven behaviors.

In summary, this study provides evidence to suggest that motivation is very predictably organized along a continuum-like structure, and that this continuum-like structure is the most important factor in defining motivation. However, it does not preclude the addition of additional dimensions, and indeed found that the addition of a second dimension formed a pattern strongly resembling a semi-circle, indicating that a more complex view of motivation is perhaps warranted and thereby supports the half-radex interpretation.

Theoretical Implications

In combining these results with evidence gathered from previous authors, it appears that motivation is neither definable as a continuum nor as individually separable regulations despite evidence at times supporting both sides of this debate. Instead it is
proposed that motivation forms a half-radex structure which organizes motivation by both degree (the ordering of regulations based upon amount of self-determination), and kind (high/low scores on each individual regulation). This structure is not explainable solely through a simplex because of the ordering of complexity requirement of a simplex. An ordering of complex requires all lower/less complex tests to be endorsed in order to endorse the higher more complex tests. For example, if regulations were ordered by complexity, an individual who reported very high levels of intrinsic motivation would also be required to experience high levels of all of the less “complex” regulations, resulting in profiles endorsing all regulation highly. Alternatively if it were argued that external regulation is the more complex end of the “simplex”, then an externally regulated individual would also require high levels of intrinsic motivation, which clearly is also not supported by the evidence (See Chapter 3). This additive ordering of complexity is not evident between the regulations, and is in fact prohibited by one of the fundamental principles of SDT which states that motivation is not a developmental or stage theory requiring direct progression through the regulations (Gagné & Deci, 2005). Instead SDT suggests that individuals can change between regulations freely dependent upon the degree of need satisfaction and subsequent internalization. This proposition that an individual can experience identified and even intrinsic motivation without necessarily experiencing other regulation is supported by the evidence (See Chapter 3, Graves et al., 2015; Moran, Diefendorff, Kim, & Liu, 2012), but precludes a simplex structure between regulations. Instead, it is asserted here that the regulations are interrelated and form a predictable order (Guttman, 1954), but that this order cannot be described in terms of complexity, and therefore is a radex rather than a simplex. It is important to note that such assertions about the structure of motivation do not compete with Classical Test Theory approaches such as factor analysis, which consistently find a multidimensional structure.
of motivation (e.g., Gagne et al., 2015; Vallerand et al., 1992). Instead, the identification of distinct regulations in standard factor analysis is consistent with the idea of a radex structure. Indeed, more advanced methods of factor analysis (e.g. bifactor and bifactor ESEM) are capable of representing both the quantity and quality factors simultaneously, as demonstrated in Chapter 2, and therefore bridge the gap between these two alternate approaches. As such, these two approaches should be viewed as complementary perspectives. Specifically, this dissertation found that radex theory is best suited to uncover the full complexity of the structure of motivation. Classical test theory methods such as factor analysis, which are model based, are superior with regards to more practical issues such as creating and validating items and scales.

Additionally, if motivation as conceptualized in SDT is indeed best described by a half-radex, the theory should be adjusted to accommodate this. For the most part this would simply include more careful choice of language when describing “the continuum of motivation,” as this is overly simplistic and likely misleading for practice, as will be discussed below. Such an adjustment should however be relatively straightforward as the proposed radex structure essentially incorporates within a single model both uni- and multi-dimensional aspects of motivation. This structure could also be a rich starting point for theorizing about the processes through which individuals actually experience the combination of differing degree and kind.

Limitations and Future Research

While the current evidence does strongly suggest that motivation is structured as a radex (or more specifically a half-radex), there are a number of largely unanswered questions which should be the focus of further investigation. Firstly, it is advisable that future research conduct a direct test for a radex structure. While the current empirical evidence indicates that this is the most likely structure of motivation, testing this structure
specifically is necessary, as previously recommended by Chemolli and Gagné (2014). Multidimensional scaling, such as was used in Chapter 4, represents an exploratory method for addressing this possible structure, but as with any validation process, confirmatory approaches, as described by Gurtman & Pincus (2003) for example, are needed. Such analyses could be carried out using covariance structure modeling techniques (Fabrigar et al., 1997) which can be implemented in programs such as CIRCUM (Browne, 1992; 1995) to specifically test for such structures in a confirmatory manner.

Secondly, while this dissertation focuses on the structure of motivation, the optimal operationalization of motivation is beyond its scope. Extending this line of research from a primarily theoretical focus to more applied areas of research will be an important and natural next step. Specifically, further testing of the relative predictive powers of single- versus multi-dimensional operationalizations of motivation will be essential in providing evidence based recommendations on how best to use motivation in scientific research. Such research could build upon the present studies, including extending the scope of the bifactor modelling approach to incorporate a greater range of outcomes across multiple domains, or additionally comparing a range of competing operationalizations (as discussed above) in order to determine the relative predictive power of each method. Currently the only research comparing the relative importance of a continuum factor as opposed to the use of individual regulations is confined to the work and exercise domain and relatively few variables (see Chapter 2; Gunnell & Gaudreau, 2015). Application of the techniques presented in Chapter 2 to more diverse populations and contexts will help enlighten the relative strength of these different dimensions in predicting important outcomes. This will be essential in highlighting the practical importance of the radex structure of motivation. These analyses will be useful as radex
theory (Guttman, 1954) does not specify in detail how a radex is optimally operationalized.

Given the radex structure of regulations, it is implied that items within each of these regulations should form simplexes which do indeed range from less complex to more complex, or in other words vary in degree, such that it covers the full theoretical range of each regulation. The typical approach to scale creation in SDT is Classical Test Theory (CTT) and often results in a small number of highly correlated items (Sheldon et al., in press). The implication of this is that items validated in this manner are unlikely to form a simplex ordering of complexity but rather bunch together in the conceptual space. Item Response Theory (IRT) practices will be essential in creating this full coverage of the theoretical concept and remains an untested area of SDT scale validation. While theoretically interesting, this artifact of CTT is unlikely to have had detrimental effects on SDT research as Guttman (1954) points out that if items are arranged in a perfect simplex, scores on each of the items are predictable based on scores of other items. This means that when operationalizing these items, only a few are necessary. Guttman suggest that in fact one item (potentially accompanied by the two neighbouring items) is the ideal operationalization of a simplex in order to maintain parsimony and reduce the influence of error. This indicates that the current practice of measuring a regulation based upon one approximate level of complexity is functionally the same as the ideal operationalization of a perfectly constructed simplex-ordered test of items.

Finally and relatedly, the current work is entirely cross-sectional and as such does not address issues of how an individual’s motivation towards a behavior or context changes over time. Specifically, this issue could be essential in informing the unsolved debate about whether people truly experience multiple motivation regulations at any given time, or whether people rather cycle through individual motivations. For example,
suppose an individual reports strong feelings of introjected regulation toward their work, as well as lower levels of both external and identified regulations. When this individual decides to close facebook and resume work, are they driven by a single instance of pure introjected regulation or is it a more complex weighing up of multiple regulatory processes occurring simultaneously? If decisions to enact behaviors such as this are in fact the result of a single regulation at a single point in time, then this would be entirely in line with the continuum hypothesis. Other regulating factors may be experienced before or after the decision but the instigating motivator was entirely introjected regulation. This would be equivalent to a thermometer fluctuating around a set point but only ever reading a single temperature at a time, and therefore still acting as a continuum.

This issue of level of analysis has been raised in SDT by Vallerand (1997) and described in the hierarchical model of motivation. The majority of current research is conducted at the domain level, meaning that individuals are asked to report their motivation broadly throughout the entirety of that domain, for example, for all elements of a job. Given this, it is unsurprising to note that individuals will always report multiple forms of regulations. It may be that individuals are actually reporting aggregates of how many times they remember these factors, and not how they actually experienced motivation at the instances of initiating behavior, resulting in a frequency distribution rather than accurate representation of an experience.

Instead, this question would be more appropriately be addressed at a within-person level of analysis, such as that captured through event sampling methodologies (Dimotakis & Ilies, 2013). In this instance it could be that individuals do truly only experience one motivational reason for a given behavior, and can therefore be placed at a single point along a continuum of self-determination. In this instance, the radex structure of motivation would be relegated to little more than an artifact of how we measure
motivation with somewhat insensitive tools. This would be significant as such a finding would be a major step in establishing SDT motivation as a truly uni-dimensional theory of motivation.

**Recommendations for Operationalization**

The question of how best to operationalize SDT motivation remains unresolved. Results presented in Chapter 2 demonstrated that a general factor representing the continuum is capable of predicting the majority of variance in covariates, but the addition of individual regulation factors increased this predictive power further. One option would be to use both this general factor representing the continuum structure in conjunction with the individual regulations, which contain unique characteristics as defined by SDT, in an all-inclusive analysis. While such an approach would maximize the predictive capabilities of SDT motivation, it would result in very complex analyses and models and therefore not be feasible in the vast majority of research.

Two more commonly used methods include the use of all individual regulation factors and a composite score such as the relative autonomy index (RAI: Grolnick & Ryan, 1987). The use of all individual regulations remains a rather comprehensive and satisfactorily thorough approach, but again suffers from a lack of parsimony and from multicollinearity issues. When parsimony is not a leading concern, this approach is still recommendable. The use of a select few regulations (e.g. intrinsic motivation only), as is often opted for in studies in which motivation is not a central construct, is likely to exclude much of the information which is specific to each of the other regulations, and is therefore not recommended, despite the benefits of parsimony associated with this method.

Composite scores in which all the regulations are combined to form a single index are another commonly used approach. While these methods, most notably the RAI,
appear to take into account all of the regulation and their associated unique
characteristics, they are likely to lose a great deal of information due to the relatively
arbitrary weightings placed on regulation scores. This is particularly evident in the case of
introjected regulation as it contains both positive and negative elements (i.e. pride and
shame), and yet is given a negative weight in all RAI calculations. Furthermore, a number
of statistical concerns also influence composite scores including a lack of reliability
associated with difference scores, and the failure to account for measurement error
(depending on whether SEM is used or not). Therefore, while optimal in terms of
parsimony, composite scores such as the commonly used RAI need to be applied with a
high degree of caution focused towards minimizing the statistical concerns, and even then
may sacrifice information present in each regulation due to the rudimentary calculations
performed in the estimation of the RAI.

A potential alternative to the RAI would be to use bifactor analysis to estimate a
general factor and use this factor alone in further predictive analyses. As previously
mentioned, this will undoubtedly result in some degree of information loss (due to the
exclusion of individual regulations), but does result in clear improvements in parsimony
compared to the use of all regulations. The benefit of this approach over RAI methods is
that such a bifactor solution does not rely on ambiguous weightings, nor does it suffer
from the other statistical concerns associated with difference scores. While this statistical
technique is more complex in its application, bifactor solutions are statistically superior to
the rudimentary RAI calculations.

Higher-order models or composite scores specifying autonomous and controlled
motivations have also been applied in past research. This method is not recommended as
there exists little theoretical backing for such an approach, and furthermore, no statistical
evidence supports this method over others. Such a dichotomization is merely a half
measure between the more comprehensive method of using all individual regulation and more parsimonious single factor approaches such as the RAI, and is applied as a matter of convenience rather than any well supported theoretical or empirical reason.

An alternate, and final way to operationalize motivation is through the estimation of motivation profiles as demonstrated in Chapter 3. This approach avoids issues of multicollinearity as well as the statistical concerns of composite measures, but does require a different interpretation than is currently considered standard in motivation research. For example, this method does not allow for simple statements that one variable (e.g. regulation) predicts an outcome, but rather requires tells the researcher that when these regulations combine in such a manner, individuals characterized by this profile will be likely to score higher on the outcome. Given this added nuance, this approach may not be suitable to all types of research questions. Alternatively, it may be uniquely suited to answering other research questions, and therefore should be considered more frequently.

In summary, there remains no operationalization that is clearly both comprehensive and practical. There is a constant balance to be struck between the degree of parsimony required in a study and the amount of information researchers are willing to sacrifice in order to achieve it. It is, however, recommended that dichotomizations of autonomous/controlled motivation are avoided due to a lack of overall support. Additionally, while popular due to its simplicity, the RAI is not recommended as bifactor models are capable of estimating a general factor in a more statistically rigorous manner, circumventing many of the disadvantages associated with difference scores. Accordingly, the current recommendation for operationalizing SDT motivation is to either a) specify bifactor models to estimate a general factor representing the continuum of self-determined motivation, or b) specify all of the individual regulations through CFA or preferably ESEM, or c) when appropriate, apply latent profile analysis.
However, it is important to note that this issue is far from settled and there remains much research to be conducted in comparing these methods. For example, not much is currently known about how much construct relevant information is contained in each regulation after accounting for a general factor of self-determination, or how important this will be in predicting meaningful outcomes. Likewise, while many have theorized about the deficiencies of the RAI, no research has yet been conducted to demonstrate these problems by comparing this scoring method to other scoring methods in terms of variance accounted for in outcomes and in terms of recommended interventions each method would yield.

**Conclusion**

Motivation as defined by SDT is not a continuum, or categorically distinct regulation factors. Instead, motivation is arranged in a half-radex. The regulations are indeed ordered by the relative degree of self-determination as is a trademark of SDT, but this does not constitute a simplex or continuum structure as commonly stated. Instead, each regulation forms its own simplex/continuum, and these regulations are then arranged around a semi-circle which represents the full experience of motivation. Evidence from the three original studies using different samples and statistical techniques provided unique and consistent information supporting this conclusion. This specification of a half-radex structure furthers SDT theoretically by largely resolving an ongoing debate concerning the continuum commonly said to underlie the regulations. This proposition was first put forward by Chemolli and Gagne (2014), but the current work extends this through a more comprehensive and detailed examination of the past evidence and offers greater theoretical advancement. The current research highlights the complex multi-dimensional, yet highly ordered nature of motivation specified by self-determination.
theory and offers solution to various conflicting results and contradictions within SDT itself.
References for Dissertation Introduction and Discussion


*Structural Equation Modeling*, 16, 397-438.


Appendix 1

*Online Supplements for:*

*Using Bifactor-Exploratory Structural Equation Modeling to Test for a Continuum Structure of Motivation*  
(Manuscript ID JOM-15-0440)

**Authors’ note:**

These online technical appendices are to be posted on the journal website and hot-linked to the manuscript. If the journal does not offer this possibility, these materials can alternatively be posted on one of our personal websites (we will adjust the in-text reference upon acceptance).

We would also be happy to have some of these materials brought back into the main manuscript as Appendices if you deem it useful. We developed these materials mostly to provide additional technical information and to keep the main manuscript from becoming needlessly long.
Title: 6 Factor CFA;

! In all input files, statements preceded by ! are annotations.
! Use the following statement to identify the data set. Here, the data set is labelled BESEM.dat.
! If the data set is not in the same folder as the input file, include the complete path to the data set.
Data:
File is BESEM.dat;

! The variables names function identifies all variables in the data set, in order of appearance,
! whereas the usevar command identifies the variables used in the analysis.
Variable:
Names are
  Am1  Am5  Am6
  Esap2  Esap4  Esav1
  Emap1  Emap4  Emav4
  Inap1  Inap2  Inav1  Inav2
  Ident1  Ident3  Ident4
  Intrin2  Intrin4  Intrin6;
Usevariable are Am1  Am5  Am6
  Esap2  Esap4  Esav1
  Emap1  Emap4  Emav4
  Inap1  Inap2  Inav1  Inav2
  Ident2  Ident3  Ident4
  Intrin2  Intrin4  Intrin6;

! The next section defines the analysis. Here the Maximum Likelihood Robust (MLR) estimator is used.
Analysis:
ESTIMATOR = MLR;

! The next statement defines the model. Here, a simple CFA model with no cross loading is specified
! with 6 factors (amotiv-intrin) defined respectively with items from the usevariable list.
! The name of the factors is selected by the user and comes before the “By” command.
! The “By” command indicates with items serve to define which factor.
Model:
  Amotiv by Am1  Am5  Am6;
  ExtMat by Emap1  Emap4  Emav4;
  ExtSoc by Esap2  Esap4  Esav1;
  Introj by Inap1  Inap2  Inav1  Inav2;
  Ident by Ident2  Ident3  Ident4;
  Intrin by Intrin2  Intrin4  Intrin6;

! Specific sections of output are requested
Output: sampstat stdyx mod res svalues;
Title: Bifactor CFA;

! Common sections of inputs are skipped to focus only on changes in the MODEL section
! The next statement defines the model. Here, a bifactor CFA model is
! specified with 6 specific factors (amotiv - intrin) defined as in the CFA model.
! All items are also used to define global factor called G.

Model:
Amotiv by Am1 Am5 Am6;
ExtMat by Emap1 Emap4 Emav4;
ExtSoc by Esap2 Esap4 Esav1;
Introj by Inap1 Inap2 Inav1 Inav2;
Ident by Ident2 Ident3 Ident4;
Intrin by Intrin2 Intrin4 Intrin6;

G by
Am1 Am5 Am6
Esap2 Esap4 Esav1
Emap1 Emap4 Emav4
Inap1 Inap2 Inav1 Inav2
Ident2 Ident3 Ident4
Intrin2 Intrin4 Intrin6;

! All factors are specified as orthogonal, with their correlations (WITH) constrained to be 0 (@0).
ExtSoc with amotiv@0;
ExtSoc with Extmat@0;
ExtSoc with Introj@0;
ExtSoc with Ident@0;
ExtSoc with Intrin@0;
Extmat with amotiv@0;
ExtMat with Introj@0;
ExtMat with Ident@0;
ExtMat with Intrin@0;
Introj with amotiv@0;
Introj with Ident@0;
Introj with Intrin@0;
Ident with amotiv@0;
Ident with Intrin@0;
Intrin with amotiv@0;
g with amotiv@0;
g with ExtSoc@0;
g with ExtMat@0;
g with Introj@0;
g with Ident@0;
g with Intrin@0;

Output: sampstat stdyx mod res svalues;
TITLE: 6 factor ESEM
! Common sections of inputs are skipped to focus only on the ANALYSIS and MODEL sections.
! The Maximum Likelihood Robust (MLR) estimator is used together with the oblique target rotation.

ANALYSIS:
ESTIMATOR = MLR; ROTATION = target;
! The next statement defines the model. Here, an ESEM model is specified with target rotation.
! The 6 factors (amotiv - intrin) are defined respectively with main loadings from their respective items.

! In addition to these main loadings, all other cross-loadings are estimated but targeted
! to be as close to 0 as possible (~0). Factors forming a single set of ESEM factors (with cross-
! loadings between factors, are indicated by using the same label in parenthesis after * (*1).

MODEL:
Amotiv BY Am1 Am5 Am6
   Emap1~0 Emap4~0 Emav4~0
   Esap2~0 Esap4~0 Esav1~0
   Inap1~0 Inap2~0 Inav1~0 Inav2~0
   Ident2~0 Ident3~0 Ident4~0
   Intrin2~0 Intrin4~0 Intrin6~0 (*1);
Ext_mat by Emap1 Emap4 Emav4
   Am1~0 Am5~0 Am6~0
   Esap2~0 Esap4~0 Esav1~0
   Inap1~0 Inap2~0 Inav1~0 Inav2~0
   Ident2~0 Ident3~0 Ident4~0
   Intrin2~0 Intrin4~0 Intrin6~0 (*1);
Ext_soc by Esap2 Esap4 Esav1
   Am1~0 Am5~0 Am6~0
   Emap1~0 Emap4~0 Emav4~0
   Inap1~0 Inap2~0 Inav1~0 Inav2~0
   Ident2~0 Ident3~0 Ident4~0
   Intrin2~0 Intrin4~0 Intrin6~0 (*1);
Introj by Inap1 Inap2 Inav1 Inav2
   Am1~0 Am5~0 Am6~0
   Emap1~0 Emap4~0 Emav4~0
   Esap2~0 Esap4~0 Esav1~0
   Ident2~0 Ident3~0 Ident4~0
   Intrin2~0 Intrin4~0 Intrin6~0 (*1);
Ident by Ident2 Ident3 Ident4
   Am1~0 Am5~0 Am6~0
   Emap1~0 Emap4~0 Emav4~0
   Esap2~0 Esap4~0 Esav1~0
   Inap1~0 Inap2~0 Inav1~0 Inav2~0
   Ident2~0 Ident3~0 Ident4~0
   Intrin2~0 Intrin4~0 Intrin6~0 (*1);
Intrin by Intrin2 Intrin4 Intrin6
   Am1~0 Am5~0 Am6~0
   Emap1~0 Emap4~0 Emav4~0
   Esap2~0 Esap4~0 Esav1~0
   Inap1~0 Inap2~0 Inav1~0 Inav2~0
   Ident2~0 Ident3~0 Ident4~0 (*1);
Output: sampstat stdyx mod res svalues;

TITLE: Bifactor-ESEM (measurement model)
! Common sections of inputs are skipped to focus only on the ANALYSIS and MODEL sections.
! The next section defines the analysis. Here the Maximum Likelihood Robust (MLR) estimator is used
! together with orthogonal bifactor target rotation (making all factors orthogonal as in B-CFA).
ANALYSIS:
ESTIMATOR = MLR; ROTATION = target (orthogonal);

! The next statement defines the model. Here, an ESEM model is specified with target rotation.
! The 6 factors (amotiv - intrin) are defined respectively with main loadings from their respective items.
! In addition to these main loadings, all other cross-loadings are estimated but targeted
! to be as close to 0 as possible (~0). All items are also used to define one global factor (called G).
! Factors forming a single set of ESEM factors (with cross-loadings between factors,
! are indicated by using the same label in parenthesis after *(*1).

MODEL:
G by    Am1 Am5 Am6
        Esap2 Esap4 Esav1
        Emap1 Emap4 Emav4
        Inap1 Inap2 Inav1 Inav2
        Ident2 Ident3 Ident4
        Intrin2 Intrin4 Intrin6 (*1);

Amotiv BY Am1 Am5 Am6
        Emap1~0 Emap4~0 Emav4~0
        Esap2~0 Esap4~0 Esav1~0
        Inap1~0 Inap2~0 Inav1~0 Inav2~0
        Ident2~0 Ident3~0 Ident4~0
        Intrin2~0 Intrin4~0 Intrin6~0 (*1);

Ext_mat by Emap1 Emap4 Emav4
        Am1~0 Am5~0 Am6~0
        Esap2~0 Esap4~0 Esav1~0
        Inap1~0 Inap2~0 Inav1~0 Inav2~0
        Ident2~0 Ident3~0 Ident4~0
        Intrin2~0 Intrin4~0 Intrin6~0 (*1);

Ext_soc by Esap2 Esap4 Esav1
        Am1~0 Am5~0 Am6~0
        Emap1~0 Emap4~0 Emav4~0
        Inap1~0 Inap2~0 Inav1~0 Inav2~0
        Ident2~0 Ident3~0 Ident4~0
        Intrin2~0 Intrin4~0 Intrin6~0 (*1);

Introj by Inap1 Inap2 Inav1 Inav2
        Am1~0 Am5~0 Am6~0
        Emap1~0 Emap4~0 Emav4~0
        Esap2~0 Esap4~0 Esav1~0
        Ident2~0 Ident3~0 Ident4~0
        Intrin2~0 Intrin4~0 Intrin6~0 (*1);

Ident by Ident2 Ident3 Ident4
        Am1~0 Am5~0 Am6~0
        Emap1~0 Emap4~0 Emav4~0
        Esap2~0 Esap4~0 Esav1~0
        Inap1~0 Inap2~0 Inav1~0 Inav2~0
        Ident2~0 Ident3~0 Ident4~0
        Intrin2~0 Intrin4~0 Intrin6~0 (*1);

Intrin by Intrin2 Intrin4 Intrin6
        Am1~0 Am5~0 Am6~0
        Emap1~0 Emap4~0 Emav4~0
        Esap2~0 Esap4~0 Esav1~0
        Inap1~0 Inap2~0 Inav1~0 Inav2~0
        Ident2~0 Ident3~0 Ident4~0 (*1);

Output: sampstat stdyx mod res svalues;
TITLE: Bifactor ESEM with covariates relations with all factors freely estimated

! Common sections of inputs are skipped to focus only on the USEVARIABLE, ANALYSIS and MODEL

! sections. Variables autonomy, competence, relatedness, affective commitment (AC), and continuance

! commitment (CC) have been added to this analysis in the use variable section.

Usevariable are

Am1 Am5 Am6 Emap1 Emap4 Emav4
Esap2 Esap4 Esav1 Inap1 Inap2 Inav1 Inav2
Ident2 Ident3 Ident4 Intrin2 Intrin4 Intrin6
Autonomy Competence Relatedness AC CC ;

! The next section defines the analysis. Here the Maximum Likelihood Robust (MLR) estimator is used

! together with the orthogonal bifactor target rotation.

Analysis:

ESTIMATOR = MLR; ROTATION = target (orthogonal);

Model:

![...] The first section of the model is identical to the previous example.

! The following ON statement specifies estimation of regressions between S-factors (amotiv – to intrin)

! and G-factor and covariates (Autonomy, Competence, Relatedness, AC, and CC).

AC CC Autonomy Competence Relatedness ON Amotiv ExtMat ExtSoc Introj Ident Intrin G ;
TITLE: Bifactor ESEM with ESEM-within-CFA with covariates relations with the S-factors constrained to be zero

! ANALYSIS and MODEL sections only

Analysis: estimator is MLR;

! Start values in the following section are obtained through estimation of the bifactor-ESEM measurement

! model requesting the “svalues” section of the output.
! Using these values is required to relax some constraints of ESEM and Bifactor-ESEM. For instance
! in ESEM and Bifactor-ESEM, all factors need to present the same patterns of freely estimated relations
! to covariates. Here, the ESEM-within-CFA approach is required to constrain the relations between the
! S-factors (but not the G-factor) and the covariates to be zero.
! In ESEM-within-CFA, one referent indicator is selected for each factor (including the G-factor) and all
! cross loadings for this indicators are constrained (@) to take exactly the value it had in the freely
! estimated model. All other loadings and cross loadings are given a start value corresponding to
! their values (*) from the freely estimated model. All factor variances are constrained to be 1 (@1).
! For a bifactor model, all factor correlations are also constrained to be 0 (@0).

Model:

g BY am1@-0.39263;
g BY am5*0.33615;
g BY am6*-0.33080;
g BY esap2@0.38216;
g BY esap4*0.33666;
g BY esav1*0.03294;
g BY emap1@0.49898;
g BY emap4*0.31362;
g BY emav4*0.14727;
g BY inap1*0.63006;
g BY inap2*0.90622;
g BY inav1@0.57699;
g BY inav2*0.48894;
g BY ident2*0.77973;
g BY ident3*1.31872;
g BY ident4@1.28983;
g BY intrin2*1.14160;
g BY intrin4@1.14395;
g BY intrin6*1.12897;

Amotiv BY am1*0.68981;
amotiv BY am5*0.65837;
amotiv BY am6*0.65592;
amotiv BY emap1@0.22037;
amotiv BY emap4*0.19998;
amotiv BY emav4*0.00300;
amotiv BY esap2@0.15847;
amotiv BY esap4*0.17431;
amotiv BY esav1*0.11986;
amotiv BY inap1*0.05677;
amotiv BY inap2*-0.07635;
amotiv BY inav1@0.17945;
amotiv BY inav2*0.01314;
amotiv BY ident2*-0.14293;
amotiv BY ident3*0.07663;
amotiv BY ident4@0.08610;
amotiv BY intrin2@-0.06071;
amotiv BY intrin4@-0.08090;
amotiv BY intrin6*-0.07964;

extmat BY emap1*1.53774;
extmat BY emap4*0.84067;
extmat BY emav4*1.13499;
extmat BY am1@0.09013;
extmat BY am5*0.10347;
extmat BY am6*0.06301;
extmat BY esap2@0.40790;
extmat BY esap4*0.32382;
extmat BY esav1*0.45489;
extmat BY inap1*0.18847;
extmat BY inap2*0.05461;
extmat BY inav1@0.24750;
extmat BY inav2*0.06022;
extmat BY ident2*0.02634;
extmat BY ident3*0.00048;
extmat BY ident4@-0.01833;
extmat BY intrin2@-0.07773;
extmat BY intrin4@-0.04074;
extmat BY intrin6*-0.10479;

extsoc BY esap2*1.13210;
extsoc BY esap4*1.09945;
extsoc BY esav1*1.08788;
extsoc BY am1@0.08105;
extsoc BY am5*0.04667;
extsoc BY am6*0.12917;
extsoc BY emap1@0.11155;
extsoc BY emap4*0.58741;
extsoc BY emav4*0.61396;
extsoc BY inap1*0.54434;
extsoc BY inap2*0.08778;
extsoc BY inav1@0.35970;
extsoc BY inav2*0.10321;
extsoc BY ident2*0.02858;
extsoc BY ident3*0.06371;
extsoc BY ident4@-0.06996;
extsoc BY intrin2@-0.11342;
extsoc BY intrin4@-0.03684;
extsoc BY intrin6*-0.04847;

introj BY inap1*0.73127;
introj BY inap2*0.48896;
introj BY inav1*1.12825;
introj BY inav2*1.06249;
introj BY am1@0.01224;
introj BY am5*0.00518;
introj BY am6*0.06226;
introj BY emap1@-0.13351;
introj BY emap4*0.23147;
introj BY emav4*0.41822;
introj BY esap2@0.14887;
introj BY esap4*0.25184;
introj BY esav1*0.38897;
introj BY ident2*0.43978;
introj BY ident3*0.16744;
introj BY ident4@0.02386;
introj BY intrin2@-0.07868;
introj BY intrin4@-0.02557;
introj BY intrin6*-0.13357;
ident BY ident2*0.37232;
ident BY ident3*0.42740;
ident BY ident4*0.59507;
ident BY am1@-0.04921;
ident BY am5*0.03338;
ident BY am6*0.01853;
ident BY emap1@-0.61895;
ident BY emap4*0.15928;
ident BY emav4*0.68637;
ident BY esap2@-0.16523;
ident BY esap4*-0.02558;
ident BY esav1*0.10667;
ident BY inap1*0.06167;
ident BY inap2*0.12079;
ident BY inav1@0.12381;
ident BY inav2*-0.03615;
ident BY intrin2@-0.00746;
ident BY intrin4@0.03462;
ident BY intrin6*0.05258;
intran BY intrin2@0.64995;
intran BY intrin4*0.86685;
intran BY intrin6*0.72335;
intran BY am1@-0.05503;
intran BY am5*-0.00221;
intran BY am6*-0.06204;
intran BY emap1@-0.24644;
intran BY emap4*-0.04727;
intran BY emav4*0.14359;
intran BY esap2@-0.04745;
intran BY esap4*-0.08515;
intran BY esav1*-0.04757;
intran BY inap1*-0.05376;
intran BY inap2*-0.02423;
intran BY inav1@-0.11019;
intran BY inav2*-0.09012;
intran BY ident2*0.06175;
intran BY ident3*0.06970;
intran BY ident4@0.02096;

G-Intrin@1;

extmat WITH amotiv@0.00000;
extsoc WITH amotiv@0.00000;
extsoc WITH extmat@0.00000;
introj WITH amotiv@0.00000;
introj WITH extmat@0.00000;
introj WITH extsoc@0.00000;
ident WITH amotiv@0.00000;
ident WITH extmat@0.00000;
ident WITH extsoc@0.00000;
ident WITH introj@0.00000;
intrin WITH amotiv@0.00000;
intrin WITH extmat@0.00000;
intrin WITH extsoc@0.00000;
intrin WITH introj@0.00000;
intrin WITH ident@0.00000;
g WITH amotiv@0.00000;
g WITH extmat@0.00000;
g WITH extsoc@0.00000;
g WITH introj@0.00000;
g WITH ident@0.00000;
g WITH intrin@0.00000;

! The following inputs specify G to be freely estimated in relation to covariates while constraining ! S-factors (amotv-intrin) to be unrelated to covariates.
AC CC Autonomy Competence Relatedness ON Amotiv@0 ExtMat@0
ExtSoc@0 Introj@0 Ident@0 Intrin@0;
AC CC Autonomy Competence Relatedness ON G;
AC CC Autonomy Competence Relatedness;
Appendix 2

Online Supplemental Materials for:

Motivation Profiles at Work: A Self-Determination Theory Approach


Authors’ note:

These online technical appendices are to be posted on the journal website and hot-linked to the manuscript. If the journal does not offer this possibility, these materials can alternatively be posted on one of our personal websites (we will adjust the in-text reference upon acceptance). We would also be happy to have some of these materials brought back into the main manuscript, or included as published appendices if you deem it useful. We developed these materials to provide additional technical information and to keep the main manuscript from becoming needlessly long.
Preliminary Measurement Models

Preliminary measurement models were estimated in both samples using the robust maximum likelihood estimator (MLR) available in Mplus 7.3 (Muthén & Muthén, 2014), in conjunction with Full Information Maximum Likelihood (FIML) estimation to deal with the very low level of missing data present this data set (0% to 2.8% per item; M = 1.1%). In each sample, we contrasted a classical confirmatory factor analytic (CFA) model, in which each of the six MWMS factors was defined on the basis of it’s a priori items, with no cross-loading allowed between items and non-target factors, with an exploratory structural equation modeling (ESEM; Asparouhov & Muthén, 2009; Morin, Marsh, & Nagengast, 2013), which was defined in the same manner as the CFA model while allowing for the free estimation of cross-loadings between items and non-target factors. These ESEM models were specified using a confirmatory approach using target rotation (Asparouhov & Muthén, 2009; Browne, 2001), which allows for the pre-specification of target loadings in a confirmatory manner, while cross-loadings are targeted to be as close to zero as possible. This decision is based on the results from simulation studies (Asparouhov & Muthén, 2009; Sass & Schmitt, 2010; Schmitt & Sass, 2011) and studies of simulated data (Marsh, Lüdtke, Nagengast, Morin, & Von Davier, 2013; Morin, Arens et al., 2015) showing that forcing cross-loadings (even as small as .100, Marsh et al., 2013) present in the population model to be exactly zero (as in CFA) forces these cross-loadings to be absorbed through an inflation of the factor correlations. In contrast, these same studies show that the free estimation of cross-loadings, even when none are present in the population model, still provides unbiased estimates of the factor correlations (also see Asparouhov, Muthén, & Morin, 2015; Morin, Arens, & Marsh, 2015). Importantly, recent studies conducted on motivational data have also shown the clear advantages of using an ESEM measurement model (Guay, Morin, Litalien, & Valois, 2015; Litalien, Guay, & Morin, 2015) in terms of obtaining reduced estimates of factor correlations more in line with theoretical expectations.

Given the known oversensitivity of the chi-square test of exact fit ($\chi^2$) to sample size and minor model misspecifications (e.g., Marsh, Hau, & Grayson, 2005), we relied on goodness-of-fit indices to describe the fit of these models (Hu & Bentler, 1999): (a) the comparative fit index (CFI)
which assesses goodness-of-fit through a comparison with a baseline saturated model, (b) the root mean square error of approximation (RMSEA) and its 90% confidence interval (CI), which assesses goodness-of-fit while including a correction for parsimony; (c) the standardized root mean square residual (SRMR), which assesses goodness-of-fit on the basis of the model’s residuals. Values greater than .90 for the CFI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .08 or .06 for the RMSEA and SRMR respectively support acceptable and excellent model fit. In both samples, these results revealed the clear superiority of the ESEM measurement model, which provided a fully satisfactory level of fit to the data [(Sample 1: $\chi^2 = 124.615$, df = 72, $p < .001$; CFI = .986; RMSEA = .032; CI = .022 to .041; SRMR = .016); (Sample 2: $\chi^2 = 161.020$, df = 72, $p < .001$; CFI = .955; RMSEA = .066; CI = .052 to .079; SRMR = .020)], when compared to the CFA model [(Sample 1: $\chi^2 = 421.443$, df = 137, $p < .001$; CFI = .924; RMSEA = .054; CI = .048 to .059; SRMR = .058); (Sample 2: $\chi^2 = 401.719$, df = 137, $p < .001$ CFI = .866; RMSEA = .082; CI = .073 to .092; SRMR = .070)]. This conclusion was supported by an assessment of the parameter estimates obtained from both models, which revealed generally well-defined factors, and reduced factor correlations in the ESEM [(Sample 1: $|r| = .015$ to .760; $M_{|r|} = .281$); (Sample 2: $|r| = -.361$ to .446; $M_{|r|} = .234$)], when compared to CFA model [(Sample 1: $|r| = .057$ to .836; $M_{|r|} = .366$); (Sample 2: $|r| = .353$ to .844; $M_{|r|} = .400$)]. Factors scores used in the main study to estimate the key latent profile analyses where thus saved from these ESEM measurement models.

Mixture models (including LPAs) are usually estimated using scale scores (sum, or mean) on the profile indicators (here the commitment mindsets). Although it is well known that using latent variables controlled for measurement error (i.e., models where the items are used to estimate latent factors, which are then used as profile indicators) provides a stronger approach than the use of scale scores (e.g., Bollen, 1989), applications of fully-latent mixture models are few (e.g., Morin, Scalas, & Marsh, 2015). In fact, given the complexity of mixture models, it is often impossible in practice to implement a fully-latent approach to their estimation. An alternative, which is becoming more frequent in recent applications of mixture models, is to rely on factor scores saved from preliminary measurement models (e.g., Kam et al., 2015; Morin &
Marsh, 2015). Factor scores do not explicitly control for measurement errors the way latent variables do. However, by giving more weight to items presenting lower levels of measurement errors, they still provide a partial implicit control for measurement errors, making them a stronger alternative than scale scores, particularly when using modern approaches to their estimation such as the regression approach implemented in Mplus (Skrondal & Laake, 2001). An added advantage of factors scores is that, when they are estimated from more complex measurement models (including method controls, cross loadings, bifactor models, etc., which is not the case in this demonstration), they tend to preserve the nature of the underlying measurement structure better than scale scores.

**References used in this supplement**


Figure S1. Elbow Plot for the Information Criteria in Sample 1.

Figure S2. Elbow Plot for the Information Criteria in Sample 2.
Table S1.
**Posterior Classification Probabilities for the Most Likely Latent Profile Membership (Row) by Latent Profile (Column).**

<table>
<thead>
<tr>
<th>Sample 1</th>
<th>Profile 1</th>
<th>Profile 2</th>
<th>Profile 3</th>
<th>Profile 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profile 1</td>
<td>0.950</td>
<td>0.018</td>
<td>0.030</td>
<td>0.002</td>
</tr>
<tr>
<td>Profile 2</td>
<td>0.006</td>
<td>0.948</td>
<td>0.045</td>
<td>0.002</td>
</tr>
<tr>
<td>Profile 3</td>
<td>0.002</td>
<td>0.038</td>
<td>0.887</td>
<td>0.073</td>
</tr>
<tr>
<td>Profile 4</td>
<td>\leq 0.001</td>
<td>\leq 0.001</td>
<td>0.055</td>
<td>0.943</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sample 2</th>
<th>Profile 1</th>
<th>Profile 2</th>
<th>Profile 3</th>
<th>Profile 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profile 1</td>
<td>0.935</td>
<td>0.017</td>
<td>0.030</td>
<td>0.019</td>
</tr>
<tr>
<td>Profile 2</td>
<td>0.035</td>
<td>0.923</td>
<td>0.042</td>
<td>0.000</td>
</tr>
<tr>
<td>Profile 3</td>
<td>0.031</td>
<td>0.025</td>
<td>0.942</td>
<td>0.002</td>
</tr>
<tr>
<td>Profile 4</td>
<td>0.020</td>
<td>0.000</td>
<td>0.000</td>
<td>0.980</td>
</tr>
</tbody>
</table>

Table S2
**Mean Levels of Motivation in the Retained Latent Profile Models.**

<table>
<thead>
<tr>
<th>Sample 1</th>
<th>Profile 1</th>
<th>Profile 2</th>
<th>Profile 3</th>
<th>Profile 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>Variances</td>
<td>Mean</td>
<td>Variances</td>
<td>Mean</td>
</tr>
<tr>
<td>Amotivation</td>
<td>1.025</td>
<td>1.169</td>
<td>-0.554</td>
<td>0.019</td>
</tr>
<tr>
<td>External-M</td>
<td>0.053</td>
<td>0.841</td>
<td>-1.075</td>
<td>0.112</td>
</tr>
<tr>
<td>External-S</td>
<td>0.242</td>
<td>0.786</td>
<td>-1.308</td>
<td>0.006</td>
</tr>
<tr>
<td>Introjected</td>
<td>-0.331</td>
<td>0.764</td>
<td>-0.467</td>
<td>0.761</td>
</tr>
<tr>
<td>Identified</td>
<td>-0.840</td>
<td>1.005</td>
<td>0.143</td>
<td>0.498</td>
</tr>
<tr>
<td>Intrinsic</td>
<td>-0.867</td>
<td>1.009</td>
<td>0.288</td>
<td>0.54</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sample 2</th>
<th>Profile 1</th>
<th>Profile 2</th>
<th>Profile 3</th>
<th>Profile 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>Variances</td>
<td>Mean</td>
<td>Variances</td>
<td>Mean</td>
</tr>
<tr>
<td>Amotivation</td>
<td>1.679</td>
<td>4.131</td>
<td>-0.338</td>
<td>0.002</td>
</tr>
<tr>
<td>External-M</td>
<td>-0.050</td>
<td>1.152</td>
<td>-0.675</td>
<td>0.193</td>
</tr>
<tr>
<td>External-S</td>
<td>0.292</td>
<td>0.624</td>
<td>-0.805</td>
<td>0.260</td>
</tr>
<tr>
<td>Introjected</td>
<td>-0.335</td>
<td>1.301</td>
<td>-0.236</td>
<td>0.510</td>
</tr>
<tr>
<td>Identified</td>
<td>-0.597</td>
<td>1.352</td>
<td>-0.034</td>
<td>0.611</td>
</tr>
<tr>
<td>Intrinsic</td>
<td>-1.450</td>
<td>0.974</td>
<td>0.437</td>
<td>0.267</td>
</tr>
</tbody>
</table>

Note. External-M = External-Material Regulation; External-S = External-Social Regulation; Indicators are estimated from factor scores with mean of 0 and a standard deviation of 1.
### Table X. Correlation Matrices for all Scales included in Meta-analysis

#### MWMS

<table>
<thead>
<tr>
<th></th>
<th>Intrinsic</th>
<th>Integrated</th>
<th>Identified</th>
<th>Introjected</th>
<th>External</th>
<th>Amotivation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intrinsic</td>
<td>97.600 (0)</td>
<td>91.537 (0)</td>
<td>74.176 (0)</td>
<td>93.529 (0)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Integrated</td>
<td>-.761 (40)</td>
<td>-.656 (40)</td>
<td>-.171 (14)</td>
<td>.274 (18)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Identified</td>
<td>.358 (40)</td>
<td>.194 (45)</td>
<td>.516 (45)</td>
<td>98.148 (0)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Introjected</td>
<td>.077 (45)</td>
<td>.403 (14)</td>
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### SRQ (Education)

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Note: Correlations and (number of studies) are below the diagonal. $I^2$ and (Chi-squared associated with $Q$) statistics are presented above the diagonal. The AMS results do not include three subscales of intrinsic regulation.
Table X. Correlation Matrices for Scales Including Intrinsic Motivation Sub-scales

### SMS (Sport)

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<th>Stimulation</th>
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### SMS (Physical Education)

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Note: Correlations and (number of studies) are below the diagonal. $I^2$ and (Chi-squared associated with $Q$) statistics are presented above the diagonal. The AMS results do not include three subscales of intrinsic regulation. Intrinsic motivation (composite) refers to studies which applied these scales but created a single intrinsic factor by combining the three intrinsic subscales.
Table X. *Correlation Matrices by Nationality*

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Note: Correlations and (number of studies) are below the diagonal. $I^2$ and (Chi-squared associated with $Q$) statistics are presented above the diagonal. The AMS results do not include three subscales of intrinsic regulation.
Published studies included in meta-analysis


doi:10.1016/j.psychsport.2006.11.001


doi:10.1016/j.psychsport.2010.09.006


Fasczewski, K. (2012). *So you are having a bad day: Gender, goal orientation and incompitition attrition rate in competitive cyclists.*


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