UNIVERSITAT DE BARCELONA

Trajectory-based motivational profiles and performance: evidence from the academic context

Emilia A. Wietrak

TESIS DOCTORAL

Trajectory-Based Motivational Profiles and Performance:

Evidence from the Academic Context

Perfiles Basados en Trayectorias de Motivación y Desempeño:

Evidencia desde el Contexto Académico

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PERFILES BASADOS EN TRAYECTORIAS DE MOTIVACIÓN Y DESEMPEÑO: EVIDENCIA DESDE EL CONTEXTO ACADÉMICO

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Autora: Emilia A. Wietrak

Directores: Dr. José Navarro Cid, Dr. David Leiva Ureña

Departamento de Psicología Social y Psicología Cuantitativa

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CHAPTER 1

ABSTRACT

The purpose of the present doctoral thesis is to contribute to the research on motivation quality by analyzing longitudinal profiles of different motivational variables and their relationship with performance in higher education setting in Spain. Specifically, this thesis targets the following objectives: (1) To study the trajectories of different forms of motivation in samples of university students in Spain during a prescribed period of time; (2) to test whether respondents can be grouped based on different configurations of motivation that they experience over time; (3) to explore the qualitative characteristics of the motivational profiles; (4) to analyze the predictive validity of the profiles regarding academic performance. Two empirical studies were conducted in order to address these objectives.

The first study (Study 1) was grounded in flow and self-determination (SDT) theories, and applied latent class mixed models analysis in a sample of 291 undergraduate students in order to study (1) whether different patterns of dynamics in academic motivation can be distinguished, and (2) whether the observed patterns are related to students' performance. Two obtained latent classes were characterized as *strong increase* and *modest increase* observed in the studied flow- and SDT-related variables. The comparison of these two groups of students confirmed that those whose motivation increased more sharply over the semester were likely to achieve better performance, compared to the participants whose motivation increased modestly.

The second study (Study 2) focused on the continuum of motivation proposed by SDT. In this investigation, data was collected in five waves from a sample of 979 undergraduate students, applying the Multidimensional Work Motivation Scale

(MWMS, Gagné et al., 2015) adapted to the academic context. A non-parametric clustering procedure was implemented to investigate whether the respondents could be grouped according their trajectories in MWMS adapted to the academic context. Two profiles of students were observed: *Highly motivated* (average to high levels of all motivational forms over time, except social external regulation; low amotivation), and *Reward oriented* (high but slightly decreasing external-material regulation; moderate and decreasing identified and introjected regulation and intrinsic motivation; low and increasing external-social regulation and amotivation). Students in the *Highly motivated* profile achieved better performance. They were also characterized by higher levels of perceived competence and perceived challenge over a course of the semester, compared to the respondents in the *Reward oriented* profile. Furthermore, Study 2 was the first to consider both facets of external regulation, material and social, in the educational setting, and provided evidence of different evolution of these two forms of motivation in a sample of undergraduate students.

The results of the aforementioned studies stress the importance of person-centered longitudinal research to detect different patterns of motivational evolution in the academic context which, in turn, are useful to predict academic outcomes.

RESUMEN

El objetivo de la presente tesis doctoral es contribuir a la investigación sobre la calidad de la motivación mediante el análisis de perfiles longitudinales de diferentes variables motivacionales, y su relación con el rendimiento, en el ámbito de la educación universitaria en España. En concreto, esta tesis tiene los siguientes objetivos: (1) estudiar las trayectorias de diferentes formas de motivación en muestras de estudiantes universitarios en España durante un período de tiempo determinado; (2) analizar si los participantes pueden agruparse en función de las diferentes configuraciones de motivación que experimentan a lo largo del tiempo; (3) explorar las características cualitativas de los perfiles motivacionales; (4) analizar la validez predictiva de los perfiles en cuanto al desempeño académico. Se realizaron dos estudios empíricos para abordar estos objetivos.

El primer estudio (Estudio 1) está basado en teorías de *flow* y de la auto-determinación (*self-determination theory*, SDT), y aplicó análisis de modelos mixtos de clases latentes en una muestra de 291 estudiantes de grado para estudiar (1) si es posible distinguir diferentes patrones de cambio en la motivación académica, y (2) si los patrones observados están relacionados con el desempeño de los estudiantes. Dos clases latentes obtenidas se caracterizaron por un *fuerte aumento* y un *modesto aumento* observado en las variables estudiadas relacionadas con *flow* y SDT. La comparación de estos dos grupos de estudiantes confirmó que aquellos cuya motivación aumentó de manera más intensa a lo largo del semestre tendieron a lograr mayor desempeño, en comparación con los participantes cuya motivación aumentó modestamente.

El segundo estudio (Estudio 2) se centró en el continuum de motivación

propuesto por la SDT. En ambas investigaciones, se utilizaron datos recogidos en cinco ocasiones de medida de una muestra de 979 estudiantes de grado, aplicando la Escala de Motivación Laboral Multidimensional (MWMS, Gagné et al., 2015) adaptada al contexto académico. Se implementó un procedimiento no paramétrico para agrupar a los individuos según sus trayectorias multivariantes en la MWMS adaptada al contexto académico. Se observaron dos perfiles de estudiantes: *Altamente motivado* (niveles de medio a altos de todas las formas motivacionales a lo largo del tiempo, excepto la regulación social externa; baja amotivación) y *Orientado a la recompensa* (alta y decreciente regulación material externa; moderada y decreciente regulación identificada, regulación introyectada, y motivación intrínseca; baja y creciente regulación social externa y amotivación). Los estudiantes en el perfil *Altamente motivado* lograron mayor desempeño. Estos estudiantes se caracterizaron también por niveles más altos de competencia percibida y desafío percibido durante el semestre, en comparación con los estudiantes en el perfil *Orientado a la recompensa*. Además, el Estudio 2 fue el primero en considerar ambas facetas de la regulación externa, material y social, en el ámbito educativo, y proporcionó evidencia de diferente evolución de estas dos formas de motivación en una muestra de estudiantes universitarios.

Los resultados de los dos estudios enfatizan la importancia de la investigación longitudinal centrada en la persona para detectar diferentes patrones de evolución motivacional en el contexto académico, que a su vez son útiles para predecir los resultados académicos.

"*That is the way to learn the most, that when you are doing something with such enjoyment that you don't notice that the time passes*."

Albert Einstein

1. Introduction and General Objectives of the Thesis

The outcomes of our behavior are an important part of almost every productive area of life. From a very young age, first at school and then at work, people are constantly evaluated and expected to achieve great results. Not surprisingly, such interest in high performance leads to the questions of how it can be accomplished. What actions help achieve the best results? How to make people engage in these actions? How to intensify people's focus and efforts on the goal they aim to meet? How to sustain the focus and effort over time? These questions can be summarized under the term *motivation*, which refers to the processes that initiate, guide, and sustain goal-oriented behaviors. The concept of motivation, practically inexistent in scientific literature until the second half of the last century, today is considered a "cornerstone" of psychology, and a crucial factor for the success and well-being of individuals in all aspects of their lives (Cerasoli et al., 2014; Kanfer et al., 2017). Over the years, the understanding of motivation has evolved from a term limited to the physical drives and instincts, to a complex concept based on internal psychological processes. The interest in developing motivation has shifted from quantitative (*how to increase motivation*) to qualitative (*how to improve motivation quality*) approach. Contemporary theorists and researchers focus on qualitatively different reasons for engaging in behavior, distinguishing between extrinsic and intrinsic motivation. While extrinsic motivation is related to some external pressures (reward or punishment), intrinsic motivation involves performing an action for its own sake. In the last decades, scientists and practitioners' attention has been particularly focused on intrinsic motivation, related to enjoyment and well-being. Numerous studies have confirmed a positive link between intrinsic motivation and a series of adaptive outcomes, such as performance (Cerasoli et al., 2014), creativity (de Jesus et al., 2013), or persistence (Renaud-Dubé et al., 2015), to name just a few. At the same time, researchers acknowledge that external rewards are an inherent part of almost every productive activity. Hence, the studies which investigate interactions between the two forms of motivation, intrinsic and extrinsic, have been treated with particular regard.

Keen interest in motivation in the last decades, as well as increasing complexity of the research questions, have contributed to a fast development of research methods. One of the methodological and conceptual trends which have been growing fast since the beginning of the century is a longitudinal approach. Many authors confirmed that motivation is a dynamic phenomenon, calling for research which would treat this concept as such and reflect the dynamic nature of motivation in the study design (Kanfer et al., 2017). Another important tendency in research is a person-centered approach. This method alludes to the questions about interactions of different forms of motivation, allowing to explore profiles characterized by configurations of these forms. In the last years, person-centered and longitudinal approaches have received considerable attention of motivation theorists and researchers. Nevertheless, few studies attempted to join both methods and explore trajectory-based profiles of motivation.

This doctoral thesis aims to contribute to the research on motivation quality by exploring longitudinal profiles of motivation and their relationship with performance in the context of higher education in Spain. After explaining the concept of motivation and its evolution in the scientific literature, I discuss the recent methodological advances in research on motivation, paying particular attention to person-centered and longitudinal studies. With the purpose of having an overview of the progress made in this field of research, I provide a review of the studies which investigated motivation profiles considering both, different qualitative components of motivation and their temporal evolution. The core part of the dissertation is empirical research of the trajectory-based motivational profiles and their relationship to performance on samples of university students in Spain. This research is divided into two parts, in which motivational profiles were studied from two perspectives. The first part focuses on intrinsic motivation, integrating insights from self-determination theory and flow theory; the profiles are based on variables related to autonomous forms of motivation: perceived competence, intrinsic motivation, and flow. In the second part, the profiles were created using the continuum of motivation proposed in self-determination theory, and included qualitatively different forms of motivation: intrinsic, extrinsic and amotivation. Moreover, different methods were applied to analyze the profiles: latent class mixed models and longitudinal cluster analysis. The final part of the thesis includes a general discussion of the results and limitations of the two studies, as well as recommendation for future research and practical implications.

2. Theoretical background and Literature Review

2.1. Intrinsic Motivation – Evolution of the Concept

Over the years, many attempts have been made to define motivation. Given the similarities of the classical definitions (e.g., Atkinson, 1964; Campbell & Pritchard, 1976; Kanfer, 1990; Pinder, 2008; Vroom, 1964), it can be concluded that motivation refers to the processes that determine the intensity, direction and persistence of the actions performed by an individual to achieve certain goal. In other words, following the definition proposed by Steers et al. (2004, p. 379), motivation comprehends “factors or events that energize, channel, and sustain human behavior over time”. According to Reeve (2008), the study of motivation amounts to two questions: “What causes behavior?” and “Why does behavior vary in its intensity?”. More specifically, the first question aims to explore why behavior starts and comes to an end, why it is maintained over time, what determines goals toward which it is directed, or why this direction changes. The second question alludes to the differences in quantity of motivation. Such focus on the amount or intensity level (*how much?*) is quite common among professionals in the applied fields of human activity. For instance, practitioners like managers, teachers or coaches frequently attempt to improve the results of their workers, students or athletes relying on a belief that motivation is a unitary concept, which can be described with a single “amount” scale. Conversely, theorists are inclined to define motivation as a complex phenomenon, qualitative characteristics of which may vary (Ames & Archer, 1988; Atkinson, 1964; Elliot, 1999; Ryan & Deci, 2020). For example, one of the common classifications distinguishes between extrinsic and intrinsic motivation (e.g., Ryan & Deci, 2000). A person whose motivation is extrinsic acts to achieve some separable, external outcome. In contrast, an intrinsically motivated individual engages in behavior for its own sake – because of the enjoyment and pleasure derived from a task at hand. As noted by Ryan and Deci (2000, p.70): “Perhaps no single phenomenon reflects the positive potential of human nature as much as intrinsic motivation, the inherent tendency to seek out novelty and challenges, to extend and exercise one's capacities, to explore, and to learn”.

Given this unique ability of intrinsic motivation to explain human behavior, large attention that theorists and researchers have paid to this phenomenon in the last decades does not surprise. Nevertheless, the term intrinsic motivation has not always been well integrated into psychological theory and research. The first notions of this concept date back to the first half of the last century and are visible in the early works of ethologists and behavioral scientists, such as Groos (1901), Dewey (1922), Woodworth (1918) or Allport (1937). Even then, the researchers were paying attention to inherent experience of pleasure derived from play (Groos, 1901), and to the importance of interest for the development of mind and culture (Dewey, 1922). They also emphasized the relevance of autonomous activities (Allport, 1937), and of spontaneous behavior and the *pleasure of being a cause* of actions (Woodworth, 1918, 1958). However, these early understandings of motivation were quickly overshadowed with behaviorism, which in the mid-twentieth century became mainstream psychology. Early behavioristic theories (e.g., operant theory, Skinner, 1953) greatly overlooked internal processes as a possible driver for action, assuming that individuals were passive, and all their actions could be explained by interactions with external environment – seeking reward or avoiding punishment. Although certain behavioristic approaches acknowledged the inner nature of animals and humans (e.g., learning theory, Hull, 1943), the reinforcement process they were proposing was limited to the physiological needs (i.e., drives). Despite a strong position in scientific psychology, reinforcement approaches were not without limitations. Paradoxically, these limitations were demonstrated in experiments, which are considered a behaviorism's keystone. More specifically, several studies confirmed that animals and humans showed an innate tendency to explore their environment out of pure curiosity, demonstrating that certain behaviors were not motivated by reward or punishment, and could not be explained by reinforcement processes (Berlyne, 1955; Butler, 1953; Butler & Harlow, 1957; Montgomery, 1954; Myers & Miller, 1954;

Welker, 1956). These findings inspired researchers to seek an alternative explication of behaviors such as exploration, manipulation, and play. White's effectance motivation theory (1959) was probably the most groundbreaking approach, which still inspires intrinsic motivation theorists. According to White, exploration, manipulation, and play cannot be explained through the mechanisms of drives or reinforcements and should be instead reconsidered as *innate psychological tendencies*. White considered these tendencies as a motive to cause effects (i.e., effectance motivation), and summarized them under the concept of competence. Furthermore, the effectance motivation was related to the feeling of pleasure and satisfaction in being active, which was considered an essential biological endowment (White, 1959). White's postulates were the first to change the focus of the motivation theory from the environment to the object, that is, to an organism capable to grow through internal psychological processes derived from the actions it performs. The ideas proposed by White initiated a shift in the conceptualization of reinforcements, encouraging focus on future outcomes and related underlying cognitive processes, rather than on past events. Such change of paradigm was visible, for example, in Festinger's cognitive dissonance theory (1957) – individuals tend to reduce inconsistencies in ideas, beliefs or values they hold, or in Berlyne's theory (1960) – individuals are motivated to act through curiosity and arousal. At roughly the same time, humanistic perspective started rising to prominence. Humanistic theories (e.g., Maslow, 1943; Rogers, 1961) perceived people as complex organisms that possess "free will", are able to make choices, and are aware that their actions have an impact on future events. Although the premises of humanistic psychology were subjective and not tested at that time, they provided a background for intrinsic motivation theories. For instance, Maslow's distinction between basic and higher order needs (1943), could be considered one of the first formal distinctions between intrinsic and extrinsic forms of motivation. Another example of a concept that inspired contemporary theories of intrinsic motivation is the internal perceived locus of causality introduced by de Charms (1968). Building upon the idea of humans as conscious and responsible for their actions, de Charms proposed that human behavior was motivated by the need of being the origin of one's faith and experiencing personal causation in an interaction with one's environment. This concept of autonomy, together with White's effectance motive, became a ground for self-determination theory (Deci, 1975; Deci & Ryan, 1985), according to which the innate psychological needs for autonomy and competence are essential conditions for intrinsic motivation and psychological growth. Nowadays, self-determination theory is considered a dominant approach to intrinsic motivation (Cerasoli et al., 2014; Howard et al., 2017) with some fundamental texts (e.g., Deci & Ryan, 2000; Ryan & Deci, 2000) reaching 50,000 citations, and used by researchers in many contexts, including education (e.g., Deci et al., 1991; Niemiec & Ryan, 2009), work (e.g., Deci et al., 1989; Gagné & Deci, 2005) or sport, physical activity and exercise (e.g., Ntoumanis, 2012; Ryan & Deci, 2017, Chapter 19).

Despite its dominant position, self-determination theory is not the only approach that attempts to explain human behavior through intrinsic motives. Another important theory related to intrinsic motivation is Csikszentmihalyi's flow theory (1975). Drawing on the concept of competence and positive intrinsic reinforcements, Csikszentmihalyi introduced a notion of optimal experience (i.e., flow) – a mental state of enjoyment and absorption, where the demand at hand is well-matched to one's skills. In the following parts of this dissertation these two approaches – self-determination theory and flow theory, will be explained more in detail.

2.1.1. Self-Determination Theory

Self-determination theory (SDT; Deci & Ryan, 1985; Ryan & Deci, 2000) offers a comprehensive framework to understand mechanisms underlying human motivation and well-being. Its authors, Edward Deci and Richard Ryan, describe motivation not only in terms of its quantity, that is, how much individuals are motivated toward a task they perform, but also, and above all, in terms of quality (e.g., Ryan & Deci, 2000). According to SDT, psychological growth and integration, which are inherent parts of human nature, cannot exist without satisfying three fundamental conditions, defined as the basic psychological needs for autonomy, competence, and relatedness (e.g., Deci & Ryan, 2000; Ryan & Deci, 2017; Vansteenkiste et al., 2020). Autonomy refers to the ownership, volition, and willingness in one's action. Autonomous behavior is self-regulated and independent from internal or external pressures. However, it is not equal to independence – according to Ryan and Deci (2017, Chapter 1) independent, interdependent and dependent behaviors can be both, self-regulated or controlled. The need for competence denotes mastery, and a feeling of confidence and proficient in one's action. It refers to the subjective perception of one's effectiveness in performed activity and should not be confused with capacity or skill level. The need for relatedness concerns sense of belonging and connection. It is satisfied with care, respect, and bonding with others. The fulfillment of the three needs drives a person toward growth and well-being and enhance self-motivation; contrarily, frustration of these needs is likely to lead to ill-being, non-optimal functioning, and diminished motivation (Deci & Ryan, 2000; Ryan & Deci, 2000; Vansteenkiste et al., 2020). The needs for autonomy, competence and relatedness are considered as universal and relevant for human development regardless the cultural or sociodemographic context (e.g., Ryan & Deci, 2017; Vansteenkiste et al., 2020).

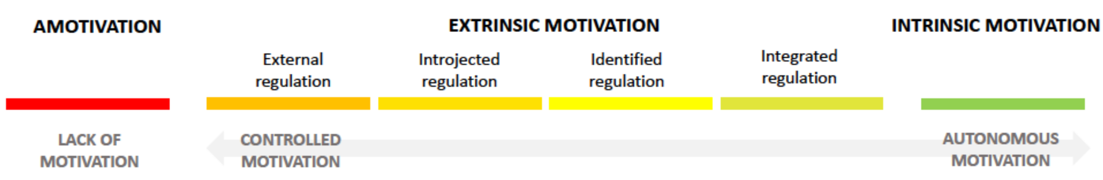
SDT is a macro-theory that encompasses six sub-theories. The earliest of the six, cognitive evaluation theory (CET; Deci & Ryan, 1985; Ryan & Deci, 2017), pays particular attention to intrinsic motivation. According to CET, intrinsic motivation depends on the social context and can be enhanced or undermined by external events, like rewards or feedback. Whereas tangible rewards or punishment are believed to trigger extrinsic motivation and inhibit self-determination of behavior, positive feedback could be perceived as a verbal compensation, which enhances intrinsic motivation through the mechanism of perceived competence. Information about the progress in work, or about how such progress can be achieved, helps individuals develop a sense of mastery and competence in a performed activity, related to the basic psychological need for competence. In turn, satisfying the need for competence increases self-determination of one's motivation (Ryan & Deci, 2017, Chapter 6). The feeling of being competent is necessary, but not a sufficient condition to enhance intrinsic motivation. The second essential requirement is the sense of ownership of one's action – the internal perceived locus of causality, related to the need for autonomy. Only if these two conditions are met, a person can develop intrinsic motivation toward an activity at hand (Ryan & Deci, 2017, Chapter 6). Furthermore, people can only develop intrinsic motivation for the actions that they find intrinsically interesting, that is, actions which are novel, challenging or aesthetically valuable. This intrinsic appeal for an activity is considered an essential condition for CET principles to function (Ryan & Deci, 2000).

At the beginning, the central focus of SDT was on intrinsic motivation. However, with time, the attention of Deci and Ryan, as well as of the researchers who contributed to the development of SDT, turned to non-self-determined forms of motivation (Deci & Ryan, 1985; Ryan & Connell, 1989; Ryan & Deci, 2000; see also Gagné et al., 2015; Lonsdale et al., 2008, Mullan et al., 1997; Vallerand et al., 1992). Currently, SDT is known for emphasizing the importance of detailed examination of motivation quality. Apart from a basic differentiation between intrinsic and extrinsic motivation, the theory proposes a motivation continuum (see Figure 2.1), distinguishing between different types of extrinsic motivation (e.g., Deci & Ryan, 1985; Ryan & Deci, 2002). One extreme of this continuum is intrinsic motivation, which refers to the behaviors driven by the pure interest and enjoyment derived from a performed activity. The other end is amotivation, defined as a lack of motivation. Amotivated individuals do not understand the reason for their actions, or do not undertake actions at all. The continuum between intrinsic motivation and amotivation includes various forms of extrinsic motivation, which refer to different kinds of person's regulation: external, introjected, identified, and integrated. External regulation is the least autonomous type of extrinsic motivation. The behavior is driven by external demands or separable outcomes: a person acts to get a reward or avoid punishment. The reward or punishment can be both, material – for example, monetary rewards, and social – for example, recognition or blame (Gagné et al., 2015). Introjected regulation is related to ego and still quite controlling, a person is motivated to act to enhance or maintain their self-esteem. Identification means that behavior was identified as personally important and accepted as own. Finally, integrated regulation is the most autonomous and the closest to intrinsic motivation. It is volitional and fully assimilated by the self, but, in contrast to intrinsic motivation, it refers to behaviors done for some instrumental value, and related to an outcome separate from the behavior (Ryan & Deci, 2002). However, it is important to mention that, although conceptually different, the construct of integrated regulation is hard to separate from intrinsic motivation and identified regulation (Gagné et al., 2015; Mallett et al., 2007; Tremblay et al., 2009; Vallerand et al., 1992). For this reason, popular scales that measure self-determination of motivation, such as the Multidimensional Work Motivation Scale (MWMS; Gagné et al., 2015), the Academic Motivation Scale (AMS; Vallerand et al., 1992), or the Behavioral Regulation in Sport Questionnaire (BRSQ; Lonsdale et al., 2008), do not include integrated regulation.

The continuum of motivation is described in organismic integration theory, one of the micro-theories which constitutes SDT (Deci & Ryan, 1985; Ryan & Deci, 2020).

Figure 2.1

Continuum of Self-Determined Motivation



Over the years, numerous research confirmed that the autonomous forms of motivation are likely to induce the most positive consequences (e.g., Cerasoli et al., 2014; Taylor et al., 2014), whereas external regulation and amotivation tend to be associated with less positive or maladaptive outcomes (Gagné & Deci, 2005; Ryan & Deci, 2020). Nevertheless, SDT does not exclude a possibility that a person may be motivated by several qualitatively different reasons at the same time (e.g., Deci & Ryan, 2000; Gillet et al., 2009; Lepper et al., 2005; Vansteenkiste et al., 2009). Moreover, researchers argue that in certain contexts (e.g., education) pure forms of intrinsic motivation are rare to be observed in isolation, highlighting the importance of different types of extrinsic motivation (e.g., Hayenga & Corpus, 2010; Lepper et al., 2005; Ratelle et al., 2007). In the further chapters of this dissertation, I will discuss in detail the results of research focused on profiles characterized by combinations of qualitatively different forms of motivation and their relationship with performance.

Finally, it is important to mention that SDT is being applied to address a broad range of questions related, among others, to psychological needs (e.g., Vansteenkiste et al., 2020), causality orientations (e.g., Hagger & Chatzisarantis, 2011), emotions and emotion regulation (e.g., Roth et al., 2019), or goals, values, and aspirations (e.g., Kasser et al., 2007). However, these topics are out of the scope of this thesis, which principal focus is on motivation.

2.1.2. Flow Theory

Another well-known theory that attempts to explain why people undertake activities out of pure pleasure of performing them, is flow theory proposed by Mihaly Csikszentmihalyi (1975). It is rooted in Csikszentmihalyi's pioneer study, according to which professionals from a wide range of occupations, like chess players, dancers, rock climbers, or surgeons, were able to get fully absorbed in performed activities in the absence of any extrinsic reward. The state of such deep concentration on the task at hand has been called flow, and to the present day it is defined as "a state in which an individual is completely immersed in an activity without reflective self-consciousness but with a deep sense of control" (Engeser & Schiepe-Tiska, 2012, p.1). It is worth of mentioning that Csikszetnmihalyi was the first to study the subjective phenomenology of intrinsic motivation, making a significant contribution to a better understanding of this concept (Fullagar & Kelloway, 2013).

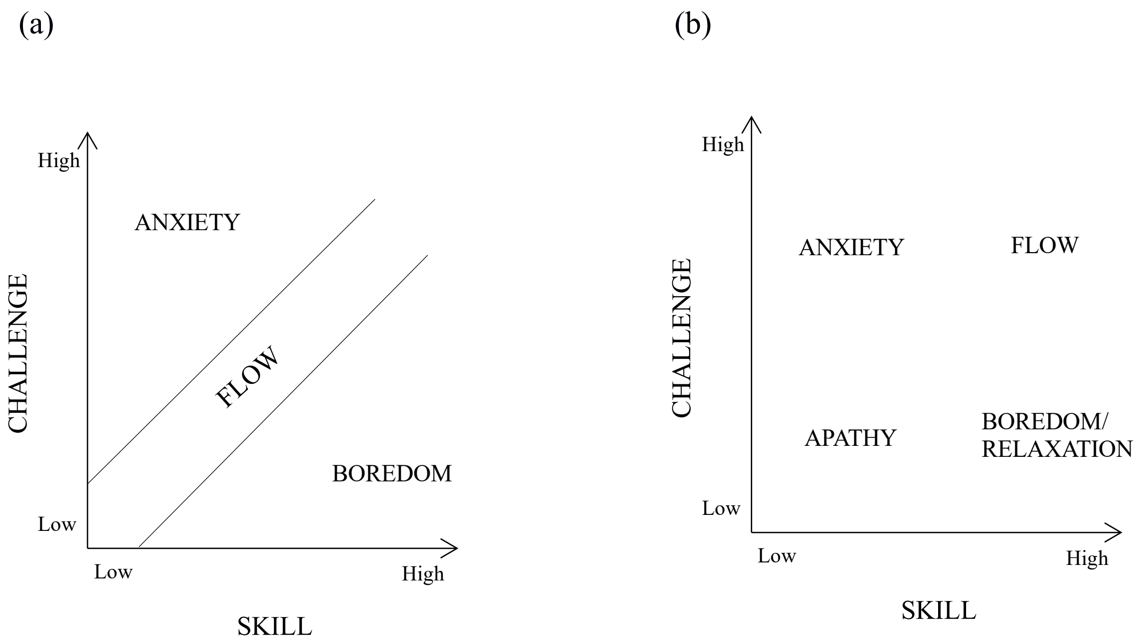
The experience of flow is typically described with six characteristics (Csikszentmihalyi, 1975; Fullagar et al., 2017). The first of them is an intense concentration on the task at hand – an individual is deeply involved in the performed activity and experiences a blur of action and self. This characteristic is considered a core flow dimension, necessary for other components to appear. Secondly, a person is intrinsically motivated towards the task. The flow experience is independent from external factors (i.e., rewards or punishments), the source of motivation is intrinsic and related to the activity itself. The third characteristic is an effortless sense of control over the activity outcomes and process. Moreover, the strong involvement in the task causes merging of action and awareness, and loss of reflective self-consciousness, considered another two features of flow. The last characteristic is a transformation of time – individuals in flow have a sense of time distortion, commonly related to a perception that time has passed faster than normal.

From the beginning of his work, Csikszentmihalyi had been studying the conditions that are fundamental for flow to occur. His observations led him to a conclusion that flow's core requirement is a balance between the challenge at hand, and one's skill level. Specifically, a person can experience flow when their skills are sufficient to accomplish the challenge derived from a performed activity (Csikszentmihalyi, 1975; Fullagar et al., 2017). Several models have been proposed to depict a dependency between the challenge-skill balance and the experience of flow. According to the first model proposed by Csikszentmihalyi in 1975 (see Figure 2.2a), flow can appear independently on whether the level of challenge and skills is low, medium, or high, as long as the two are in balance. The challenge-skill imbalance leads to anxiety or boredom. Anxiety is experienced when one’s skills are not sufficient to overcome the demands of the activity. On the contrary, if the challenge is low compared to the person’s skills, boredom appears. The original model of flow has evolved over time. Some researchers claimed that the flow state corresponds only to higher levels of challenge and skills, proposing a quadrant model of flow (Csikszentmihalyi & LeFevre, 1989; see Figure 2.2b). Such *high intense* flow has been named an optimal experience, and characterized as “extremely positive, complex and gratifying experience”, influenced by affective, motivational, and volitional components, and requiring significant cognitive investment (Bassi & Delle Fave, 2012b, p. 425). The quadrant model, besides anxiety, boredom, and flow, includes also a state of apathy, which corresponds to the *low intense* flow (i.e., levels of challenge and skills low; Csikszentmihalyi & LeFevre, 1989).

Further research on flow resulted in new models, which aimed to represent the essence of flow experience more accurately: the experience fluctuation model (also known as the “channel model” or the “octant model”; Massimini & Carli 1988; Massimini et al. 1987), the regression model (Moneta & Csikszentmihalyi, 1996) and the componential model (Jackson & Eklund, 2002, 2004). Some authors attempted to conceptualize the dynamic and developmental nature of flow; for instance, basing on catastrophe theory, Ceja and Navarro (2012) proposed a non-linear model, which represents abrupt and intermittent dynamics typical for the flow process. However, despite the advances, the original model of flow (Csikszentmihalyi, 1975) is still used. In certain contexts (e.g., education, child development), where individuals have no previous experience with the task at hand and their skill level is low, this model can help capture the flow, which appears in the lower levels of the challenge-skill balance.

Figure 2.2

Flow Models – Original (a) and Quadrant (b)



Note. (a) Original flow model and (b) reformulated quadrant model of flow. Adapted from "Flow, performance and moderators of challenge-skill balance", by S. Engeser, and F. Rheinberg, 2008, *Motivation and Emotion*, *32*(3), p. 160 (http://doi.org/10.1007/s11031-008-9102-4). Copyright 2008 by Springer Science+Business Media, LLC.

The first studies on flow focused on the leisure domain, that is, freely chosen activities which enhance the development of personal skills and creative self-expression. Nonetheless, the flow research quickly expanded to productive and compulsory life areas such as education (Abuhamdeh & Csikszentmihalyi, 2012; Bassi & Delle Fave, 2012b; Engeser & Rheinberg, 2008) and work (Bakker, 2008; Bassi & Delle Fave, 2012a; Csikszentmihalyi & LeFevre, 1989; Delle Fave et al., 2011; Ilies et al., 2017; Zito et al., 2016). Interestingly, the findings of these studies showed that optimal experience tends to appear more frequently in a work setting, rather than in leisure

(Csikszentmihalyi & LeFevre, 1989; Fullagar & Kelloway, 2013).

2.1.3. SDT and Flow Theory – Joining Perspectives

Self-determination and flow theories are two important approaches within a broader domain of positive psychology (Seligman & Csikszentmihalyi, 2000). The two theories focus on human well-being and psychological growth. They both investigate intrinsically motivated behaviors, claiming that intrinsic motivation, understood as an innate tendency towards integration, spontaneous curiosity, exploration, and mastery, is an essential condition for happiness and cognitive and social development (Csikszentmihalyi & Rathunde, 1993; Ryan, 1995). Despite these similarities, SDT and flow theory conceptualize intrinsically driven behaviors in a slightly different way. To begin with, they build upon two different traditions of defining motivation, based on the behavioristic operant and drive approaches. The flow theory's focus is on an optimal challenge, which makes a task intrinsically rewarding. Such inherent reward, related to the activity at hand and independent from external conditions, is said to be an answer of humanistic and positive psychology to the idea of reinforcements, introduced by Skinner in the operant theory. To feel motivated, a person requires continuous intrinsic reinforcements in a form of challenges adapted to the skill level. Conversely, the notion of basic psychological needs, which are the fundament of SDT, echoes the Hullian idea of drives. Intrinsically motivated activities contribute to satisfaction of psychological needs for autonomy and competence, alluding to the mechanism proposed in the learning theory, according to which all behaviors are stimulated by physiological drives (Ryan & Deci, 2017). Probably one of the most frequently recalled differences between SDT and flow theory, is that the former highlights the importance of both, competence, and autonomy, whereas the latter focuses mostly on the optimal balance of challenge and skills (Deci & Ryan, 2000). Although the optimal experience is defined as an autotelic, meaning that the activity is performed for its own sake, in the absence of any external reward, the concept of autonomy is not formalized within the flow model. In contrast, the need for autonomy is one of the pillars of SDT and a necessary condition for intrinsic motivation to appear. Furthermore, as noted by Bassi and Delle Fave (2012b), the flow theory focuses primarily on intrinsic motivation and does not investigate different non-intrinsic forms of motivation. On the contrary, SDT distinguishes between different forms of extrinsic regulation that vary according to the level of internalization – from the least to the most autonomous.

Given a common focus and slightly different ways of explaining intrinsically motivated behaviors, several theorists and researchers in the field of positive psychology claimed that SDT and flow theory may complement each other, attempting a joint study of the two approaches (e.g., Abuhamdeh 2012; Abuhamdeh & Csikszentmihalyi 2012; Bassi & Delle Fave, 2012b; Ersöz & Eklund, 2017; Ilies et al., 2017). Studying intrinsic motivation from two different angles and considering the importance of both, basic psychological needs and optimal challenge, can certainly contribute to a more comprehensive understanding of this phenomenon.

2.2. Methodological Advances in Research on Motivation

The conceptual evolution of intrinsic motivation has been accompanied by an intensive development of research methods, particularly vivid in the last two decades (Ryan & Deci, 2020). These methodological advances allowed for a more precise measurement of motivation, resulting in a better understanding of its nature and characteristics. In the following paragraphs I discuss two methodological trends in research on motivation, which are applied and combined in the current dissertation: *person-centered* and *longitudinal* approaches.

2.2.1. Person-Centered Approach

Over many years the field of psychological research has been dominated by studies focused on variables and their association with diverse antecedents and outcomes. According to this variable-centered approach, individuals that participate in the study belong to a homogeneous population and can be characterized with a single set of "averaged" parameters (Morin et al., 2018; Morin, McLarnon, et al., 2020). Such approach certainly provides insights on the psychological constructs, their precursors and consequences. However, it must be acknowledged that the focus on a single variable cannot mirror human complexity and diversity. For example, variable-centered research on intrinsic motivation could explain what conditions are necessary for this phenomenon to appear, inform about its average score in the studied sample, and describe the outcomes related to this score. Nevertheless, this kind of research would not allow to explore differences in levels of intrinsic motivation between individuals from the studied sample. The limitations of the variable-centered studies seem particularly important in the context of SDT that proposes a spectrum of qualitatively different forms of motivation. Variable-focused research on self-determined motivation may lead to an equivocal conclusion that autonomous and controlled forms of regulation are antagonistic and cannot coexist. In fact, the self-determination researchers and theorists (e.g., Deci & Ryan, 2000; Gillet et al., 2009; Lepper et al., 2005; Vansteenkiste et al., 2009) postulate that different forms of behavioral regulation are not mutually exclusive and can simultaneously appear within a person. For example, students can engage and put effort in activities because they enjoy them (intrinsic motivation), but at the same time they are concerned about receiving a good grade (external regulation), and they consider putting effort in these activities of personal relevance (identified regulation). A possibility that intrinsic and extrinsic motivation can coexist encouraged researchers to focus on a person, rather than on a variable, and to study profiles characterized by different configurations of motivation forms. Contrarily to the variable-centered method, person-centered approach (known also as profile-based or configural approach) allows to group individuals from one sample according to different configurations of their characteristics (Morin et al., 2018; Morin, McLarnon, et al., 2020). Hence, person-centered approaches seem particularly pertinent to study complex, multidimensional constructs, capturing their nature in a more realistic and holistic way. For instance, person-centered studies on self-determined motivation can provide valuable information about its quality (i.e., configuration of different forms of regulation – intrinsic, identified, introjected, external, and amotivation), and quantity (i.e., how intense is each of the forms). Given these advantages, a keen interest in the person-centered studies in the SDT context is not surprising. In the last decade the research on profiles of self-determined motivation has been intensively growing in various fields of human activity, including education (e.g., Guay et al., 2021; Hayenga & Corpus, 2010; Litalien et al., 2019; Nishimura & Sakurai, 2017; Vansteenkiste et al., 2009), work (Fernet, Litalien, et al., 2020; Fernet, Morin, et al., 2020; Gillet, Fouqureau, et al., 2018; Howard et al., 2016; Van den Broeck et al., 2013), or sport and physical education (Bechter et al., 2018; Cece et al., 2018; Gillet, Berjot, et al., 2012; Lindwall et al., 2017; Ullrich-French et al., 2016).

Three important issues are frequently raised by the researchers who apply person-centered approach to study motivation: (1) the statistical method applied for creation of the profiles, (2) the number of motivational forms considered in profiling, and (3) the number of measurement occasions. Below these three questions are discussed in detail.

2.2.1.1. Statistical Methods Used in Profile Analysis. The first important methodological issue commonly discussed by authors when adopting a person-centered approach is the statistical method to be employed to analyze the profiles. In behavioral and social sciences, cluster analysis has been probably the most frequently used profiling technique. Over the years, this method dominated person-centered studies in the field of motivation (e.g., Boiché et al., 2008; González et al., 2012; Hayenga & Corpus, 2010; Moran et al., 2012; Ratelle et al., 2007; Ullrich-French & Cox, 2009; Van den Broeck et al., 2013; Vansteenkiste et al., 2009), as well as in other domains of research on human behavior (e.g., Joshi et al., 2014; Kozusznik et al., 2015; Somers, 2010; Wasti, 2005). One of the best-known clustering techniques is the *k-means* algorithm, which aims to find an optimal partition of the data, minimizing the distance between the individual scores in the cluster and the cluster centroid (i.e., the cluster mean on the studied variables), while maximizing the distances between clusters. That is to say, the clusters are determined such that the deviations of the individual scores within each cluster have the smallest squared errors from the centroid and, simultaneously, sum of squares for the between-clusters term is maximum. Thus, the k-means clustering algorithm optimize the partition criterion to minimize variability within each cluster and maximize the differences between clusters. As a result, the sample is segmented into clearly defined, distinct, homogeneous, and compact sets of individual scores (Aldenderfer & Blashfield, 1984; Härdle & Simar, 2007; MacQueen, 1967). Nevertheless, in the recent years, k-means clustering method has been repeatedly criticized. The most frequently mentioned weaknesses of this approach are a strong dependence on the clustering algorithm and measurement scale, a lack of unambiguous guidelines to determine an optimal number of clusters, and strict underlying assumptions, which do not always represent accurately the real-life data (e.g., Meyer & Morin, 2016; Morin et al., 2018; Morin et al., 2011; Morin, McLarnon et al., 2020). To address these limitations, person-centered research on motivation have started to rely on *mixture modeling*, proposed as a solid alternative to the traditional k-means technique (McLachlan & Peel, 2000). Person-centered analysis based on mixture models has been characterized by three essential attributes (e.g., Meyer & Morin, 2016; Morin et al., 2018). First, it is typological. It results in a classification system to categorize individuals into profiles described by sets of qualitatively or quantitatively distinct features (e.g., Bergman, 2000). Second, it is prototypical. Contrarily to the k-means cluster analysis, mixture models use a probabilistic approach – they are based on statistical models and aim to optimize the fit between these models and the data points. More specifically, they aim to identify the optimal number of model latent subgroups based on objective criteria and assign the respondents according to their degree of resemblance with each profile (McLachlan & Peel, 2000). Third, mixture model analysis is commonly considered exploratory. The suitability of an *a priori* model cannot be directly evaluated through conventional goodness-of-fit indexes, hence, the optimal solution needs to be selected by examination and comparison of the available solutions representing different numbers of profiles. Nevertheless, despite of their exploratory nature, the mixture model method can be applied for confirmatory purposes, to approve or disapprove theory-based assumptions about the number and characteristics of the extracted profiles (Morin et al., 2018; Morin, Myers et al., 2020). Researchers who advocate the superiority of mixture models over a conventional cluster analysis, mention several advantages of the former method over the latter (Meyer & Morin, 2016; Morin et al., 2018; Morin et al., 2011; Morin, McLarnon et al., 2020). First, being a probabilistic and model-based approach, mixture modeling allows for a direct specification of comparable alternative models (Meyer & Morin, 2016; Muthén, 2002). Second, when estimating the models, some of the rigid assumptions typical for cluster analysis (e.g., the assumption about equal indicators' variances across profiles), can be gradually relaxed (Meyer & Morin, 2016). Third, mixture modeling enables to apply a multilevel structure to the data, and concurrent examination of variables measured on different scales (i.e., continuous, ordinal, categorical) in one model (Muthén, 2002). Finally, mixture models allow for a direct inclusion of covariates (predictors and outcomes) in the model, minimizing Type 1 errors (Meyer & Morin, 2016). Specifically, such joint analysis of the profiles and covariates in a single step, has been demonstrated to decrease bias in the estimation of their relationships (Bolck et al., 2004; Lubke & Muthén, 2007).

Although mixture modeling seems to be a clear trend in the person-centered research and a good alternative for the traditional cluster analysis, it is not without limitations. Given the probabilistic character of this approach (i.e., no partition, but a probability to belong to each of the profiles), the clusters can overlap. Hence, compared to the k-mean clusters, the interpretation of the profiles obtained through the mixed models technique is more difficult, and could be particularly challenging when the profiles are based on several dimensions of a single variable (e.g., profiles which reflect temporal dynamics of several forms of one variable). Such complexity of the data could make the profile interpretation very difficult, if not impossible. Moreover, mixture models are more sensitive to convergence errors (i.e., converging on improper solutions, or failing to reach convergence; Morin, McLarnon et al., 2020); the more complex the model (i.e., the more parameters are included in the model), the higher possibility of convergence errors. Summing up, despite the clear benefits of using mixture modeling in person-centered studies, this approach should not be treated as a universal solution.

2.2.1.2. Motivation Profiles – Number of Dimensions. The second important issue frequently raised by researchers refers to the number of construct-related dimensions considered in profiling. Early person-centered studies on motivation tended to rely on two broad categories – autonomous (or intrinsic) and controlled (or extrinsic) regulation (Gillet et al, 2009; Gillet, Vallerand, et al., 2012; González et al., 2012; Hayenga & Corpus, 2010; Kusurkar et al., 2013; Van den Broeck et al., 2013; Vansteenkiste et al., 2009; Wormington et al., 2012). Commonly in these studies up to four profiles were distinguished, representing combinations of high versus low levels of autonomous and controlled motivation: (1) relatively high levels of both autonomous and controlled regulation (HA-HC, also called *high quantity* profile), (2) high levels of autonomous regulation, but low levels of controlled regulation (HA-LC, or *good quality* profile), (3) low levels of autonomous regulation, but high levels of controlled motivation (LA-HC, or *poor quality* profile), and (4) low levels of both dimensions (LA-LC, or *low quantity* profile). Undoubtedly, such dichotomization of motivation simplifies estimation and interpretation of the profiles. However, at the same time, it suppresses the diversity of self-determined regulation that one can experience and may hide potentially relevant combinations of motivational forms. Given these limitations, certain attempts of providing more accurate and detailed description of the profiles have been made. For example, some authors described the profiles not only in terms of controlled and autonomous motivation, but also amotivation (Boiché & Stephan, 2014;

Cannard et al., 2016; Gillet, Morin, et al., 2017; Hill, 2013; Liu et al., 2009; Ratelle, et al., 2007). Typically, these authors differentiated between three to five configurations. Four of them were similar to the profiles based on the controlled–autonomous dichotomy and can be summarized as: (1) high autonomous and controlled regulation, and low amotivation (HAu-HC-LAm), (2) high autonomous regulation, low controlled regulation and amotivation (HAu-LC-LAm), (3) low autonomous regulation, high controlled regulation and amotivation (LAu-HC-HAm), and (4) low to moderate scores on all three dimensions (LAu-LC-LAm). Furthermore, the fifth profile characterized by low levels of autonomous and controlled regulation, and high levels of amotivation (LAu-LC-HAm) was identified. Some researchers went one step further and considered various forms of regulation proposed by self-determination theory, i.e., intrinsic motivation, identified regulation, introjected regulation, external regulation and amotivation (Boiché et al., 2008; Cox et al., 2013; Gillet, Becker, et al., 2017; Gillet, Fouqureau, et al., 2018; Graves et al., 2015; Howard et al., 2016; Lindwall et al., 2017; Litalien et al., 2019; Ullrich-French & Cox, 2009; Ullrich-French et al., 2016). For example, in the work setting, Howard et al. (2016) identified four profiles: Profile 1, called *amotivated*, was characterized by very high levels of amotivation and moderate to low levels of intrinsic and extrinsic forms of regulation. Profile 2 – *moderately autonomous*, was defined by very low levels of external regulation, low levels of amotivation, and average levels of identified regulation and intrinsic motivation. Respondents who belonged to Profile 3 were characterized as *highly motivated* – they presented low level of amotivation, and moderate to high levels of other motivation forms. Finally, Profile 4, named *balanced*, showed average levels of all forms of motivation, including amotivation. In the study by Litalien et al. (2019), conducted in the context of education, five profiles were distinguished. Some of them coincided with profiles found in previous research. For example, the *Multifaceted* profile defined by high levels of most types of motivation and low levels of amotivation can be compared to the HAu-HC-LAm (Boiché & Stephan, 2014; Cannard et al., 2016; Hill, 2013; Ratelle, et al., 2007) or *highly motivated* (Howard et al., 2016) profiles. Likewise, the *Unmotivated* profile characterized by low levels of most types of motivation and high levels of amotivation is similar to the LAu-LC-HAm (Cannard et al., 2016) or *amotivated* (Howard et al., 2016) profiles. Finally, the *Controlled* profile, defined by moderate levels of autonomous motivation (intrinsic motivation and identified regulation), low levels of amotivation and relatively high levels of controlled motivation (introjected and external regulations) is comparable to the profiles found in research by Boiché, & Stephan (2014), Hill (2013), and Ratelle et al. (2007). It is noteworthy that the study by Litalien et al. (2019) was the first to investigate three forms of intrinsic motivation (i.e., to know, to accomplish, and to experience stimulation, cf. Vallerand, 1997) in person-centered research. In some profiles the levels of these three forms of autonomous regulation were not aligned. For example, the *Knowledge oriented* profile presented low levels of amotivation, relatively high levels of intrinsic motivation to know, and moderate levels of other forms of regulation (including intrinsic motivation to accomplish and to experience stimulation). Interestingly, one profile found by Litalien et al. (2019) did not fit in any of the previously described categories. This profile was named *Hedonistic*, and presented very high levels of amotivation, relatively high levels of intrinsic motivation to experience stimulation and identified regulation, average levels of intrinsic motivation to know, intrinsic motivation to accomplish, and external regulation, and low levels of introjected regulation.

A comparison of motivational profiles extracted by Howard et al. (2016) and Litalien et al. (2019) reveals one important difference. Whereas some of the profiles (e.g., *highly motivated* and *amotivated* profiles, Howard et al., 2016) represent a nearly perfect continuous structure of motivation (and thus may be represented with one global score of self-determination), the pattern found in other profiles (e.g., *Hedonist* profile, Litalien et al., 2019) do not fit the self-determination continuum. This finding supports the importance of considering different qualitative characteristics of motivation, to obtain an accurate and comprehensive illustration of the structure of motivation.

2.2.1.3. Temporal Dynamics in Profile Analysis. The last issue, which is gaining attention in the person-centered research on motivation is the dynamic aspect of the studied variables. Several cross-sectional studies on motivational profiles recognized the importance of exploring the temporal changes that may occur in the studied variables (e.g., Howard et al., 2016; Litalien et al., 2019; Vansteenkiste et al., 2009). For this reason, in the last years the interest in profiles based on variables' trajectories, rather than on static sets of data, has grown significantly (a review of person-centered studies which consider temporal aspects of the data is available in the Appendix A). Some authors examined the stability of motivational profiles over time (Cece et al., 2018; Corpus & Wormington, 2014; Emm-Collison et al., 2020; Fernet, Litalien, et al., 2020; Gillet, Morin, et al., 2017; Hayenga & Corpus, 2010; Howard et al., 2020; Schiefele & Löweke, 2018). In these studies, the probability of changing the profile from one measurement point to another ranged from 0% to 64%, suggesting that whereas some profiles tend to be very stable over time, others present quite high variability levels. However, there is no agreement about what characteristics related to motivation quality may determine the stability or variability observed in the profiles. In some studies, the most stable profiles were characterized by high levels of autonomous regulation and low levels of controlled regulation and amotivation (Cece et al., 2018; Corpus & Wormington, 2014; Schiefele & Löweke, 2018). Conversely, according to other research (Fernet, Litalien, et al., 2020; Gillet, Morin, et al., 2017; Hayenga & Corpus, 2010), profiles with high levels of amotivation and/or controlled regulation showed the highest stability. It is important to notice that the aforementioned studies were conducted in diverse settings, what may suggest that profile stability is related to the context. The profiles characterized by high levels of autonomous regulation and low levels of controlled motivation regulation were likely to be more stable in the context of sport (Cece et al., 2018) and primary education (Corpus & Wormington, 2014; Schiefele & Löweke). Conversely, the profiles, in which amotivation and controlled forms of regulation were dominant, tended to show the highest stability in the setting of work (Fernet, Litalien, et al., 2020), and secondary and higher education (Gillet, Morin, et al., 2017; Hayenga & Corpus, 2010). It is noteworthy that certain evolution in the methodology applied to study changes in motivational profiles has been observed. Whereas the first research on profile stability (Corpus & Wormington, 2014; Hayenga & Corpus, 2010) relied on cluster analysis, the most recent studies (Cece et al., 2018; Fernet, Litalien, et al., 2020; Gillet, Morin, et al., 2017; Schiefele & Löweke, 2018) relied on a combination of latent profile analysis (LPA) and latent transition analysis (LTA).

Without a doubt, the research on profile stability provided valuable insights on the evolution of different motivational configurations. However, the profiles identified in these studies were based on cross-sectional measures and did not reflect the within-person changes that may occur in the measured variables over time. Recently, some authors addressed this limitation, focusing on the profiles based on trajectories of a global level of self-determined motivation (Fernet, Morin, et al., 2020; Gillet et al., 2018; Guay et al., 2021). This global self-determination score was obtained through the application of bifactor exploratory structural modeling (bifactor-ESEM) framework, that recently was proved to represent accurately the self-determined motivation continuum in contexts of work (Howard et al., 2018), education (Litalien et al., 2017), and sport (Cece et al., 2019). The important advantage of the bifactor-ESEM framework is that it allows a simultaneous estimate of the global score of self-determination and of the specific motivation factors. Gillet et al. (2018) were of the first to analyze profiles characterized by trajectories of a global score of self-determination. In this study, based on a sample of police officers participating in a vocational training program, three profiles were identified. Profile 1 (*Moderate)* was defined by overall moderate levels of self-determination, a very small decline, and a marginal curvilinear tendency. This profile was the largest one and represented nearly half of the participants (47.6%). Slightly above one fourth of the respondents (29.7%) were assigned to Profile 2 (*High),* characterized by high initial self-determination score and mild inverted U-shape trajectory. In contrast, the trajectory observed in the Profile 3 (*Low*) started with low levels of self-determination and followed a mild U-shape pattern. This profile represented 22.7% of participants.

The study by Fernet, Morin, et al. (2020) is another research on trajectory-based profiles conducted in the work setting. It used a sample of French-Canadian nurses, and, similarly to the study by Gillet et al. (2018), identified three profiles. The participants that belonged to the Profile 1 presented average initial levels of self-determination, which decreased slightly over time. This profile was defined as *Slightly Decreasing* and characterized 51.26% participants. The participants assigned to Profile 2 presented the opposite tendency – their initial moderate levels of self-determination tended increase over time. This *Increasing* profile was found for 41.04% of participants. Finally, Profile 3 called *Decreasing*, was defined by the pronounced decline of self-determination, and characterized 7.70% of the sample.

To the best of my knowledge, the first attempt of exploring the self-determination trajectories in the academic context was made by Guay et al. (2021). These authors explored profiles based on the dynamics of the global self-determination level in a sample of secondary school students, during a period of three years (with three measurement points). Five different trajectories were distinguished. Profile 1 and 3 (named *High-stable* and *High* respectively) were characterized by high initial levels of self-determination and a slight increment over time; however, Profile 1 presented lower state-like deviations from the average trait-like trajectories than Profile 3. Moreover, these two subgroups differed in size: whereas the *High* profile characterized about half of the sample (50.43%), the *High-stable* profile represented a much smaller proportion of participants (5.75%). Profile 2 (*Moderate*), similarly to Profile 1 and 3, showed a slight increasing tendency over time; however, both, the initial and the overall level of self-determination was moderate. This profile characterized 24.26% of the students. Profile 4, called *Low*, was the smallest in size and characterized only 3.97% of the sample. It was described by constant low levels of global self-determination. Finally, Profile 5 (*Increasing*) represented 15.58% of participants who experienced an increase of self-determination – although their initial score was low, it was growing over time and achieved average levels.

Undoubtedly, these three studies contributed to the understanding of dynamics that may occur in the profiles of self-determine motivation over time. However, they focused exclusively on the global factor of self-determination and did not consider specific factors of motivation (i.e., different autonomous and controlled forms of motivation and amotivation) and their trajectories. Given the recent developments related to the bifactor models of motivation, a shift towards studies that investigate trajectory-based profiles of motivation based on a global factor seems a logical move. Nevertheless, the global self-determination factor only demonstrates quantitative differences between the profiles (i.e., amount of self-determination); the qualitative differences (i.e., configurations of self-determined motivation) between the groups of individuals are hidden. Although in some cross-sectional person-centered research (e.g., Howard et al., 2016) the profiles follow the continuous structure of regulation, other studies demonstrated that this underlying structure of motivation should not be taken for granted. For example, some of the profiles distinguished by Litalien et al. (2019) were characterized by similar levels of the motivational forms, which are laid on the opposite sites of the self-determination continuum (e.g., intrinsic motivation and amotivation). For this reason, different motivational forms should not be overlooked in the longitudinal person-centered studies. Moreover, in some research (Cece et al., 2019; Fernet, Litalien, et at., 2020), the global score of self-determination was not always in line with the continuous structure of motivation. Following postulates of SDT (e.g., Ryan & Deci, 2020) and the evidence from the research on structure of motivation (Howard et al., 2018; Litalien et al., 2017), a strong positive correlation between global self-determination score and intrinsic motivation levels could be expected. However, contrarily to these expectations, in the study by Fernet, Litalien et al. (2020) the *Strongly Motivated* profile characterized by a very high score of global self-determination, also presented below-average levels of intrinsic motivation, and relatively high levels of controlled motivation (i.e., introjected and external regulation). Relying only on the global self-determination score, the respondents assigned to this profile would be expected to be intrinsically motivated, when in fact, they presented higher levels of controlled motivation. This example shows how important in profiling are the specific factors of motivation, not only the global self-determination score.

To the best of my knowledge, the research by Nishimura and Sakurai (2017) and by Chevrier and Lannegrand (2021) are the only attempts of examining profiles based on the trajectories of several forms of motivation. Nishimura and Sakurai based on a sample of Japanese junior high school students interviewed three times during a two-year period and identified two longitudinal profiles. The first of these profiles represented 22.2% of the sample and was characterized by a decline of intrinsic motivation and identified regulation over a two-year period. More than three quarters (77.8%) of participants belonged to the second profile, characterized by an increment of introjected and external regulations. The study by Chevrier and Lannegrand applied longitudinal cluster analysis to distinguish four profiles in two waves of students in their university freshman year in France. The first profile, named *combined stable*, showed high and stable levels of autonomous and controlled motivation, and low and stable amotivation; the second profile, characterized by low and stable autonomous motivation, moderate and stable controlled motivation, and increasing amotivation, was defined as *low autonomous with increase of amotivation*; *demotivated stable* profile was described by moderate and stable autonomous motivation, very low and stable controlled motivation, low and stable amotivation; and finally, in the last profile, *amotivated with decrease*, very low and stable autonomous motivation, low and stable controlled motivation, and very high but decreasing amotivation were observed. Without a doubt, the studies by Nishimura and Sakurai, and by Chevrier and Lannegrand can be considered milestones in research on motivational profiles. Nevertheless, there are also certain limitations of both investigations. First, only linear terms in motivation dynamics were analyzed. Second, due to a specific context of both study (public high schools' students in the area Tokyo and surroundings; students of freshman in France), the generalizability of the findings is limited. Moreover, and most importantly, the Nishimura and Sakurai did not examine the criterion-related validity of the identified profiles. Chevrier and Lannegrand, in turn, focused on quite broad categories of motivation (i.e., autonomous, controlled and amotivation), rather than on different forms of regulatory styles (i.e., intrinsic motivation, identified regulation, introjected regulation, etc.).

2.2.2. Longitudinal Approach

Over many years, there have been an important discrepancy between motivation theory and research method. Whereas theories emphasized a dynamic nature of motivation, research relied mostly on its cross-sectional measures. Moreover, researchers and practitioners were frequently assuming that both designs, cross-sectional and longitudinal, would lead to the identical outcomes, expecting that the findings from cross-sectional and longitudinal studies would overlap. Therefore, they equivocally applied the inter-individual outcomes to the intra-individual level and vice-versa. Contemporary researchers treat these two levels of analysis with caution, emphasizing that they cannot be considered equal, as they address different sources of variability, between- and within-person, and may lead to unrelated results (Molenaar, 2004; Molenaar & Campbell, 2009). An increasing preoccupation with the research accuracy, as well as an intense development of research method, have initiated a quick grow of longitudinal studies, which are considered an important direction of future research on motivation (Kanfer et al., 2017). As mentioned in the previous chapter, the studies that explore trajectory-based profiles of motivation are scarce. However, there is extensive evidence that motivation is a dynamic phenomenon from variable-centered research in the fields of education (Corpus et al., 2020; Gillet, Vallerand et al., 2012; Oga-Baldwin et al., 2017; Spinath & Steinmayr, 2012; Weidinger et al., 2017), work (Navarro & Arrieta, 2010; Navarro et al., 2007; Navarro et al., 2013) and sport (Roberts et al., 2007), to name just a few.

Longitudinal studies on motivation explored both, short-term dynamics (days/weeks; Guastello et al., 1999; Navarro & Arrieta, 2010; Navarro et al., 2007; Navarro et al., 2013), as well as the changes that occur in motivation across longer periods of time (months/years; Corpus et al., 2020; Gillet, Vallerand et al., 2012; Gnambs & Hanfstingl, 2016; Scherrer & Preckel, 2019). The long-term approach has been frequently applied in the academic context to analyze trends of students' motivation. Multiple studies indicated a general decline of intrinsic motivation over time (Corpus et al., 2020; Gillet, Vallerand et al., 2012; Scherrer & Preckel, 2019; Spinath & Steinmayr, 2012; Weidinger et al., 2017). However, a closer look at characteristics of studied populations suggests that the tendency of intrinsic motivation dynamics may depend on the context. Specifically, whereas a decreasing tendency was frequently observed in primary and secondary education setting (Weidinger et al., 2017), the transition to college seemed to be related to the improvement in students' motivation quality (Kyndt et al., 2015; Ratelle et al., 2007). However, although initially high, autonomous motivation tends to decrease with time also in the higher education context (Corpus et al., 2020). It is worth mentioning that, whereas long-term studies were focused mainly on the general tendency of changes in motivation, intensive longitudinal research demonstrated that in the short term the dynamics of motivation tend to follow a non-linear trend (Navarro & Arrieta, 2010; Navarro et al., 2007; Navarro et al., 2013).

On the final note, it is interesting to mention that, although scarce, longitudinal person-centered studies are a clear trend in research on motivation. To illustrate, in the summary of the longitudinal person-centered studies on motivation (Appendix A), seven out of fourteen studies has been published in the last two years (2020-2021).

2.3. Motivation and Performance

Behavior is a visible consequence of motivation, thus, the two are related to each other by definition. According to Campbell et al. (1993, p. 40) performance is “synonymous with behavior. It is something that people actually do and can be observed”. As noted by Motowildo et al. (1997), performance, unlike behavior, includes evaluative components. Performance can be operationalized in different ways, for example, emphasizing quantity or quality of the outcome. For instance, in education setting, performance could be understood as the *quality* of an essay written by a student, or as a *number* of correctly solved mathematical equations.

The theory and research on motivation quality have been always emphasizing beneficial effects of intrinsic motivation on performance. The association of these two variables has been documented by numerous studies, and there is certain meta-analytical evidence that intrinsic motivation has been consistently related to performance in education, work, and sport settings (Cerasoli et al., 2014; Taylor et al., 2014). Specifically, intrinsic motivation was found to predict better school grades (e.g., Burton et al., 2006; Gottfried et al., 2005; Lepper et al., 2005), self-reported academic performance (e.g., Komarraju et al., 2009), work performance (e.g., Grant, 2008; Landry et al., 2017), and achievement in sport (e.g., Vansteenkiste et al., 2004, Study 3), among others. Furthermore, the experience of flow, closely related to intrinsic motivation, was found to be related to positive outcomes in the context of education (Engeser & Rheinberg, 2008; Keller & Landhäußer, 2012), work (e.g., Demerouti, 2006; Nielsen & Cleal, 2010) and sport (e.g., Garcia et al., 2019; Swann et al., 2017). Extrinsic motivation has been usually related with less positive or maladaptive outcomes (e.g., Gagné & Deci, 2005; Landry et al., 2017). Moreover, according to the SDT's original postulates (e.g., Ryan & Deci, 2017, Chapter 6), external rewards not only are less effective in improving performance, but can also undermine the positive effect of intrinsic motivation on performance. Nevertheless, certain studies demonstrated that controlled regulation did not necessarily lead to negative results. For example, in the study by Parker et al. (2010) controlled regulation was positively associated with work engagement. In the academic context, a recent study by Diseth et al. (2020) demonstrated that students' perceived performance correlated positively with some subscales of extrinsic motivation. Moreover, several researchers defended the importance of extrinsic incentives that are impossible to avoid in more controlled environments like work or school (Bassi & Delle Fave, 2012b; Hayenga & Corpus, 2010; Lepper et al., 2005; Ratelle et al., 2007). These opposite positions towards the consequences of extrinsic motivation were a trigger for research on a joint effect of intrinsic and extrinsic regulation on performance. However, the results of these studies were not straightforward, showing that the combined effect of the two forms of motivation for achievement may depend on different conditions. For example, in their meta-analysis, Cerasoli et al. (2014) demonstrated that the relationship between motivation quality and performance depends on how the latter is defined. Specifically, whereas intrinsic motivation tends to be a better predictor of quality-oriented performance related to complex and creative tasks (e.g., writing an article), motivation caused by extrinsic incentives seems to better explain performance focused on quantity, typical for repetitive and straightforward activities (e.g., entering survey data from pen-and-paper questionnaires into a spreadsheet). An important contribution to the debate on the outcomes related to extrinsic motivation was made by person-centered studies, which are naturally suited to examine a combined effect of different motivational forms on performance. Nevertheless, also in case of research on motivational profiles, the results are not conclusive. On one hand, certain studies demonstrated that individuals who present high levels of autonomous motivation outperform those, whose motivation is controlled (Boiché et al., 2008; Boiché & Stephan, 2014; Corpus & Wormington, 2014; Hayenga & Corpus, 2010, Vansteenkiste et al., 2009). In these studies, the profiles characterized by high and/or dominating levels of extrinsic regulation (Boiché et al., 2008; Boiché & Stephan, 2014; Hayenga & Corpus, 2010; Vansteenkiste et al., 2009), amotivation (Boiché & Stephan, 2014), or those which presented low levels of all motivational forms (Vansteenkiste et al., 2009), tended to achieve the lowest performance. On the other hand, several studies showed that the profiles characterized by equal levels of intrinsic and extrinsic motivation do not perform worse that the individuals characterized exclusively by high levels of intrinsic motivation (Gillet, Morin, et al., 2017; González et al., 2012; Howard et al., 2016; Moran et al., 2012; Ratelle et al., 2007; Schiefele & Löweke, 2018; Wormington et al., 2012). Researchers try to explain these findings in different ways. Some authors (e.g., Howard et al., 2016) consider them evidence for the superiority of intrinsic over extrinsic motivation. They claim that when the levels of both forms of regulations are high, intrinsic motivation buffers the undermining effect of extrinsic motivation. Hence, the effect of the latter seems unimportant for performance. Other authors link this result to the research context or with the task characteristics. For example, according to Corpus and Wormington (2014), when coupled with autonomous motivation, controlled motivation may promote performance in achievement-oriented, competitive contexts (e.g., high school). Regarding the attributes of the task, Vallerand et al. (2008) suggested that intrinsic motivation appeared to be less relevant for the activities, which are not perceived as interesting. In a similar way, the meta-analysis by Cerasoli et al. (2014) demonstrated that the association of intrinsic motivation and performance was stronger for quality-, rather that quantity-oriented activities. Moreover, Cerasoli et al. (2014) analyzed how the characteristics of the incentive might moderate a positive relationship of motivation and performance. They found that the link between intrinsic motivation and performance was weakened only if the incentives were directly tied to performance; such effect was not found for the incentives indirectly related to performance. It is worth noting that some of the research on motivational profiles and performance provided quite unexpected results. For instance, in the study conducted by Fernet, Litalien, et al. (2020) the individuals who achieved the best results presented a very high level of global self-determination, high levels of identified, introjected and external regulation, and average levels of amotivation and intrinsic motivation (*Strongly Motivated* profile). Surprisingly, the respondents who belonged to the *Self-Determined* profile (moderately high levels of intrinsic motivation, moderate levels of global self-determination and identified regulation, and low levels on introjected regulation and external regulation and amotivation) achieved poor performance, which was just slightly better than performance in the *Poorly Motivated* profile.

Valuable insights on the relationship of different forms of regulation and performance were provided by the person-centered studies based on trajectories of motivation (Gillet el al., 2018; Guay et al., 2021). The results of the study by Gillet et al. (2018) are in line with the findings from cross-sectional research, showing that participants characterized by the highest levels of global self-determination over time (*High* profile) presented the best performance. However, according to Guay et al. (2021) performance of the students who displayed the highest score of self-determination (*High* and *High-stable* profiles) was moderate and comparable to the performance of respondents who presented average levels of global self-determination over time (*Moderate* profile). Interestingly, the students who experienced a strongest increase in autonomous forms of motivation (*Increasing* profile), were consistently achieving the best grades. This finding may suggest that not only quality of motivation, but also the pattern of change in the quality, may play an important role for performance.

2.4. Motivation of the Present Research and Specific Objectives of the Thesis

The last decades witnessed an intensive development of motivation theory and research. Without a doubt, this progress contributed enormously to a better understanding of the concept of motivation, its antecedents, and consequences. At the same time, the advances have brought new questions and have suggested new study directions. Building upon the limitations and recommendations included in the previous studies, this doctoral thesis aims to make an incremental contribution to the longitudinal person-centered research on motivation. During the last years, longitudinal and person-centered approaches have been two of the most relevant trends in research on motivation. Moreover, insights from cross-sectional studies on motivation profiles emphasized the importance of considering temporal aspects of the measured variables in order to draw conclusions regarding the direction of effects (Howard et al., 2016; Litalien et al., 2019; Ratelle et al., 2007; Vansteenkiste et al., 2009; Wormington et al., 2012). Hence, the combination of both approaches seems a logical next step. The existing person-centered studies which investigate temporal changes in motivation, focus either on stability of the profiles, or on the trajectory-based profiles built on a limited number of dimensions – a global score of self-determination (Cece et al., 2018; Emm-Collison et al., 2020; Fernet, Litalien et al., 2020; Fernet, Morin et al., 2020; Howard et al., 2020; Gillet, Morin, et al, 2017; Gillet et al., 2018; Guay et al., 2021; Schiefele & Löweke, 2018) or three categories of motivation (i.e., autonomous, controlled, amotivation; Chevrier & Lannegrand, 2021). Thus, the main contribution of the current dissertation is analyzing the profiles based on configurations of temporal trajectories of different motivational forms. To the best of my knowledge, the authors who first investigated longitudinal profiles based on several motivational variables were Nishimura & Sakurai (2017). In that research, the predictive validity of the profiles was not assessed. The present thesis addresses this limitation and examines the association of motivational profiles and performance. Furthermore, contrary to the studies that rely exclusively on self-reported outcome measures (Fernet, Morin et al., 2020; Howard et al., 2020), in this thesis two measures of performance were included: self-assessed performance and academic grades. Finally, one of the frequently mentioned limitations of the previous longitudinal studies on motivational profiles is their poor generalizability (Cece et al., 2018; Emm-Collison et al., 2020; Fernet, Litalien et al., 2020; Fernet, Morin et al., 2020; Gillet, Morin, et al., 2017; Gillet et al., 2018; Schiefele & Löweke, 2018). The present dissertation aims to broaden the context of person-centered longitudinal studies on motivation, using a sample of undergraduate students from a Spanish university, which has not been investigated so far in this type of research.

To summarize, this doctoral dissertation aims to explore longitudinal profiles of motivation and their relationship with academic performance in the context of higher education in Spain. Specifically, the main objectives of this thesis are the following:

- To study the trajectories of different forms of motivation in samples of university students in Spain during a prescribed period.
- To study whether respondents can be grouped based on different configurations of motivation that they experience over time.
- To explore the qualitative characteristics of the motivational profiles found in the studied samples.
- To analyze the predictive validity of the profiles regarding academic performance.

The research conducted to address the aforementioned objectives was divided into two studies. I will refer to them as Study 1 and Study 2.

Study 1 focused on intrinsic motivation. Its objective was to explore longitudinal profiles, based on the trajectories of four variables: precondition of flow, flow experience, intrinsic motivation, and perceived competence. Motivation (Ryan & Deci, 2017) and optimal experience (Rathunde & Csikszentmihalyi, 2007) have been commonly conceptualized as processes characterized by high levels of within-person fluctuations, and there is certain evidence that these phenomena are dynamic (e.g., Ceja & Navarro, 2017; Guay et al., 2021; Navarro et al., 2013; Roe, 2014). Nevertheless, in previous research in the academic context different trends of intrinsic motivation dynamics were observed: decrements (e.g., Lepper et al., 2005; Weidinger et al., 2017; Wigfield & Eccles, 2002) or increments (e.g., Lee & Kim, 2014). Based on these results, the following hypotheses were proposed:

Hypothesis 1.1: Academic motivation (i.e., precondition of flow, flow experience, intrinsic motivation, and perceived competence) of undergraduate students changes over one academic semester.

Hypothesis 1.2: Different direction and pattern of possible changes in motivation can be distinguished.

Hypothesis 1.3: Students can be grouped in terms of the motivational dynamics they experience.

Additionally, the relationship between the distinguished profiles and performance (self-assessed and students' final grades) was analyzed. Given the scarcity of person-centered research on intrinsic motivation trajectories and academic performance, formulating precise hypotheses was challenging. However, according to the aforementioned literature, I expected significant differences in self-assessed performance and final grades between students who showed different patterns of change in motivation over the course of the semester. Specifically, the following hypothesis was proposed:

Hypothesis 1.4: The students who increase in motivation across the semester (if such phenomenon is found) will demonstrate better performance (i.e., higher self-reported performance and final course grades).

Whereas in Study 1 the profiles were based on the variables related to intrinsic motivation, optimal experience and their derivatives, Study 2 also considered controlled regulation and amotivation – the profiles were based on qualitatively different forms of motivation proposed by SDT and measured with Multidimensional Work Motivation Scale (MWMS, Gagné et al., 2015) adapted to the academic context in Spain. To apply MWMS on a student sample, the following methodological aspects of the scale were tested: (1) the continuum structure of motivation through the application of the bifactor exploratory structural equation modeling framework (bifactor-ESEM); (2) longitudinal invariance of the applied instrument (i.e., MWMS). In the main body of the thesis, I report only the most relevant results related to the adaptation of the scale. In Appendix C, however, I include the study "Stability of a Continuum Structure of Students' Self-Determination: A Longitudinal Approach to the Bifactor Exploratory Structural Equation Modeling", in which detailed analysis and discussion of different models to represent MWMS in the academic context are provided.

The purpose of Study 2 was to investigate profiles characterized by different combinations of various qualitative forms of motivation, and to analyze the relationship between these profiles and their possible antecedents (i.e., perceived competence and perceived challenge), and consequences (i.e., performance). Specifically, the first objective of this study was to identify profiles among undergraduate students, characterized by (1) configurations of different forms of motivation proposed by SDT (Gagné et al., 2015; Ryan & Deci, 2000), and (2) different multivariate trajectories of these motivational forms. The second goal was to describe these profiles in terms of trajectories of perceived competence and perceived challenge. The last objective was to assess predictive validity of the profiles through association with self-reported performance and final grades. Although the previous person-centered research that relied on trajectories of self-determined motivation are scarce and it is difficult to define precise assumptions about the nature of the profiles to be determined, I proposed several hypotheses. First, given the results obtained in the available studies on trajectory-based profiles of academic motivation (Chevrier & Lannengrand, 2021; Nishimura & Sakurai, 2017), I expected to find a rather small number of profiles in the studies sample:

Hypothesis 2.1.1: Students' self-determined motivation trajectories will be determined by small number of profiles (two to four).

Relying on previous results from the context of higher education (e.g., Chevrier & Lannengrand, 2021; Gillet, Morin, et al., 2017; Ratelle et al., 2007; Vansteenkiste et al., 2009), I hypothesized that part of participants would demonstrate high and stable levels of autonomous motivation:

Hypothesis 2.1.2: At least one of the extracted profiles will be characterized by high and stable levels of autonomous motivation.

As far as I am aware, the relationship between academic motivation profiles and students' perceptions of competence and challenge has not been explored so far. However, based on the assumptions of the flow theory (Csikszentmihalyi, 1975) and CET (e.g., Ryan & Deci, 2017), as well as on the insights from variable-centered research that confirm predictive power of perceived competence and perceived challenge (e.g., Diaconu-Gherasim et al., 2020; Guay et al., 2001; Koka & Hein, 2003; Meng et al., 2016, Moneta, 2004; Van den Broeck et al., 2016), I proposed the following hypotheses:

Hypothesis 2.2.1: The profiles described by high and stable or increasing levels of autonomous motivation will also be characterized by higher levels of perceived competence over time, compared to the profiles where levels of autonomous motivation are low and/or decreasing.

Hypothesis 2.2.2: The profiles described by high and stable or increasing levels of autonomous motivation will be characterized by higher levels of perceived challenge over time, compared to the profiles where levels of autonomous motivation are low and/or decreasing.

Finally, I wanted to study differences in academic performance related to motivational profiles. Considering the evidence from previous person-centered studies on motivation and performance (Baars & Wijnia, 2018; Boiché & Stephan, 2014; Gillet, Morin, et al., 2017; González et al., 2012; Hayenga & Corpus, 2010; Kusurkar et al., 2013; Vansteenkiste et al., 2009), I hypothesized the following:

Hypothesis 2.3.1: The profiles characterized by high and stable or increasing levels of autonomous motivation will be associated with higher scores of self-assessed performance, compared to the profiles where levels of autonomous motivation are low and/or decreasing.

Hypothesis 2.3.2: The profiles characterized by high and stable or increasing levels of autonomous motivation will be associated with final grades, compared to the profiles where levels of autonomous motivation are low and/or decreasing.

The summary of the studies is available in Table 2.1.

The studies presented in this thesis make some additional contributions to the research on motivation that are important to mention. First, in Study 1, motivation defined according to the premises of SDT is complemented with flow-related variables. As explained in the chapter 2.1.3 (SDT and Flow Theory – Joining Perspectives), the two theories may complement each other, and a combination of both can provide a better understanding of motivation, its preconditions and outcomes. Second, in Study 2, two possible predictors of motivational profiles, perceived competence and perceived challenge, are analyzed. Both variables were found to predict intrinsic motivation in previous variable-centered studies (e.g., Diaconu-Gherasim et al., 2020; Honicke & Broadbent, 2016; Koka & Hein, 2003; Mitchell, 1996). However, to the best of my knowledge, their association with motivational profiles in the academic context has not been investigated so far. Finally, in Study 2, I used MWMS (Gagné et al., 2015) that was adapted to the academic context in Spain for the purpose of this dissertation. Compared to other scales applied to measure motivation in the context of education (e.g., Academic Motivation Scale, Vallerand et al., 1992), the main benefit of using MWMS is a possibility of studying two forms of extrinsic regulation: material and social. Given that the relevance of material and social rewards in the academic context may depend on different factors, e.g., culture (Nishimura & Sakurai, 2017), respondents' age (Altikulaç et al. 2019) or educational stage (Ratelle et al., 2007), such detailed analysis of students' external regulation could provide valuable insights about their motivation.

Table 2.1

Summary of the Studies Included in the Thesis

	Study 1	Study 2
Research objectives	(1) To study evolution of motivation-related variables: flow preconditions, flow experience, intrinsic motivation, and perceived competence (direction and pattern of change) during one academic semester. (2) To study whether the students can be grouped in terms of the motivational dynamics they demonstrate. (3) To investigate whether different patterns of motivational change (if found) may be related to students' self-assessed performance and final grades.	(1) To implement a non-parametric procedure for clustering individuals according to their multivariate trajectories in the Multidimensional Work Motivation Scale (MWMS, Gagné et al., 2015) adapted to the academic context. (2) To assess the role of perceived competence and perceived challenge to predict likelihood of membership into different motivational profiles. (3) To demonstrate clustering predictive validity with respect to the academic performance.
Hypotheses	Hypothesis 1.1: Academic motivation (i.e., precondition of flow, flow experience, intrinsic motivation, and perceived competence) of undergraduate students changes over one academic semester. Hypothesis 1.2: Different direction and pattern of possible changes in motivation can be distinguished. Hypothesis 1.3: Students be grouped in terms of the motivational dynamics they demonstrate. Hypothesis 1.4: The students who increase in motivation across the semester (if such phenomenon is found) will demonstrate better performance (i.e., higher self-reported performance and final course grades).	Hypothesis 2.1.1: Students' self-determined motivation trajectories will be determined by small number of profiles (two to four). Hypothesis 2.1.2: At least one of the extracted profiles will be characterized by high and stable levels of autonomous motivation. Hypotheses 2.2.1: The profiles described by high and stable or increasing levels of autonomous motivation will also be characterized by higher levels of perceived competence over time, compared to the profiles where levels of autonomous motivation are low and/or decreasing. Hypothesis 2.2.2: The profiles described by high and stable or increasing levels of autonomous motivation will be characterized by higher levels of perceived challenge over time, compared to the profiles where levels of autonomous motivation are low and/or decreasing. Hypothesis 2.3.1: The profiles characterized by high and stable or increasing levels of autonomous motivation will be associated with higher scores of self-assessed performance, compared to the profiles where levels of autonomous motivation are low and/or decreasing. Hypothesis 2.3.2: The profiles characterized by high and stable or increasing levels of autonomous motivation will be associated with final grades, compared to the profiles where levels of autonomous motivation are low and/or decreasing.

Table 2.1 (Continued)

The summary of the studies

	Study 1	Study 2
Method: - Sample - Measures/ Instrument - Design	- 291 undergraduate students (Spain). - Short Flow State Scale; Intrinsic Motivation Inventory (perceived competence and intrinsic motivation scales); questionnaire about self-assessed performance; students' final grades. - Longitudinal design: up to 10 measurement occasions, a total of 2087 repeated assessments.	- 979 undergraduate students (Spain). - Multidimensional Work Motivation Scale (MWMS), Intrinsic Motivation Inventory (perceived competence scale); Flow State Scale (perceived challenge items); questionnaire about self-assessed performance; students' final grades. - Longitudinal design: up to 5 measurement occasions, a total of 3063 repeated assessments.
Analysis	- Latent class mixed models. - Parametric tests	- Longitudinal cluster analysis. - Linear mixed models. - Parametric tests.
Results	For both sets of variables, FBM-related and SDM-related, two latent classes were obtained; they were characterized as *strong increase* and *modest increase*. Parametric tests confirmed an effect of different motivational trajectories on self-assessed performance, when comparing trajectories for either the FBM-related, or the SDM-related latent processes. Regarding final grades, such effect was found only for SDM-related latent process.	Two obtained profiles were characterized as *Highly motivated* (average to high levels of all motivational forms over time, except social external regulation; low amotivation), and *Reward oriented* (high but slightly decreasing external-material regulation; moderate and decreasing identified and introjected regulation and intrinsic motivation; low and increasing external-social regulation and amotivation). Participants who belonged to the *Highly motivated* profile were characterized by higher perceived competence and challenge. They also achieved higher self-assessed performance and better final grades.
Conclusions	The students can be grouped according to different patterns of within-person changes in motivation experienced over time. Those whose motivation increased more sharply over the semester tended to achieve better performance, compared with students whose motivation increased modestly.	Results derived from person-centered approach has proven to be necessary to detect different patterns of motivational evolution in the academic context which, in turn, are useful to predict academic outcomes.

3. Research Methodology

3.1. Study 1

3.1.1. Participants and Procedure

The data were collected in a public Spanish university. At the initial stage of recruitment, participants consisted of 534 students from different faculties (psychology, public management, and labor relations), divided into ten "class-groups" (i.e., ten sections in three different academic courses). Participation in the study was voluntary and anonymous. Informed consent was obtained from all participants included in the study. The data were collected ten times over the course of the semester, approximately every two weeks. Following the recommendation of Bolger and Laurenceau (2013) for an ideal minimum number of repeated observations per individuals in an intensive longitudinal design, in the final analysis only those participants who provided a minimum of five repeated measurements were included. This left a total sample of 291 participants. Ages ranged from 17 to 54 years, with a median of 21 (IQR = 3)[1]. Forty-five participants were male, 163 were female, and 83 did not reveal their gender. Various activities were proposed during the course sessions, including lectures, small-group exercises, or role-plays. Motivation-related variables were measured at the end of each of the ten sessions. Self-assessed performance was measured once, at the last session. When the semester ended, teachers provided the students' final grades. In order to match the answers to the questionnaires and the students' final grades, ensuring respondents' anonymity, the questionnaires were coded using the identification numbers.

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[1] As the distribution of the variable "age" was asymmetric, the median and IQR are provided.

A total of 2087 repeatedly measured questionnaires was collected (average of 7.17 per participant). The number of students who responded in each measurement occasion is as follows: Time 1 (T1) – 732 students (67.70%), Time 2 (T2) 634 students (77.32%), Time 3 (T3) 627 students (70.79%), Time 4 (T4) 568 studens (75.60%), Time 5 (T5) 502 students (67.35%), Time 6 (T6) – 732 students (84.88%), Time 7 (T7) 634 students (70.10%), Time 8 (T8) 627 students (73.54%), Time 9 (T9) 568 students (64.26%), Time 10 (T10) 502 students (65.64%).

3.1.2. Measures

Academic Motivation

The flow-based motivation (FBM) was measured with the items from the Flow State Scale (Jackson & Marsh, 1996) translated and adapted to the Spanish context by García Calvo et al. (2008). Three items about the preconditions of flow (e.g., "I had a good idea about how well I was doing while I was involved in the task/activity") and six items about the flow experience (e.g., "I was completely focused on the task at hand"; "I had a feeling of total control over what I was doing") were used.

The measures of self-determined motivation (SDM) components, perceived competence and intrinsic motivation, were adapted from the Intrinsic Motivation Inventory (Ryan, 1982). Given a longitudinal character of the study, the requirements of measurement criteria typical for cross-sectional designs (i.e., to cover the entire range of components included in the studies construct), as well as the criteria required for repeated evaluation (i.e., brevity of the applied instruments) were considered. For this reason, three items from the interest/enjoyment scale (e.g., "I enjoyed doing this activity very much"; "I thought it was a boring activity" – negatively phrased item) and three items from the perceived competence scale (e.g., "I think I am pretty good at this activity"; "This was an activity I couldn't do very well" – negatively phrased item) were applied. Selected items were those characterized by the highest level of the factor loading (McAuley et al., 1989). All the items were rated using a Likert Scale, ranging from 1 (I strongly disagree) to 7 (I strongly agree). Focal reliability measures (RC; see Bolger & Laurenceau, 2013 p. 137) of the scales were acceptable (.77 for FBM and .82 for SDM) suggesting that both scales allow us to reliably evaluate within-person changes. All the items referred to the activities engaged in during that specific class session.

Performance

Self-assessed performance was measured with a questionnaire created for the purpose of the present research. The questionnaire consisted of six items, for example: "I think that I have performed very well during this semester"; "I feel that I could have done better on this course" (negatively phrased item). The items were rated using a Likert scale ranging from 1 (I strongly disagree) to 7 (I strongly agree). Exploratory factor analysis (EFA) for one factor (following the theoretical framework underlain) was conducted. Factor loading ranged from 0.65 to 0.83; 40% of variance was explained just for this one factor, and fit indexes were: RMSR = 0.17 and TLI = 0.75. To compare, the two-factor solution accounted for 53% of the variance in the items, the first and the second factor explained 42% and 11% of variance respectively (RMSR = 0.04 and TLI = 0.99). Reliability of the scale was satisfactory ($\alpha = .77$).

Students' final grades were used as a second measure of performance. According to the Spanish education system, the grades range from 0 to 10, with 5 as the lowest passing grade. The measures were standardized in each "class-group", in order to make the results comparable.

3.1.3. Data Analysis

Descriptive analyses were carried out, considering the measurement scale of the variables. Additionally, reliability of all measures was provided. To assess whether the students could be grouped based on the trajectories of FBM and the SDM, the analysis of latent class mixed models (Proust-Lima et al., 2017) was employed, as it allowed us to evaluate heterogeneity in students' trajectories over time (see sections S1.1 and S1.2 in the supplementary material). The final step was to investigate whether the different latent classes found when modeling the trajectories were associated with students' self-assessed performance and final grades. The classes were compared on the performance outcomes using the t-test statistic. Analyses were conducted using R (R Core Team, 2020) and Mplus (Muthén & Muthén, 1998-2017).

3.2. Study 2

3.2.1. Participants and Procedure

The sample was composed of 979 undergraduate students from different faculties of a public Spanish university: psychology, public management, labor relations, and sociology. Five hundred eighty-two participants (59.45%) provided sociodemographic data. In this group, ages ranged from 18 to 49 years, with a mean of 19.69 and a standard deviation of 2.08 years. Four hundred forty-four participants (76.29%) were female; five hundred fifty-three participants (95.02%) were Spanish.

Participation in the study was voluntary and anonymous. Informed consent was obtained from all participants. The data were collected five times during one academic semester (approx. 4 months), every 2-3 weeks, in the core courses that were mandatory for all the students. Academic motivation and self-assessed performance were measured at the end of each session. Once the course ended, students' final grades were collected. In order to match the answers to the questionnaires and the students' final grades ensuring participants' anonymity, both were coded using identification numbers (student identification numbers that were converted into numerical codes created for the purpose of the study).

A total of 3063 repeatedly measured questionnaires was collected (average of 3.13 per participant). At Time 1 (T1), 732 students responded to the questionnaire (74.77%), at Time 2 (T2) 634 responded (64.76%), at Time 3 (T3) 627 responded (64%), at Time 4 (T4) 568 responded (58%), and at Time 5 (T5) 502 responded (51.28%).

3.2.2. Measures

Academic Motivation

To measure students' motivation, the Multidimensional Work Motivation Scale (MWMS; Gagné et al., 2015) translated into Spanish and adapted to the academic context was used. The participants were asked the following question: "Thinking about this course, why do you, or would you, put effort into the activities proposed in this course?". The scale included 19 items, which assessed six dimensions of motivation: intrinsic motivation (e.g., "Because I have fun doing these activities"), identified regulation (e.g., "Because putting efforts in these activities aligns with my personal values"), introjected regulation (e.g., "Because otherwise I will feel ashamed of myself"), extrinsic regulation – social (e.g., "To get others' approval – professor, colleagues, family, etc.)", extrinsic regulation – material (e.g., "Because I risk failing the course if I don't put enough effort in it"), and amotivation (e.g., "I don't, because I feel that I'm wasting my time on these activities"); full scale is included in the Appendix B. The participants rated each item on a seven-point Likert scale, ranging from 1 (I strongly disagree) to 7 (I strongly agree).

Although the most used tool to measure motivation in the educational context is the Academic Motivation Scale (AMS; Vallerand et al., 1992, 1993), I decided to apply MWMS (Gagné et al. 2015) for two reasons. First, I was interested in exploring two different forms of external regulation – material and social. These two forms of external regulation can be easily observed in the academic context, for example, students may engage in an activity because they want to receive a good grade (material form of external regulation), or because of the praise they would receive from a teacher or parents. Second, I decided to conceptualize intrinsic motivation as unidimensional, given that the three dimensions of intrinsic motivation proposed by AMS, did not received strong support in previous studies (Howard et al., 2017).

Perceived Competence

Perceived competence was measured with a corresponding subscale of the Intrinsic Motivation Inventory (Ryan et al., 1991). Given a repeated evaluation, three out of six items included in this subscale were used, choosing those that were characterized by the highest level of the factor loading (McAuley et al., 1989). The participants were asked to answer the following question: "Thinking about this course, why do you or would you put effort into the activities proposed in this course?" rating the items (e.g., "I think I am pretty good at these activities.") with a Likert scale ranging from 1 (I strongly disagree) to 7 (I strongly agree).

Perceived Challenge

To measure students' perception of challenge the participants were asked to rate three statements: "The proposed activities are a challenge for me", "The activities require that I give the best of myself", "The proposed activities are not very challenging" (negatively framed item), thinking about the activities performed during the course. The items were created based on the concept of perception of challenge included in the Spanish adaptation of the Flow State Scale (García Calvo et al., 2008), rated with a 1-to-7 Likert scale, where 1 = strongly disagree, and 7 = strongly agree.

Performance

Self-assessed performance was measured with a scale which consisted of three items: "I think that I have performed very well"; "I think I have had problems with my performance" (negatively phrased item); "I'm happy with my performance". The items were rated with a Likert scale ranging from 1 (I strongly disagree) to 7 (I strongly agree). Exploratory factor analysis (EFA) for one factor was conducted separately for all measurement occasions. Factor loading ranged from 0.58 to 0.91; variance explained just for this one factor ranged from 58% (T1) to 68% (T4). Focal reliability measure (RC) was acceptable (.77) suggesting that the scale allows to reliably evaluate within-person changes.

Similar to Study 1, students' final grades (ranging from 0 to 10, with 5 as the lowest passing grade) were used as a second measure of performance. The measures were standardized in each "class-group".

3.2.3. Data Analysis

Adaptation of the MWMS

First, confirmatory factor analysis (CFA), bifactor-CFA, exploratory structural equation modeling (ESEM), and bifactor-ESEM models were compared (the bifactor models estimated specific factors and a global factor of motivation). Second, the temporal invariance on the MWMS in the academic context was tested, using the model with the best fit, and examining increasingly constrained models: configural, metric, scalar, and strict invariance. A detailed description of these procedures is provided in the non-published study “Stability of a Continuum Structure of Students’ Self-Determination: A Longitudinal Approach to the Bifactor Exploratory Structural Equation Modeling” (Appendix C). The statistical analyses were conducted using Mplus version 7.4 (Muthén & Muthén, 1998-2017).

Longitudinal Clusters Analysis

Longitudinal cluster analyses were carried out for identifying homogeneous student trajectories concerning different forms of academic motivation. In this regard, a joint trajectory can be inferred by inspecting the temporal evolution (i.e., changes) of the motivational variables and, given this trajectory, student’s membership to a certain group is decided with the aim of getting groups composed by individuals with homogeneous motivational trajectories. Specifically, *k-means* procedure was used to find these clusters as detailed in Genolini et al. (2015) by running the R package *kml3d* developed by these authors. A more detailed description of this procedure is available in section S2.1 of the supplementary materials. To determine the optimal partition, I applied indices based on the ratio between-clusters and within-cluster variabilities implemented in *kml3d*, information criteria, and posterior probabilities, amongst others (Genolini et al., 2015). In short, a partition was kept when these indices were maximized. In order to avoid local solutions, the employed algorithm sets different starting points (i.e., centers of the clusters) according to nondeterministic procedures to guarantee that the optimal partition is not a local maximum. By default, partitions were done starting from two clusters up to a maximum of six clusters, running 50 redrawings (starting points) for each partition.

Given a high missingness (both monotonic and intermittent) in the study, an imputation procedure for keeping the maximum information was applied, using a so-called *Copy Mean* procedure that was proved to be more efficient than alternative methods (Genolini et al., 2013). The imputation procedure is described in section S2.2 of the supplementary materials.

Cluster Profiling

For modeling longitudinal changes in the motivational measures, linear mixed models (LMM) with random intercepts and slopes were employed. In this regard, I considered the possibility that participants might have different intercepts defining their motivational trajectories, in addition to different slopes representing various temporal patterns of change in their motivation. Statistical models were specified including the following independent variables or predictors as fixed effects: registers (from Time 1 to Time 5), group (defined by the clustering procedure detailed above), and their interaction (time x group). By specifying group and evaluation time as factors, it is possible to test pairwise comparisons of the estimated marginal means in the dependent variables for each group and at each time of evaluation. Separate models were conducted for each dependent variable: amotivation, social and material extrinsic motivation, introjected regulation, identified regulation, and intrinsic motivation. Cluster A was the reference group. LMMs assuming Gaussian response were employed when modeling changes in the six motivational scores. All models included random effects for intercepts and slopes as well as heteroskedasticity due to groups whenever necessary. By using a beyond-optimal model in the fixed part (i.e., the one including all possible predictors and interactions) the optimal structure for the random part was chosen after running nested models and looking at information criteria indices. As for the modeling of the fixed part concerning the relationship between responses and predictors, a general procedure was followed: First, a null model including only the intercept was estimated (model 1). Group and time predictors, as well as their interaction including both linear and non-linear trends, were gradually added in four subsequent models (2 to 5). Several goodness-of-fit indices were employed (e.g., Akaike's Information Criterion, AIC) to choose best models for each response. Once an optimal partition was found, the resulting categorical variable (i.e., belonging to clusters/profiles) was used as a predictor of both studied performance indicators (self-assessed performance and final grades). When including students' grades as the response, parametric tests were used for comparing central tendency indices of this academic performance type, whereas LMMs were used for studying different change patterns of self-assessed performance along the course depending on the motivational cluster. Similarly, to the linear models explained above, groups and assessment times were used as predictors of the changes in self-assessed performance along the course. Finally, clusters were profiled by using students' self-reported scores of perceived competence and perceived challenge along the course. Again, LMMs were employed for these variables following the general procedure detailed above concerning motivational scores. All the analyses were conducted using R (R Core Team, 2020).

4. Results

4.1. Study 1

4.1.1. Descriptive Statistics

Descriptive statistics for all study variables (FBM composite, SDM composite, self-assessed performance, and final grades.) are presented in Table 4.1. Descriptive statistics of the measures in each assessment occasion are reported in the section S1.3 of the supplementary materials.

Of particular note are the intraclass correlation coefficients, that is, ICC(1), for SDM (.23) and FBM (.32), reflecting a considerable proportion of within-person variability in both of the motivational variables (77% and 68% respectively), and supporting the dynamic nature of the motivational processes. As expected, statistically significant and moderate-to-strong positive correlations between the variables at both within- and between-participants levels of analysis were found (Table 4.2).

Latent Class Trajectory Analysis

Latent class mixed models (Proust-Lima et al., 2017) were used to investigate whether students could be grouped based on change trajectories of their motivation over the course of the semester (see section S1.4 in the supplementary materials). When defining the number of classes, different temporal patterns of motivational change observed in previous studies were considered: increasing (e.g., Lee & Kim, 2014), decreasing (e.g., Weidinger et al., 2017), or no significant change (e.g., Bieg et al., 2017). I also decided to treat the FBM and SDM variables separately, as they represent theoretically different aspects of motivation development (Abuhamdeh, 2012). Furthermore, although a strong correlation between the two composite measures of motivation was observed (Table 4.2), a multilevel confirmatory factor analysis of the FBM and SDM items confirmed that a 2-factor model fit the data significantly better than a 1-factor model ($\Delta\chi^2$ (1) = 24.91, p < .001). Different models were tested, assuming a two latent class solution as a starting point. In this regard, different trends over time (linear and nonlinear), as well as several possibilities for the random effects part of the model were tested. Looking at their performance, the models that better fitted the data were kept. Those models were then tested under different number of classes and, as a result, a solution with two classes for both, the FBM-related and SDM-related latent processes was taken (see Table 4.3 and Table 4.4).

Looking at the predicted trajectories for the obtained classes in SDM-related latent process (Figure 4.1), two classes were observed; first, for which a strong linear increase over time was observed (labelled as *strong increase*; linear effect = .21, $p < .001$), and second, with a more modest linear increase trend (labelled *modest increase*; linear effect = .03, $p < .01$). Nevertheless, the classes were very unbalanced in terms of classified individuals: 256 (88%) and 35 individuals (12%), for the strong increase and modest increase classes respectively. As for the FBM-related latent process, two classes were found: one with a weak nonlinear trend, but overall increasing (labelled as *modest increase*), and another characterized by *strong increase*; in both classes the linear effect was statistically significant and had the largest absolute standardized coefficient). Different sizes were again observed for the two classes: 271 (93%) and 20 (7%) individuals classified as modest increase and strong increase, respectively.

4.1.2. Latent Class Trajectories and Performance

The next step was test whether students classified as presenting different patterns of motivational dynamics over the semester also showed differences in academic performance at the end of the course. The t-test results confirmed an effect of different motivational change patterns (i.e., trajectories) on self-assessed performance, when comparing trajectories for either the FBM-related ($t(18.56) = 6.43$, $p < .001$) or the SDM-related latent processes ($t(153) = 4.53$, $p < .001$). Moreover, the measures of effect size (Cohen's d) showed strong effects in these pairwise comparisons ($d = 1.15$ for FBM-related latent process, and $d = 1.04$ for SDM-related latent process), such that those individuals classified as presenting a strong increase over the course of the semester also reported higher self-assessed performance. Regarding the final grades, t-test analysis confirmed an effect of different motivational change patterns in SDM-related latent process ($t(41.59) = 2.59$, $p = .01$). The measures of effect size (Cohen's *d*) demonstrated small to medium effects in these pairwise comparisons ($d = .20$ for FBM-related latent process, and $d = .60$ for SDM-related latent process). Those students, who demonstrated a strong increase over the course of the semester also reported higher final grades. No statistically significant effect was found for the patterns in FBM-related process ($t(283) = 1.11$, $p = .26$); the effect size in this pairwise comparison was small ($d = 0.26$).

Table 4.1

Descriptive Statistics of the Measures (Study 1)

	N	Mean	SD^w	SD^b	Median	Min	Max	Skew	Kurtosis	ICC(1)
FBM	2038	5.04	0.78	0.52	5.08	1.5	7	-0.38	0.14	.32
SDM	2049	5.30	0.86	0.47	5.33	1.83	7	-0.50	-0.01	.23
Self-assessed performance	185	4.75	-	0.92	4.83	2.17	7	-0.28	-0.02	-
Final grades	285	7.85	-	0.91	7.81	4.50	10	-0.41	0.46	-

Note. The range for all measures is 1 to 7, except for the measure of final grades which is 0 to 10. SD^w is the within-person standard deviation; SD^b is the between-person standard deviation.

Table 4.2

Correlations of Variables at the Within- and Between-Persons Levels of Analysis (Study 1)

	FBM	SDM	SP	FG
Flow-based motivation (FBM)	(.77)	.81***	.31***	-.02
Self-determined motivation (SDM)	.81***	(.82)	.33***	.02
Self-assessed Performance (SP)	-	-	(.77)	.37***
Final Grades (FG)	-	-	-	-

Note. Within-person correlation coefficients are based on 2087 repeated measures across 291 individuals (below the main diagonal). Between-person correlation coefficients based on 291 individuals (above the main diagonal). Diagonal contains RC indices for FBM and SDM measures, and Cronbach's alpha value for the SP scale. SP and FG were measured only on between-participants level.
*** $p \leq .001$.

Table 4.3

Latent Class Mixed Models for FBM-Related Latent Process (Study 1)

			Coefficient (SE)
Intercepts		Strong increase	0.92 (0.22)**
Time effect	Linear	Modest increase	3.91 (1.19)**
		Strong increase	43.31 (5.09)**
	Quadratic	Modest increase	-1.48 (1.09)ns
		Strong increase	12.04 (4.36)*
	Cubic	Modest increase	5.30 (1.09)**
		Strong increase	3.06 (3.95)ns
Goodness of fit	AIC		5013.11
	BIC		5071.89

Note: Two classes were kept: *strong increase* (weak nonlinearity) and *modest increase* (weak nonlinearity). *Modest increase* is the reference class, and its intercept was constrained to be 0. AIC = Akaike information criterion; BIC = Bayesian information criterion

** $p \leq .001$; * $p \leq .01$; ns $p > .05$.

Table 4.4

Latent Class Mixed Models for SDM-Related Latent Process (Study 1)

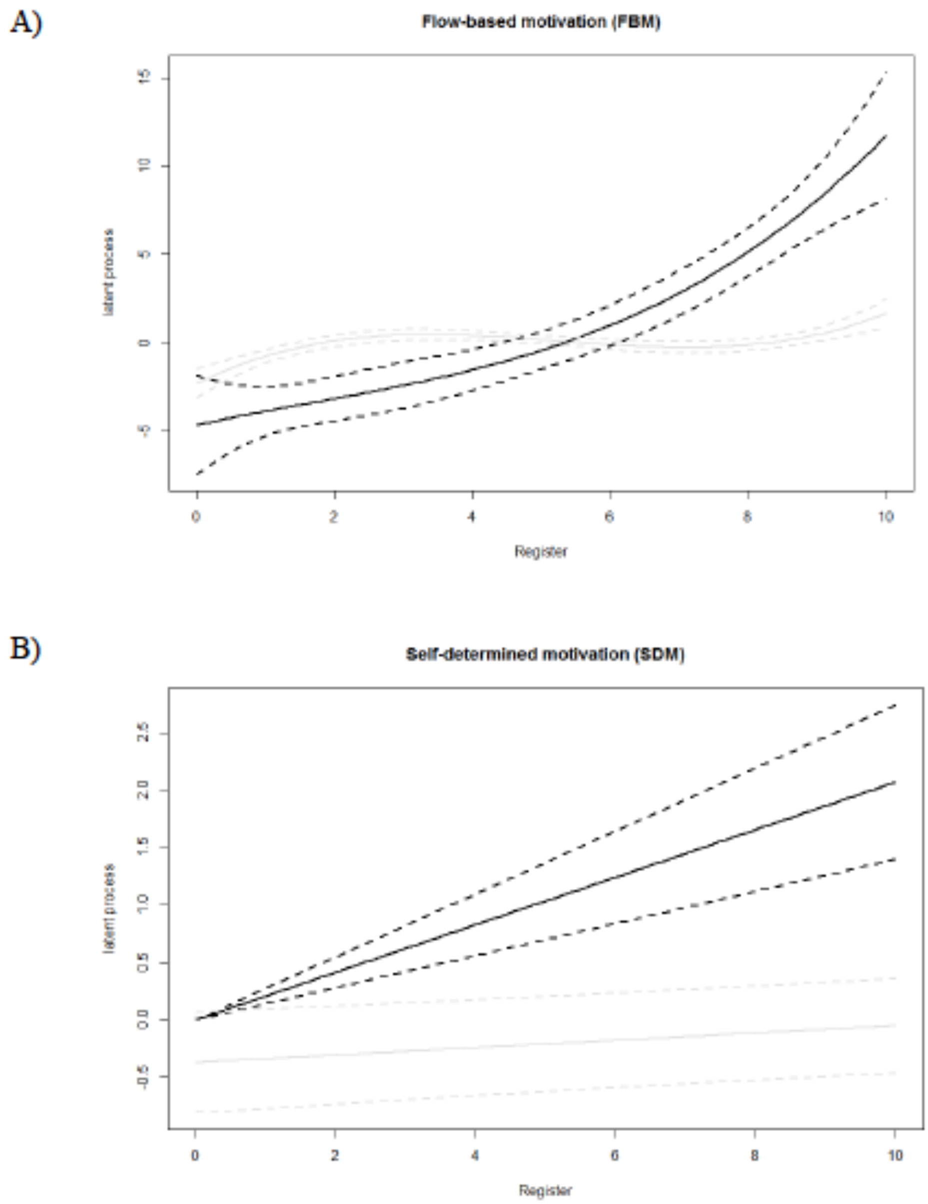
			Coefficient (SE)
Intercepts		Strong increase	-0.37 (0.22)^{ns}
Time effect	Linear	Modest increase	0.21 (0.03)**
		Strong increase	0.03 (0.01)*
Goodness of fit	AIC		5240.14
	BIC		5284.22

Note: Two classes were kept: *strong increase* (linear) and *modest increase* (linear). *Modest increase* is the reference class and its intercept is constrained to be 0. AIC = Akaike information criterion; BIC = Bayesian information criterion

** $p \le .01$; * $p \le .05$; ns $p > .05$.

Figure 4.1

Predicted Trajectories According the Latent Mixed Models for FBM and SDM (Study 1)



Note. 2-classes additive model based on FBM (A) and SDM variables (B). In both, FBM-related and SDM-related latent process, black lines correspond to the *strong increase* class and grey lines to the *modest increase* class. Fitted trajectories are shown with solid lines and 95% error bands are represented with dashed lines.

4.2. Study 2

4.2.1. Longitudinal Cluster Analyses

Following the analytical procedure described section 3.3.2 (Data Analysis, Study 2), the solution with 2 clusters was found to be optimal. In this regard, some discordant results were obtained when comparing the set of quality criteria for the different partitions. For this reason, the solution with more concordant quality criteria that was retained corresponded to the partition with two clusters (8 out of the 12 indicators used; see Table 4.5). Considering the two clusters representation in the sample, 543 individuals were classified as members of Profile 1 (55.46%) and 436 as members of Profile 2 (44.54%). Means and standard deviations of the motivational variables across the five measurement points for each profile are reported in Table 4.6. Additionally, Table 4.7 shows a descriptive summary of the measures of perceived competence, perceived challenge, and self-reported performance along the five occasions, as well as of the grades at the end of the course, for the two profiles.

Table 4.5

Quality Indices Corresponding to Examined Cluster Solutions (Study 2)

	2 clusters	3 clusters	4 clusters	5 clusters	6 clusters	Optimal
1. Calinski. Harabatz	266.24	205.65	175.06	162.13	146.03	2
2. Calinski. Harabatz2	0.27	0.42	0.54	0.67	0.75	6
3. Calinski. Harabatz3	266.24	290.84	303.21	324.26	326.53	6
4. Ray.Turi	-0.03	-0.03	-0.03	-0.04	-0.04	5
5. Davies. Bouldin	-1.61	-1.61	-1.63	-1.61	-1.62	4
6. BIC	-77768.96	-75462.83	-73811.13	-72189.19	-71271.79	2
7. BIC2	-77976.43	-75772.34	-74222.68	-72702.77	-71887.41	2
8. AIC	-77470.88	-75018.15	-73219.86	-71451.32	-70387.33	2
9. AICc	-77479.13	-75037.03	-73254.31	-71506.83	-70469.99	2
10. AICc2	-77471.14	-75018.72	-73220.87	-71452.89	-70389.59	2
11. Posterior Prob	0.97	0.96	0.96	0.96	0.95	2
12. Random	2.31	-0.52	-1.46	-0.64	0.83	2

Note. Summary table for the quality indices corresponding to different partitions of the whole dataset (see Genolini et al. 2015 pp. 9-11, for further details regarding these indices). Optimal values correspond either to maximum values of the indicators 1 to 3, 11, and 12 or to minimum values of indicators 4 to 10. The last column details the optimal number of clusters according to the corresponding quality criterion.

Table 4.6

Descriptive Statistics of the Motivational Variables (Study 2)

	Sample (n = 979)					Cluster A (n = 543)					Cluster B (n = 436)				
	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5
Intrinsic motivation															
M	3.59	3.54	3.43	3.29	3.34	4.26	4.29	4.21	4.06	4.10	2.75	2.59	2.44	2.34	2.41
SD	1.42	1.45	1.45	1.40	1.37	1.21	1.19	1.20	1.18	1.15	1.21	1.18	1.10	1.00	1.00
Identified regulation															
M	4.67	4.51	4.40	4.22	4.30	5.32	5.30	5.22	5.06	5.11	3.86	3.53	3.37	3.16	3.28
SD	1.30	1.37	1.36	1.37	1.37	1.03	1.01	0.96	1.03	1.03	1.15	1.10	1.04	0.95	1.01
Introjected regulation															
M	4.39	4.48	4.36	4.25	4.29	4.96	5.12	5.04	4.99	5.03	3.68	3.67	3.50	3.33	3.36
SD	1.29	1.30	1.34	1.38	1.37	1.07	1.03	1.06	1.10	1.06	1.20	1.15	1.16	1.12	1.14
Social external regulation															
M	2.06	2.24	2.29	2.37	2.45	2.13	2.33	2.45	2.61	2.80	1.98	2.12	2.10	2.08	2.03
SD	1.15	1.20	1.22	1.23	1.22	1.13	1.19	1.25	1.25	1.24	1.17	1.21	1.16	1.14	1.05
Material external regulation															
M	5.77	5.80	5.74	5.70	5.76	5.75	5.86	5.87	5.84	5.88	5.79	5.72	5.57	5.53	5.61
SD	1.12	1.02	1.03	1.02	0.97	1.13	1.00	0.98	0.95	0.91	1.10	1.04	1.08	1.07	1.03
Amotivation															
M	1.80	1.87	1.94	1.95	1.94	1.47	1.5	1.58	1.64	1.68	2.20	2.33	2.40	2.34	2.26
SD	0.95	1.00	0.98	0.95	0.90	0.66	0.65	0.68	0.69	0.70	1.08	1.15	1.11	1.08	1.02

Note. The range for all measures is 1 to 7.

Table 4.7

Descriptive Statistics of Perceived Competence, Perceived Challenge, Self-Assessed Performance and Final Grades (Study 2)

		Sample					Cluster A					Cluster B				
		T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5
Perceived competence																
	N	726	633	624	566	501	399	357	352	327	298	327	276	272	239	203
	M	4.42	4.45	4.36	4.22	4.23	4.71	4.79	4.77	4.59	4.64	4.08	4.01	3.83	3.70	3.63
	SD	0.94	1.02	1.10	1.11	1.16	0.87	0.87	0.96	1.01	1.06	0.90	1.02	1.04	1.04	1.01
Perceived challenge																
	N	726	633	624	566	501	399	357	352	327	298	327	276	272	239	203
	M	4.43	4.51	4.62	4.70	4.83	4.68	4.75	4.86	4.89	5.05	4.12	4.19	4.31	4.43	4.52
	SD	1.04	1.07	1.11	1.09	1.11	0.97	0.94	0.98	0.97	0.97	1.05	1.14	1.19	1.20	1.23
Self-assessed performance																
	N	726	633	624	566	501	399	357	352	327	298	327	276	272	239	203
	M	4.45	4.45	4.41	4.20	4.26	4.69	4.74	4.74	4.53	4.57	4.15	4.09	3.97	3.76	3.80
	SD	1.11	1.18	1.20	1.31	1.28	1.02	1.10	1.11	1.26	1.22	1.13	1.17	1.19	1.26	1.23
Final Grades																
	N					815					453					362
	M					5.69					5.88					5.45
	SD					1.95					2.02					1.83

Note. The range for all measures is 1 to 7, except for the final grades measure which is 0 to 10.

4.2.2. Cluster Profiling – Motivational Variables

In the following lines, I describe the differences between Profile 1 and Profile 2, comparing results obtained on the MWMS sub-scales.

Intrinsic Motivation

Table 4.8 includes a summary for the LMMs with intrinsic motivation as response. The model including interaction between registers and groups was kept ($\chi^2(2) = 11.47$; $p = .003$). Profile 1 scored statistically significantly higher than Profile 2 in all measurement occasions (estimated marginal differences between groups ranging from 1.53 to 1.76 points; $p < .001$). As for the trends of change along the semester, Profile 1 showed a linear decrease (difference T1-T5 = 0.23; $t(3912) = 4.12$; $p < .001$), and Profile 2 displayed a non-linear decrease (difference T1-T5 = 0.37; $t(3912) = 6.26$; $p < .001$). The measures of effect size (Cohen's *d*) demonstrated small to medium effects in these comparisons ($d = 0.35$ for Profile 1, and $d = 0.60$ for Profile 2).

Identified Regulation

When modeling trajectories for identified regulation explained by measurement occasion and obtained clusters (Table 4.9), model 5 characterized by non-linear trends across time and its interaction with clusters (χ^2 (2) = 43.53; $p < .001$) showed the best fit. Pairwise comparisons between-groups using estimated marginal means showed statistically significant differences in all measurement occasions, being the students in Profile 1 those who scored higher (estimated differences between 0.14 and 0.77). Both profiles significantly decreased their scores in this motivation sub-scale. Specifically, Profile 1 showed a linear decrease of 0.26 points when comparing measurement occasions 1 and 5 ($t(3912) = 3.65$; $p < .001$), however, it corresponded to a small effect size ($d = 0.31$). In Profile 2 a non-linear decrease of 0.61 points ($t(3912) = 10.73$; *p*

< .001) was observed, and its effect was large (*d* = 1.03).

Table 4.8

Models Summary for Intrinsic Motivation (Study 2)

	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**
Intercept	3.44^{***}	4.39^{***}	4.35^{***}	4.48^{***}	4.32^{***}
	(0.04)	(0.01)	(0.06)	(0.07)	(0.08)
Register (linear)		-0.07^{***}	-0.06^{***}	-0.16^{***}	-0.03
		(0.01)	(0.01)	(0.04)	(0.06)
Register (quadratic)				0.01^{*}	-0.004
				(0.01)	(0.01)
Cluster B		-1.64^{***}	-1.56^{***}	-1.65^{***}	-1.30^{***}
		(0.06)	(0.09)	(0.06)	(0.12)
Register x Cluster B (linear)			-0.03		-0.27^{***}
			(0.02)		(0.08)
Register x Cluster B (quadratic)					0.04^{**}
					(0.01)
Observations	4,895	4,895	4,895	4,895	4,895
Log Likelihood	-6,455.76	-6,156.90	-6,158.99	-6,158.69	-6,159.44
AIC	12,929.51	12,335.80	12,341.98	12,341.38	12,346.88
BIC	12,987.97	12,407.25	12,419.92	12,419.32	12,437.80

Note. All models included random intercepts and slopes as well as heteroskedasticity due to clusters of students. Model (1): Null mixed model; Model (2): Mixed model with main effects (linear); Model (3): Mixed model with main and interaction effects (linear); Model (4): Mixed model with main effects (quadratic); Model (5): Mixed model with main and interaction effects (quadratic). AIC = Akaike information criterion; BIC = Bayesian information criterion

**p* < .05; ** *p* < .01; ****p* < .001

Table 4.9

Models Summary for Identified Regulation (Study 2)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Intercept	4.48***	5.49***	5.40***	5.68***	5.42***
	(0.04)	(0.05)	(0.05)	(0.06)	(0.07)
Register (linear)		-0.10***	-0.06***	-0.26***	-0.08
		(0.01)	(0.01)	(0.04)	(0.05)
Register (quadratic)				0.03***	<0.01
				(0.01)	(0.01)
Cluster B		-1.75***	-1.51***	-1.74***	-1.09***
		(0.05)	(0.08)	(0.05)	(0.11)
Register x Cluster B (linear)			-0.07***		-0.44***
			(0.02)		(0.07)
Register x Cluster B (quadratic)					0.06***
					(0.01)
Observations	4,895	4,895	4,895	4,895	4,895
Log Likelihood	-6,181.45	-5,788.10	-5,782.86	-5,781.30	-5,766.61
AIC	12,380.90	11,598.20	11,589.73	11,586.59	11,561.22
BIC	12,439.36	11,669.65	11,667.67	11,664.53	11,652.14

Note. All models included random intercepts and slopes as well as heteroskedasticity due to clusters of students. Model (1): Null mixed model; Model (2): Mixed model with main effects (linear); Model (3): Mixed model with main and interaction effects (linear); Model (4): Mixed model with main effects (quadratic); Model (5): Mixed model with main and interaction effects (quadratic). AIC = Akaike information criterion; BIC = Bayesian information criterion

*$p < .05$; ** $p < .01$; *** $p < .001$

Introjected Regulation

Mixed models estimated for the remaining motivation score (Table 4.10) showed a statistically significant interaction between patterns of change and groups ($\chi^2(2) = 30.44$; $p < .001$). Profile 1 displayed higher scores than Profile 2 in all measurement occasions (marginal differences ranged between 1.28 and 1.67 points; $p < .001$). Regarding the patterns of change, the individuals in Profile 1 did not changed their scores significantly along the course (difference T1-T5 = -0.002; $t(3912) = -0.048$; $p = .99$), the effect size was trivial ($d = -0.004$). The students in Profile 2 showed a statistically significant non-linear decrease in their scores (difference T1-T5 = 0.39; $t(3912) = 7.29$; $p < .001$), which corresponded to a medium effect size ($d = 0.70$).

Social External Regulation

Given the different models estimated for the social extrinsic regulation scores as response (see Table 4.11), model 5 including non-linear terms across time, as well as its interaction with groups ($\chi^2(2) = 78.56$; $p < .001$), was kept as the final solution. Pairwise comparisons between groups showed statistically significant differences in all measurement occasions except Time 1. Profile 1 scored higher in the first measurement occasion and gradually increased its average level of social external regulation with respect to Profile 2 (estimated differences between 0.14 and 0.77). The social external regulation of the students in Profile 1 linearly increased from Time 1 to Time 5 (estimated difference = -0.65; $t(3912) = -12.65$; $p < .001$), the effect size of this change was large ($d = -1.09$). The students in Profile 2 presented a non-linear increase, however, this result was not statistically significant (estimated difference = -0.02; $t(3912) = -0.34$; $p = .94$), and its effect size was trivial ($d = -0.03$).

Table 4.10

Models Summary for Introjected Regulation (Study 2)

	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**
Intercept	4.38***	5.15***	5.04***	5.10***	4.92***
	(0.04)	(0.05)	(0.05)	(0.06)	(0.07)
Register (linear)		-0.05***	-0.01	-0.01	0.09*
		(0.01)	(0.01)	(0.04)	(0.05)
Register (quadratic)				-0.01	-0.02*
				(0.01)	(0.01)
Cluster B		-1.49***	-1.24***	-1.49***	-1.08***
		(0.06)	(0.08)	(0.06)	(0.11)
Register x Cluster B (linear)			-0.09***		-0.22**
			(0.02)		(0.07)
Register x Cluster B (quadratic)					0.02*
					(0.01)
Observations	4,895	4,895	4,895	4,895	4,895
Log Likelihood	-5,876.16	-5,637.90	-5,628.04	-5,641.55	-5,633.32
AIC	11,770.33	11,297.80	11,280.08	11,307.10	11,294.65
BIC	11,828.79	11,369.25	11,358.02	11,385.04	11,385.58

Note. All models included random intercepts and slopes as well as heteroskedasticity due to clusters of students. Model (1): Null mixed model; Model (2): Mixed model with main effects (linear); Model (3): Mixed model with main and interaction effects (linear); Model (4): Mixed model with main effects (quadratic); Model (5): Mixed model with main and interaction effects (quadratic). AIC = Akaike information criterion; BIC = Bayesian information criterion

*$p < .05$; ** $p < .01$; *** $p < .001$

Table 4.11

Models Summary for Social External Regulation (Study 2)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Intercept	2.24***	2.19***	1.98***	2.12***	1.98***
	(0.03)	(0.05)	(0.06)	(0.06)	(0.07)
Register (linear)		0.09***	0.16***	0.16***	0.16***
		(0.01)	(0.01)	(0.04)	(0.05)
Register (quadratic)				-0.01*	<0.01
				(0.01)	(0.01)
Cluster B		-0.44***	0.03	-0.44***	-0.12
		(0.06)	(0.08)	(0.06)	(0.10)
Register x Cluster B (linear)			-0.16***		0.01
			(0.02)		(0.07)
Register x Cluster B (quadratic)					-0.03*
					(0.01)
Observations	4,895	4,895	4,895	4,895	4,895
Log Likelihood	-5,898.88	-5,842.34	-5,810.65	-5,844.10	-5,812.96
AIC	11,815.75	11,706.67	11,645.30	11,712.21	11,653.93
BIC	11,874.22	11,778.12	11,723.24	11,790.15	11,744.85

Note. All models included random intercepts and slopes as well as heteroskedasticity due to clusters of students. Model (1): Null mixed model; Model (2): Mixed model with main effects (linear); Model (3): Mixed model with main and interaction effects (linear); Model (4): Mixed model with main effects (quadratic); Model (5): Mixed model with main and interaction effects (quadratic). AIC = Akaike information criterion; BIC = Bayesian information criterion

p* < .05; ** *p* < .01; * *p* < .001

Material External Regulation

Table 4.12 shows a summary of the models estimated for the material external regulation scores as response. The model including non-linear terms across time, as well as its interaction with groups (χ^2 (2) = 28.97; $p < .001$), was kept as the final solution. In this regard, although the fit indices were better for less complex models, model 5 included several significant terms. Pairwise comparisons between groups showed statistically significant differences in measurement occasions 2 to 5, but not in the first one. Students in Profile 2 scored higher in the first occasion and experienced a gradual decrease in the average level of material external regulation, compared to Profile 1 (estimated differences between -0.05 and 0.32). Two different non-linear trends were found for the scores in these two groups. Students in Profile 2 showed a statistically significant decrease of material external regulation levels when comparing the scores at the beginning and at the end of the course (estimated difference = 0.22; $t(3912) = 4.03$; $p < .001$); in Profile 1 the increase of material external regulation between Time 1 and Time 5 followed a nonlinear pattern, however, this result was statistically non-significant (estimated difference = -0.1; $t(3912) = -2.03$; $p = .10$). In both cases the size of effect was small ($d = -0.17$ for Profile 1, and $d = 0.39$ for Profile 2).

Amotivation

According to the analysis of five LMMs of the amotivation scores as response, the fit indices, and the global tests for the different terms included in model 5 (Table 4.13), the model including non-linear terms across time and its interaction with groups ($\chi^2(2)$ = 25.12; $p < .001$) was kept as the final solution. Pairwise comparisons between and within groups were used to assess differences in amotivation along the course by employing estimated marginal means under the fittest model. Between-groups tests showed statistically significant differences in the five measurement occasions, being Profile 2 the one with higher amotivation scores (estimated differences between -0.56 and -0.82; $p < .001$). A linear rate of change across time was found for Profile 1; the change experienced by the students in Profile 2 followed a non-linear trend. The observed increase between the first and the last measurement occasions was statistically significant in Profile 1 (estimated difference = -0.23; $t(3912) = -6.01$; $p < .001$) but not in Profile 2 (estimated difference = -0.05; $t(3912) = -1.02$; $p = .58$). The changes corresponded to small to medium effects ($d = -0.52$ for Profile 1, and $d = -0.29$ for Profile 2).

The trajectories of the motivational forms in both profiles are presented in Figure 4.2. A detailed comparison of the profiles, separately for each motivation variable, is included in section S2.3 of the supplementary materials.

Summing up, Profile 1 is characterized by above average and quite stable levels of intrinsic motivation, more autonomous forms of extrinsic motivation (i.e., identified regulation and introjected regulation), and material external regulation, as well as by low, albeit increasing, levels of social external regulation and amotivation. In Profile 2, the levels of amotivation and both forms of external regulation are similar to those in Profile 1. However, the levels of intrinsic motivation, identified regulation and introjected regulation are lower, and display a stronger decline compared to Profile 1. A similar decrease is observed for material external regulation. Finally, the increase of amotivation in Profile 2 is not statistically significant, however, the scores obtained on this sub-scale in all measurement occasion are higher than in Profile 1. It is worth mentioning that changes in Profile 2 follow a non-linear pattern, meaning that the most pronounced decrease of motivation (specifically, intrinsic motivation and identified introjected, and material external regulations) is observed in the first part of the course (Time 1 to Time 3). Considering the characteristics summarized above, I labelled Profile 1 as *Highly motivated*, and Profile 2 as *Reward oriented*.

Table 4.12

Models Summary for Material External Regulation (Study 2)

	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**
Intercept	5.76***	5.86***	5.78***	5.89***	5.67***
	(0.03)	(0.05)	(0.05)	(0.06)	(0.07)
Register (linear)		-0.01	0.02	-0.03	0.11*
		(0.01)	(0.01)	(0.04)	(0.05)
Register (quadratic)				<0.01	-0.01*
				(0.01)	(0.01)
Cluster B		-0.18**	0.02	-0.18**	0.35**
		(0.06)	(0.08)	(0.06)	(0.11)
Register x Cluster B (linear)			-0.06***		-0.34***
			(0.02)		(0.07)
Register x Cluster B (quadratic)					0.04***
					(0.01)
Observations	4,895	4,895	4,895	4,895	4,895
Log Likelihood	-5,359.04	-5,359.31	-5,356.72	-5,363.35	-5,355.83
AIC	10,736.08	10,740.62	10,737.45	10,750.70	10,739.66
BIC	10,794.55	10,812.07	10,815.39	10,828.64	10,830.58

Note. All models included random intercepts and slopes as well as heteroskedasticity due to clusters of students. Model (1): Null mixed model; Model (2): Mixed model with main effects (linear); Model (3): Mixed model with main and interaction effects (linear); Model (4): Mixed model with main effects (quadratic); Model (5): Mixed model with main and interaction effects (quadratic). AIC = Akaike information criterion; BIC = Bayesian information criterion

p* < .05; ** *p* < .01; * *p* < .001

Table 4.13

Models Summary for Amotivation (Study 2)

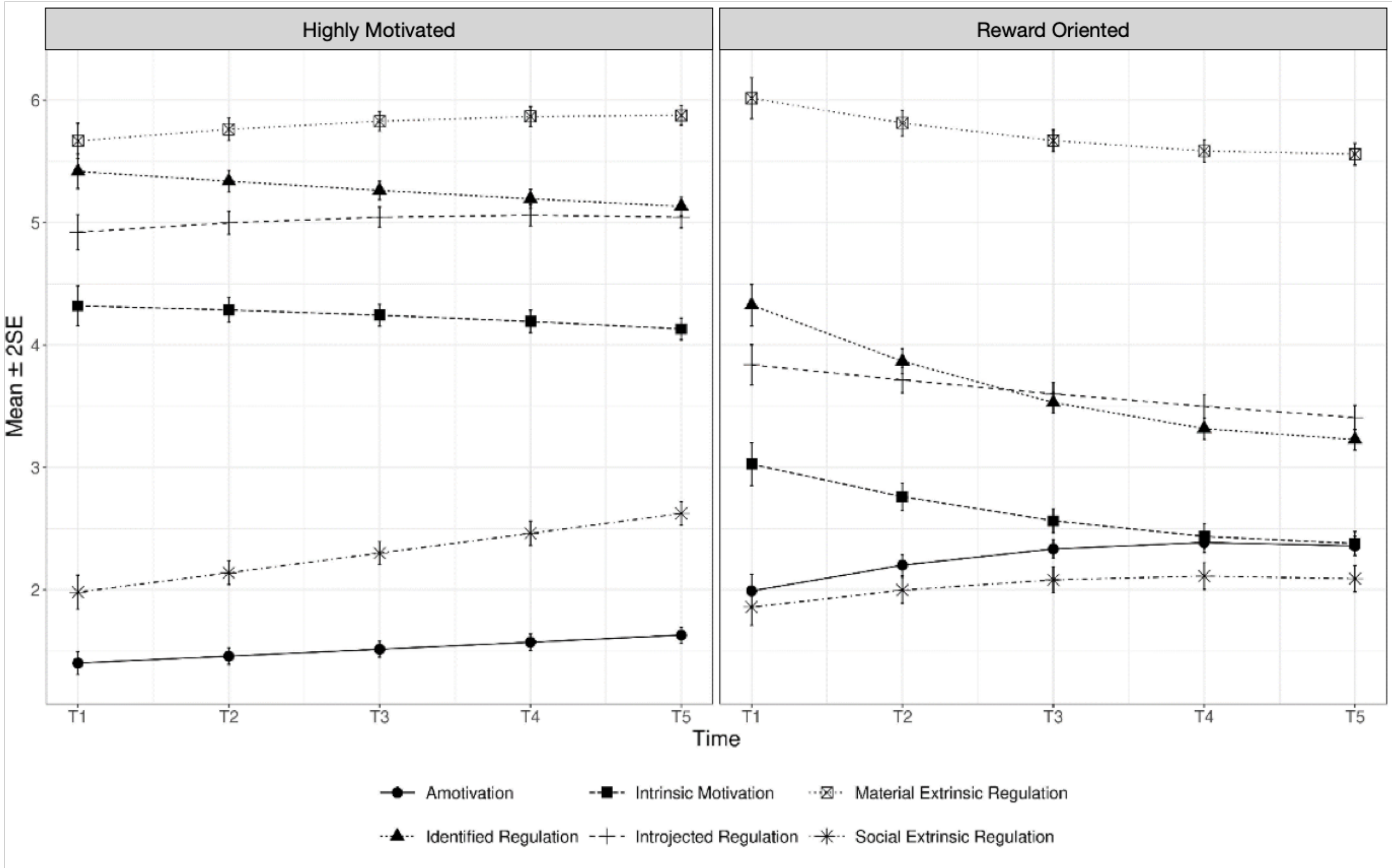
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Intercept	1.87***	1.45***	1.40***	1.39***	1.40***
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
Register (linear)		0.04***	0.06***	0.12***	0.06
		(0.01)	(0.01)	(0.03)	(0.03)
Register (quadratic)				-0.01**	<0.01
				(<0.01)	(0.01)
Cluster B		0.70***	0.83***	0.69***	0.59***
		(0.05)	(0.07)	(0.05)	(0.08)
Register x Cluster B (linear)			-0.04**		0.20***
			(0.02)		(0.06)
Register x Cluster B (quadratic)					-0.04***
					(0.01)
Observations	4,895	4,895	4,895	4,895	4,895
Log Likelihood	-4,837.88	-4,722.82	-4,722.53	-4,723.83	-4,718.36
AIC	9,693.76	9,467.64	9,469.06	9,471.65	9,464.72
BIC	9,752.22	9,539.09	9,547.00	9,549.59	9,555.65

Note. All models included random intercepts and slopes as well as heteroskedasticity due to clusters of students. Model (1): Null mixed model; Model (2): Mixed model with main effects (linear); Model (3): Mixed model with main and interaction effects (linear); Model (4): Mixed model with main effects (quadratic); Model (5): Mixed model with main and interaction effects (quadratic). AIC = Akaike information criterion; BIC = Bayesian information criterion

p* < .05; ** *p* < .01; * *p* < .001

Figure 4.2

Estimated Trajectories of Motivational Variables for the Two Profiles (Study 2)



Note. Marginal means plot showing the trajectories in motivational variables over the course of the semester for the two groups found in the multivariate clustering procedure. The means were estimated according to a mixed model with random intercepts and random non-linear trends (quadratic terms), including the interaction between occasions and groups.

4.2.3. Cluster Profiling – Perceived Competence and Perceived Challenge

Perceived Competence

Table 4.14 includes a summary of the linear mixed models estimated using students' perceived competence as the response variable. Although fit indices suggested the best fit of a simpler model (i.e., model 3), according to global tests the interaction between non-linear patterns and groups was statistically significant (χ^2 (2) = 16.02; $p < .001$). Students in *Highly motivated* profile scored significantly higher than those in *Reward oriented* profile in the five measurement occasions being the estimated differences between 0.63 and 0.95 ($p < .001$). The changes in students' perceived competence are presented in Figure 4.3. The change in *Highly motivated* profile followed a slight concave downward pattern with the difference between first and last measurement time equal to 0.18 ($t(2071) = 3.00$; $p = .01$) and corresponding to a small effect size (d = 0.26). The change in *Reward oriented* profile was more pronounced and could be characterized as a seemingly linear decrease (difference T1-T5 = 0.47; $t(2071) = 6.64$; $p < .001$); the effect size of this change was medium ($d = 0.64$).

Perceived Challenge

The summary of the mixed models including students' perceived challenge as the outcome is presented in Table 4.15. Model 2, which showed the best fit, yielded statistically significant results for the case of main effects of group ($\chi^2(1) = 99.10$; $p < .001$) and measurement occasions (linear trends; $\chi^2(1) = 58.16$; $p < .001$), but not for their interaction (χ^2 (1) = 0.41; $p = .52$). When testing estimated marginal means using the previous model, I found that students in *Highly motivated* profile scored 0.57 points higher than those in *Reward oriented* profile ($t(973) = 9.57$; $p < .001$). Regarding the change pattern across time, a linear increase was observed in both groups, and the estimated change rate was equal to 0.082 points ($t(2074) = 7.63$; $p < .001$; see Figure 4.4).

Table 4.14

Models Summary for Perceived Competence (Study 2)

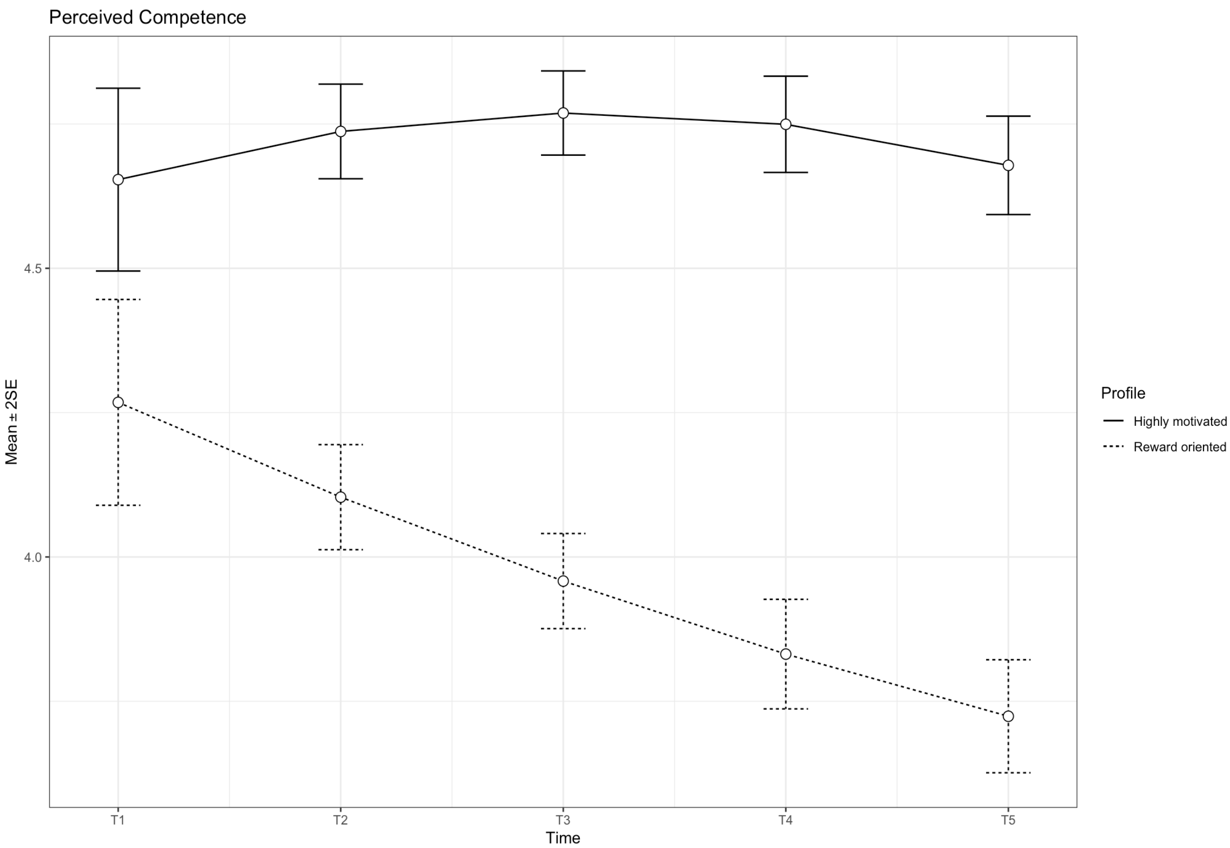
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**
Intercept	4.38***	4.89***	4.82***	4.83***	4.65***
	(0.03)	(0.04)	(0.05)	(0.07)	(0.08)
Register (linear)		-0.08***	-0.04**	-0.02	0.11
		(0.01)	(0.02)	(0.05)	(0.06)
Register (quadratic)				-0.01	-0.03*
				(0.01)	(0.01)
Cluster B		-0.78***	-0.61***	-0.78***	-0.39**
		(0.05)	(0.07)	(0.05)	(0.12)
Register x Cluster B (linear)			-0.08**		-0.28**
			(0.02)		(0.09)
Register x Cluster B (quadratic)					0.04*
					(0.02)
Observations	3,050	3,050	3,050	3,050	3,050
Log Likelihood	-3,968.19	-3,846.99	-3,844.58	-3,850.08	-3,848.26
AIC	7,952.37	7,713.97	7,711.16	7,722.15	7,722.52
BIC	8,000.55	7,774.19	7,777.40	7,788.39	7,800.79

Note. All models included random intercepts and slopes. Model (1): Null mixed model; Model (2): Mixed model with main effects (linear); Model (3): Mixed model with main and interaction effects (linear); Model (4): Mixed model with main effects (quadratic); Model (5): Mixed model with main and interaction effects (quadratic). AIC = Akaike information criterion; BIC = Bayesian information criterion

*$p < .05$; ** $p < .01$; *** $p < .001$

Figure 4.3

Estimated Trajectories of Perceived Competence for the Two Profiles (Study 2)



Note. Marginal means plot shows the trajectories in perceived competence over the course of the semester for the two groups found in the multivariate clustering procedure. Means were estimated according to a mixed model with random intercepts and random non-linear trends (quadratic terms), including the interaction between occasions and groups.

Table 4.15

Models Summary for Perceived Challenge (Study 2)

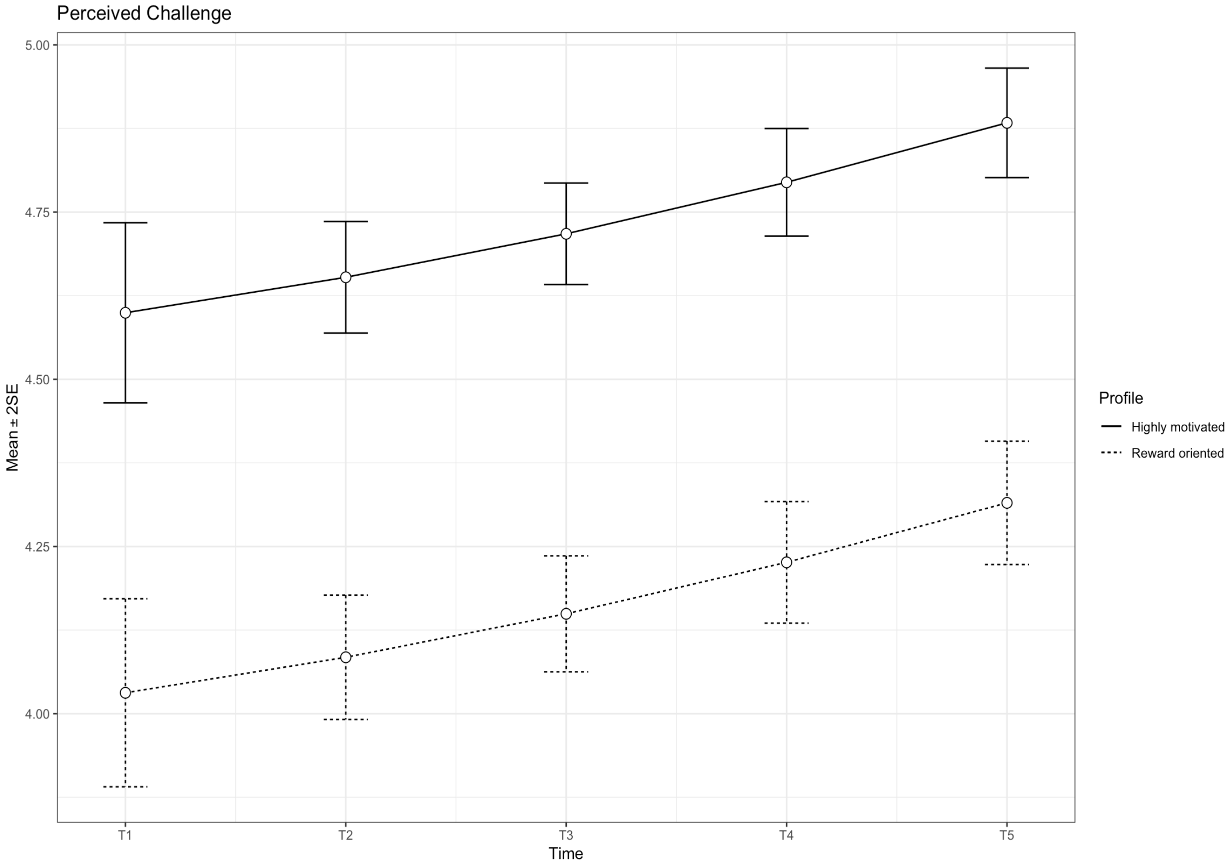
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Intercept	4.51^{***}	4.56^{***}	4.57^{***}	4.60^{***}	4.63^{***}
	(0.03)	(0.05)	(0.05)	(0.07)	(0.08)
Register (linear)		0.08^{***}	0.08^{***}	0.05	0.02
		(0.01)	(0.01)	(0.05)	(0.06)
Register (quadratic)				0.01	0.01
				(0.01)	(0.01)
Cluster B		-0.57^{***}	-0.60^{***}	-0.57^{***}	-0.66^{***}
		(0.06)	(0.08)	(0.06)	(0.13)
Register x Cluster B (linear)			0.01		0.06
			(0.02)		(0.10)
Register x Cluster B (quadratic)					-0.01
					(0.01)
Observations	3,050	3,050	3,050	3,050	3,050
Log Likelihood	-4,039.61	-3,979.04	-3,981.73	-3,982.68	-3,988.44
AIC	8,097.23	7,974.08	7,981.46	7,983.36	7,998.88
BIC.	8,151.43	8,022.26	8,035.66	8,037.55	8,065.11

Note. All models included random intercepts and slopes as well as heteroskedasticity due to clusters of students. Model (1): Null mixed model; Model (2): Mixed model with main effects (linear); Model (3): Mixed model with main and interaction effects (linear); Model (4): Mixed model with main effects (quadratic); Model (5): Mixed model with main and interaction effects (quadratic). AIC = Akaike information criterion; BIC = Bayesian information criterion

$^{*}p < .05$; $^{**}\ p < .01$; $^{***}\ p < .001$

Figure 4.4

Estimated Trajectories of Perceived Challenge for the Two Profiles (Study 2)



Note. Marginal means plot shows the trajectories in perceived challenge over the course of the semester for the two groups found in the multivariate clustering procedure. The means were estimated according to a mixed model with random intercepts and random linear trends.

4.2.4. Cluster Profiling – Academic Performance

Self-Assessed Performance

Mixed models estimated for the students' self-assessed performance showed a statistically significant interaction between non-linear patterns of change and groups ($\chi^2(2) = 6.70$; $p = .04$; Table 4.16). Students in *Highly motivated* profile scored significantly higher compared to *Reward oriented* profile in all measurement occasions (marginal differences ranged between 0.55 and 0.78 points; $p < .001$). The patterns of change for both groups are presented in Figure 4.5. Comparing the first and the last measurement occasion, individuals in *Highly motivated* profile experienced a non-linear decrease in their scores (difference T1-T5 = 0.22; $t(2070) = 3.20$; $p < 0.01$) that corresponded to a small effect size ($d = 0.27$). A decrease was also observed in *Reward oriented* profile, however, in this case the change pattern is more linear (difference T1-T5 = 0.39; $t(2070) = 4.88$; $p < .001$) and its effect was medium ($d = 0.47$).

Final Grades

Finally, the final course grades of the students in both profiles were compared. The results of both are presented in Figure 4.6. The average grade was 5.87 in *Highly motivated* profile and 5.45 in *Reward oriented* profile. The estimated difference of 0.42 point was statistically significant ($t(799.2) = 3.13$; $p = .002$), however, it corresponded to a small effect size ($d = 0.22$). Similar results were obtain for standardized values, the difference of 0.14 point between the two profiles was statistically significant ($t(796.94) = 2.09$; $p = .04$), and its effect size was small ($d = 0.15$).

Table 4.16

Models Summary for Self-Assessed Performance (Study 2)

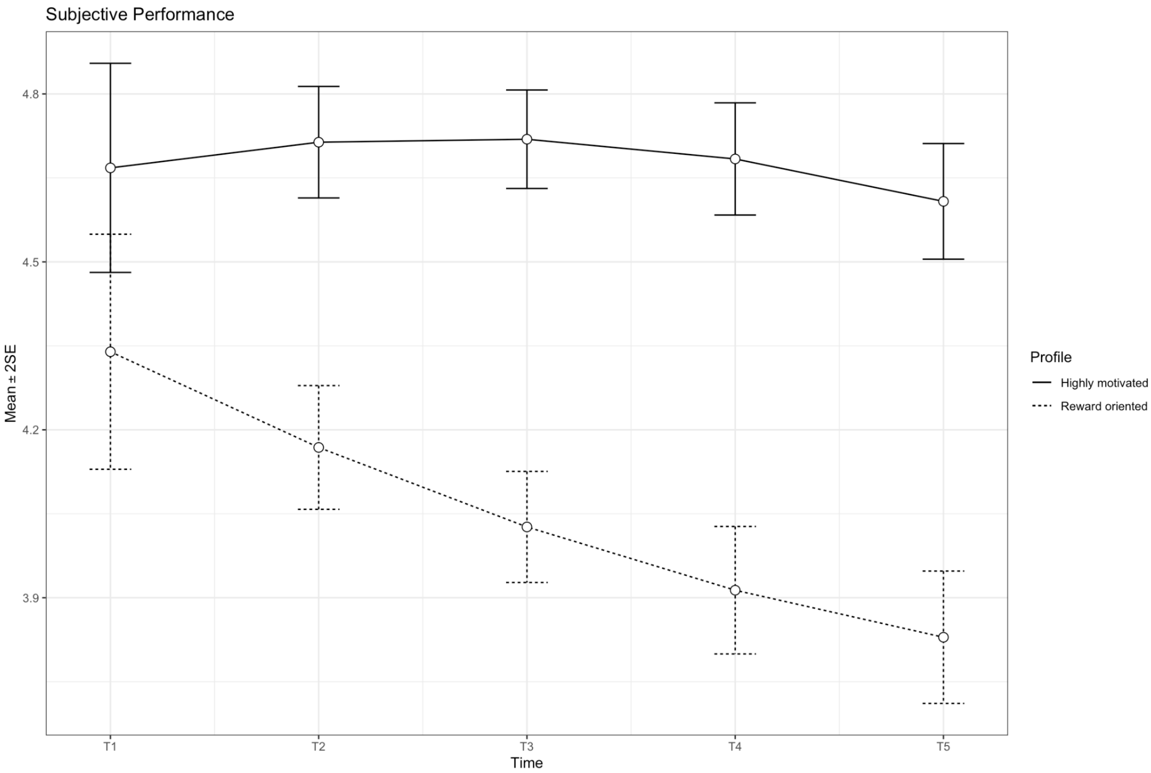
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**
Intercept	4.38***	4.85***	4.80***	4.81***	4.67***
	(0.03)	(0.05)	(0.06)	(0.08)	(0.10)
Register (linear)		-0.07***	-0.06**	-0.04	0.07
		(0.01)	(0.02)	(0.05)	(0.07)
Register (quadratic)				-0.01	-0.02
				(0.01)	(0.01)
Cluster B		-0.66***	-0.55***	-0.66***	-0.33*
		(0.06)	(0.09)	(0.06)	(0.14)
Register x Cluster B (linear)			-0.04		-0.25*
			(0.03)		(0.11)
Register x Cluster B (quadratic)					0.04*
					(0.018)
Observations	3,049	3,049	3,049	3,049	3,049
Log Likelihood	-4,323.46	-4,261.04	-4,262.38	-4,264.69	-4,267.19
AIC	8,662.92	8,542.08	8,546.77	8,551.39	8,560.37
BIC	8,711.10	8,602.29	8,613.00	8,617.62	8,638.64

Note. All models include random intercepts and slopes. Model (1): Null mixed model; Model (2): Mixed model with main effects (linear); Model (3): Mixed model with main and interaction effects (linear); Model (4): Mixed model with main effects (quadratic); Model (5): Mixed model with main and interaction effects (quadratic). AIC = Akaike information criterion; BIC = Bayesian information criterion

p* < .05; ** *p* < .01; * *p* < .001

Figure 4.5

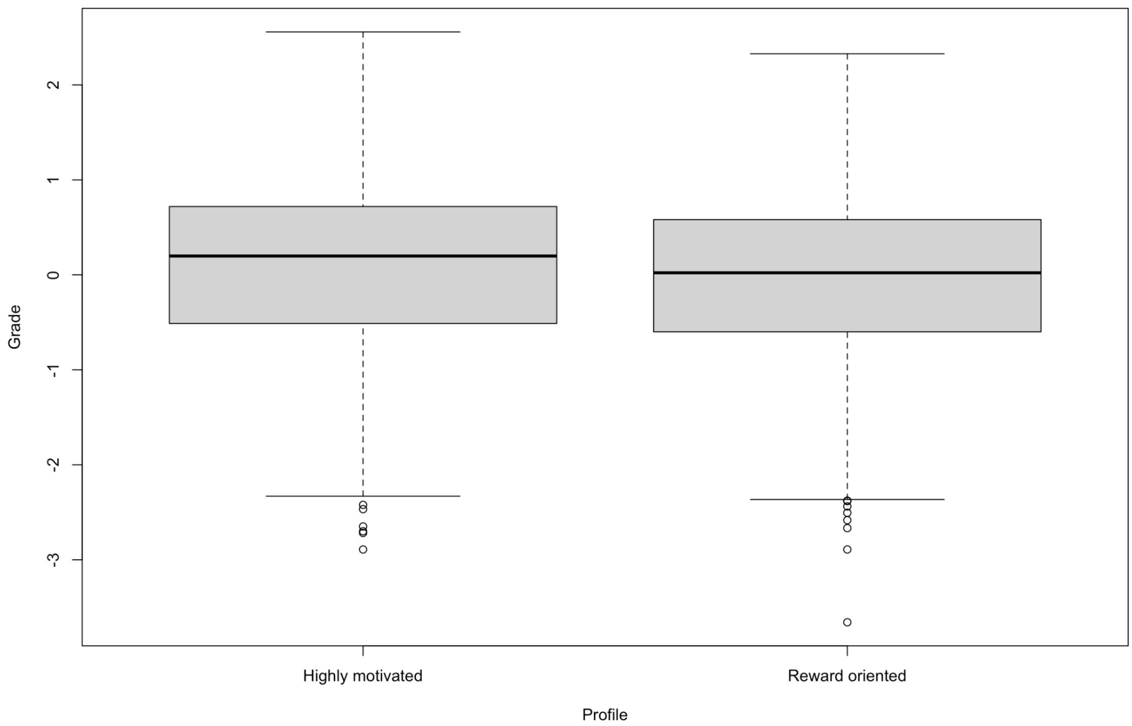
Estimated Trajectories of Self-Assessed Performance for the Two Profiles (Study 2)



Note. Marginal means plot shows the trajectories in perceived competence over the course of a semester for the two groups found in the multivariate clustering procedure. Means were estimated according to a mixed model with random intercepts and random non-linear trends (quadratic terms), including the interaction between occasions and groups.

Figure 4.6

Empirical Distribution of Standardized Final Grades in the Two Profiles (Study 2)



Note. Empirical distributions of standardized final grades in the two groups found in the multivariate clustering procedure. *Highly motivated* profile, *n* = 453; *Reward oriented* profile, *n* = 362.

5. Discussion

In the following lines, I first discuss the specific results obtained in Study 1 and Study 2. Then, I provide a general discussion integrating the findings from the two studies.

5.1. Study 1

The study had three aims. First, to investigate how academic autonomous motivation evolved over the course of an academic semester. Second, to explore whether students could be grouped in terms of motivational temporal dynamics they exhibited. Third, to examine whether different patterns of motivational change were related to students' self-assessed performance and final grades. The findings revealed that there was a general increasing trend in all motivation-related variables (i.e., flow preconditions and experiences, as well as intrinsic motivation and perceived competence) over one academic semester. Moreover, different patterns of increase were found across students. Finally, the association of these patterns with students' self-assessed performance and final grades was analyzed.

The results of the present research are consistent with the findings that confirm the existence of a dynamic character of motivation and flow in the academic context (e.g., Guay et al., 2021; Navarro et al., 2014), and with studies claiming that motivation and flow change over time in the work context (Ceja & Navarro, 2017; Gillet et al., 2018; Navarro et al., 2013; Roe, 2014). The ICC(1) values (.23, .32) demonstrated that 68-77% of the variability in academic motivation reflected within-person fluctuations. In other words, the observed variability occurred not only because students differed between each other in terms of the flow and intrinsic motivation they experience, but also because levels of motivation changed over time within students. Therefore, the analysis of longitudinal data allowed to examine individual change and capture a more detailed and complete accounting of student motivational processes.

Overall, high levels of intrinsic motivation and a general tendency for all the motivational variables to increase were observed – these results are in line with the findings of previous studies on university students' motivation (e.g., Kyndt et al., 2015; Ratelle et al., 2007). It is worth mentioning that the context of higher education exhibits two important characteristics. First, the studies are not compulsory. Second, compared to the lower levels of education, students can decide on the area of study to larger extent. Thus, one can assume that the motivation of university students might be higher than that of primary and secondary school students. Furthermore, it is important to highlight that participation in the present study was voluntary and, thus, a certain bias towards higher motivation or performance might be expected. Additionally, in the final analysis only those students who participated over at least five repeated assessments were included. The students who participated in additional, freely chosen activities, such as voluntary research, and attended most sessions were probably the most motivated students from the group. This fact is a limitation of the study and should be addressed in future investigation.

Strong statistically significant correlations were found between FBM and SDM on both levels of analysis (within- and between-persons) and moderate statistically significant correlations between both motivational variables and self-assessed performance. These findings confirm the results of previous research that support the relationship between flow and intrinsic motivation (Jackson et al., 2010), and between the two measures mentioned above and performance (e.g., Keller & Landhäußer, 2012). Nonetheless, previous studies focused only on between-persons correlations and the current research enhances these analyses with within-person measures. Regarding the final grades, the only statistically significant and positive correlation was with self-assessed performance, and it was relatively low (r = .37). However, it should be noted that in this case the final grade was the outcome of many partial evaluations, including teamwork grades. This might explain a lack of correlation between final grades and the motivational variables, and a weak correlation between the final grades and self-assessed performance.

While the general trend observed was for motivation to increase over the course of the semester, a more detailed analysis allowed for the distinction between two different patterns of motivational change among students: one reflecting modest increase and another reflecting strong increase. Given the conceptual background of the measures, these classes can be interpreted in terms of the requirements that the activities should meet to enhance flow, perceived competence, and intrinsic motivation. One can easily observe that motivation levels of some students were clearly increasing over time, suggesting that the learning activities proposed during the sessions helped these participants get the optimal experience, perceive themselves as competent, and maintain intrinsic motivation over the semester. However, most of the participants did not experience substantial increases in motivation. It is likely that for the group with a modest increase, the activities proposed during some sessions did not meet the conditions required for flow, perceived competence, and intrinsic motivation to the same extent, as would be the case in the group with a strong increase. These findings may be of great relevance for both practitioners (i.e., teachers) and researchers, as they make us think about what may provoke these differences in response to the activities observed among students. The important questions to answer may be: which students' individual differences are important to understand this heterogeneity in motivational patterns? How the design of learning activities can be improved to enhance the learning experience of more students? Given that the participants were rather homogenous in terms of a general trend of motivational change, one can hypothesize that in more heterogeneous samples these differences would be greater, or that more different classes would be distinguished (e.g., a class where motivation decreases).

All these questions encourage further exploration of this area of research on motivation. Specifically, it would be interesting to pay more attention to the details of the learning activities that students perform. The current study provides little information on the nature, organization, and delivery styles of the activities that the students completed over the semester, and we consider this a limitation. For example, one can expect that the students would be more intrinsically motivated towards an elective course that is closely related to their interests, than towards a mandatory core course in case of which the link with the preferred area of study is weaker (e.g., psychology students interested in clinical psychology may find a psychometrics core course less appealing than an elective course on anxiety disorders). Another factor related to students' motivation is the learning environment created by the teacher. For example, numerous studies confirmed that the teaching style that supports students' basic needs of autonomy, competence, and relatedness (e.g., provides positive feedback, shows, empathy, offers choice) foster intrinsic motivation (e.g., Reeve & Cheon, 2021). On the contrary, a need-thwarting style that relies on extrinsic rewards and punishment and uses social comparisons and controlling feedback decreases intrinsic motivation (e.g., Orsini et al., 2015). I also recommend collecting qualitative data about the learning process of the students and include other variables that address students' individual differences (e.g., related to the different learning styles; Kolb et al., 2001). Such information could provide important insights to understand different patterns of students' motivational changes.

The final aim of this study was to examine whether different patterns of motivational change were associated with performance. Given the high percentage of variability reflected in the intra-personal changes, the longitudinal design of the current study reflects much more accurately the relationship between students' overall motivation during the course and their academic results, compared with the cross-sectional designs. These findings confirm that FBM- and SDM-related patterns are associated with students' self-assessed performance. Specifically, statistically significant differences in performance were found between the strong improvement and the modest improvement pattern groups. A similar relationship was also found between SDM-related change patterns and students' final grades. These results are in line with the findings of Guay et al. (2021), according to which, the students that experienced a strong increase in a global score of self-determined motivation, were achieving the highest performance over three consecutive school years. However, similar differences were not observed for FBM-related patterns and final grades. It is important to keep in mind that the sample was rather homogenous – I speculate that the more diverse the students are in terms the patterns of motivational dynamics they experience, the greater the individual differences in performance. Thus, I recommend further exploration of this issue in future research.

The way performance was assessed in the present study can also be improved. First, I recommend examining validity of the self-assessed performance scale. Second, given the differences between the activities evaluated in each "class-group", as well as limited time that that we had to apply the questionnaire in every session, in the present study performance was measured only once. However, findings from previous studies demonstrate that performance is dynamic rather than static and it may vary even over a short extent of time (e.g., Sonnentag & Frese, 2012). For this reason, I recommend treating performance as a process, instead of as a distal outcome, and measure it repeatedly over the course of the semester. With more repeated measurements of performance levels, we could have studied academic performance dynamics with more detail and accuracy. Furthermore, it would be possible to analyze patterns of change among students and to make predictions about their results for the future. Such knowledge could have practical implications for teachers and be an important tool for improving students' performance.

5.1.1. Additional Limitations and Recommendations for Future Research

One of the important limitations of the study is its exclusive focus on intrinsic motivation. According to previous research in the educational setting, students tend to perceive schoolwork as compulsory, not freely chosen (e.g., Bassi & Delle Fave, 2012b), thus, their motives may be more extrinsic than purely intrinsic. For this reason, extrinsic motivation should be considered and measured in future research. Considering both dimensions of motivation, intrinsic and extrinsic, would certainly give a more detailed insight into the dynamics that occur during the learning process. The current study is strongly influenced by the model proposed by Abuhamdeh (2012) and focused on the variables reflected in that model. However, it would be interesting to include the measure of students' autonomy related to performed activities, as well as the quality of the interpersonal relationships they experience in those educational activities. This would allow testing the effects of different psychological ingredients or needs on motivation. Moreover, the relationship between motivational variables could be further explored. For instance, it would be interesting to conduct cross-lagged analyses of measures and study how motivation and flow may influence each other over time. Finally, in Study 1, the data analysis was conducted using latent class mixture growth modeling applied to questionnaire data obtained in class sessions. However, other sources of information could be considered in future work to get a more in-depth description of the learning process. In this regard, using daily diary data combined with longitudinal modeling (see Schmitz & Wiese 2006, for example) might be a useful alternative to the approach implemented in this study.

5.2. Study 2

The first goal of this study was to identify motivation profiles, based on configurations of different forms of motivation and different multivariate trajectories of these forms. The second objective was to describe the identified profiled in terms of trajectories of perceived competence and perceived challenge. Finally, the study aimed to analyze self-reported performance and final grades of the students who belonged to different profiles.

According to the results, the differences in motivation in the studied sample were best represented by two profiles, what is in line with Hypothesis 2.1.1, and with the number of profiles obtained by Nishimura and Sakurai (2017). However, this result is different from the findings of a considerable number of person-centered studies on motivation (Baars & Wijnia, 2018; Boiché & Stephan, 2014; Cannard et al., 2016; Gillet, Morin, et al., 2017; González et al., 2012; Hayenga & Corpus, 2010; Hill, 2013; Kusurkar et al., 2013; Litalien et al., 2019; Liu et al., 2009; Ratelle, et al., 2007; Vansteenkiste et al., 2009; Wormington et al., 2012), in which the number of distinguished subgroups was higher, typically ranging from three to six. According to Gillet et al. (2018) the number of profiles can be related to the complexity of the applied model. Specifically, low number of profiles may be a result of using several, highly correlated processes in profiling. In turn, profiling based on one process at a time or on a single global self-determination score may result in higher number of subgroups.

The first profile obtained in the current study was characterized by high and relatively stable levels of intrinsic motivation, identified, introjected, and material external regulations, and low levels of social external regulation and amotivation, supporting Hypothesis 2.1.2. This profile, labelled *Highly motivated*, can be compared to the *Multifaced* profile found by Litalien et al., (2019), the *Combined* profile distinguished by Cannard et al. (2016), *Combined stable* profile in the study by Chevrier & Lannegrand (2021), the *High* and *High-Stable* profiles found by Guay et al. (2021), or to the *High* profile obtained by Gillet et al. (2018). It is worth noticing, however, that in the studies by Gillet et al. (2018) and Guay et al. (2021), the trajectory analysis relies on a global factor of self-determination, thus, it is impossible to explore the changes that occurred in specific factors of motivation. Although the trajectories in *Highly motivated* profile were characterized as stable, I observed a slight decrease in more autonomous forms of motivation and an increase in external regulation. I hypothesize that this change might be caused by external pressures related to the course evaluation, which in this case was more present at the end of the semester. The second profile, labelled *Reward oriented*, was characterized by high levels of material external regulation, moderate and decreasing levels of intrinsic motivation, identified regulation and introjected regulation, and relatively low levels of social external regulation and amotivation. The configuration of motivational forms found in this profile can be compared to the results obtained by Boiché et al. (2014; *Non-self-determined* profile), and by Litalien et al. (2019; *Controlled* profile). Nevertheless, in these studies the profile analysis is based on only one measurement occasion.

Previous person-centered studies on academic motivation provided certain evidence for a profile characterized by high autonomous motivation and low controlled motivation and amotivation (e.g., Boiché & Stephan, 2014; Cannard et al., 2016; Gillet, Morin, et al., 2017; Ratelle et al., 2007). However, in the current research such profile was not distinguished. This finding may be related to strong external controls and constrains present in the studied context. Given that higher education is considered a less constrained setting (Ratelle et al., 2007), the results of the present study are surprising. One could expect that a non-mandatory and freely chosen studies are a context that enhances a development of intrinsic motivation. Therefore, a lack of a group where intrinsic motivation is dominant may suggest that some characteristics of the setting enhanced the development of controlled forms of motivation and inhibited autonomous motivation. Although the courses the participants of the study took were a part of higher, non-mandatory education, it is worth noting that they were also core courses, which are compulsory for all the students. Moreover, some of these courses might not be directly related to the students' interest (e.g., psychology students who are interested in clinical psychology, are required to complete a statistics course). Ratelle et al. (2007) highlighted the opportunities to make choices as an important characteristic of the contexts that support autonomous motivation. In case of the students who participated in the present research, the span of choice might be limited. Another factor existing in the studied context and related to the quality of students' motivation may be the evaluation system based on the use of extrinsic incentives (i.e., grades). Undermining effect of external rewards, such as grades or scholarships, for intrinsic motivation has been well documented in previous research (e.g., Cameron et al., 2001; Deci et al., 1999; Moller & Sheldon, 2020). Therefore, one could hypothesize that the use of external rewards enhanced external motivation and hindered intrinsic motivation in the studied sample. One of the important contributions of the present research is analyzing two forms of external regulation, material and social, in a student sample. Although differences between these two dimensions were signalized by the authors of SDT (e.g., Deci et al., 1999), and documented in the work setting (e.g., Gagné et al., 2015; Howard et al., 2018), to the best of my knowledge, they have never been explored in the academic context. However, the evidence from neuroscience suggests that diverse reactions to material and social stimuli can be observed in humans at any age (e.g., Rademacher et al., 2010; Spreckelmeyer et al., 2009; Wang et al., 2020). The results of this investigation revealed differences between material and social form of external regulation: whereas in both profiles material external regulation was the motivational variable that consistently showed the highest values over time, the levels of social external regulation were low. These findings are in accordance with insights from previous research that demonstrated a stronger response to material than to social rewards in samples of students (Wang et al., 2020). It is often suggested that the relevance of social and material rewards changes with age. For example, Altikulaç et al. (2019) demonstrated that the importance of social rewards (specifically, the importance of positive attention from others) shows a peak in late adolescence/young adulthood (age of 21 – 22 years). These conclusions are quite different from the findings of the current research. Such discrepancies may suggest the existence of other factors that determine the importance of social rewards. For instance, students' extrinsic motivation or their attitudes toward social rewards may be determined by culture (e.g., Carlo et al., 2018; Nishimura & Sakurai, 2017). As an example, social demands and norms are considered an important motivator in the academic context in East Asian cultures (Nishimura & Sakurai, 2017). For this reason, the distinction between two forms of external regulation may be particularly interesting in cross-cultural studies.

Once the two clusters were identified, we analyzed the trajectories of perceived competence and perceived challenge in each profile. In accordance with Hypotheses 2.2.1 and 2.2.2, and with the insights from previous research (e.g., Diaconu-Gherasim et al., 2020; Fong et al., 2015; Honicke & Broadbent, 2016; Koka & Hein, 2003; Mitchell, 1996), the levels of perceived competence and perceived challenge were higher in the *Highly motivated* profile which, compared to the *Reward oriented* profile, showed higher and more stable levels of autonomous motivation over time. It is important to notice, however, that students in both groups showed strong orientation toward material external rewards. This finding shed new light on previous of integrating perceived competence and perceived challenge in one theoretical framework. According to the model proposed by Abuhamdeh (2012), the exploratory potentials of perceived competence and perceived challenge depend on one's motivational orientation: whereas the exploratory potential of perceived challenge is higher when the motivational orientation is intrinsic, perceived competence explains better motivation driven extrinsically. Given the results of this study, as well as growing evidence from person-centered research suggesting that individuals can experience multiple configurations of motivation, a model that consider intrinsic and extrinsic orientations the opposite poles of one motivation continuum (i.e., a strong inclination to one of the poles excludes high levels of the other pole) seems too simplistic. In this research, the levels of external regulation, material and social, were similar in both profiles. Undoubtedly, comparing these profiles with groups where autonomous or controlled motivation is clearly dominant would be very insightful. However, in the present study such profiles were not distinguished.

Given the longitudinal design of the current research, it was possible to analyze trajectories of perceived competence and perceived challenge. The change patterns of perceived competence were in line with the trajectories of intrinsic motivation: stable in *Highly motivated* profile, and slightly decreasing in *Reward oriented* profile, what is in line with the theoretical underpinnings (Ryan & Deci 2017, 2020) and previous research (Diaconu-Gherasim et al., 2020; Guay et al., 2001; Vallerand & Reid, 1984; Van den Broeck et al., 2016). The optimal challenge, however, showed an increasing trend in both samples, what is contrary to the premises of flow theory. Considering the basic assumptions of flow theory and CET, one could expect that an increase in perception of the challenge as optimal, would be related to an increase of intrinsic motivation. On the contrary, in the current research, an increase of perceived challenge observed in both profiles, was not related to an increase in intrinsic motivation. A possible justification of this result may be supported by the said model proposed by Abuhamdeh (2012). Given that explanatory potential of perceived challenge is expected to be weaker when the motivational orientation is extrinsic, one could hypothesize that the high levels of material external regulation inhibited the power of optimal challenge as a condition to enhance intrinsic motivation. Research on enjoyment, which is closely related to intrinsic motivation (Reeve, 1989), provide some additional insights that may be helpful to understand the opposite trends of optimal challenge and intrinsic motivation. For example, Engeser and Rheinberg (2008) showed that the relationship between the challenge difficulty and enjoyment was moderated by perceived outcome importance, and in case of tasks which outcome was perceived as important, the participants enjoyed more when their skills were higher than the challenge. Assuming that the grades are perceived as an important outcome for most of the students, it is reasonable to expect that in the sample used in this study lower levels of challenge would be associated with greater enjoyment and intrinsic motivation.

The final goal of the study was to analyze predictive validity of the two profiles with respect to students' self-reported performance and their final grades. The students in the *Highly motivated* profile experienced higher and more stable levels of self-assessed performance than the participants in *Reward oriented*. Moreover, the *Highly motivated* students obtained significantly higher grades, compared to their *Reward oriented* colleagues. Therefore, Hypotheses 2.3.1 and 2.3.2 are supported. Moreover, these results are in line with the findings of previous person-oriented studies on motivation (González et al., 2012; Kusurkar et al., 2013; Vansteenkiste et al., 2009; Wormington et al., 2012). Nevertheless, given that in the present research a profile characterized by high levels of autonomous motivation and low levels of controlled motivation was not observed, the effect that external motivation may have on the of intrinsic motivation and students' results could not be assessed.

5.2.1. Limitation and Recommendations for Future Research

There are four principal aspects that I recommend to further develop in future research. First, I suggest examining relationship between the profiles based on the trajectories of regulatory styles and variables considered antecedents or outcomes of academic motivation. Although in the present research the trajectories of perceived competence, perceived challenge and self-assessed performance, and students' final grades were analyzed, I acknowledge that certain variables crucial for the development of intrinsic motivation in academic context, for example autonomy (Dysvik et al., 2013; Pulfrey et al., 2013), could also have been examined. Furthermore, using study designs that allow analyzing the causal relationship between the variables (e.g., randomized controlled trials, cross-lagged designs) and exploring possible moderators and mediators of these relationships, would be of particular interest.

Second, I recommend measuring social and material external regulation in the educational setting. Given the obtained results and insights from previous research on different impact of material and social rewards on motivation (Altikulaç et al., 2019; Rademacher et al., 2010; Wang et al., 2020), analyzing these two external regulation forms in samples of students from different stages of education (i.e., primary school, secondary school, high school, college), or cultural contexts (e.g., collectivistic versus individualistic cultures) is strongly suggested.

Third, I encourage to study more in detail the research context. In particular, information about factors that contribute to the development of autonomous and controlled motivation (e.g., teaching strategies that satisfy or frustrate students' basic psychological needs, or the choices that students can make regarding the courses they take) would be of enormous value to understand the configurations of regulatory styles observed within profiles.

Finally, it must be acknowledged that in the present research the decision regarding the best cluster solution relies strongly on the statistical criterion. Given the exploratory character of the research on profiles of academic motivation, the statistical adequacy is a dominant criterion to define the optimal number of clusters in many person-centered studies on motivation (e.g., Chevrier & Lannegrand, 2021; Gillet, Morin, et al., 2017). However, it is important to highlight that the optimal number of profiles should be also sustained by substantive meaningfulness and theoretical conformity (e.g., Marsh et al., 2009). Thus, I strongly recommend complementing the statistical analysis with a careful exploration and comparison of the profiles' meaning and theoretical significance in future research.

5.3. General discussion

The present thesis offers several contributions to the person-centered studies on motivation. First, it contributes to the ongoing debate about the direction of changes observed in academic intrinsic motivation. Although according to some studies students' intrinsic motivation tends to increase over time (Kyndt et al., 2015; Lee & Kim, 2014), a substantial body of research suggested the opposite trend (Eccles et al., 1996; Gottfried et al., 2001; Lepper et al., 2005; Otis et al., 2005; Weidinger et al., 2017; Wigfield & Eccles, 2002). The results obtained in the current dissertation are not conclusive. In Study 1, intrinsic motivation was increasing during the semester, and in Study 2, autonomous forms of regulation (i.e., intrinsic motivation and identified regulation) were decreasing. Frequently, the differences in the direction of motivational trajectories are attributed to the context, specifically, to the education stage (i.e., primary school, secondary school, high school, etc.). The current research based on the very similar samples of undergraduate students from the same Spanish university, thus, in this case, the differences in the direction of motivational dynamics cannot be explained by diversity related to participants' education stage. Nevertheless, it is important to highlight that the previous studies were focused rather on long-term changes in motivation (i.e., years), which may be related to the process of human development or to the general characteristics or demands of different levels of education. On the contrary, the studies that are part of this thesis focus on short/mid-term changes in motivation (i.e., one semester). In this sense, different directions of motivational dynamics can be a result of specific characteristics of the context (e.g., type of classes: theoretical vs practice-oriented; teacher's characteristics: autonomy support, teacher's motivation level). A more detailed analysis of these context-related factors could help understand better the differences in motivational trends that characterized specific groups of students.

The second objective of the thesis was to explore whether students can be grouped based on different configurations of motivation that they experience over time. Similarly to the result was obtained by Nishimura & Sakurai (2017), in Study 1 and Study 2 two profiles were distinguished. This outcome is different from the results of the most of previous person-centered longitudinal studies, which distinguished typically between three and six subgroups of respondents (see Annex A.2). As suggested by Gillet et al. (2018), a lower number of profiles may be related to the fact that the profiling was based on several, highly correlated growth processes. Using one process at a time, or relying on a single score of global self-determination, might have resulted in more numerous profiles.

The third aim was to analyze qualitative characteristics of the motivational profiles found in the studied sample. Before describing the details of the obtained profiles, it is worth reminding that Study 1 focused exclusively on the variables related to autonomous regulation (intrinsic motivation, perceived competence, preconditions of flow and flow experience), what is considered a limitation. For this reason, in Study 2, different forms of motivational regulation (i.e., autonomous, controlled, amotivation) were included. According to the results of Study 1, in which latent class analysis was conducted separately for flow-related and self-determination-related variables, the differences between the profiles were based on the trajectory trend. Whereas in one of the profiles the level of motivation-related variables was growing strongly over time, the second profile was characterized by a modest increase. Similar results were found by Guay et al. (2021), the profiles found by these authors varied depending not only on the level of self-determination, but also on the growth intensity observed over time. Although four out of five profiles were characterized by rather stable trends, Profile 5 (*Increasing*) presented a marked incrementing trend of global self-determination. In Study 2, the fluctuations of motivation were more subtle. The differences between the two profiles were based mainly on the level of different forms of motivation (rather than on the trajectory trend). Both profiles were characterized by very high levels of external-material regulation. First of them presented also average to high, slightly decreasing levels of all motivational forms over time, except social external regulation, which, similarly to amotivation presented low levels and slightly increasing trend. This subgroup was called *Highly motivated* and could be compared to the *Multifaced* profile found by Litalien et al., (2019), or to the *Combined* profile distinguished by Cannard et al. (2016). The second profile, named as *Reward oriented*, presented high but slightly decreasing levels of external-material regulation, moderate and decreasing levels of identified and introjected regulations and intrinsic motivation, and low but increasing levels of external-social regulation and amotivation. A similar trend was previously found by Boiché et al. (2014; *Non-self-determined* profile), and by Litalien et al. (2019; *Controlled* profile). Interestingly, most of the previous person-centered studies on academic motivation distinguished a profile, in which autonomous forms of motivation were clearly dominant (e.g., Boiché & Stephan, 2014; Cannard et al., 2016, Gillet, Morin, et al., 2017; Ratelle et al., 2007). Such profile was not obtained in Study 2. This result may suggest that the context of the study is characterized by strong extrinsic controls and constraints. Considering the evidence from previous research (Ratelle et al., 2007), as well as the high and increasing levels of variables in Study 1, this result is quite surprising. Non-mandatory and freely chosen university studies are considered a setting characterized by lesser constraints, in which students (at least some of them) can develop autonomous motivation and are less driven by external rewards. For this reason, a more detailed examination of the context characteristics is advised, as it could help understand the mechanisms underlying students' autonomous and controlled motivation. It is important to mention that previous person-centered studies conducted in the context of education did not explore different forms of external regulation. On the contrary, in the current thesis the MWMS (Gagné et al., 2015) was adapted to the academic context and applied to measure students' material and social external regulation. Additionally, the temporal invariance of MWMS applied to the sample of university students was confirmed. In Study 2 the two types of external regulation show very different levels in both profiles; whereas the material regulation was considered the main motivator in both subgroups, the levels of social regulation were very low and comparable to amotivation. This result is in line with the findings of previous studies on reward processes (e.g., Rademacher et al., 2010; Wang et al., 2020), according to which material rewards are more likely to elicit a response in participants' behavior than social rewards. On the other hand, given the evidence from research, in which the relevance of social rewards had its peak in adolescence/young adulthood (e.g., Altikulaç et al., 2019), the low levels of social external regulation found in Study 2 may surprise. However, it is important to bear in mind that the levels of extrinsic motivation, or attitudes toward social reward may be shaped by several factors, such as culture (Carlo et al., 2018; Nishimura & Sakurai, 2017), or reward magnitude (Wang et al., 2020). Therefore, a further and more detailed analysis of the differences between social and material forms of external regulation is highly recommended.

The fourth goal of the current dissertation was to analyze how the obtained profiles are associated with academic achievement. It is important to highlight that the measure of students' performance used in this thesis relied not only on self-assessment, but also on the evaluation provided by the teachers, i.e., final grades. The results of both studies confirmed that intrinsic motivation is positively related to both forms of academic performance (self-reported, as well as students' final grades). Specifically, in Study 1, the students that experienced a stronger increase of motivation-related variables (*Strong increase* profiles) achieved better results than the students, whose motivation increased more modestly (*Moderate increase* profiles). To the best of my knowledge, no previous study has analyzed the relationship between profiles based on trajectories of different forms of motivation and performance. However, a similar result was obtained by Guay et al. (2021), who compared performance of students characterized by different trajectories of the global self-determination score. In this research, students who experienced the highest increase of the global level of self-determination (*Increasing* profile) were achieving the best performance consistently over two consecutive school years. It is important to mention that the students from the *Increasing* profile outperformed their colleagues whose global score of self-determination was consistently high (*High* and *High-stable* profiles). According to the results of Study 2, students that presented moderate to high levels of different forms of self-determination (except for social external regulation) and low level of amotivation, outperformed the students whose regulation was mainly external material. Given that in Study 2 a profile in which autonomous forms of motivation would be dominant was not distinguished, it was impossible to draw conclusions regarding the effect of extrinsic motivation on the relationship of intrinsic motivation and performance. However, the results confirm that students from the profile in which external regulation was accompanied by moderate to high levels of autonomous forms of motivation achieved better performance, compared to the profile in which external-material regulation clearly dominated other forms of regulation. These findings are aligned with the results of previous person-centered cross-sectional studies on motivation (González et al., 2012; Kusurkar et al., 2013; Vansteenkiste et al., 2009; Wormington et al., 2012). Moreover, in Study 2, the self-assessed performance was measured longitudinally, thus, we could observe the pattern of change of this variable in the two profiles. Specifically, self-assessed performance of *Highly motivated* students, was not only higher, but also more stable, compared to the *Reward oriented* students.

In addition, this thesis examined some possible antecedents of the motivational profiles. In the first study no predictor variable was included. However, this limitation was addressed in the second study, in which perceived competence and perceived challenge were measured. In accordance with previous research, both perceived competence and perceived challenge were related more strongly to the profiles with higher levels of autonomous motivation (e.g., Diaconu-Gherasim et al., 2020; Fong et al., 2015; Honicke & Broadbent, 2016; Koka & Hein, 2003; Mitchell, 1996).

Finally, it is important to mention that the research included in this dissertation make an important contribution to the longitudinal and person-centered research on motivation. Responding to the limitation of Study 1 related to the exclusive focus on intrinsic motivation, in Study 2, we decided to use the MWMS (Gagné et al., 2015) to measure a broader spectrum of motivational forms. To ensure that the changes observed in the latent constructs correspond to actual variance in motivation, and not to the changes in measurement, the temporal invariance of the MWMS was examined. To my best knowledge, the additional study conducted for the purpose of this thesis (Appendix C) is the first research to analyze psychometric properties of the MWMS applied longitudinally in an educational setting, using the state-of-art bifactor-ESEM model. The results confirmed that this model represented best the structure of academic motivation in the studied sample, distinguishing both, a global factor and specific factors of motivation. Moreover, the findings supported strict longitudinal invariance of the MWMS applied in the educational context across five measurement occasions, ensuring that the variance in the MWMS scores across time was a result of the dynamics of motivation, not of the variability of the measurement tool. These results encourage further use of the MWMS to measure academic motivation longitudinally.

5.3.1. Limitations and Directions for Future Research

Although the present doctoral thesis makes several important contributions to the person-centered research on motivation, it has certain limitations, which need to be kept in mind. First, only two predictors of the motivational profiles have been examined. Although in Study 2 perceived competence and perceived challenge were analyzed, exploring more variables that may determine motivational trajectories and profiles related to these trajectories is strongly recommended. Different kinds of variables could be examined: context-related, e.g., the format of the session (theory- or practice-oriented), teacher characteristics (e.g., teacher's motivation, autonomy support; Vansteenkiste et al., 2004) or individual differences between the students (e.g., their perceived autonomy, which, according to SDT, is one of the essential conditions for autonomous motivation; Ryan & Deci, 2017, Chapter 6; or learning styles; Kolb et al., 2001). Such information can certainly shed light on the mechanisms underlying motivational profiles and bring valuable insights about why some students are more prone to develop autonomous motivation than others.

Second, a further exploration of material and social external regulation in the academic context is suggested. Given the evidence about variability in attitudes towards social and material rewards (Altikulaç et al., 2019; Wang et al., 2020), analyzing differences in levels of these two forms of external regulation in samples of students from different stages of education (i.e., primary school, secondary school, high school, college), or cultural contexts (e.g., collectivistic versus individualistic cultures) would be particularly interesting.

Regarding the context of the research, both studies included in this thesis focused exclusively on a sample of undergraduate students in a Spanish university. Hence, the third recommendation is to continue broadening the context of person-centered studies by including samples, in which the trajectories of specific dimensions of motivation have not been studied so far (e.g., students from different levels of education, employees, athletes).

Fourth, we suggest considering further improvements in the measurement of academic performance. In the current research, both forms of performance, self-reported and final grades, were studied. However, only self-assessed performance was measured longitudinally. Thus, I strongly recommend examining temporal evolution of students' academic. Furthermore, I encourage to investigate how changes in performance may affect different motivational profiles.

Finally, given the increasing number of person-centered research on motivation, including studies with longitudinal design, a systematic review and meta-analysis of the results about motivational profiles is recommended. A good starting point for such analysis could be the summary of the trajectory-based person-centered studies on motivational profiles included in Appendix A of this thesis. Meta-analysis may provide answers to some unsolved issues, for instance, the cumulative effect of autonomous and controlled motivation on performance. It would also increase the generalizability of the findings of individual studies.

6. Conclusions and Practical Implications

In summary, there are several conclusions that emerge from the thesis. First, academic motivation is dynamic and different patterns of changes can be observed in students' motivation over the period of a semester. Second, students are characterized by different configurations of motivational forms (i.e., autonomous vs controlled) and trajectories. Third, extrinsic motivation of undergraduate students can have two different sources: material and social. Whereas university students tend to be strongly motivated by material rewards (e.g., grades), social rewards (e.g., recognition or praise) seem to motivate them in a lesser extent. Fourth, the students who show higher and more stable or increasing levels of autonomous motivation, compared to the colleagues whose autonomous motivation is lower and decreasing, are likely to perform better, to perceive themselves as more competent, and to see the challenge at hand as more optimal.

Furthermore, the present doctoral dissertation allows to draw several conclusions that are relevant for practitioners. In general, person-centered approaches enable a more holistic and realistic study of individuals, what makes them particularly relevant for practitioners. In the academic context, this approach allows to distinguish subgroups of students, which share similar characteristics or pattern of behavior. Therefore, the teaching practices can be adjusted more accurately to address specific needs of different groups of students. Regarding the specific findings of the research included in this thesis, there are two important implications for practitioners that need to be highlighted. First, although external rewards (e.g., grades) are a very strong motivator and seem an inherent part of most educational systems across the globe, students tend to achieve better results when motivated by a combination of intrinsic and extrinsic reasons. Therefore, it is important to incorporate practices, which help increase students' autonomous motivation. In the present research two variables relevant for students' intrinsic motivation have been explored: perceived competence and perceived challenge. According to the premises of SDT, perceived competence could be improved through feedback (Ryan & Deci, 2000). Several research examined which feedback's characteristics can contribute to higher perceived competence and to the development of intrinsic motivation. For example, in their meta-analysis, Fong et al., (2019) found that intrinsic motivation tends to be higher after receiving positive feedback than after receiving negative feedback. However, if negative feedback provides constructive criticism, or instructions about how one can improve, it is more intrinsically motivating than negative feedback which does not have such informational value (Deci et al., 1999). Hence, complementing quantitative grades with qualitative feedback, which would inform students about their progress, and the way they can improve, is strongly recommended. Optimal challenge is the second condition, which was found to be related with higher levels of autonomous motivation in the distinguished profiles. This finding suggests the importance of adapting the difficulty level of the learning activities to the students' skill level. Given the challenges related to the context (e.g., large class size) or individual differences between the students (e.g., intelligence, skills and abilities, learning style, personality) that teachers frequently face, monitoring and adjusting the difficulty of the task individually seem particularly demanding. Nevertheless, there are certain teaching advances that aim to address this issue. One strategy that helps create engaging learning environment may be a combination of gamification (i.e., applying game features in the non-game environment) and technology, that is, learning programs where the students can study in their individual pace adapting the task difficulty to their individual skill level. Another strategy could be offering students more autonomy in learning (e.g., possibility of choosing a specific topic to analyze within a broader area of study).

Another factor that the practitioners should be aware of is related to the dynamic aspects of motivation. The profiles characterized by increasing levels of autonomous motivation and related variables (Study 1), or those, which presented a stable and moderate to high levels of motivation (Study 2) obtained the best results. Thus, teachers should consider the importance of maintaining (or increasing) motivation over semester, when designing learning activities and evaluation system. The practices that aim to develop students autonomous should be ongoing. For example, it is recommended to provide students with continuous feedback on their progress rather that evaluate their performance only once, in the occasion of the final exam.

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Supplementary materials

S1. Study 1

S1.1. Latent Class Mixed Models

Latent process mixed models are carried out to describe linear and nonlinear trajectories (Proust-Lima et al., 2017). This approach separates the structural model that describes the latent process according to time (and, if necessary, depending on a set of different covariates) from the measurement model, which links the latent process to the observed variables across time.

The general expression of a linear mixed model is:

$$Y_{ij} = X_{Li}(t_{ij})^T\beta + Z_i(t_{ij})^T u_i + w_i(t_{ij}) + E_{ij}$$

where X and Z are vectors of covariates associated to the fixed (β) or random effects (u) to predict responses (*Y*) at *j*-th time *t* for the *i*-th individual.

When having a latent process, the mixed model is:

$$\Lambda_i(t) = X_{Li}(t_{ij})^T\beta + Zi(t)^T u^i + wi(t), \forall t \in R$$

The response now corresponds to a latent variable, $\Lambda_i(t)$, that relates to the observed indicators by a specific link function. To include nonlinearity, this family of models allows to add flexible nonlinear link functions in the measurement model (for technical details regarding this model see Proust-Lima et al., 2017), that is, different relationships between observed indicators and latent variables. We used splines for the measurement model including flow-based motivation (FBM) and linear transformations for the model with self-determined motivation (SDM). The reason for this decision was the fact that splines could not be used with (SDM) since most of the models did not converge to a solution.

In case of dealing with latent classes the previous model becomes:

$$\Lambda_i(t)|_{ci=g} = X_{L1i}(t)^T\beta + X_{L2i}(t)^T\upsilon_g + Z_i(t)^T u_{ig} + w_i(t_{ij})$$

Note that now the fixed effects have a common and a class-specific part for each class *g*. In this regard, latent class membership is specified by using posterior classification according to heterogeneous trajectories of the latent process along time.

The previous model imposes the location constraint that the intercept of the first class (i.e., the reference class) is equal to 0. Besides, it has a scale constraint: the variance of the intercepts is equal to 1.

References

Proust-Lima, C., Philipps, V., & Liquet, B. (2017). Estimation of extended mixed models using latent classes and latent processes: The R package lcmm. *Journal of Statistical Software*, *78*, 1–56. https://doi.org/10.18637/jss.v078.i02

S1.2. Modeling Routine

The steps to fit different latent mixed (i.e., latent growth) models to the individual trajectories using latent class mixed models are the following:

1. Specify a null model with random intercepts. We started specifying 2 classes in the model.

2. Add a linear time-dependent change in trajectories, that is, latent processes vary linearly as a function of time.

3. Add a quadratic time-dependent change in trajectories allowing, thus, that latent processes vary non-linearly as a function of time.

4. Add a cubic time-dependent change to include more complexity in the nonlinear trajectories of the latent processes over time.

5. In steps (2) to (4) we studied different specifications for the random part. In decreasing order of complexity: all random effects (e.g., linear, quadratic, and cubic terms as well as intercepts in models of step (4), only random linear effects and intercepts, and only random intercepts.

6. Choose the best model by inspecting the goodness of fit indices (AIC and BIC).

7. For the best model chosen so far, we tried to reduce the complexity of the model (i.e., the number of parameters to be estimated) by fitting this model under a number of different classes. Those models with lower BIC were kept as a final model.

8. To avoid the risk of having obtained a local maximum as a final solution we re-estimated the best model found 100 times using random starting points for the initials parameters values.

S1.3. Statistical Description of Measurement Occasions

Table S1.3.1

Descriptive Statistics of the Measures in Each Measurement Occasion for Students that Participated at Least Five Times

		Time 1	Time 2	Time 3	Time 4	Time 5	Time 6	Time 7	Time 8	Time 9	Time 10
FBM	N	197	225	206	220	196	247	204	214	187	191
	% response	67.70	77.32	70.79	75.60	67.35	84.88	70.10	73.54	64.26	65.64
	Mean	4.73	5.02	4.96	5.20	4.84	5.12	4.93	5.16	5.04	5.38
	SD	0.80	0.85	0.85	0.98	0.91	0.88	0.98	0.99	1.17	0.84
SDM	N	197	225	206	220	196	247	204	214	187	191
	% response	67.70	77.32	70.79	75.60	67.35	84.88	70.10	73.54	64.26	65.64
	Mean	4.97	5.28	5.23	5.40	5.07	5.51	5.19	5.45	5.24	5.66
	SD	0.84	0.90	0.87	0.95	0.96	0.96	1.03	1.05	1.16	0.84

Note. Total number of participants who at least provided with five measurements: N = 291.

Table S1.3.2

Descriptive Statistics of the Measures in Each Measurement Occasion for all Participants in the Study

		Time 1	Time 2	Time 3	Time 4	Time 5	Time 6	Time 7	Time 8	Time 9	Time 10
FBM	N	253	293	256	272	225	309	236	262	233	254
	% response	38.98	45.15	39.45	41.91	34.67	47.61	36.36	40.37	35.90	39.14
	Mean	4.72	4.97	4.86	5.17	4.79	5.10	4.93	5.15	5.05	5.36
	SD	0.76	0.83	0.81	0.93	0.90	0.89	0.94	0.97	1.11	0.82
SDM	N	253	293	256	272	225	309	236	262	233	254
	% response	38.98	45.15	39.45	41.91	34.67	47.61	36.36	40.37	35.90	39.14
	Mean	4.96	5.16	5.13	5.36	5.02	5.49	5.23	5.40	5.22	5.65
	SD	0.82	0.91	0.91	0.97	0.96	0.96	1.01	1.06	1.13	0.80

Note. Total number of participants: N = 649. FBM – flow-based motivation; SDM – self-determined motivation.

S1.4. Multivariate Latent Mixed Models Comparisons

Table S1.4.1

Initial Models – FBM Variables

			Model 0	Model 1a	Model 1b	Model 2a	Model 2b	Model 2c	Model 3a	Model 3b	Model 3c
Fixed effects											
Intercepts		Class 2	-0.17 (1.96)^{ns}	-1.38 (0.21)^{ns}	0.25 (0.25)^{ns}	-1.06 (0.27)^{ns}	0.9 (0.23)*	-0.95 (0.22)^{ns}	-0.89 (0.30)^{ns}	-0.71 (0.22)^{ns}	-0.92 (0.22)**
Time effect	Linear	Class 1	-	-0.03 (0.03)^{ns}	0.32 (0.04)^{ns}	-5.33 (4.94)^{ns}	4.08 (1.19)^{ns}	42.91 (5.00)^{ns}	1.09 (0.27)^{ns}	-10.61 (4.2)^{ns}	43.31 (5.09)**
		Class 2	-	0.08 (0.01)^{ns}	0.03 (0.01)^{ns}	9.14 (1.79)^{ns}	43.52 (5.10)^{ns}	3.95 (1.18)^{ns}	0.25 (0.09)^{ns}	11.06 (1.60)^{ns}	3.91 (1.19)**
	Quadratic	Class 1	-	-	-	-7.96 (3.74)^{ns}	-1.46 (1.09)^{ns}	11.32 (4.30)^{ns}	-0.3 (0.07)^{ns}	-6.79 (3.40)^{ns}	12.04 (4.36)**
		Class 2	-	-	-	0.76 (1.25)^{ns}	12.3 (4.50)*	-1.44 (1.09)^{ns}	-0.06 (0.03)^{ns}	1.12 (1.22)^{ns}	-1.48 (1.09)^{ns}
	Cubic	Class 1	-	-	-	-	-	-	0.02 (0.01)^{ns}	14.52 (3.90)^{ns}	3.06 (3.95)^{ns}
		Class 2	-	-	-	-	-	-	0 (0.00)*	2.96 (1.25)^{ns}	5.3 (1.09)**
Random effects											
Intercepts			0.46 (0.17)	0.1 (0.05)	0.44 (0.06)	0.39 (0.06)	0.41 (0.07)	0.46 (0.06)	0.3 (0.10)	0.16 (0.06)	0.47 (0.06)
Time effect	Linear		-	0 (0.00)	-	93.96 (38.00)	0 (0.00)	-	0.04 (0.04)	0 (0.00)	-
	Quadratic		-	-	-	13.34 (9.90)	-	-	0 (0.00)	-	-
	Cubic		-	-	-	-	-	-	0 (0.00)	-	-
Goodness of fit											
AIC			5120.99	5049.97	5038.64	5048.41	5036.87	5033.91	5025.06	5023.57	5013.11
BIC			5157.72	5101.4	5082.72	5118.2	5095.64	5085.34	5116.89	5089.69	5071.89

Note. Estimated coefficients (and SE) for the fixed effects. Intercepts of the reference class is constrained to be 0 and variance of intercepts is constrained to be 1.

Model 0: intercepts only. Models 1a and 1b include linear effect of time with and without random effects for time, respectively. Models with quadratic effect of time are 2a (random effects for quadratic and linear terms), 2b (random effects for linear terms), and 2c (random intercepts only). Models with cubic effects of time are 3a (random effects for cubic, quadratic, and linear terms), 3b (random effects for linear terms) and 3c (random intercepts only).

** $p \leq .01$; * $p \leq .05$; ns $p > .05$.

Table S1.4.2

Initial Models – SDM Variables

			Model 0	Model 1a	Model 1b	Model 2a	Model 2b	Model 2c	Model 3a	Model 3b	Model 3c
Fixed effects											
Intercepts		Class 2	-1.31 (0.24)^{ns}	-0.38 (0.22)^{ns}	-0.37 (0.22)^{ns}	-1.53 (0.23)^{ns}	-1.54 (0.24)^{ns}	-1.14 (0.16)^{ns}	-1.54 (0.23)^{ns}	-1.54 (0.25)^{ns}	-1.1 (0.22)**
Time effect	Linear	Class 1	-	0.21 (0.03)^{ns}	0.21 (0.03)^{ns}	12.45 (6.70)^{ns}	12 (7.13)^{ns}	26.32 (4.40)^{ns}	11.59 (7.30)^{ns}	10.89 (7.90)^{ns}	28.36 (6.5)**
		Class 2	-	0.03 (0.01)^{ns}	0.03 (0.01)^{ns}	7.13 (1.31)^{ns}	7.16 (1.29)^{ns}	4.03 (1.26)^{ns}	7.33 (1.34)^{ns}	7.31 (1.30)*	4.03 (1.26)**
	Quadratic	Class 1	-	-	-	-8.69 (4.65)^{ns}	-7.54 (4.97)^{ns}	0.01 (0.81)^{ns}	-8.82 (4.67)^{ns}	-7.77 (5.00)^{ns}	0.32 (3.79)^{ns}
		Class 2	-	-	-	-0.41 (1.11)^{ns}	-0.49 (1.08)^{ns}	-1.2 (1.16)^{ns}	-0.32 (1.11)^{ns}	-0.44 (1.08)^{ns}	-1.23 (1.19)^{ns}
	Cubic	Class 1	-	-	-	-	-	-	4.37 (5.22)^{ns}	4.32 (4.98)^{ns}	-0.54 (3.34)^{ns}
		Class 2	-	-	-	-	-	-	3.9 (1.12)*	3.83 (1.09)^{ns}	4.55 (1.16)**
Random effects											
Intercepts			0.2 (0.04)	0.25 (0.07)	0.2 (0.05)	0.22 (0.04)	0.15 (0.06)	0.21 (0.05)	0.19 (0.08)	0.15 (0.07)	0.23 (0.08)
Time effect	Linear		-	0 (0.00)	-	81.94 (31.00)	0 (0.00)	-	0.04 (0.04)	0 (0.00)	-
	Quadratic		-	-	-	11.62 (9.70)	-	-	0 (0.00)	-	-
	Cubic		-	-	-	-	-	-	0 (0.00)	-	-
Goodness of fit											
AIC			5310.66	5243.11	5240.14	5249.31	5249.38	5243.05	5242.51	5239.27	5231.40
BIC			5347.40	5294.54	5284.22	5319.10	5308.15	5294.48	5334.34	5305.39	5290.18

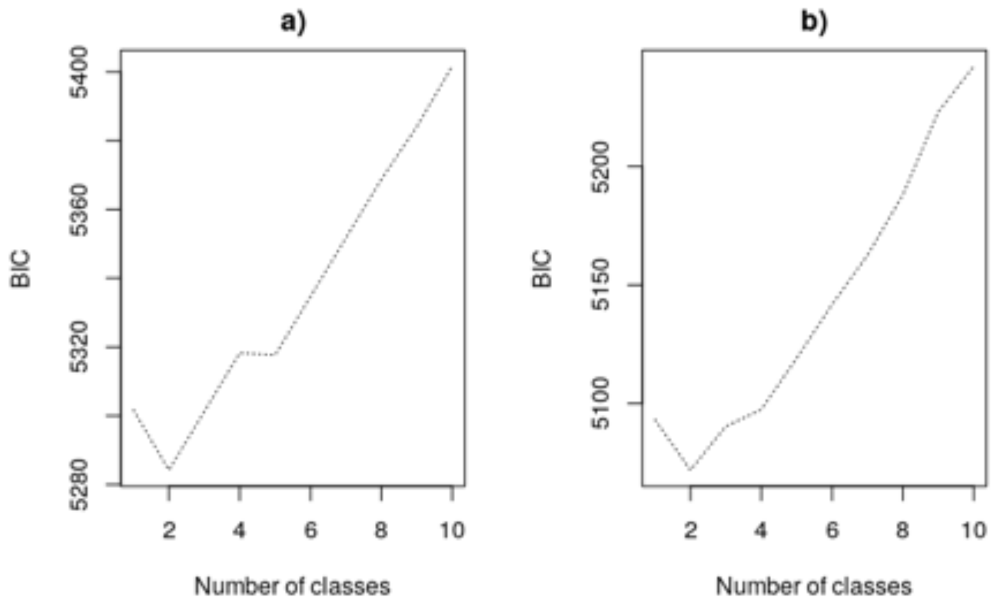
Note. Estimated coefficients (and SE) for the fixed effects. Intercepts of the reference class is constrained to be 0 and variance of intercepts is constrained to be 1.

Model 0: intercepts only. Models 1a and 1b include linear effect of time with and without random effects for time, respectively. Models with quadratic effect of time are 2a (random effects for quadratic and linear terms), 2b (random effects for linear terms), and 2c (random intercepts only). Models with cubic effects of time are 3a (random effects for cubic, quadratic, and linear terms), 3b (random effects for linear terms) and 3c (random intercepts only).

** $p \leq .01$; * $p \leq .05$; ns $p > .05$.

Figure S1.4.1

BIC Indices for the Chosen Models Under Different Number of Classes



Note. BIC indices for chosen models in FBM (a) and SDM (b) variables under different number of classes. Better fit in a) corresponds to two classes whereas keeping three classes in b) implies a better performance in terms of BIC.

S2. Study 2

S2.1. Longitudinal Cluster Analysis

In the current study *k-means* procedure was used to identify clusters based on the trajectories of different forms of motivation. Here we introduce some notation to ease the presentation of some methods used in the study.

Let *S* a set of students (*i*) that reported their scores in *M* motivational variables at *t* different occasions. Suppose that an individual score in a variable at a certain time is noted as y_{ijk}, where $i = 1, \ldots, S$ is the individual, $j = 1, \ldots, M$ is the variable of interest and $k = 1, \ldots, t$ is the measurement occasion. Then, a single trajectory (e.g. concerning *k*th-variable) for an individual is noted as $Y_{i.k} = (y_{i1k}, y_{i2k}, \ldots, y_{itk})$, and joint trajectories can be represented by the following matrix:

$$\begin{pmatrix} y_{i11} & y_{i21} & \cdots & y_{it1} \\ y_{i12} & y_{i22} & \cdots & y_{it2} \\ \vdots & \vdots & \ddots & \vdots \\ y_{i1M} & y_{i2M} & \cdots & y_{itM} \end{pmatrix}$$

As described by Genolini et al. (2015), the distance between two joint variable trajectories, say trajectories y1.. and y2.. for individuals 1 and 2, can be defined as follows:

$$Dist(y_{1..}, y_{2..}) = \sqrt[p]{\sum_{j,k} | y_{1jk} - y_{2jk}|^p}$$

It corresponds to the general expression of Minkowski distance. In this study euclidean distance was employed to find out groups of homogeneous motivational trajectories, that is, $p = 2$. Therefore, k-means routine firstly assigns individuals to clusters, depending on euclidean distances between motivational trajectories, and then it iteratively alternates expectation (computing centroids) and maximization (changing assignation to clusters by using distances between individuals and clusters) steps to find an optimal partition. Standardization of longitudinal data was done by using the expression:

$$\frac{y_{ijk} - \overline{y_{..k}}}{s_{..k}}$$

where $\overline{y_{..k}}$ is average of the whole variable trajectory and $s_{..k}$ the standard deviation of the set of scores for this trajectory. The new set of M standardized single trajectories compose a normalized joint trajectory.

References

Genolini, C., Alacoque, X., Sentenac, M., & Arnaud, C. (2015). kml and kml3d: R packages to cluster longitudinal data. *Journal of Statistical Software*, *65*(4), 1–34.

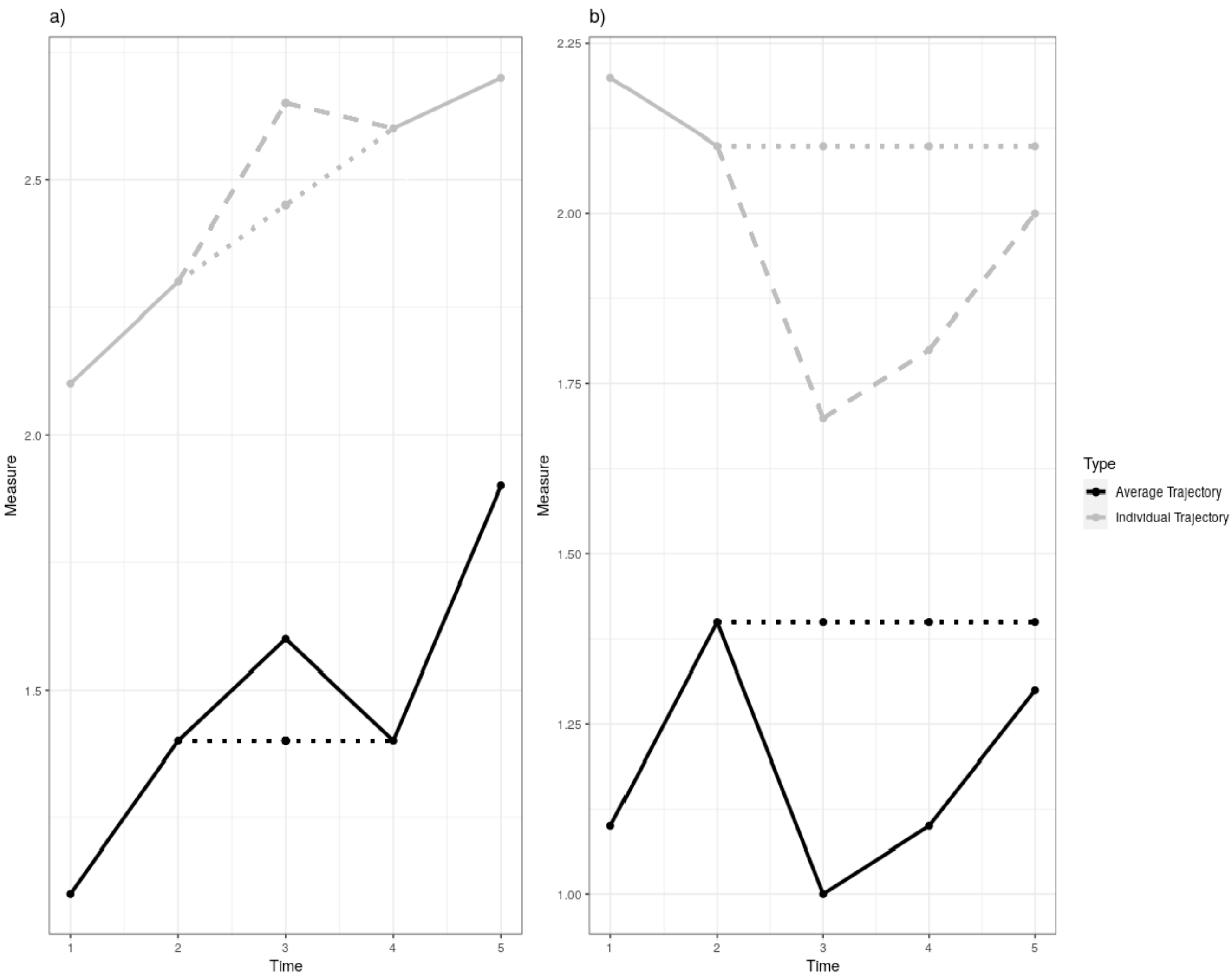
S.2.2. Imputation Procedure for Missing Data

The imputation procedure for missing data used in the present research was *Copy Mean* procedure. To illustrate this imputation routine, let's suppose two individuals with missing observations (see grey lines in Figure S2.2.1a and S2.2.1b): individual *a* missed to answer the questionnaire in time 3, whereas individual *b* only answered at times 1 and 2. The first case is an example of intermittent missing data, and the second example illustrates monotonic missing data type. Figure S2.2.1 also represents the average single trajectories for these two hypothetical variables (i.e., sample means of the variable along the measurement occasions).

Copy Mean procedures modifies two types of data imputation techniques depending on the missingness kind (see Genolini et al., 2015, for further details). When having intermittent missing data this procedure adds a variation in linear interpolated data ensuring thus that the average shape is kept in the imputed individual trajectory. Similarly, in the case of monotonic missing data, Last Occurrence Carried Forward procedure is slightly modified to keep average pattern in the individual trajectory.

Figure S2.2.1

Examples of Longitudinal Imputation Using Cross-Sectional and Longitudinal Available Information for a) Intermittent and b) Monotonic Missing Data



Note. The examples are adapted from Genolini et al. (2013). Dotted lines represent imputed observations using either a) linear interpolation (LI) or b) Last Occurrence Carried Forward (LOCF) procedures, whereas dashed lines represent imputed observations using Copy Mean method. Note that LI and LOCF procedures have been also drawn to the corresponding points in the average trajectories to ease examination that average shape is kept in imputed individual trajectories.

References

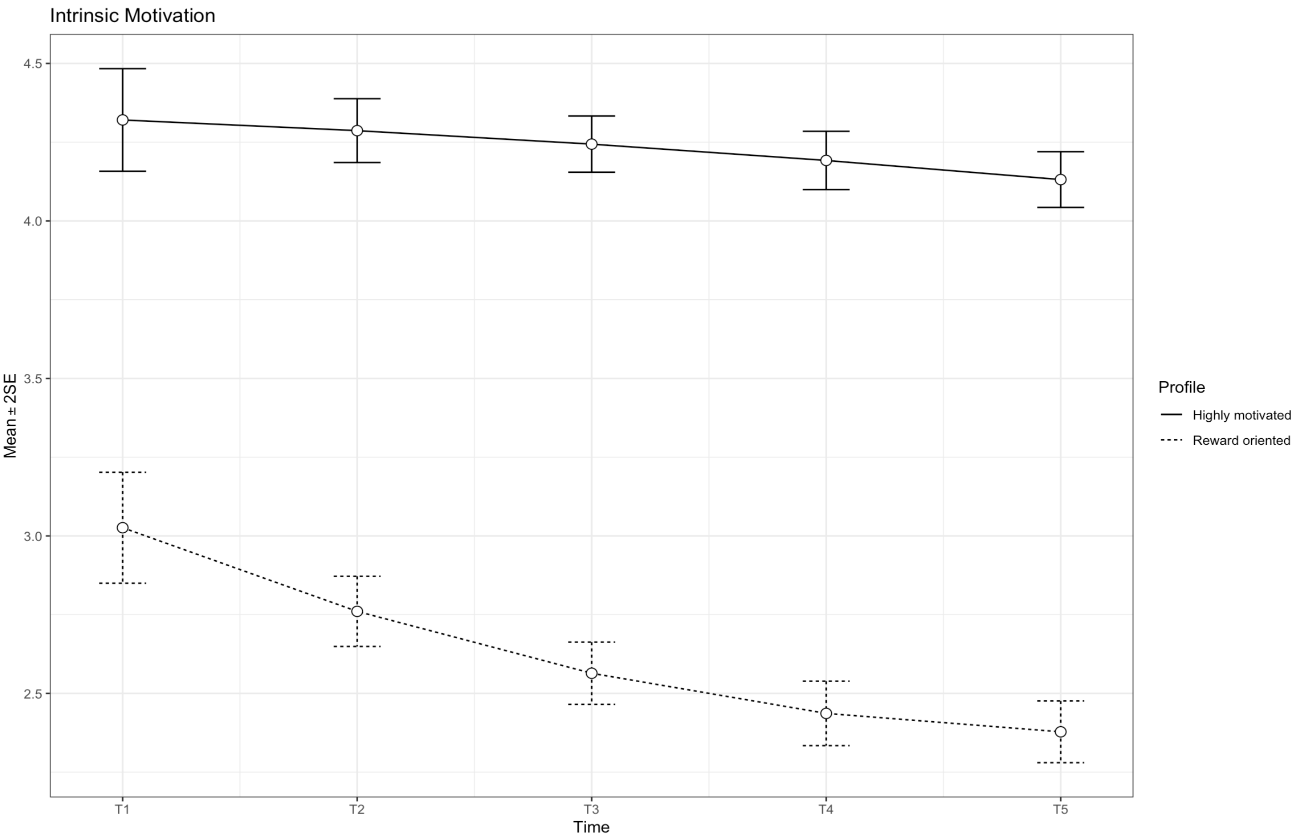
Genolini, C., Alacoque, X., Sentenac, M., & Arnaud, C. (2015). kml and kml3d: R packages to cluster longitudinal data. *Journal of Statistical Software*, *65*(4), 1–34.

Genolini, C., & Jacqmin-Gadda, H. (2013). Copy Mean: A new method to impute intermitent missing values in Longitudinal Studies. *Open Journal of Statistics*, *3*(04), 26–40. http://dx.doi.org/10.4236/ojs.2013.34A004

S2.3. Plots With Estimated Trajectories Separately for Each Motivation Variable

Figure S2.3.1

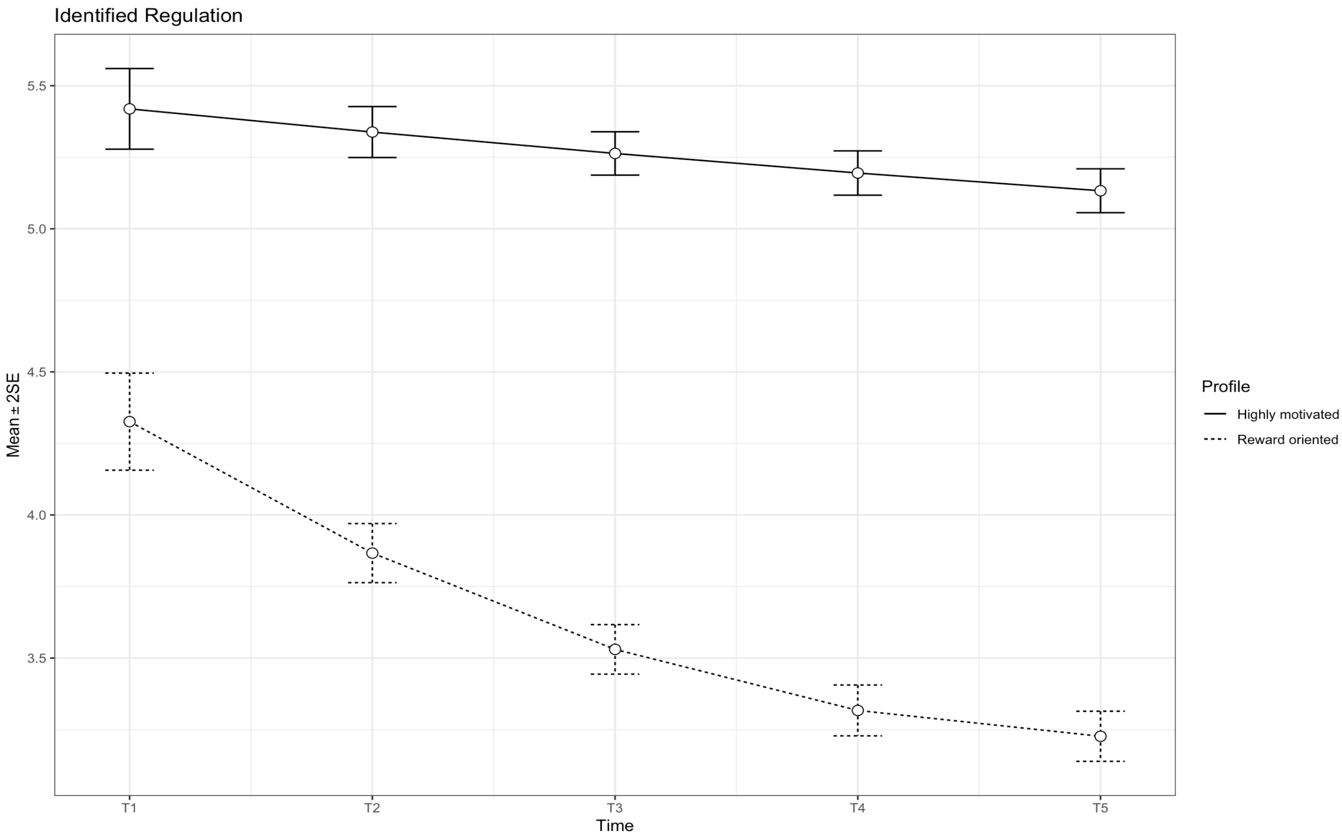
Estimated Trajectories of Intrinsic Motivation for the Two Profiles



Note. Marginal means plot shows the trajectories in intrinsic motivation along the course for the groups found in the multivariate clustering procedure. The means were estimated according to a mixed model with random intercepts and random non-linear trends (quadratic terms), including the interaction between occasions and groups.

Figure S2.3.2

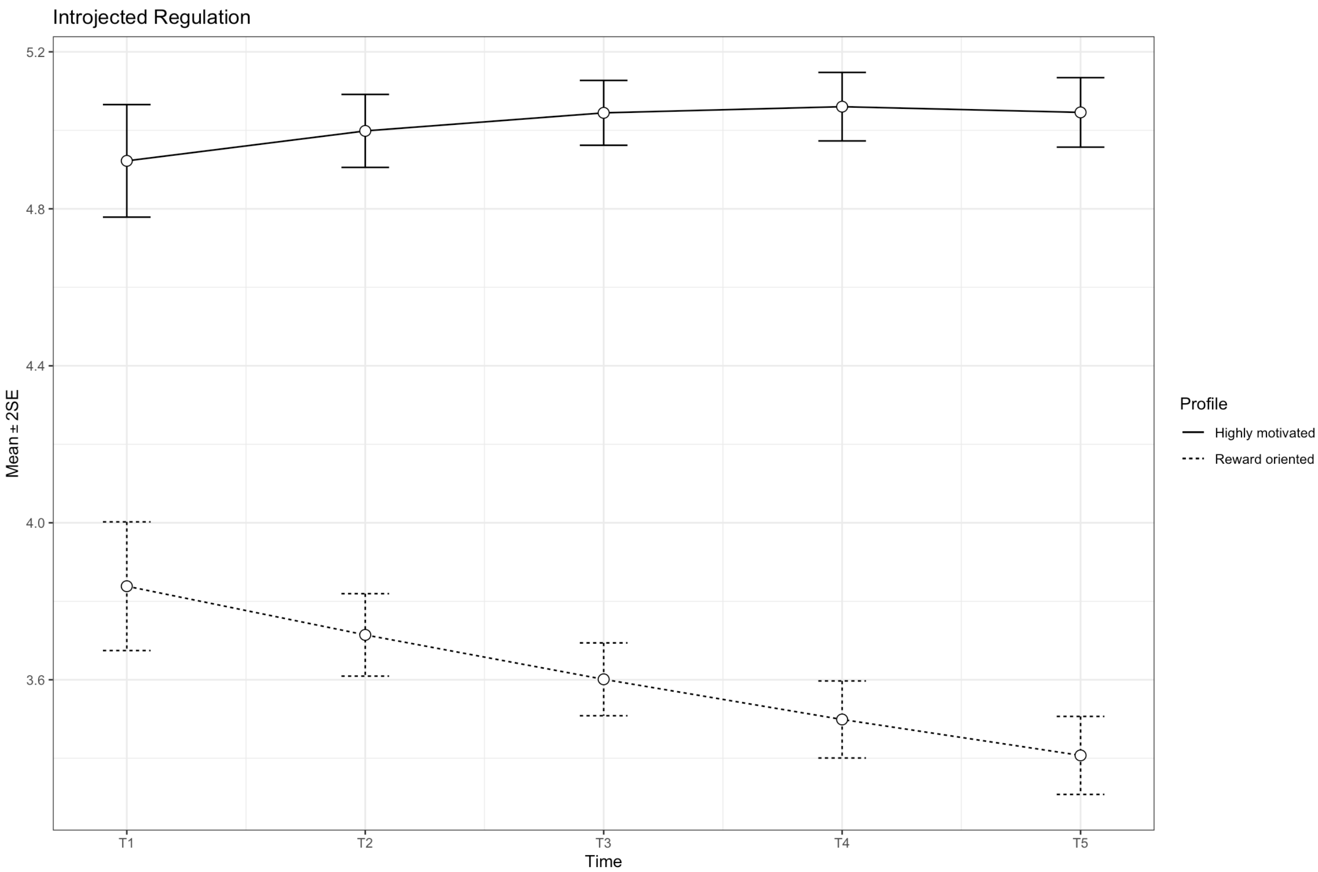
Estimated Trajectories of Identified Regulation for the Two Profiles



Note. Marginal means plot shows the trajectories in identified regulation along the course for the groups found in the multivariate clustering procedure. The means were estimated according to a mixed model with random intercepts and random non-linear trends (quadratic terms), including the interaction between occasions and groups.

Figure S2.3.3

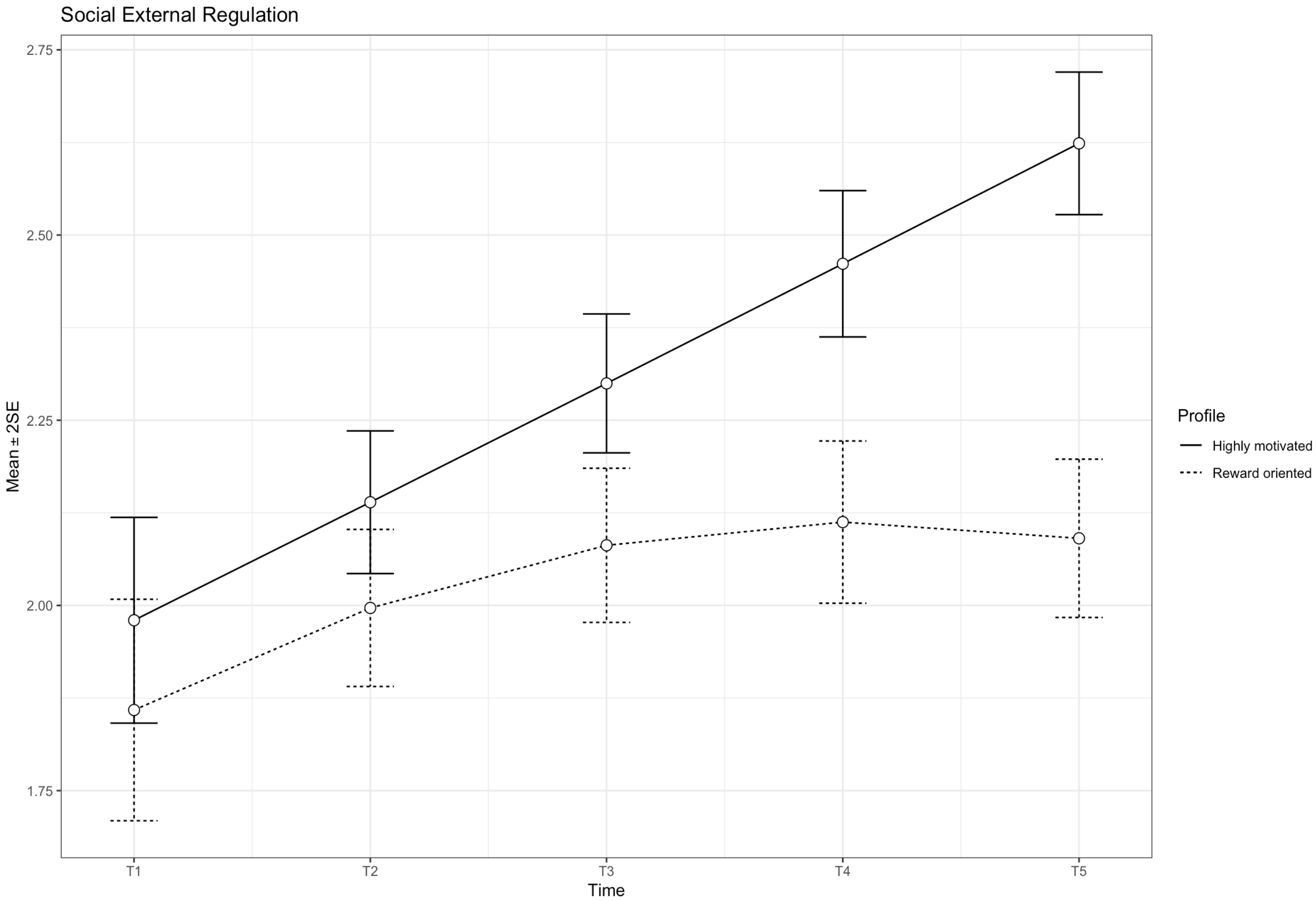
Estimated Trajectories of Introjected Regulation for the Two Profiles



Note. Marginal means plot shows the trajectories in introjected regulation along the course for the groups found in the multivariate clustering procedure. The means were estimated according to a mixed model with random intercepts and random non-linear trends (quadratic terms), including the interaction between occasions and groups.

Figure S2.3.4

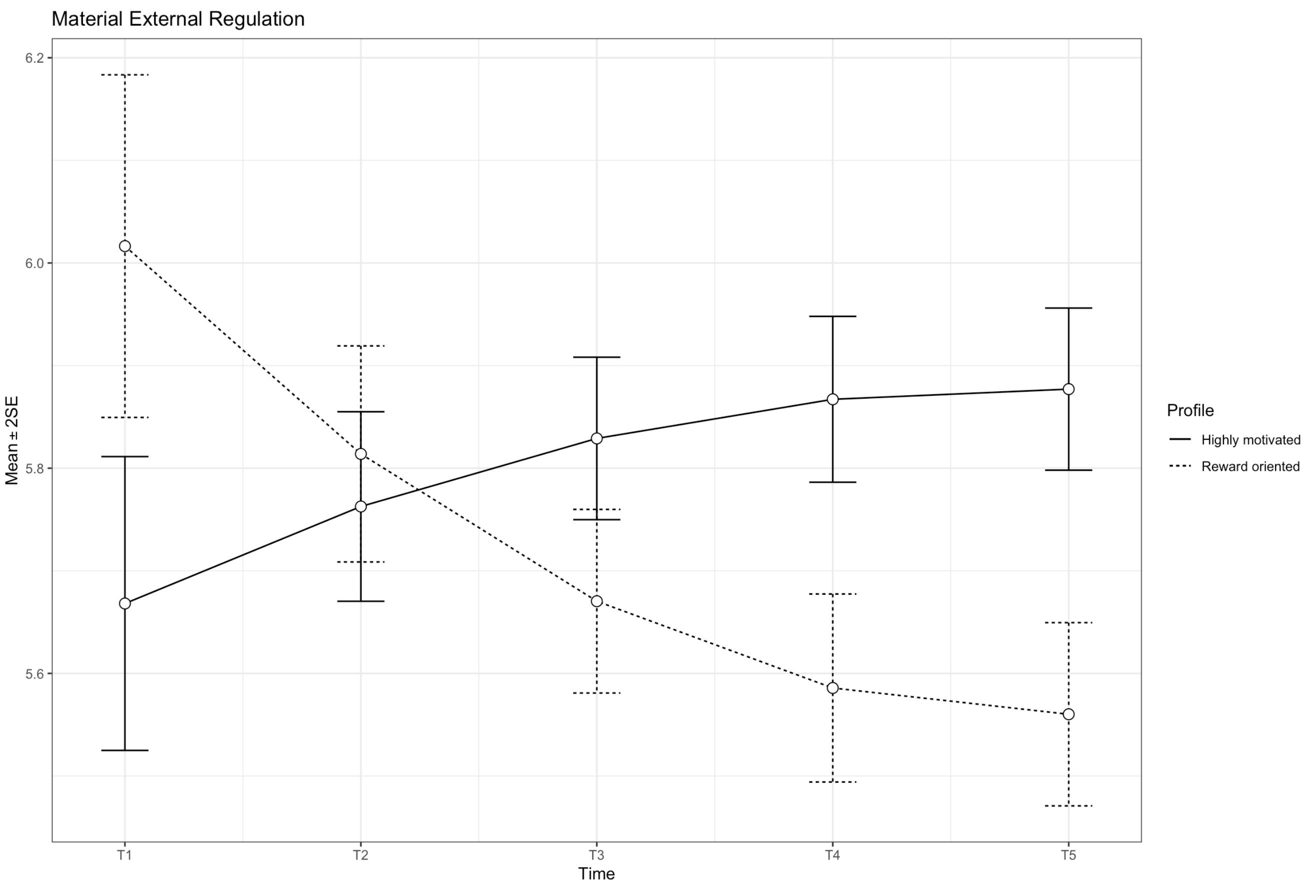
Estimated Trajectories of Social External Regulation for the Two Profiles



Note. Marginal means plot shows the trajectories in social external regulation along the course for the groups found in the multivariate clustering procedure. The means were estimated according to a mixed model with random intercepts and random non-linear trends (quadratic terms), including the interaction between occasions and groups.

Figure S2.3.5

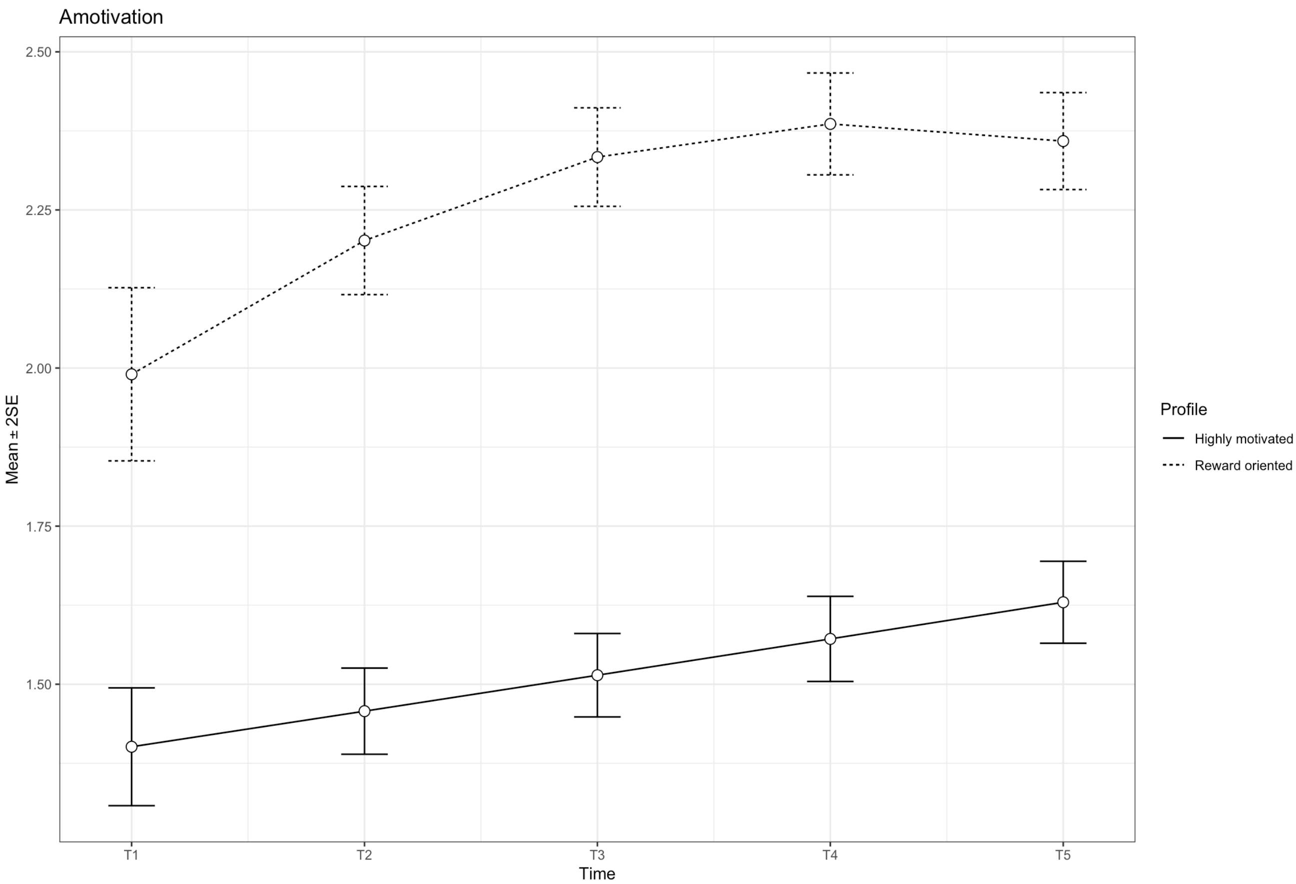
Estimated Trajectories of Material External Regulation for the Two Profiles



Note. Marginal means plot shows the trajectories in material external regulation along the course for the groups found in the multivariate clustering procedure. The means were estimated according to a mixed model with random intercepts and random non-linear trends (quadratic terms), including the interaction between occasions and groups.

Figure S2.3.6

Estimated Trajectories of Amotivation for the Two Profiles



Note. Marginal means plot shows the trajectories in amotivation along the course for the groups found in the multivariate clustering procedure. The means were estimated according to a mixed model with random intercepts and random non-linear trends (quadratic terms), including the interaction between occasions and groups.

Appendices

Appendix A.

Previous trajectory-based person-centered studies on motivational profiles

A.1. Search Strategy

The search of the longitudinal, person-centered studies was threefold. First, I run a search in four databases (PsycInfo, PubMed, ERIC, Scopus), using predefined search strings, which denoted three categories of keywords (motivation, person-centered approach, longitudinal design); TITLE-ABSTRACT-KEYWORDS. The detailed search strings (were adapted to the databases), as well as the results of the database search are presented in the Table A.1.

Search performed on September 12th, 2021, limited to the articles published in peer-reviewed journals between 1975/01/01 and 2021/09/12.

Table A.1

The Search of Longitudinal, Person-Centered Studies – Search Strings and Results

	PsycInfo	ERIC	PUB MED	Scopus
S1 – Motivation (motivation AND ("self-determin*" OR "self determin*" OR intrinsi* OR extrinsi* OR autonomous* N2 motivat* OR autonomous* N2 regulat* OR control* N2 motivat* OR control* N2 regulat* OR flow OR "optimal experienc*"))	9,931	17,231	123	19,897
S2 – Person-centered approach (profil* OR "person-centered" OR "person centered" OR cluster*)	137,012	100,871	44,209	2,519,076
S3 – Longitudinal design (longitudina* OR temporal* OR trajector* OR transition* OR dynami*)	387,539	37,201	67,672	5,786,251
S1 AND S2 AND S3	**64**	**41**	**2**	**217**

Second, the reference list of the eligible studies was reviewed. Finally, the articles which cited eligible studies were reviewed.
In order to be included, the studies must meet the following inclusion criteria:

- To implement quantitative analysis of the data.
- To use person-centered approach.
- To build profiles basing exclusively on the motivation-related variables components

  Inclusion example: Profiles based on the global self-determination factor.

  Exclusion example: Profiles based on the variable “emotional intelligence”, motivation is an outcome (Méndez Giménez et al., 2020).
- To consider temporal aspects of the profiles (e.g., temporal stability, trajectory-based profiles); at least two measurement points of motivational variables should be included.
- To be published in English in a journal article.

A.2. Summary of the Eligible Studies

Study	Context	Motivation variables	Method	No of profiles	Labels of the profiles	Association with outcomes
Cece et al., 2018	Sport	Motivation toward sport. Intrinsic motivation, identified regulation, introjected regulation, external regulation, amotivation.	Latent profiles analysis; latent transition analysis. Three time points.	4	T1, T2: Highly self-determined (1), self-determined (2), moderate autonomous and controlled motivation (3), moderately self-determined (4) T3: Highly self-determined (1), self-determined (2), moderate autonomous and controlled motivation (3), high autonomous and controlled motivation (4)	-
Chevrier & Lannegrand, 2021	Education	Academic motivation. Autonomous (intrinsic motivation-knowledge, intrinsic motivation-accomplishment, intrinsic motivation-stimulation, and identified regulation) and controlled (introjected and external regulation) motivation, amotivation.	Longitudinal cluster analysis Two time points.	4	Combined stable (1), low autonomous with increase of amotivation (2), demotivated stable (3), amotivated with decrease (4).	Longitudinal profiles of basic psychological needs: - satisfied stable (n=100): 1>3>2>4 - autonomy frustrated becoming undifferentiated (n=63): 1>2>3>4 - undifferentiated becoming frustrated (n=52): 1>2>3>4 - frustrated with decrease (n=31): 4>2>1>3
Corpus & Wormington, 2014	Education	Motivation toward school. Intrinsic (independent mastery, challenge-seeking, curiosity-driven engagement) and extrinsic (orientation toward pleasing authority figures, desire for easy work, dependence on the teacher for guidance) motivation.	Cluster analysis.	3	High quantity (1), Primarily Intrinsic (2), Primarily Extrinsic (3).	Achievement: 2>1=3
Emm-Collison et al., 2020	Physical activity/ exercise	Motivation toward exercise. Intrinsic motivation, identified regulation, introjected regulation, external regulation,	Latent profiles analysis; latent transition analysis.	6	Strongly amotivated (1), amotivated (2), controlled and amotivated (3), low in motivation (4), autonomously motivated and introjected (5), autonomously motivated (6).	Moderate-to-vigorous physical activity (MVPA, T1): 6>5>3>4>2>1 (MVPA, T2):

		amotivation.	Three time points.			6>5>2>3>4>1 (MVPA, T3): 6>2>5>4>3>1
Fernet, Litalien, et al., 2020	Work	Motivation toward job. Intrinsic motivation, identified regulation, introjected regulation, external regulation, amotivation.	Latent profiles analysis; latent transition analysis. Two time points.	4	Moderately Motivated (1), Poorly Motivated (2), Self-Determined (3), Strongly Motivated (4).	Emotional exhaustion: 2>3>1=4 In-role performance: 4>1>2=3 Turnover intentions (organization): 2>3>1=4 Turnover intentions (occupation): 2>3>1=4
Fernet, Morin, et al., 2020	Work	Motivation toward job. Global level of self-determination.	Longitudinal growth mixture analyses. Four time points.	3	Slightly Decreasing (1), Increasing (2); Decreasing (3).	Affective commitment (organization): 2>1>3 Affective commitment (occupation): 2>3>1 Turnover intentions (organization): 3>1>2 Turnover intentions (occupation): 1=3>2
Gillet, Morin, et al., 2017	Education	Motivation toward studying. Intrinsic motivation, identified regulation, introjected regulation, external regulation, amotivation.	Latent profiles analysis; latent transition analysis. Two time points.	6	Autonomous (1), Strongly Motivated (2), Moderately Autonomous (3), Moderately Unmotivated (4), Controlled (5), Poorly Motivated (6).	Positive Affect: 1>2=3>4>6>5 Interest: 1>2=3>4>6>5 Effort: 1>2=3>4>6>5 Boredom: 5>6>4>2>3>1

						Disorganization: 6>2=4=5>1=3 Critical thinking: 1>2=3>4=6>5 Dropout intentions: 5>6>4>2=3; 2>1: 5>6>4>1=3 Expected Achievement: 2=3>4=6>5; 1>2; 1=3>4=6>5 Observed Achievement: 1=2=3>4=6>5
Gillet et al., 2018	Work/training	Motivation toward vocational training. Global level of self-determination.	Longitudinal growth mixture analyses. Four time points.	3	Moderate (1), High (2), Low (3).	Positive affect: 2>1; 2=3, 1=3 Negative affect: 1>2; 3>2; 1=3 Performance: 2>1; 2=3, 1=3
Guay et al., 2021	Education	Motivation toward school-related activities. Global level of self-determination.	Longitudinal growth mixture analyses. Three time points.	5	High-stable (1), Moderate (2), High (3), Low (4), Increasing (5).	Achievement (intercept): 4<3<1=2<5 Achievement (slope): 5<4<1=2<3 Engagement (intercept): 4<3=5<1<2 Engagement (slope): 5<1=2<3<4 Risk behaviors (intercept): 5<2<1=3<4 Risk behaviors (slope): 3<1=2<5<4

						Aggressive behaviors (intercept): 1<2<3=5<4 Aggressive behaviors (slope): 4<5<3<1<2
Hayenga & Corpus, 2010	Education	Intrinsic and extrinsic motivation toward school.	Cluster analysis	4	High quantity (1), good quality (2), poor quality (3), low quantity (4)	Achievement (fall semester): 2>1=3=4 Achievement (spring semester): 2>1=3; 2=4
Howard et al., 2020	Work	Motivation toward job. Intrinsic motivation, identified regulation, introjected regulation, external regulation, global level of self-determination.	Latent profiles analysis; latent transition analysis. Two time points.	4	Highly Self-Determined (1), Identified (2), Low Self-Determined (3), Externally Regulated (4)	Turnover intentions: 1<4<2<3 Perceived proficiency: 3<4<2<1 Perceived proactivity: 3<4=2<1 Perceived adaptivity: 3<4=2<1
Nishimura & Sakurai, 2017	Education	Motivation toward school. Autonomous (intrinsic and identified regulation) and controlled (introjected and external regulation) motivation.	Latent curve model and the growth mixture model. Three time points.	2	Decreases only in autonomous motivation (1), increases only in controlled motivation (2).	-
Schiefele & Löweke, 2018	Education	Motivation toward reading. Intrinsic motivation (involvement and curiosity), extrinsic motivation (recognition and competition)	Latent profiles analysis; latent transition analysis. Two time points.	4	High-quantity profile (1), high-intrinsic profile (2), high-involvement profile (3), moderate-quantity profile (4).	Reading amount: 2>3>1>4 Reading comprehension (word): 2>3>1>4

						Reading comprehension (sentence): 3>2>1>4 Reading comprehension (passage): 3>2>1>4
Xie et al., 2021	Education	Motivation toward school activities. Intrinsic motivation, identified regulation, introjected regulation, and external regulation.	Latent profiles analysis; latent transition analysis. Two time points.	6	Amotivated (1), externally regulated (2), balanced demotivated (3), moderately motivated (4), balanced motivated (5), autonomously motivated (6).	-

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Appendix B.

The Multidimensional Work Motivation Scale (MWMS) Translated to Spanish and Adapted to the Academic Context

Pensando en esta asignatura**, ¿por qué te esfuerzas o te esforzarías** para hacer las actividades que se proponen en la asignatura? *Thinking about this course, why do you or would you put efforts into the activities proposed in this course?*	
Amotivation	
Am 1	No lo hago, porque creo que estoy perdiendo el tiempo en estas actividades. *I don't because I feel that I'm wasting my time on these activities.*
Am 2	Me esfuerzo poco, porque no creo que valga la pena poner esfuerzo en estas actividades. *I put little effort because I don't think these activities are worth putting efforts into.*
Am 3	No sé bien porque hago estas actividades, es un trabajo inútil. *I don't know why I'm doing these activities, it's a pointless work.*
Extrinsic regulation—social	
Ext – soc 1	Lo hago para conseguir las aprobaciones de otros (del profesor, compañeros, familiares, etc.). *To get others' approval (e.g., professor, colleagues, family, etc.)*
Ext – soc 2	Lo hago porque así se me respetará más (el profesor, compañeros, familiares, etc.). *Because others will respect me more (e.g., professor, colleagues, family, etc.)*
Ext – soc 3	Lo hago para evitar ser criticado por los demás (el profesor, colegas, familiares, etc.). *To avoid being criticized by others e.g., professor, colleagues, family, etc.)*
Extrinsic regulation—material	
Ext – mat 1	Lo hago debido a que recibiré una buena evaluación si me esfuerzo lo suficiente en estas actividades. *Because I will get good grades if I put enough effort in these activities.*
Ext – mat 2	Lo hago porque si me esfuerzo lo suficiente podré continuar sin problemas con mis estudios de Grado. *Because if I put enough effort, I can continue with my bachelor studies without problems.*
Ext – mat 3	Lo hago porque si no me esfuerzo lo suficiente me arriesgo a suspender esta materia. *Because I risk failing the course if I don't put enough effort in it.*
Introjected regulation	
Introj 1	Lo hago porque tengo que probarme a mí mismo de que puedo hacer bien estas actividades. *Because I have to prove to myself that I can do well these activities*.
Introj 2	Lo hago porque me siento orgulloso de mí mismo al realizar estas actividades. *Because doing these activities makes me feel proud of myself.*

Introj 3	Lo hago porque de lo contrario podría sentirme avergonzado de mí mismo. *Because otherwise I will feel ashamed of myself.*
Introj 4	Lo hago porque de lo contrario podría sentirme mal conmigo mismo. *Because otherwise I will feel bad about myself.*
Identified regulation	
Ident 1	Lo hago porque personalmente considero que es importante poner esfuerzo en estas actividades. *Because I personally consider it important to put efforts in these activities.*
Ident 2	Lo hago porque poner esfuerzo en estas actividades se alinea con mis valores personales. *Because putting efforts in these activities aligns with my personal values.*
Ident 3	Lo hago porque poner esfuerzo en estas actividades tiene un significado personal para mí. *Because putting efforts in these activities has personal significance to me.*
Intrinsic motivation	
Intrin 1	Lo hago porque me divierto haciendo estas actividades. *Because I have fun doing these activities.*
Intrin 2	Lo hago porque estas actividades me resultan emocionantes. *Because these activities are exciting.*
Intrin 3	Lo hago porque las actividades son interesantes. *Because these activities are interesting.*

The items were measured on seven-point Lickert scale, where 1 = strongly disagree; 7 = strongly agree

Appendix C.

Stability of a Continuum Structure of Students' Self-Determination: A Longitudinal Approach to the Bifactor Exploratory Structural Equation Modeling

Emilia Wietrak[1], Simon Houle[2], David Leiva[1], Jacques Forest[3] and José Navarro[1],

[1] University of Barcelona, [2] Concordia University, [3] École des sciences de la gestion (ESG UQAM)

Author note:

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Abstract

The study aims (1) to test the continuum structure of motivation proposed by self-determination theory, through the application of bifactor exploratory structural equation modeling framework (bifactor-ESEM); (2) to test longitudinal invariance of the Multidimensional Work Motivation Scale (MWMS; Gagné et al., 2015) adapted to the academic context. The data were collected five times during one academic semester from 979 undergraduate students in Spain. First, confirmatory factor analysis (CFA), bifactor-CFA, exploratory structural equation modeling (ESEM), and bifactor-ESEM models were compared (the bifactor models estimated specific factors and a global factor of motivation). Second, we tested the temporal invariance on the MWMS in the academic context, using the model with the best fit, and examining increasingly constrained models: configural, metric, scalar, and strict invariance. Bifactor-ESEM solution fitted data best at five measurement occasions and displayed full strict invariance across five measurement points. The continuum structure of academic motivation was best represented by the bifactor-ESEM model. Furthermore, the MWMS adapted to the academic context was invariant across time. The adopted approach allowed a longitudinal estimation of a global factor, which represented the overarching level of students' self-determined motivation, as well as the specific factors related to different types of regulation, providing a more precise test of the motivation continuum proposed by the self-determination theory.

Keywords: academic motivation, self-determination theory, continuum, Multidimensional Work Motivation Scale (MWMS), Bifactor-ESEM, longitudinal invariance

Human behavior can be explained by different motives. For example, students can get involved in academic activities because of their internal interest in learning, or because they consider these activities important. They may also feel responsible for completing their academic tasks successfully or may be experiencing external pressures and incentives to complete these tasks. The continuum of human motivation proposed by self-determination theory (SDT; Ryan & Deci, 2000) illustrates well such diversity, qualifying the main motivational drivers experienced by people from the most to the least autonomous (or self-determined). Certain attempts have been made to investigate the most appropriate way of representing the motivation continuum. While some researchers focused on the correlations between the specific forms of motivation (e.g., Guay et al., 2015), others estimated a global level of self-determination (Chemolli & Gagné, 2014). Finally, the most recent studies proposed the bifactor exploratory structural equation modeling (bifactor-ESEM) as a comprehensive framework to test human motivation (Cece et al., 2019; Howard et al., 2018; Litalien et al., 2017). The advantage of the bifactor-ESEM over the other approaches is, above all, the possibility of testing simultaneously two sources of construct-relevant psychometric multidimensionality, which proves useful for many complex instruments applied in psychological and educational research (e.g., Morin, Arens, & Marsh, 2016; Morin, Arens, Tran, et al., 2016). The first of these sources refers to the evaluation of different, but conceptually related constructs (i.e., specific factors), which are reflected in the measurement scale (e.g., different forms of motivation). The second one is related to the hierarchical nature (i.e., a global factor) of the construct (e.g., global motivation). Nevertheless, previous research examining a bifactor-ESEM representation of motivation suffer from one critical limitation that restricts the interpretation of the latent constructs derived from measurement scales. That is, most of the prior research using a bifactor-ESEM framework to represent SDT's motivation continuum focused on only one measurement point (Howard et al., 2018; Litalien et al., 2017); the studies that explore a temporal invariance of scales designed to measure self-determination continuum in education or work contexts are scarce. Given the growing interest in research on dynamics of motivation (Kanfer et al., 2017; Roe, 2014), new studies testing the temporal stability of these tools are needed to establish the longitudinal measurement invariance of the scales currently in use. Doing so will ensure that observed changes on the latent constructs (i.e., the global and specific factors of motivation) represent actual changes in motivation, and not changes in how these constructs are being measured over time.

The Continuum of Motivation – an SDT Perspective

According to SDT, the quality of human motivation can vary depending on the grade of autonomy and can be categorized into different forms: intrinsic motivation, integrated regulation, identified regulation, introjected regulation, and external regulation (Ryan & Deci, 2000). The most autonomous form is intrinsic motivation, which refers to behaviors driven for the pure interest or pleasure derived from the performed activity. Integrated regulation is similar to intrinsic motivation as it addresses the volitional reasons for behavior fully assimilated to the self; however, even if the motive of behavior is volitional and valued by the self, it is related to an outcome separate from the behavior. Although integrated regulation is one of the motivation forms proposed by Ryan and Deci (2000) in SDT, from a statistical point of view it is barely distinguishable from intrinsic motivation and identified regulation (Gagné et al., 2015; Mallett et al., 2007; Tremblay et al., 2009; Vallerand et al., 1992). For this reason, integrated regulation is frequently omitted in the popular scales that measure self-determination of motivation, such as the Multidimensional Work Motivation Scale (MWMS; Gagné et al., 2015), the Academic Motivation Scale (AMS; Vallerand et al., 1992) or the Behavioral Regulation in Sport Questionnaire (BRSQ; Lonsdale et al., 2008). Identification refers to a state, in which behavior is recognized as personally important, and regulation is accepted as own. Introjected regulation, in turn, is internalized but not accepted as own; a person gets involved in an activity due to the feeling of guilt or obligation, or to maintain or boost their self-esteem. Finally, extrinsic regulation refers to behaviors motivated by some separable outcome: receiving a reward or avoiding punishment. According to Gagné et al. (2015), extrinsic motivation may have two different sources – material and social. Such diversity can be easily observed in the academic context – students may be motivated towards their tasks because they want to receive good grades or to benefit from a scholarship (tangible form of extrinsic regulation), or because of the recognition they would receive from others, for example, from teachers, parents, or peers (social form of extrinsic regulation). The distinction between social and material source of extrinsic motivation is well established in the work context. For instance, both forms of extrinsic incentives, material (e.g., monetary rewards) and social (e.g., recognition or praise) are important elements of behavioral management, a practice that aims to increase employees' motivation and, in consequence, improve their performance (Stajkovic & Luthans, 2003). Furthermore, previous studies in the educational setting demonstrated that not only material, but also social incentives are related to students' motivation and relevant academic outcomes (Xue et al., 2020). Finally, it is important to mention that research on motivation focused not only on different forms of motivation quality, but also on amotivation – a state in which motivation does not appear, represented as one of the extremes of the continuum (Ryan & Deci, 2000).

The Bifactor-ESEM

The continuum proposed by SDT has frequently been used to study human motivation, and certain attempts have been made to analyze whether common measurement instruments are able to accurately represent the multidimensional character of this phenomenon. Prior research on the continuous structure of motivation (Howard et al., 2018; Litalien et al., 2017), as well as studies on the psychometric properties of measurement models (e.g., Morin, Arens, & Marsh, 2016; Morin, Arens, Tran, et al., 2016), lend support for a bifactor-ESEM representation of motivation, which is thought to occur in a continuum that ranges from amotivation to intrinsic motivation. Specifically, it is likely that individuals simultaneously experience all forms of motivations to varying degrees, hence they possess an overall level of motivation that can be represented by a global factor using bifactor-ESEM. Moreover, the extent to which people are driven, or not driven, by specific types of motivation over and above this global level can also be investigated. In essence, bifactor-ESEM allows for global and specific motivation to be simultaneously modeled, thus taking into account two important sources of construct-relevant psychometric multidimensionality. Specifically, the first source of the construct multidimensionality reflected in the measurement instruments refers to the elusive nature of the scales' items (Morin, Arens, & Marsh, 2016). Over the decades, CFA has been considered a benchmark for the research on the psychometric characteristics of measurement tools. However, this approach has important limitations. For example, it has been observed that, when applying CFA, many well-established scales do not obtain a satisfactory model fit indices (e.g., Marsh et al., 2014). This may be related to the underlying structure of CFA as an independent cluster model (ICM), which assumes that the cross-loading between items and non-target factors are equal to zero (Marsh et al., 2014). According to Morin, Arens and Marsh (2016), it is likely that most items included in common psychological measurement scales may be related not only to their target constructs, but also minimally to non-target conceptually related constructs. Accordingly, since exploratory models (e.g., ESEM) include cross-loadings (i.e., loadings on the non-target factors), they seem more appropriate to represent construct-relevant sources of psychometric multidimensionality inherent in measurement scales with conceptually related factors (Asparouhov & Muthen, 2009; Howard et al., 2018; Litalien et al., 2017; Morin, Arens, & Marsh, 2016; Marsh et al., 2014; Marsh et al., 2009). The second source of multidimensionality considered here is related to the hierarchical nature of the examined constructs, meaning the theoretical expectation about the existence of a higher-order or global factor, which underlies shared variance amongst all items in the scale. In that sense, the advantage of bifactor models is the possibility to simultaneously estimate both global and specific factors reflected in the measurement structure of many instruments. In bifactor-ESEMs, the covariance among the items is represented by a set of f orthogonal factors: one global factor (G-factor) and $f - 1$ specific factors (S-factors). Every item loads on both the G-factor and all of the S-factors, but cross-loadings to non-target constructs are force to approach zero, thus providing a confirmatory structure to the model. Specifically, the covariance is explained simultaneously by a G-factor overarching all the items, and by $f - 1$ S-factors, reflecting the variance not explained by the G-factor but explained primarily through its target loadings, and to a lesser extent by non-target cross loadings. Alternatively, higher-order (hierarchical) models estimate the covariance among first-order factors, calculating one or more higher-order factors. Such models are characterized by so-called proportionality constraints, meaning that the proportion of the variance explained by the higher-order factor over the variance explained by the first-order factor must be equal for all the items loading on the same first-order factor (Morin, Arens, & Marsh, 2016). This may be one of the main reasons why the higher-order approach often does not meet the goodness-of-fit criteria (Gignac, 2016; Morin, Arens, & Marsh, 2016). Moreover, in such models, the only source of variance explained by the higher-order factor is the one already explained by the first-order factors (Gignac, 2016).

For all the reasons presented above, the bifactor-ESEM seems to be a comprehensive approach that offers a solution to the limitations of the alternative models. The advantage of bifactor-ESEM over these alternative models has already been demonstrated in research inside (e.g., Garn et al., 2019; Gillet et al., 2019; Sánchez-Oliva et al., 2017; Tóth-Király et al., 2018; Tóth-Király et al., 2019) and outside (e.g., Arens & Morin, 2017; Fadda et al., 2019; Morin, Arens, & Marsh, 2016; Morin, Arens, Tran, et al., 2016; Perera et al., 2018; Perreira et al., 2018; Vajda et al., 2019) the field of SDT.

Longitudinal Approach to the Bifactor-ESEM

Undoubtedly, the authors who studied the continuum of motivation using bifactor-ESEM (Howard et al., 2018; Litalien et al., 2017) have made significant progress towards a better understanding of the complex structure of this phenomenon. Nevertheless, there is a clear lack of studies investigating the longitudinal measurement invariance of the instruments used to measure SDT's conceptualization of motivation. Temporal changes of motivation are considered a current research trend (Kanfer et al.,

2017) and there is emerging evidence that human motivation is dynamic (e.g., Navarro & Arrieta, 2010; Navarro et al., 2013; Roe, 2014; Zhang et al., 2019). Several studies demonstrated that, in the academic context, motivation may change over long periods of time, such as months or years (e.g., Nishimura & Sakurai, 2017; Weidinger et al., 2017), as well as over short periods of time, such as weeks (e.g., Wietrak et al., 2019). However, these studies rarely examine the longitudinal invariance of the applied measurement instruments. Establishing temporal measurement invariance verifies whether the items of the scale measure the constructs in the same way over time (Horn & McArdle, 1992; Meredith, 1993), permitting a less ambiguous interpretation of the longitudinal changes of the construct. The longitudinal non-invariance may cause a biased understanding of differences in mean scores and correlations between measurement occasions. When examining the dynamics of any construct, it is important to ensure that the changes observed in the distribution of the scores are a consequence of time, not of the variance of the measurement tool (Marsh et al., 2010; Vandenberg & Lance, 2000).

Although establishing longitudinal measurement invariance should be an essential condition that longitudinal research should meet, it has been rarely considered in the organizational and educational studies on motivation. Some attempts have been made to establish the longitudinal invariance of scales represented with the bifactor-ESEM model, to investigate stability of certain psychological constructs, e.g., work engagement (Perera et al., 2018) and basic psychological needs (Garn et al., 2019). Regarding the different types of motivation according to SDT, the longitudinal invariance of common measurement tools has been examined in the contexts of education (Guay et al., 2021), work (Gillet et al., 2018) and sport (Cece et al., 2019;

Stenling et al., 2018). However, it is important to note that both, within the motivation literature (Gillet et al., 2018; Guay et al., 2021), as well as in other fields of study such as memory (de Frias & Dixon, 2005), well-being (Maitland et al., 2001), burnout (Kim & Ji, 2009), mental health (Murray et al., 2019), depression (Mogos et al., 2015; Motl et al., 2005), or self-concept (Ferro & Boyle, 2013), the longitudinal measurement invariance of the applied measurement instruments is not always supported, and sometimes only partially supported.

The procedure of establishing the longitudinal invariance involves several steps that aim to examine configural, metric (weak), scalar (strong) and strict invariance. Configural invariance estimates the similarity in the general pattern of associations between items and factors across time with no equality constraints (factor loading pattern). Metric invariance tests whether the magnitude of the factor loadings is the same at all measurement points, and it is an essential condition for comparison of latent variances, latent covariances, and latent relations over time. Scalar invariance assumes that not only the factor loadings, but also the item intercepts are equal across time, and it is a requirement necessary to compare the latent means. Finally, strict invariance implies that the factor loadings, item intercepts and item uniquenesses are equal across time, and it is needed for subsequent analyses using factor scores saved from the measurement model. The absence of strict invariance suggests different levels of construct reliability across time, which remains unmodelled when using factor scores as opposed to fully latent variables.

The Current Research

The main interest of the present study is to investigate the psychometric properties of the MWMS (Gagné et al., 2015) applied longitudinally in the academic context. More specifically, the first objective is to contribute to the research on the multidimensional psychometric representations of the continuous structure of motivation, by replicating the comparison of different models: CFA, bifactor-CFA, ESEM and bifactor-ESEM, performed in previous research (Howard et al., 2018; Litalien et al., 2017). This is in line with the recommendations for a sequential analytical strategy that emphasize the importance of comparing these four models when psychometric investigations are the primary purpose of the study (Morin et al., 2020). In addition, previous studies were based on samples of Canadian students and employees exclusively, which was highlighted as a limitation. Thus, following recommendations of Howard et al. (2018) and Litalien et al. (2017), in the present research, we have broadened the cultural context, using a sample of Spanish undergraduate students.

Second, we aim to extend the prior research by exploring the stability of multidimensional structure of the continuum of motivation proposed by SDT and applying the bifactor-ESEM longitudinally. Thus far, little attention has been devoted to the stability of a full range of motivation forms proposed by SDT. Moreover, previous studies in the education and work contexts (Gillet et al., 2018; Guay et al., 2021) supported the partial longitudinal invariance of the motivation continuum.

Finally, to the best of our knowledge, the current study is the first to apply MWMS (a scale designed to measure work motivation) in the context of education, examining two forms of academic external regulation: material and social. It is worth mentioning that, although MWMS was created to measure work motivation, its underlying theoretical model (SDT) has been broadly used in other contexts, including education.

Method

Sample and Procedure

A total of 979 undergraduate students from different faculties (psychology, public management and labor relations, and sociology), of a public Spanish university participated in the study. The students were divided into 15 “class-groups” (i.e., 15 sections in three different academic courses). Five hundred eighty-two participants (59.45%) provided sociodemographic data. In this group, ages ranged from 18 to 49 years, with a mean of 20. Four hundred forty-four participants (76.29%) were female; five hundred fifty-three participants (95.02%) were Spanish. We collected 3063 repeatedly measured questionnaires (average of 3.13 per participant). The data were collected five times during one academic semester (approx. 4 months), every 2-3 weeks, at the end of each session. At Time 1 (T1), 732 students responded to the questionnaire, at Time 2 (T2) 634 responded, at Time 3 (T3) 627 responded, at Time 4 (T4) 568 responded, and at Time 5 (T5) 502 responded. Besides motivation, we also collected data about students’ performance, perceived competence, and perceived challenge, however, the analysis of these variables is out of the scope of this study (the data were collected to serve several research).

The participation in the research was voluntary and anonymous. Informed consent was obtained from all participants included in the study.

Measures

The MWMS (Gagné et al., 2015) translated into Spanish and adapted to the academic context was applied to measure students’ motivation. We decided to use the MWMS since it allows exploring two forms of external regulation – material and social. This is an important advantage of the MWMS over the AMS (Vallerand et al., 1992), the scale commonly used to measure motivation in the educational field. Moreover, the MWMS permits measuring two forms of introjected motivation: approach and avoidance. The question that the participants were asked was: "Thinking about this course, why do you or would you put effort into the activities proposed in this course?". The scale included 19 items, which assessed six dimensions of motivation: intrinsic motivation (e.g., "Because I have fun doing these activities"), identified regulation (e.g., "Because putting efforts in these activities aligns with my personal values"), introjected regulation (e.g., "Because I have to prove to myself that I can" – approach-focused item; or "Because otherwise I will feel ashamed of myself" – avoidance-focused item), extrinsic regulation – material (e.g., "Because I risk failing the course if I don't put enough effort in it"), extrinsic regulation – social (e.g., "To get others' approval, e.g., professor, colleagues, family, etc."), and amotivation (e.g., "I don't, because I feel that I'm wasting my time on these activities"). Full scale is available in Appendix B. The participants rated each item on a seven-point Likert scale, ranging from 1 (strongly disagree), to 7 = (strongly agree).

Data Analysis

The robust maximum likelihood estimator (MLR; Enders, 2010; Graham, 2009) was used to handle missing data at the item level (T1: 25,45%, T2: 35,37%, T3: 36,24%, T4: 42,16%, T5: 48,84%). Data analysis included several phases. First, we conducted a series of CFA, bifactor-CFA, ESEM, and bifactor-ESEM models for each of the five measurement points. CFA models were defined according to the underlying theory: each item was only allowed to load on the target factor. ESEM was specified using target rotation; each item was allowed to define both the target factor and non-target factors and all cross-loadings were targeted to be close to zero. The bifactor-CFA model was specified as orthogonal; each item was allowed to load on a G-factor, as well as on the target S-factor. Finally, bifactor-ESEM was estimated using orthogonal bifactor target rotation, which allows free estimation on the target S-factor and the G-factor, and estimation of the cross-loadings without restrictions, but targeted to be close to zero. For all models, standardized factor loadings (λ, lambda; indicating the strength of association between scores obtained for each specific item and for the underlying factors), and uniquenesses (δ, delta; indicating the proportion of variance that is unique to the rating of each specific items and which incorporate item-specific random measurement error) were reported.

The second stage of analyses aimed to compare the fit of the four models. The following goodness-of-fit measures were applied: comparative fit index (CFI), the Tucker–Lewis index (TLI), the root mean square error of approximation (RMSEA) and its 90% confidence interval, the standardized root mean square residual (SRMR), and the chi-square test of model fit. In agreement with interpretation guidelines (Hu & Bentler, 1999; Marsh et al., 2005; Marsh et al., 2004) the model fit is considered good for CFI and TLI values greater than .95, and for RMSEA and SRMR values smaller than .05; the model fit is considered acceptable for CFI and TLI values greater than .90 and for RMSEA and SRMR values smaller than .08. Additionally, the Akaike information criteria (AIC), Bayesian information criteria (BIC), and sample size adjusted BIC (ABIC) were applied to compare alternative models. According to the common interpretation guidelines (e.g., Morin et al., 2017), lower AIC, BIC, and ABIC values support a better fit of the model.

Finally, we tested the temporal invariance of the MWMS in the academic context, using the model with the best fit. We followed the sequence proposed by Meredith (1993), examining increasingly constrained models: configural, metric, scalar, and strict invariance. The least restrictive, configural invariance, assumes that all parameters are freely estimated across the measurement occasions. In a metric invariance model, the factor loadings are constrained to be equal across time. Scalar invariance assumes equality of the factor loadings and item's intercepts at all measurement point. Lastly, in a strict invariance model, the factor loadings, items' intercepts, and items' uniquenesses are constrained to be invariant across time. Following the suggestion of Chen (2007), we considered a difference of CFI, RMSEA and SRMR values of two nested models (e.g., metric and scalar) as an indicator of temporal invariance. More specifically, a change of less than .010 in CFI, .015 in RMSEA, and .030 in SRMR (.010 for scalar and strict invariance) evidenced longitudinal invariance.

All the statistical analyses were conducted using Mplus version 7.4 (Muthén & Muthén, 1998-2017).

Results

Measurement Models

The goodness-of-fit indices for each model at five measurement times are presented in Table 1. The CFA displayed, in general, poor fit to the data; only CFI at T2 and at T5, and SRMR demonstrated acceptable fit (CFI > .90, SRMR < .07). The bifactor-CFA models had marginally acceptable fit for CFI at all measurement points, for TLI at T3 and T5, and for RMSEA at T1, T2, T3, T5 (CFI > .90, TLI > .90, RMSEA < .08); however, TLI at T1, T2 and T4, RMSEA at T4, and SRMR at all measurement times indicated poor fit (TLI > .88, RMSEA < .08, SRMR < .09). The ESEM models had overall adequate fit to the data, CFI and TLI > .92; RMSEA and SRMR < .07. Finally, the bifactor-ESEM models demonstrated excellent fit to the data at all measurement points, CFI and TLI >.96; RMSEA and SRMR < .03. The analysis of AIC, BIC and ABIC values confirmed better fit of the bifactor-ESEM model, compared to CFA, ESEM, and bifactor-CFA models. Better fit of the ESEM and bifactor-ESEM models, compared to CFA and bifactor-CFA solutions, suggests the presence of cross-loadings. The presence of cross-loadings is reflected in the factor correlations, which are expected to be lower in the models that consider interrelatedness of the factors. In line with these expectation, the comparison of the first order models – CFA and ESEM (Table 2), revealed that overall factor correlations were marginally lower in ESEM (T1: $|r| = .07 – .51$, $|M| = .25$; T2: $|r| = .02 – .57$, $|M| = .25$; T3: $|r| = .01 – .57$, $|M| = .26$; T4: $|r| = .02 – .47$, $|M| = .20$; T5: $|r| = .08 – .60$, $|M| = .29$) than in CFA (T1: $|r| = .01 – .76$, $|M| = .30$; T2: $|r| = .01 – .76$, $|M| = .29$; T3: $|r| = .01 – .80$, $|M| = .30$; T4: $|r| = .04 – .80$, $|M| = .31$; T5: $|r| = .11 – .85$, $|M| = .34$), in five measurement occasions. The ESEM model represented the continuum structure of motivation more accurately than the CFA; in general, the correlations in the ESEM solution were stronger for the conceptually adjacent factors (e.g., intrinsic motivation and identified regulation, $|r| = .47 – .60$), than for the conceptually distant factors (e.g., intrinsic motivation and material form of external regulation, $|r| = .01 – .11$). The standardized factor loadings of CFA, bifactor-CFA, ESEM, and bifactor-ESEM are presented in Tables 3 to 6. In the CFA solution, high and statistically significant factor loadings were found for all factors ($\lambda = 0.58$ to 0.95; $M = 0.81$). In turn, the ESEM model revealed several unexpected results. First, three of the introjected regulation items: Item 1 ("Because I have to prove to myself that I can do well these activities") at T1, T3, T4 and T5, Item 2 ("Because doing these activities makes me feel proud of myself") at all measurement points, and Item 4 ("Because otherwise I will feel bad about myself") at T4, had stronger cross-loadings on non-target factors, with the highest values for identified regulation (λ = 0.41 to 0.64), than on the target factor (λ = 0.09 to 0.31). For the rest of the items, the target factor loadings were higher (λ = 0.46 to 2.75) than the cross-loadings (λ = -0.22 to 0.38). Second, the ESEM model contained several Heywood cases (i.e., standardized factor loading > 1). These improper solutions were found for Item 2 ("Because these activities are exciting") of intrinsic motivation at T5, Item 3 ("Because otherwise I will feel ashamed of myself") of introjected regulation at T2, T3, T4 and T5, and Item 2 ("Because others will respect me more, e.g., professor, colleagues, family, etc.") of external – social regulation at T5 (λ = 1.01 to 2.75). According to Chen et al., (2001), Heywood cases often suggest model misspecification, related to the omitted paths from the correctly specified model. We consider that one of the sources of construct-relevant multidimensionality–a hierarchical nature of motivation, not reflected in the ESEM solution–may be an example of an omitted path. Indeed, the number of Heywood cases decreases to one (Item 3 of introjected regulation at T2, λ = 1.05) in the bifactor-ESEM, which, according to the goodness-of-fit indices, is the best model.

Regarding the bifactor models, the incorporation of the G-factor in the bifactor-CFA provided a further confirmation that the CFA may be too simplistic to adequately represent the complex structure of motivation proposed in SDT self-determined motivation. We observed that several items loaded low on the specific target factor, but high on the global factor. These results were found for Item 1 ("Because I personally consider it important to put efforts in these activities") and Item 3 ("Because putting efforts in these activities has personal significance to me") of identified regulation (G-factor: λ = 0.74 to 0.79, target S-factor: λ = 0.16 to 0.23, and G-factor: λ = 0.64 to 0.72, target S-factor: λ = 0.25 to 0.32, respectively), and for Item 1 ("Because I have to prove to myself that I can do well these activities") and Item 2 ("Because doing these activities makes me feel proud of myself") of introjected regulation (G-factor: $\lambda = 0.62$ to 0.80, target S-factor: $\lambda = 0.04$ to 0.2, and G-factor: $\lambda = 0.76$ to 0.88, target S-factor: $\lambda = 0.03$ to 0.21, respectively). With these exceptions, the specific factors were well defined by high and statistically significant factor loadings ($\lambda = 0.57$ to 0.94; $M = 0.76$). According to our expectations, the loadings on the G-factor were high and positive for the items related to autonomous motivation ($\lambda = 0.49$ to 0.59 for intrinsic motivation and $\lambda = 0.64$ to 0.79 for identified regulation), small or negative for the items related to controlled motivation ($\lambda = 0.05$ to 0.30 for external-material regulation and $\lambda = -0.13$ to 0.22 for external-social regulation), and negative for items related to amotivation ($\lambda = -0.50$ to -0.34). A surprising result was found for introjected regulation, where Item 3 and Item 4 presented moderate loadings on the G-factor ($\lambda = 0.26$ to 0.56), but the loadings for Item 1 and Item 2 were high ($\lambda = 0.62$ to 0.88). In the bifactor-ESEM, in line with the results obtained for bifactor-CFA, the highest G-factor loadings were obtained for the items related to autonomous motivation ($\lambda = 0.47$ to 0.57 for intrinsic motivation and $\lambda = 0.63$ to 0.76 for identified regulation), small or negative loadings for the items related to controlled motivation ($\lambda = 0.10$ to 0.28 for external-material regulation and $\lambda = -0.10$ to 0.22 for external-social regulation), and negative loadings for items related to amotivation ($\lambda = -0.46$ to -0.32). Similarly, to the results of the bifactor-CFA solution, Item 1 and Item 2 of introjected regulation presented the highest loadings ($\lambda = 0.70$ to 0.93), and the loadings for Item 3 and Item 4 were moderate, ($\lambda = 0.29$ to 0.62). In case of Item 1 and Item 2 of introjected regulation, and Item 1 and Item 3 of identified regulation, the loadings on the G-factor were higher than the loadings on the specific target factors ($\lambda = -0.25$ to 0.36). With this exception, the S-factors were well defined (λ = .46 to 1.05; M = .02), and the cross-loadings remained lower than target loadings (λ = -0.24 to 0.26; M = .74). The bifactor-ESEM model included one Haywood case: the target factor loading for Item 3 of Introjected Regulation at T4 was higher than one (λ = 1.05). As expected, the factor loadings tended to be lower in the bifactor-ESEM models than in the ESEM solution. This result may indicate that in ESEM the unmodelled G-factor was reflected in the S-factor cross-loading.

Longitudinal Invariance

The final step of the analysis was testing the temporal invariance of MWMS scores using the model with the best fit, that is, the bifactor-ESEM. The comparison of goodness-of-fit indices for the longitudinal invariance test of the increasingly constrained models: configural, metric, scalar and strict, are provided in Table 1. The configural invariance model without any constrains, as well as the models in which invariance constraints were consecutively placed on item loadings, item intercepts and error variances, displayed excellent fit to the data (CFI and TLI >.96; RMSEA and SRMR < .03). Following interpretational guidelines proposed by Chen (2007; also see Cheung & Rensvold, 2002) suggesting that a decrease in CFI and TLI greater than .01 or an increase in RMSEA greater than .015 provides evidence against the invariance hypothesis, we obtained full longitudinal invariance for the bifactor-ESEM (metric invariance: ΔCFI = 0, ΔTLI = 0.003, ΔRMSEA = 0.001, ΔSRMR = -0.004; scalar invariance: ΔCFI = 0.002, ΔTLI = 0.002, ΔRMSEA = -0.001, ΔSRMR = 0; strict invariance: ΔCFI = 0.006, ΔTLI = 0.006, ΔRMSEA = -0.001, ΔSRMR = -0.003). These results confirm the full longitudinal measurement invariance of the MWMS over one academic semester. The standardized factor loadings and uniquenesses of the strict invariance model are presented in the Table 7.

Table 1

Goodness-of-Fit Statistics of CFA, ESEM, Bifactor-CFA, and Bifactor-ESEM Models and Longitudinal Invariance for Bifactor-ESEM Models

Model	Time	χ^2	df	CFI	TLI	AIC	BIC	ABIC	RMSEA	90% CI RMSEA	SRMR
CFA	1	831.79	137	.879	.849	43466.42	43797.32	43568.69	.083	[.078, .089]	.073
	2	683.71		.903	.879	36716.43	37036.97	36808.38	.079	[.073, .085]	.064
	3	742.93		.895	.869	36298.95	36618.70	36390.11	.084	[.078, .090]	.064
	4	728.29		.896	.871	32256.82	32569.46	32340.89	.087	[.081, .093]	.068
	5	608.50		.914	.892	28326.14	28629.88	28401.34	.083	[.076, .090]	.065
Bifactor CFA	1	696.04	133	.902	.874	43325.31	43674.60	43433.27	.076	[.071, .082]	.103
	2	653.55		.908	.881	36669.46	37007.81	36766.52	.079	[.073, .085]	.096
	3	550.80		.928	.907	36078.42	36415.93	36174.64	.071	[.065, .077]	.093
	4	701.06		.900	.872	32194.87	32524.87	32283.60	.087	[.080, .093]	.111
	5	507.37		.932	.912	28205.12	28525.74	28284.51	.075	[.068, .082]	.095
ESEM	1	214.52	72	.975	.941	42925.25	43554.87	43119.85	.052	[.044, .060]	.018
	2	252.67		.968	.924	36348.35	36958.28	36523.32	.063	[.055, .071]	.019
	3	192.99		.979	.950	35817.57	36425.98	35991.02	.052	[.043, .061]	.016
	4	245.32		.970	.928	31811.84	32406.71	31971.80	.065	[.056, .074]	.018
	5	197.11		.977	.946	27992.27	28570.21	28135.37	.059	[.049, .069]	.015
Bifactor ESEM	1	85.01*	59	.995	.987	42804.24	43493.60	43017.31	.025	[.011, .036]	.008
	2	120.19		.989	.969	36219.41	36887.22	36410.98	.040	[.030, .051]	.011
	3	89.10*		.995	.985	35719.66	36385.80	35909.57	.029	[.015, .040]	.009
	4	114.80		.990	.972	31691.38	32342.70	31866.52	.041	[.030, .052]	.010
	5	105.51		.991	.975	27913.93	28546.72	28070.61	.040	[.027, .052]	.010
Bifactor ESEM longitudinal invariance	Configural	4109.06	3045	.975	.964	164298.15	172165.47	167052.09	.019	[.017, .020]	.024
	Metric	4453.75	3381	.975	.967	164096.07	170321.51	166275.27	.018	[.017, .019]	.028
	Scalar	4589.95	3429	.973	965	164141.81	170132.70	166238.90	.019	[.017, .020]	.028
	Strict	4896.13	3505	.967	.959	164403.68	170023.19	166370.78	.020	[.019, .021]	.031

Note. CFA = confirmatory factor analysis; ESEM = exploratory structural equation modeling; df = degrees of freedom; CFI = comparative fit index; TLI = Tucker–Lewis index; AIC = Akaike information criterion; BIC = Bayesian information criterion; ABIC = sample-size-adjusted BIC; RMSEA = root-mean-square error of approximation; SRMR = standardized root-mean-square residual; CI = confidence interval.
*All chi-square values are statistically significant at $p < .001$. except of B-ESEM T1: $p < 0.05$, T3: $p < 0.01$

Table 2

Standardized Factor Correlations for the CFA and ESEM Solution Across Five Measurement Times

	1	2	3	4	5	6
Time 1						
1. Intrinsic motivation		0.316(0.051) **	-0.090(0.049)	-0.303(0.062) **	-0.440(0.041) **	-0.342(0.042) **
2. Identified regulation	0.510(0.045)**		0.256(0.039) **	0.211(0.073) **	-0.010(0.046)	-0.109(0.041) **
3. Introjected regulation	0.193(0.045) **	0.426(0.046) **		0.412(0.046) **	0.139(0.049) **	-0.115(0.046) *
4. External regulation – material	-0.084(0.042) *	0.205(0.039) **	0.326(0.040) **		0.755(0.044) **	0.360(0.064) **
5. External regulation – social	-0.121(0.041) **	-0.066(0.043)	0.307(0.044) **	0.170(0.038) **		0.602(0.033) **
6. Amotivation	-0.364(0.040) **	-0.399(0.039) **	-0.137(0.044) **	-0.139(0.046) **	0.344(0.047) **	
Time 2						
1. Intrinsic motivation		0.295((0.048) **	-0.205(0.054) **	-0.278(0.049) **	-0.430(0.045) **	-0.346(0.043) **
2. Identified regulation	0.565(0.038) **		0.120(0.045) **	0.211(0.048) **	0.004(0.048)	-0.030(0.049)
3. Introjected regulation	0.260(0.045) **	0.510(0.053) **		0.346(0.053)**	0.149(0.053) **	-0.119(0.049) *
4. External regulation – material	-0.106(0.046) *	0.172(0.048) **	0.293(0.050) **		0.757(0.032) **	0.409(0.045) **
5. External regulation – social	-0.047(0.048)	-0.024(0.042)	0.280(0.044) **	0.110(0.042) **		0.609(0.036) **
6. Amotivation	-0.353(0.040) **	-0.374(0.047) **	-0.156(0.047) **	-0.208(0.051) **	0.320(0.045) **	
Time 3						
1. Intrinsic motivation		0.325(0.047) **	-0.186(0.052) **	-0.324(0.054) **	-0.418(0.047) **	-0.296(0.041) **
2. Identified regulation	0.566(0.037) **		0.138(0.045) **	0.233(0.063) **	0.017(0.053)	-0.029(0.044)
3. Introjected regulation	0.342(0.041) **	0.491(0.051) **		0.425(0.045) **	0.239(0.050) **	-0.006(0.047)
4. External regulation – material	0.011(0.044)	0.244(0.042) **	0.346(0.040) **		802(0.035) **	0.474(0.043) **
5. External regulation – social	-0.036(0.045)	0.009(0.047)	0.313(0.044) **	0.119(0.045) **		0.641(0.031) **
6. Amotivation	-0.339(0.036) **	-0.385(0.042) **	-0.198(0.046) **	-0.217(0.048) **	0.325(0.047) **	

Note. Standardized factor correlations for the CFA are reported above the diagonal; and for the ESEM are reported below the diagonal). Standard errors are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$.

Table 2 (Continued)

Standardized Factor Correlations for the CFA and ESEM Solution Across Five Measurement Times

	1	2	3	4	5	6
Time 4						
1. Intrinsic motivation		0.305(0.048)**	-0.173(0.055)**	-0.296(0.053)**	-0.456(0.045)**	-0.282(0.039)**
2. Identified regulation	0.472(0.042)**		0.181(0.048)**	0.301(0.056)**	0.037(0.050)	0.068(0.046)
3. Introjected regulation	0.123(1.279)	0.100(1.086)		0.423(0.045)**	0.166(0.055)**	-0.048(0.050)
4. External regulation – material	-0.015(0.162)	0.318(0.195)	0.116(1.119)		0.797(0.029)**	0.482(0.040)**
5. External regulation – social	0.082(0.135)	0.163(0.384)	0.170(1.422)	0.255(0.185)		0.683(0.034)**
6. Amotivation	-0.354(0.053)**	-0.328(0.058)**	-0.050(0.634)	-0.195(0.086)*	0.248(0.147)	
Time 5						
1. Intrinsic motivation		0.172(0.054)**	-0.257(0.056)**	-0.490(0.046)**	-0.519(0.042)**	-0.269(0.046)**
2. Identified regulation	0.597(0.042)**		0.154(0.045)**	0.282(0.046)**	0.129(0.053)*	0.182(0.046)**
3. Introjected regulation	0.376(0.044)**	0.499(0.064)**		0.354(0.047)**	0.146(0.052)**	-0.111(0.048)*
4. External regulation – material	-0.078(0.048)**	0.175(0.047)**	0.329(0.048)**		0.853(0.025)**	0.558(0.038)**
5. External regulation – social	0.180(0.048)**	0.088(0.045)	0.360(0.043)**	0.161(0.045)**		0.648(0.036)**
6. Amotivation	-0.348(0.041)**	-0.493(0.044)**	-0.301(0.047)**	-0.254(0.052)**	0.174(0.053)**	

Note. Standardized factor correlations for the CFA are reported above the diagonal; and for the ESEM are reported below the diagonal). Standard errors are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$.

Table 3

Standardized Factor Loadings (λ) and Uniquenesses (δ) for CFA

	λ					δ				
	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5
1. Intrinsic motivation										
Item 1	0.89	0.92	0.94	0.94	0.94	0.22	0.16	0.11	0.12	0.11
Item 2	0.90	0.91	0.93	0.92	0.95	0.18	0.17	0.13	0.16	0.10
Item 3	0.79	0.83	0.82	0.85	0.84	0.37	0.31	0.33	0.28	0.30
2. Identified regulation										
Item 1	0.76	0.80	0.82	0.79	0.79	0.42	0.36	0.33	0.38	0.38
Item 2	0.81	0.86	0.83	0.80	0.86	0.34	0.26	0.31	0.36	0.26
Item 3	0.76	0.77	0.75	0.77	0.82	0.43	0.41	0.43	0.41	0.33
3. Introjected regulation										
Item 1	0.67	0.75	0.73	0.80	0.80	0.56	0.44	0.46	0.36	0.35
Item 2	0.74	0.81	0.80	0.84	0.87	0.45	0.34	0.35	0.30	0.25
Item 3	0.58	0.61	0.68	0.66	0.62	0.66	0.63	0.54	0.57	0.62
Item 4	0.65	0.62	0.71	0.66	0.65	0.58	0.62	0.50	0.57	0.58
4. External regulation – material										
Item 1	0.76	0.74	0.81	0.78	0.84	0.43	0.46	0.34	0.40	0.30
Item 2	0.83	0.89	0.85	0.93	0.90	0.32	0.21	0.29	0.13	0.18
Item 3	0.78	0.71	0.67	0.69	0.72	0.39	0.50	0.55	0.53	0.49
5. External regulation – social										
Item 1	0.79	0.81	0.88	0.88	0.88	0.37	0.35	0.23	0.23	0.23
Item 2	0.87	0.93	0.86	0.94	0.95	0.25	0.14	0.27	0.12	0.09
Item 3	0.74	0.79	0.82	0.84	0.81	0.45	0.38	0.34	0.29	0.34
6. Amotivation										
Item 1	0.86	0.88	0.88	0.89	0.92	0.26	0.22	0.24	0.21	0.16
Item 2	0.82	0.89	0.86	0.91	0.89	0.32	0.21	0.27	0.17	0.21
Item 3	0.72	0.80	0.76	0.78	0.80	0.47	0.36	0.43	0.39	0.36

Table 4

Standardized Factor Loadings (λ) and Uniquenesses (δ) for ESEM

	Factor 1 (λ)					Factor 2 (λ)					Factor 3 (λ)					Factor 4 (λ)				
	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5
1. Intrinsic motivation																				
Item 1	**0.90**	**0.89**	**1.00**	**0.98**	**0.95**	-0.01	0.01	-0.07	-0.02	0.00	0.03	0.02	-0.02	-0.01	0.00	-0.05	-0.04	0.00	0.04	-0.01
Item 2	**0.92**	**0.96**	**0.93**	**0.91**	**1.03**	-0.01	-0.03	0.02	0.01	-0.08	-0.01	-0.03	0.00	0.00	0.01	0.00	0.03	0.00	-0.01	0.02
Item 3	**0.76**	**0.80**	**0.76**	**0.79**	**0.79**	0.04	-0.01	0.05	0.04	0.02	-0.05	0.03	0.01	-0.01	-0.02	0.07	-0.01	-0.01	-0.06	-0.04
2. Identified regulation																				
Item 1	0.08	0.09	0.13	0.18	0.11	**0.61**	**0.64**	**0.59**	**0.53**	**0.52**	0.10	0.04	0.09	0.05	0.15	0.12	0.07	0.11	0.06	0.03
Item 2	0.08	-0.06	0.04	0.16	0.05	**0.67**	**0.89**	**0.74**	**0.62**	**0.75**	0.13	0.04	0.12	0.06	0.10	-0.05	-0.03	-0.01	-0.01	-0.01
Item 3	0.16	0.17	0.17	0.38	0.15	**0.62**	**0.59**	**0.58**	**0.46**	**0.59**	0.13	0.18	0.18	0.08	0.22	-0.16	-0.11	-0.13	-0.05	-0.10
3. Introjected regulation																				
Item 1	-0.05	0.08	0.02	0.04	0.10	0.41	0.29	0.41	0.59	0.48	**0.21**	**0.30**	**0.23**	**0.09**	**0.16**	0.21	0.20	0.16	0.24	0.18
Item 2	0.15	0.12	0.11	0.14	0.16	0.46	0.43	0.48	0.64	0.47	**0.22**	**0.31**	**0.25**	**0.09**	**0.21**	0.10	0.09	0.12	0.15	0.10
Item 3	0.00	0.01	-0.02	-0.02	-0.01	-0.17	-0.22	-0.18	-0.07	-0.16	**0.98**	**1.02**	**1.10**	**2.75**	**1.07**	-0.07	-0.07	-0.07	-0.02	-0.05
Item 4	-0.06	-0.09	-0.04	-0.03	-0.06	0.06	0.05	0.04	0.41	0.10	**0.75**	**0.76**	**0.77**	**0.20**	**0.72**	0.07	0.04	0.06	0.18	0.07
4. External regulation – material																				
Item 1	0.07	0.02	0.00	0.02	0.04	-0.06	-0.03	-0.01	-0.10	-0.04	0.03	-0.02	0.04	0.01	-0.03	**0.74**	**0.76**	**0.79**	**0.77**	**0.84**
Item 2	0.05	0.05	0.08	0.08	0.02	-0.02	-0.01	-0.04	-0.16	-0.01	-0.02	-0.01	-0.05	0.00	-0.02	**0.85**	**0.90**	**0.88**	**1.00**	**0.90**
Item 3	-0.10	-0.10	-0.10	-0.16	-0.11	-0.10	-0.08	-0.09	-0.05	-0.12	0.08	0.11	0.09	0.01	0.12	**0.77**	**0.68**	**0.67**	**0.71**	**0.72**
5. External regulation – social																				
Item 1	-0.02	0.02	-0.02	-0.03	0.01	0.00	-0.03	0.00	-0.04	-0.06	0.00	-0.05	-0.06	0.00	0.00	0.10	0.05	0.04	0.04	0.04
Item 2	0.00	0.01	-0.02	0.04	-0.04	0.09	0.04	0.09	-0.07	0.04	-0.06	-0.02	0.02	0.00	-0.05	0.01	-0.01	-0.04	-0.02	-0.03
Item 3	0.01	-0.04	0.04	-0.01	0.03	-0.07	-0.01	-0.12	-0.07	-0.07	0.11	0.08	0.06	0.01	0.09	-0.04	-0.03	0.01	-0.07	-0.01
6. Amotivation																				
Item 1	0.04	0.03	-0.01	0.06	0.04	0.06	0.01	0.06	0.08	0.04	-0.02	-0.02	-0.01	0.02	-0.01	0.04	0.00	0.00	0.01	-0.02
Item 2	0.05	0.04	0.06	0.06	0.05	-0.09	0.01	0.05	0.02	0.05	0.06	0.02	0.01	0.01	0.01	-0.02	-0.03	-0.02	-0.02	0.01
Item 3	-0.10	-0.10	-0.06	-0.08	-0.09	0.10	-0.04	-0.03	-0.03	0.00	-0.05	0.00	0.00	-0.01	-0.03	0.00	0.07	0.08	0.03	0.02

Note. Boldface indicates target ESEM factor loadings.

Table 4 (Continued)

Standardized Factor Loadings (λ) and Uniquenesses (δ) for ESEM

	Factor 5 (λ)					Factor 6 (λ)					δ				
	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5
1. Intrinsic Motivation															
Item 1	-0.01	0.01	0.02	-0.01	0.01	0.04	0.00	0.01	0.06	0.05	0.20	0.17	0.09	0.10	0.13
Item 2	0.01	0.02	0.02	0.01	-0.01	0.01	0.02	0.04	0.03	0.06	0.19	0.15	0.15	0.17	0.08
Item 3	-0.02	-0.05	-0.06	0.03	0.02	-0.07	-0.06	-0.07	-0.10	-0.11	0.35	0.30	0.31	0.27	0.28
2. Identified regulation															
Item 1	-0.11	-0.04	-0.04	-0.02	-0.05	-0.10	-0.17	-0.14	-0.25	-0.19	0.37	0.34	0.32	0.37	0.37
Item 2	0.03	0.00	-0.04	-0.02	-0.02	-0.06	-0.03	-0.02	-0.11	-0.05	0.38	0.20	0.31	0.42	0.26
Item 3	0.09	0.04	0.08	0.02	0.05	-0.02	0.04	0.01	-0.04	0.00	0.40	0.38	0.41	0.44	0.32
3. Introjected regulation															
Item 1	-0.04	0.02	0.04	0.08	0.06	-0.06	-0.07	-0.11	-0.07	-0.07	0.61	0.56	0.52	0.38	0.43
Item 2	-0.03	0.00	0.00	0.07	0.04	-0.07	0.03	-0.06	-0.08	-0.14	0.47	0.47	0.40	0.29	0.32
Item 3	0.06	0.06	-0.01	-0.02	0.00	0.02	0.02	0.04	0.01	0.02	0.15	0.13	<0.01	-6.48	0.05
Item 4	-0.02	-0.06	0.02	0.20	0.04	0.01	-0.01	-0.01	-0.02	-0.01	0.39	0.41	0.34	0.59	0.37
4. External regulation – material															
Item 1	0.11	0.05	0.03	0.07	0.06	0.02	0.04	0.03	-0.05	-0.01	0.41	0.44	0.36	0.40	0.29
Item 2	0.00	-0.01	0.01	-0.06	-0.01	0.00	-0.01	-0.01	0.01	-0.03	0.31	0.22	0.26	0.11	0.19
Item 3	-0.01	-0.02	-0.03	-0.03	-0.06	0.00	-0.02	0.02	0.05	0.06	0.37	0.48	0.52	0.49	0.44
5. External regulation – social															
Item 1	**0.76**	**0.80**	**0.90**	**0.87**	**0.86**	0.01	0.03	-0.03	0.03	0.05	0.37	0.34	0.22	0.23	0.24
Item 2	**0.92**	**0.96**	**0.87**	**0.94**	**1.01**	-0.05	-0.04	-0.03	0.01	-0.08	0.22	0.12	0.25	0.12	0.05
Item 3	**0.70**	**0.76**	**0.77**	**0.87**	**0.77**	0.06	0.01	0.07	0.00	0.06	0.43	0.38	0.32	0.28	0.34
6. Amotivation															
Item 1	-0.08	-0.05	-0.03	-0.02	0.01	**0.96**	**0.91**	**0.90**	**0.95**	**0.94**	0.21	0.21	0.24	0.19	0.16
Item 2	-0.02	0.01	-0.02	-0.02	-0.04	**0.80**	**0.90**	**0.91**	**0.94**	**0.94**	0.34	0.21	0.25	0.18	0.20
Item 3	0.12	0.05	0.08	0.11	0.06	**0.67**	**0.75**	**0.72**	**0.73**	**0.76**	0.46	0.34	0.41	0.36	0.35

Note. Boldface indicates target ESEM factor loadings.

Table 5

Standardized Factor Loadings (λ) and Uniquenesses (δ) for Bifactor-CFA

	G-Factor (λ)					S-Factor (λ)					δ				
	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5
1. Intrinsic motivation															
Item 1	0.49	0.55	0.54	0.56	0.59	0.74	0.73	0.79	0.76	0.72	0.22	0.17	0.09	0.11	0.13
Item 2	0.51	0.54	0.57	0.55	0.57	0.76	0.75	0.72	0.73	0.78	0.17	0.15	0.15	0.16	0.08
Item 3	0.54	0.56	0.56	0.56	0.59	0.59	0.62	0.59	0.64	0.60	0.36	0.31	0.33	0.29	0.30
2. Identified regulation															
Item 1	0.74	0.76	0.79	0.75	0.75	0.17	0.23	0.17	0.16	0.17	0.42	0.38	0.34	0.41	0.42
Item 2	0.64	0.72	0.71	0.68	0.74	0.94	0.70	0.68	0.84	0.80	(-0.30)	(-1.47)	0.03	(-0.17)	(-0.18)
Item 3	0.64	0.65	0.64	0.64	0.72	0.26	0.32	0.32	0.27	0.25	0.52	0.52	0.49	0.52	0.41
3. Introjected regulation															
Item 1	0.62	0.67	0.72	0.77	0.80	0.18	0.22	0.11	0.15	0.04	0.58	0.51	0.47	0.39	0.37
Item 2	0.78	0.76	0.82	0.86	0.88	0.15	0.21	0.10	0.11	0.03	0.37	0.39	0.31	0.25	0.22
Item 3	0.26	0.32	0.45	0.46	0.51	0.85	0.89	0.94	0.80	0.81	0.20	0.14	(-0.09)	0.15	0.09
Item 4	0.39	0.42	0.52	0.47	0.56	0.69	0.61	0.58	0.68	0.57	0.37	0.44	0.39	0.32	0.36
4. External regulation – material															
Item 1	0.18	0.13	0.29	0.28	0.24	0.73	0.72	0.74	0.70	0.80	0.44	0.47	0.37	0.43	0.31
Item 2	0.25	0.23	0.30	0.30	0.26	0.81	0.88	0.82	0.92	0.87	0.29	0.17	0.24	0.06	0.17
Item 3	0.09	0.09	0.15	0.10	0.05	0.78	0.69	0.65	0.67	0.73	0.39	0.52	0.55	0.54	0.47
5. External regulation – social															
Item 1	-0.08	-0.07	0.00	0.11	0.09	0.77	0.80	0.88	0.87	0.87	0.40	0.35	0.23	0.24	0.24
Item 2	0.00	0.03	0.11	0.12	0.22	0.90	0.94	0.86	0.93	0.94	0.20	0.12	0.26	0.12	0.07
Item 3	-0.13	-0.04	-0.05	0.06	0.13	0.73	0.78	0.81	0.84	0.80	0.46	0.39	0.34	0.29	0.35
6. Amotivation															
Item 1	-0.40	-0.42	-0.40	-0.34	-0.49	0.80	0.78	0.78	0.83	0.77	0.20	0.22	0.24	0.19	0.16
Item 2	-0.44	-0.36	-0.35	-0.40	-0.46	0.68	0.82	0.79	0.82	0.77	0.35	0.20	0.25	0.17	0.19
Item 3	-0.37	-0.47	-0.40	-0.40	-0.50	0.60	0.65	0.64	0.66	0.62	0.50	0.36	0.44	0.39	0.37

Table 6

Standardized Factor Loadings (λ) and Uniquenesses (δ) for Bifactor-ESEM

	G-Factor (λ)					S-Factor 1 (λ)					S-Factor 2 (λ)					S-Factor 3 (λ)				
	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5
1. Intrinsic Motivation																				
Item 1	0.47	0.54	0.54	0.56	0.57	**0.74**	**0.72**	**0.78**	**0.75**	**0.72**	0.07	0.08	0.04	0.03	0.07	-0.01	-0.02	-0.03	-0.03	-0.04
Item 2	0.50	0.53	0.57	0.56	0.55	**0.74**	**0.74**	**0.72**	**0.71**	**0.77**	0.06	0.03	0.06	0.04	0.04	-0.04	-0.06	-0.03	-0.01	-0.02
Item 3	0.52	0.54	0.55	0.55	0.55	**0.60**	**0.62**	**0.60**	**0.62**	**0.62**	0.02	0.01	0.04	0.09	0.06	-0.08	-0.03	-0.03	-0.05	-0.05
2. Identified regulation																				
Item 1	0.70	0.71	0.76	0.73	0.71	0.04	0.08	0.08	0.08	0.09	**0.28**	**0.28**	**0.22**	**0.18**	**0.26**	0.03	0.00	-0.02	-0.04	0.00
Item 2	0.64	0.71	0.71	0.70	0.73	0.07	0.01	0.04	0.02	0.06	**0.65**	**0.68**	**0.63**	**0.72**	**0.56**	0.06	0.03	0.01	-0.01	-0.02
Item 3	0.63	0.64	0.64	0.64	0.71	0.15	0.18	0.16	0.26	0.15	**0.34**	**0.33**	**0.34**	**0.29**	**0.36**	0.08	0.11	0.08	0.10	0.07
3. Introjected regulation																				
Item 1	0.70	0.74	0.77	0.82	0.93	-0.19	-0.11	-0.11	-0.14	-0.14	-0.13	-0.11	-0.10	-0.11	-0.19	**0.09**	**0.13**	**0.03**	**0.02**	**-0.25**
Item 2	0.81	0.83	0.85	0.87	0.82	0.00	-0.07	-0.03	-0.04	0.06	-0.04	-0.05	-0.04	-0.03	0.09	**0.10**	**0.13**	**0.04**	**0.02**	**-0.02**
Item 3	0.29	0.34	0.50	0.51	0.62	-0.02	0.00	-0.03	-0.02	-0.08	0.05	0.03	-0.01	-0.01	-0.08	**0.86**	**1.05**	**0.88**	**0.95**	**0.73**
Item 4	0.40	0.43	0.53	0.52	0.60	-0.09	-0.11	-0.05	-0.09	-0.09	0.08	0.10	0.08	0.07	0.05	**0.60**	**0.48**	**0.54**	**0.47**	**0.46**
4. External regulation – material																				
Item 1	0.16	0.12	0.28	0.26	0.21	-0.04	-0.10	-0.11	-0.09	-0.08	0.02	-0.02	-0.02	-0.02	0.00	0.09	0.03	0.06	0.06	0.03
Item 2	0.23	0.21	0.26	0.26	0.25	-0.07	-0.08	-0.03	-0.06	-0.11	-0.02	0.02	0.03	0.01	0.00	0.04	0.06	0.02	0.04	0.01
Item 3	0.11	0.10	0.16	0.12	0.10	-0.19	-0.19	-0.17	-0.24	-0.22	-0.05	-0.05	-0.09	-0.10	-0.09	0.12	0.10	0.09	0.06	0.09
5. External regulation – social																				
Item 1	-0.07	-0.04	0.02	0.12	0.11	-0.04	-0.01	-0.05	-0.03	0.03	0.06	-0.03	-0.01	-0.02	-0.02	0.13	0.08	0.07	0.09	0.08
Item 2	0.04	0.05	0.13	0.14	0.22	-0.03	0.00	-0.04	0.03	0.02	-0.02	-0.01	0.02	0.00	0.01	0.08	0.10	0.10	0.12	0.04
Item 3	-0.10	-0.02	-0.04	0.09	0.17	-0.01	-0.03	0.01	0.00	0.04	0.00	0.03	-0.02	-0.04	-0.05	0.20	0.16	0.16	0.14	0.12
6. Amotivation																				
Item 1	-0.39	-0.41	-0.38	-0.32	-0.46	-0.02	-0.02	-0.04	-0.01	0.03	0.00	-0.01	-0.02	-0.02	-0.02	0.02	0.02	0.02	0.04	0.03
Item 2	-0.42	-0.34	-0.34	-0.38	-0.44	0.00	-0.03	0.02	0.00	0.03	-0.07	-0.05	-0.03	-0.03	-0.02	0.09	0.04	0.03	0.05	0.04
Item 3	-0.36	-0.46	-0.39	-0.39	-0.46	-0.11	-0.10	-0.06	-0.10	-0.09	0.04	0.03	0.04	-0.01	-0.06	0.02	0.07	0.07	0.04	0.01

Note. Boldface indicates target ESEM S-factor loadings.

Table 6 (Continued)

Standardized Factor Loadings (λ) and Uniquenesses (δ) for Bifactor-ESEM

	S-Factor 4 (λ)					S-Factor 5 (λ)					S-Factor 6 (λ)					δ				
	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5
1. Intrinsic Motivation																				
Item 1	-0.15	-0.16	-0.11	-0.11	-0.16	-0.03	0.00	-0.01	-0.01	0.05	-0.01	-0.04	-0.01	0.01	0.03	0.20	0.17	0.09	0.10	0.13
Item 2	-0.11	-0.10	-0.10	-0.14	-0.14	-0.02	0.01	0.00	0.00	0.04	-0.03	-0.03	0.01	-0.01	0.04	0.19	0.15	0.15	0.17	0.08
Item 3	-0.05	-0.12	-0.09	-0.15	-0.15	-0.06	-0.06	-0.10	0.00	0.02	-0.08	-0.09	-0.09	-0.10	-0.10	0.35	0.30	0.31	0.27	0.28
2. Identified regulation																				
Item 1	0.09	0.06	0.06	0.00	0.01	-0.09	-0.06	-0.06	-0.08	-0.10	-0.06	-0.14	-0.10	-0.16	-0.16	0.40	0.38	0.35	0.39	0.38
Item 2	-0.02	-0.02	-0.02	-0.05	-0.03	0.03	-0.01	-0.04	-0.05	-0.06	-0.02	-0.01	0.00	-0.02	-0.05	0.16	0.03	0.10	-0.02	0.15
Item 3	-0.15	-0.11	-0.13	-0.11	-0.11	0.09	0.07	0.08	-0.01	0.04	0.02	0.06	0.04	0.00	0.01	0.42	0.41	0.42	0.42	0.32
3. Introjected regulation																				
Item 1	0.14	0.15	0.09	0.15	0.08	0.02	0.06	0.05	0.04	0.00	0.08	0.04	0.02	0.06	0.11	0.41	0.39	0.37	0.27	0.00
Item 2	0.02	0.03	0.04	0.06	0.05	0.02	0.05	0.02	0.03	0.01	0.06	0.14	0.05	0.04	-0.06	0.33	0.26	0.27	0.24	0.30
Item 3	0.08	0.04	0.05	0.05	0.07	0.25	0.21	0.20	0.23	0.17	0.05	0.05	0.07	0.08	0.09	0.10	-0.28	-0.08	-0.24	0.04
Item 4	0.17	0.14	0.13	0.14	0.15	0.14	0.08	0.17	0.16	0.15	0.04	0.03	0.02	0.06	0.04	0.41	0.53	0.37	0.45	0.37
4. External regulation – material																				
Item 1	**0.73**	**0.72**	**0.73**	**0.69**	**0.80**	0.18	0.10	0.08	0.14	0.12	0.01	-0.02	0.00	-0.06	-0.07	0.40	0.44	0.37	0.42	0.29
Item 2	**0.79**	**0.85**	**0.84**	**0.93**	**0.85**	0.07	0.04	0.04	0.04	0.04	-0.02	-0.08	-0.06	-0.04	-0.10	0.31	0.21	0.23	0.05	0.19
Item 3	**0.75**	**0.68**	**0.63**	**0.64**	**0.70**	0.08	0.04	0.03	0.05	0.02	-0.01	-0.05	-0.01	0.03	0.01	0.37	0.48	0.53	0.50	0.44
5. External regulation – social																				
Item 1	0.18	0.08	0.08	0.11	0.09	**0.74**	**0.78**	**0.86**	**0.84**	**0.84**	0.12	0.16	0.13	0.18	0.17	0.38	0.35	0.22	0.23	0.24
Item 2	0.08	0.04	0.00	0.07	0.03	**0.88**	**0.92**	**0.84**	**0.90**	**0.94**	0.11	0.12	0.14	0.17	0.08	0.20	0.12	0.25	0.12	0.05
Item 3	0.05	0.04	0.06	0.02	0.04	**0.70**	**0.76**	**0.78**	**0.81**	**0.76**	0.16	0.13	0.19	0.15	0.17	0.44	0.38	0.32	0.29	0.34
6. Amotivation																				
Item 1	0.01	-0.08	-0.04	-0.04	-0.09	0.09	0.10	0.15	0.16	0.17	**0.80**	**0.77**	**0.76**	**0.82**	**0.77**	0.20	0.22	0.24	0.19	0.16
Item 2	-0.04	-0.10	-0.08	-0.06	-0.06	0.13	0.17	0.15	0.16	0.13	**0.67**	**0.80**	**0.78**	**0.80**	**0.76**	0.34	0.20	0.24	0.18	0.20
Item 3	0.01	0.04	0.07	0.03	-0.02	0.23	0.19	0.22	0.25	0.18	**0.58**	**0.64**	**0.62**	**0.64**	**0.63**	0.46	0.33	0.40	0.36	0.34

Note. Boldface indicates target ESEM S-factor loadings.

Table 7

Standardized Factor Loadings (λ) and Uniquenesses (δ) for Strict Longitudinal Invariance of Bifactor-ESEM

	G-Factor (λ)					S-Factor 1 (λ)					S-Factor 2 (λ)					S-Factor 3 (λ)				
	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5
1. Intrinsic Motivation																				
Item 1	0.46	0.46	0.46	0.50	0.49	**0.78**	**0.76**	**0.75**	**0.73**	**0.71**	0.08	0.07	0.07	0.07	0.06	-0.04	-0.03	-0.03	-0.03	-0.03
Item 2	0.47	0.46	0.47	0.51	0.49	**0.78**	**0.75**	**0.74**	**0.73**	**0.71**	0.08	0.07	0.07	0.07	0.06	-0.05	-0.04	-0.04	-0.04	-0.04
Item 3	0.49	0.48	0.49	0.53	0.52	**0.63**	**0.61**	**0.61**	**0.59**	**0.58**	0.08	0.07	0.07	0.07	0.06	-0.08	-0.07	-0.07	-0.07	-0.07
2. Identified regulation																				
Item 1	0.70	0.70	0.71	0.73	0.72	0.09	0.08	0.08	0.08	0.08	**0.30**	**0.27**	**0.27**	**0.27**	**0.24**	-0.03	-0.02	-0.02	-0.02	-0.02
Item 2	0.65	0.65	0.67	0.68	0.68	0.08	0.08	0.08	0.07	0.07	**0.62**	**0.57**	**0.58**	**0.58**	**0.51**	0.04	0.03	0.03	0.03	0.03
Item 3	0.59	0.60	0.60	0.62	0.62	0.20	0.20	0.20	0.18	0.18	**0.41**	**0.37**	**0.37**	**0.37**	**0.33**	0.09	0.09	0.09	0.08	0.08
3. Introjected regulation																				
Item 1	0.79	0.83	0.83	0.83	0.87	-0.16	-0.17	-0.17	-0.15	-0.16	-0.17	-0.17	-0.17	-0.16	-0.15	**-0.02**	**-0.02**	**-0.02**	**-0.02**	**-0.02**
Item 2	0.83	0.84	0.84	0.85	0.87	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	**0.02**	**0.02**	**0.02**	**0.02**	**-0.02**
Item 3	0.39	0.40	0.40	0.43	0.44	-0.05	-0.05	-0.05	-0.05	-0.05	-0.01	-0.01	-0.01	-0.01	-0.01	**0.88**	**0.83**	**0.82**	**0.79**	**0.82**
Item 4	0.44	0.45	0.46	0.48	0.48	-0.08	-0.08	-0.08	-0.08	-0.08	0.10	0.09	0.09	0.09	0.08	**0.60**	**0.56**	**0.56**	**0.53**	**0.54**
4. External regulation – material																				
Item 1	0.20	0.23	0.23	0.24	0.24	-0.09	-0.10	-0.10	-0.09	-0.09	-0.01	-0.01	-0.01	-0.01	-0.01	0.08	0.08	0.08	0.08	0.08
Item 2	0.25	0.29	0.29	0.30	0.30	-0.09	-0.10	-0.09	-0.09	-0.09	-0.01	-0.01	-0.01	-0.01	-0.01	0.05	0.05	0.05	0.05	0.05
Item 3	0.14	0.16	0.16	0.17	0.17	-0.20	-0.21	-0.21	-0.20	-0.20	-0.08	-0.09	-0.08	-0.08	-0.08	0.11	0.11	0.10	0.10	0.10
5. External regulation – social																				
Item 1	-0.01	-0.01	-0.01	-0.01	-0.01	-0.07	-0.06	-0.06	-0.06	-0.06	0.02	0.02	0.02	0.02	0.02	0.13	0.13	0.12	0.11	0.11
Item 2	0.08	0.08	0.08	0.08	0.08	-0.05	-0.05	-0.05	-0.04	-0.04	-0.01	-0.01	-0.01	-0.01	0.01	0.14	0.12	0.12	0.11	0.11
Item 3	-0.01	-0.01	-0.01	-0.01	-0.01	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.02	0.21	0.19	0.19	0.17	0.18
6. Amotivation																				
Item 1	-0.37	-0.33	-0.34	-0.35	-0.35	-0.05	-0.05	-0.04	-0.04	-0.04	-0.04	-0.03	-0.03	-0.03	-0.03	0.06	0.05	0.05	0.04	0.05
Item 2	-0.36	-0.33	-0.33	-0.34	-0.34	-0.04	-0.04	-0.04	-0.03	-0.03	-0.07	-0.06	-0.06	-0.06	-0.05	0.09	0.08	0.07	0.07	0.07
Item 3	-0.38	-0.37	-0.37	-0.38	-0.38	-0.12	-0.11	-0.11	-0.11	-0.11	-0.01	-0.01	-0.01	-0.01	-0.01	0.10	0.08	0.08	0.08	0.08

Note. Boldface indicates target ESEM S-factor loadings.

Table 7 (Continued)

Standardized Factor Loadings (λ) and Uniquenesses (δ) for Strict Longitudinal Invariance of Bifactor-ESEM

	S-Factor 4 (λ)					S-Factor 5 (λ)					S-Factor 6 (λ)					δ				
	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5	T1	T2	T3	T4	T5
1. Intrinsic Motivation																				
Item 1	-0.11	-0.10	-0.10	-0.10	-0.10	-0.03	-0.03	-0.03	-0.04	-0.04	-0.01	-0.01	-0.01	-0.01	-0.03	0.20	0.17	0.09	0.10	0.13
Item 2	-0.09	-0.07	-0.07	-0.08	-0.08	-0.02	-0.02	-0.02	-0.03	-0.03	-0.01	-0.01	0.01	-0.01	-0.04	0.19	0.15	0.15	0.17	0.08
Item 3	-0.08	-0.07	-0.07	-0.07	-0.07	-0.08	-0.08	-0.08	-0.08	-0.09	-0.08	-0.09	-0.09	-0.09	-0.08	0.35	0.30	0.31	0.27	0.28
2. Identified regulation																				
Item 1	0.06	0.05	0.05	0.05	0.05	-0.08	-0.09	-0.09	-0.09	-0.09	-0.10	-0.11	-0.11	-0.11	-0.10	0.40	0.38	0.35	0.39	0.38
Item 2	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	-0.02	-0.03	-0.03	-0.03	-0.03	0.16	0.03	0.10	-0.02	0.15
Item 3	-0.12	-0.10	-0.11	-0.10	-0.10	0.04	0.04	0.04	0.04	0.04	0.01	0.01	0.01	0.01	0.01	0.42	0.41	0.42	0.42	0.32
3. Introjected regulation																				
Item 1	0.10	0.09	0.09	0.09	0.09	-0.01	-0.01	-0.01	-0.01	-0.01	0.04	0.05	0.05	0.05	0.05	0.41	0.39	0.37	0.27	0.00
Item 2	0.03	0.03	0.03	0.02	0.03	-0.02	-0.02	-0.02	-0.02	-0.02	0.05	0.05	0.05	0.05	0.05	0.33	0.26	0.27	0.24	0.30
Item 3	0.03	0.03	0.03	0.03	0.03	0.18	0.19	0.19	0.20	0.21	0.04	0.05	0.05	0.05	0.05	0.10	-0.28	-0.08	-0.24	0.04
Item 4	0.13	0.12	0.12	0.12	0.12	0.11	0.11	0.11	0.12	0.13	0.03	0.03	0.03	0.03	0.03	0.41	0.53	0.37	0.45	0.37
4. External regulation – material																				
Item 1	**0.74**	**0.71**	**0.71**	**0.70**	**0.70**	0.15	0.18	0.18	0.18	0.19	-0.01	-0.01	-0.01	-0.01	-0.01	0.40	0.44	0.37	0.42	0.29
Item 2	**0.85**	**0.83**	**0.82**	**0.81**	**0.82**	0.07	0.08	0.08	0.08	0.09	-0.02	-0.03	-0.03	-0.03	-0.03	0.31	0.21	0.23	0.05	0.19
Item 3	**0.70**	**0.66**	**0.67**	**0.65**	**0.66**	0.06	0.07	0.07	0.07	0.07	0.01	0.01	0.01	0.01	0.01	0.37	0.48	0.53	0.50	0.44
5. External regulation – social																				
Item 1	0.14	0.12	0.13	0.12	0.12	**0.79**	**0.82**	**0.82**	**0.83**	**0.86**	0.10	0.11	0.11	0.11	0.10	0.38	0.35	0.22	0.23	0.24
Item 2	0.06	0.05	0.05	0.05	0.05	**0.88**	**0.89**	**0.89**	**0.89**	**0.91**	0.07	0.08	0.08	0.08	0.07	0.20	0.12	0.25	0.12	0.05
Item 3	0.05	0.05	0.05	0.04	0.04	**0.74**	**0.76**	**0.76**	**0.77**	**0.81**	0.10	0.12	0.12	0.11	0.11	0.44	0.38	0.32	0.29	0.34
6. Amotivation																				
Item 1	-0.03	-0.02	-0.02	-0.02	-0.02	0.16	0.15	0.15	0.16	0.16	**0.76**	**0.79**	**0.79**	**0.78**	**0.75**	0.20	0.22	0.24	0.19	0.16
Item 2	-0.06	-0.04	-0.04	-0.04	-0.04	0.17	0.16	0.16	0.16	0.17	**0.74**	**0.78**	**0.77**	**0.76**	**0.74**	0.34	0.20	0.24	0.18	0.20
Item 3	0.06	0.05	0.05	0.05	0.05	0.24	0.23	0.23	0.24	0.25	**0.58**	**0.63**	**0.63**	**0.62**	**0.61**	0.46	0.33	0.40	0.36	0.34

Note. Boldface indicates target ESEM S-factor loadings.

Discussion

The objective of the current study was twofold: first, we examined the self-determination continuum of the MWMS adapted to the academic context, relying on the bifactor-ESEM model. Second, we tested the temporal measurement invariance of the MWMS.

Factor Structure of MWMS in Academic Context

The first step of the analysis was comparing the goodness-of-fit scores for all solutions. The model with the worst fit was the CFA, at all measurement occasions. This finding is slightly different from the results obtained in other studies that compared the four representations of the SDT motivation structure (CFA, ESEM, bifactor-CFA, bifactor-ESEM), in which the fit of the CFA model was acceptable (Cece et al., 2019; Litalien et al., 2017), or marginally acceptable (Howard et al., 2018). In these studies, the fit of the bifactor-CFA model was poor (the worst result among the four solutions); contrarily, in the current research, the fit of the bifactor-CFA model was slightly better than that of the CFA model. We found that the fit of the ESEM was clearly better that the fit of CFA and bifactor-CFA solutions, which is in line with the results of the previous studies (e.g., Cece et al., 2019; Guay et al., 2015; Howard et al., 2018; Litalien et al., 2017). Finally, in accordance with our expectations and with the results of previous research (Cece et al., 2019; Howard et al., 2018; Litalien et al., 2017), the bifactor-ESEM was the optimal model in terms of fit indices, once again providing evidence that this measurement framework is best suited to represent the multidimensional nature of the motivation continuum. From these results, two conclusions can be drawn. First, the superiority of the ESEM and bifactor-ESEM models over the CFA and bifactor-CFA models confirms that the small cross-loadings are an integral part of the structure of

SDT motivation and cannot be ignored. Our results contribute to the work of other researchers who argue for the use of cross-loadings to overcome the basic assumption of the independent cluster model inherent in CFA (Asparouhov & Muthen, 2009; Guay et al., 2015; Marsh et al., 2014; Marsh et al., 2009; Morin, Arens, & Marsh, 2016). The ESEM approach provides a better representation of complex, multidimensional structures like SDT motivation. Second, the superiority of bifactor models over the first-order factor solutions provides strong evidence for the existence of both, global and specific motivation factors. As proposed by Howard et al. (2018), while the S-factors reflect the quality of motivation, the G-factor represents the quantity of self-determined motivation.

The general pattern of the factor loadings on the G-factor was in line with the assumption about an underlying continuum of motivation: the factor loadings were high and positive for the items related to autonomous motivation, small or negative for the items related to controlled motivation. However, a deeper analysis of the findings revealed some unexpected results. Even though the factor loadings of the intrinsic motivation items on the G-factor were high and positive, they were lower than the factor loadings of the items representing less autonomous form of motivation: identified regulation (all the items) and introjected regulation (Item 1 and Item 2). Thus, the results of the current study do not fully confirm either the "relative self-determination" structure (Grolnick & Ryan, 1987), which assumes that external and introjected regulations would load negatively on a continuum factor, nor the idea that the G-factor represents the general quantity of self-determination (Howard et al., 2018). These results require a deeper investigation of the meaning behind the global motivation factor.

Indeed, the underlying characteristics of a global factor in a bifactor-ESEM solution is that it absorbs all the variance that is shared amongst all items. Intuitively, it makes sense that the greatest amount of variance shared between items comes from those in the middle of the continuum, which have neighboring items on both sides of the continuum (e.g., neighboring factors on the continuum share stronger correlations). Thus, the global factor is likely to be mainly identified by the items that share the greatest amount of variance with all other items, which is likely to fall somewhere in the middle of the continuum. This appears to be the case as a similar study in the sport context (Cece et al., 2019) reported factor loadings on the G-factor opposite to those suggested by theory and reported in the current study: negative for intrinsic motivation and identified regulation, and positive for introjected regulation, external regulation, and amotivation. In this context, the global motivation factor is closer to amotivation or external regulation, with introjected regulation falling closer to an external source of motivation than an intrinsic one. In the current study, the strongest factor loadings for the global factor were items from the identified and introjected regulation constructs, followed by items from the intrinsic motivation and external regulation constructs, thus clearly representing an internal form of motivation. Future studies should pay attention to the conditions under which the items from the introjected regulation factor may share more variance with external forms of motivation, thus identifying the global motivation factor as being externally driven.

Regarding the S-factors, all factor loadings, except for identified and introjected regulations, provided additional confirmation for the continuum structure of motivation: the loadings on the target factor were high and positive, and the cross-loadings were small and/or negative. Although it was observed that a few of the items with target loadings on the identified and introjected regulation specific factors were low or negative, such results are to be expected in bifactor-ESEM models and do not pose any issue as long as the majority of the specific factors are well identified by a majority of their items (Morin et al., 2020). Indeed, similar unexpected factor loadings were observed in the previous studies for intrinsic motivation in the academic domain (Litalien et al., 2017), identified and introjected regulations in the work domain (Howard et al., 2018), and introjected and external regulation in the sport domain (Cece et al., 2019). These results provide further evidence that bifactor-ESEM solutions may be particularly useful in uncovering sources of misfit in psychometric measures that would remain unseen in less comprehensive models.

The results included several Heywood cases: six in the ESEM models and one in bifactor-ESEM model. According to Chen et al. (2001) the Heywood cases may have different sources, like the size of the sample, or model misspecification (e.g., too little indicators per factor, too many factors, omitted paths). Given that size of the sample used in the current study was greater than 150 (recommendation of Gerbing and Anderson, 1985) at all measurement points, we consider that the source of the improper solutions might be related to model misspecifications. We observed that in the bifactor-ESEM model the number of Heywood cases decreased to one. This finding may be interpreted as a further rational of considering the G-factor; the ESEM did not contemplate the G-factor, thus, the improper solutions could appear due to the omitted paths. However, it must be recognized that the retained model contained one Heywood case. Thus, the application of the MWMS in the academic context should proceed with caution, paying special attention to the introjected regulation factor.

Longitudinal Invariance and Temporal Evolution of the MWMS Scores

The most important contribution of the current study was establishing the longitudinal invariance of the MWMS adapted to the academic context, across five waves of data collection happening over the course of one semester (i.e., 15 weeks). This aspect, although essential for comparing scores obtained from different measurement occasions, has been neglected in the research on fluctuations of motivation. The results confirmed full longitudinal measurement invariance in the MWMS over one academic semester, providing evidence for configural, metric, scalar, and strict invariance.

In the field of research on SDT motivation continuum, similar results were obtained in the sport context. In their study, Cece et al. (2019), provide evidence for temporal invariance of the Youth Behavioral Regulation in Sport Questionnaire, represented with a bifactor-ESEM model. The results of this study support full metric and scalar temporal invariance, and partial strict invariance of the examined model. However, previous studies that investigated the temporal stability of the motivation continuum in work (Gillet et al., 2018) and academic (Guay el al., 2021) contexts failed to support a full longitudinal invariance of the measurement scales they used. A test of longitudinal measurement invariance is an essential condition to ensure that the observed changes in the scores obtained across different measurement points are the result of the fluctuations of the studied construct, and not the variation attributed to the measurement of said construct. There is evidence from other research fields (e.g., de Frias & Dixon, 2005; Ferro & Boyle, 2013; Kim & Ji, 2009; Maitland et al, 2001; Mogos et al., 2015; Motl et al., 2005: Murray et al., 2019) that the hypotheses about the longitudinal invariance of the used scale are not always supported. Given the above, we strongly recommend establishing longitudinal invariance of the measurement tool, as a precondition to comparing temporal changes and assessing heterogeneity in the motivation change patterns over time.

Limitations and Recommendations for Future Research

Although the present study makes an important contribution to the research on motivation, it has certain limitations that are worth mentioning. First, the factor loading analysis of the retained model questioned the rationale for including some of the items of identified and introjected regulation factors. Although low target factor loadings were also found in previous studies (Cece et al., 2019; Howard et al., 2018; Litalien et al., 2017), it is important to note that the current study examines for the first time the MWMS (a scale designed to be applied in the work domain) in the academic context. The main reason for using MWMS was a possibility of studying two forms of external regulation – material and social. The information about these two forms of external regulation may be of great interest for researchers and practitioners.

Second, we encourage researchers to investigate more in depth the G-factor included in the bifactor-ESEM model. Previous research (Cece el al., 2019; Howard et al., 2018; Litalien et al., 2017) did not provide clear evidence on what construct the G-factor illustrates (e.g., the relative self-determination, the quantity of self-determination, continuous or dichotomous structure of motivation, etc.). As such, we posit that the global motivation factor may be interpreted as the continuous representation of self-determination quality, to the extent where it is mainly expressed through the items of the intrinsic motivation dimensions. Evidently, further attention should be paid to this question, and to whether the differences between these G-factor representations can be related to the study context (i.e., work, education, sport, etc.).

Finally, following the recommendations from previous studies (Howard et al., 2018;

Litalien et al., 2017), we broadened the context of the research, using a sample of Spanish undergraduate students. However, we recommend further examination of the common measurement scales in other languages and cultural contexts.

Conclusion

In the current study, we demonstrated that bifactor-ESEM is the most accurate representation of the complex, multidimensional structure of motivation. Our findings are in line with the results of similar studies in the field of academia (Litalien et al., 2017), work (Howard et al., 2018), and sport (Cece et al., 2019), supporting the importance of considering a G-factor and cross-loadings to account for the theoretical underpinnings inherent to the measurement of motivation.

Furthermore, the study provided evidence of strict longitudinal invariance of the MWMS applied in the academic context, across five measurement occasions, ensuring that the differences in the MWMS scores across time are a result of the dynamics of motivation, not of the variability of the measurement tool. We hope that our study will contribute to work of other researchers, who aim to raise awareness about the importance of establishing the longitudinal measurement invariance for the accurate interpretation of the data related to the dynamics of motivation.

The measurement instrument examined in the current research is the MWMS (Gagné et al., 2015) adapted to the Spanish academic context, which is a valuable contribution to the research on academic motivation. However, further examination of the MWMS adapted to the academic context is recommended.

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