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Trajectories of motivation and their academic correlates over the first year of college

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ABSTRACT

The first year of college is a pivotal time for academic and personal development, yet there is still much to be learned about motivational change during this period. Using Self-Determination Theory (SDT), we assessed six distinct types of motivation among an initial sample of 776 students at four time points over the first year of college. Latent growth models indicated initially high but declining levels of intrinsic motivation and identified regulation, moderate but increasing levels of positive and negative introjection, and low but increasing levels of external regulation and amotivation. These patterns suggest that, on average, more autonomous types of motivation tend to decrease over the first year of college while more controlled types of motivation tend to increase. Academic functioning was predicted by (a) initial levels of both identified regulation and amotivation and (b) change trajectories for intrinsic motivation, identified regulation, and amotivation. These findings suggest that contextual supports for building autonomous motivation and minimizing amotivation appear to be essential both prior to college entry and throughout the first year.

The first year of college is a time of instability and challenge across multiple spheres of functioning (Conley, Kirsch, Dickson, & Bryant, 2014; Gall, Evans, & Bellerose, 2000; Perry, Hladkyj, Pekrun, & Pelletier, 2001; Towbes & Cohen, 1996). Students often must adjust to new roles and responsibilities, stronger academic pressures, more demanding coursework, a new living environment, more autonomy in decision-making, and changes to their social network and social supports. At the same time, they are navigating the developmental transition to emerging adulthood, which often entails substantial exploration of their personal and career-related identities (Arnett & Tanner, 2006; Kroger, 2004; Roisman, Masten, Coastworth, & Tellegen, 2004).

This convergence of contextual and developmental instability creates both an exciting opportunity for positive growth and a risk for developmental mismatch (Arnett, 2000; Eccles & Midgley, 1989; Seidman & French, 2004). Perhaps not surprisingly, the first year of college is a time of heightened stress compared to subsequent years (Towbes & Cohen, 1996), with the effects of such stress experienced most acutely during the initial transitional months (Conley et al., 2014; Gall et al., 2000). It is also the time when students are most likely to withdraw from college (McFarland et al., 2017; National Student Clearinghouse, 2019; Tinto, 1993), perhaps because they have not yet developed some of the competencies that could serve as a buffer against these stressors (Christie, Munro, & Fisher, 2004) or there are not appropriate contextual supports in place to help facilitate a smooth transition.

It is imperative, therefore, to examine both risk and protective factors that may impact students' functioning over the first year of college. Given the centrality of the academic domain to collegiate life, the present study focused on *academic motivation* as one such factor. Academic motivation – particularly when it is autonomous in nature – predicts academic success, retention, and well-being among college students (Guiffrida, Lynch, Wall, & Abel, 2013; Koestner & Losier, 2002; Ratelle, Guay, Vallerand, Larose, & Senécal, 2007; Robbins et al., 2004; Taylor et al., 2014; Vallerand & Bissonnette, 1992). In a large, multi-institution study of liberal arts education, for example, students' academic motivation assessed during the fall of their first year in college predicted both engagement and achievement at the end of college (Wu, 2019). Thus, motivation can be an important lever impacting student success.

1. Understanding motivational change

Academic motivation, however, is not an entirely stable force. It can fluctuate over time and with experience, in part because it is situated in

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the learning context. Motivational change has been documented both over major school transitions (e.g., Anderman & Midgley, 1997; Middleton, Kaplan, & Midgley, 2004; Otis, Grouzet, & Pelletier, 2005; Ratelle, Guay, Larose, & Senécal, 2004) and within the same learning context over time (e.g., Bong, 2005; Corpus, McClintic-Gilbert & Hayenga, 2009; Urdan & Midgley, 2003). Although the majority of research on motivational change has focused on K-12 education, there is growing evidence of motivational change over the transition to college and within the collegiate years as well (Dai & Cromley, 2014; Flanigan, Peteranetz, Shell, & Soh, 2017; Larose, Ratelle, Guay, Senécal, & Harvey, 2006; Musu-Gillette, Wigfield, Harring, & Eccles, 2015; Kyndt et al., 2015; Pan & Gauvain, 2012; Snyder, Barr, Honken, Pittard, & Ralston, 2018). Moreover, the early college years have recently been characterized as a time of motivational destabilization (see Robinson, Lee, et al., 2019), which may make it a high-leverage time for motivational intervention (e.g., Broda et al., 2018; Paunesku et al., 2015).

Despite a growing body of research with college populations, there is still much to be learned about the nature and shape of motivational change over the crucial first year of college. It is essential to understand academic motivation at the point of college entry when students are engaging in important planning and decision-making (e.g., selecting courses, committing to groups/part-time employment) and establishing study habits (e.g., study schedule, self-regulation strategies). Because this transitional time is characterized by instability, however, it is equally important to understand how motivational processes unfold over time. As students experience both challenges and victories in their courses, reflect on the value of the material, and more actively engage in career-related identity exploration, their academic motivation is likely to be transformed. Such motivational change, in turn, will impact subsequent academic decisions and behaviors (e.g., Dai & Cromley; Kosovich, Flake, & Hulleman, 2017; Musu-Gillette et al., 2015; Robinson, Perez, Carmel, & Linnenbrink-Garcia, 2019). This is consistent with the literature on college retention, which indicates that students' educational goals shift over time as a function of the quality of experiences with others in the collegiate environment, and that these collegiate experiences are better predictors of retention than factors that can be assessed at college entry (e.g., background variables, personality traits; Tinto, 1993). Thus, knowledge about motivational development over the first year of college is critical for understanding retention issues and effectively buffering against potential motivational decline.

Because motivation can change over time and in response to the learning environment (Kaplan & Patrick, 2016), it is important to consider precisely when motivation is measured and how frequently it is assessed. Comparing responses from the first to second year of college (e.g. Muller & Palekcic, 2005; Pan & Gauvain, 2012; Ratelle et al., 2004) or first to second semester of college (e.g. Busse & Walter, 2013; Fazey & Fazey, 1998; Kyndt et al., 2015; Stage & Williams, 1990) sheds light on motivational change across larger spans of time. However, such distal measurements can miss more nuanced fluctuations that likely occur *within* semesters as students navigate coursework in new and often unfamiliar domains. Recent studies across different theoretical traditions have documented motivational change over the smaller time scale of a single semester and provided critical insights into motivational malleability (Brahm, Jenert, & Wagner, 2017; Dai & Cromley, 2014; Flanigan et al., 2017; Kosovich et al., 2017; Robinson, Lee, et al., 2019; Young, Wendel, Esson, & Plank, 2018; Zusho & Pintrich, 2003). For example, Dai and Cromley (2014) found that students increasingly endorsed a fixed view of ability while declining in their endorsement of a malleable view of ability over the course of an introductory biology class. Using three assessments over a single semester in an introductory course, Kosovich et al. (2017) found that both expectancies for success and perceived usefulness of the material (i.e., utility value) decreased. These within-semester shifts reflect the dynamic and contextualized elements of motivation.

Including three or more motivational assessments also allows for stronger inferences about developmental change – that is, identifying not only less biased estimates of differences from one point in time to the next but also a clearer understanding of process-oriented trajectories of change (McArdle, 2009). The probing of potentially non-linear trajectories could be illuminating given the importance of identifying particular time periods when changes may be more or less dramatic, thus informing when interventions might best be administered (see Yeager & Walton, 2011).

The present study assessed academic motivation at four time points during the first year of college to conduct a fine-grained analysis of motivational change. Latent growth modeling allowed us to examine academic motivation both (1) at the moment of entry, which may be characterized by a mixture of excitement and trepidation, and (2) as it changes over time while students cope with the challenges of particular courses and establish their academic identity in a new context. The theoretical contribution of this approach lies in identifying the nature of motivational change among six distinct types of motivation during a key developmental transition. This knowledge may then be useful for the design and timing of intervention efforts to promote success and retention as well as for individual practitioners as they consider how best to support students and when that support is most crucial.

2. Self-Determination Theory and motivational change

Our conceptualization of motivational change draws upon the framework of Self-Determination Theory (SDT), which posits that motivation exists along a continuum of relative autonomy (Ryan & Deci, 2000; 2017). The most autonomous form is *intrinsic motivation*, which is inherent to the self or task and is typically characterized by interest and enjoyment. Next on the continuum are several forms of extrinsic motivation that vary in their relative autonomy but collectively refer to behaviors that are performed as a means to some separable end. The most self-determined form of extrinsic motivation is *identified regulation*, which is characterized by a sense that one's actions are important, meaningful, and consistent with one's identity, even if they are not particularly enjoyable. Next comes *introjected regulation,* which is self-directed but characterized by the contingency of self-worth, as in the case of guilt or shame as drivers of achievement behavior. The final form of extrinsic motivation is *external regulation*, which is located entirely external to the self, as in the case of behaviors performed to earn privileges, tangible rewards, or the approval of others. At the extreme end of the continuum lies *amotivation*, which is the complete absence of motivation altogether. A central tenet of SDT is that the more autonomous types of motivation (i.e., intrinsic, identified) produce more adaptive outcomes (see Ryan & Deci, 2000; 2017), which has been documented at the collegiate level in terms of higher academic achievement (e.g., Brunet, Gunnell, Gaudreau, & Sabiston, 2015; Taylor et al., 2014) and retention (e.g., Gottfried, Marcoulides, Gottfried, & Oliver, 2013; Meens, Bakx, Kilmstra, & Denissen, 2018), and lower levels of stress (e.g., Baker, 2004) and burnout (e.g., Brunet et al., 2015; Pisarik, 2009).

Patterns of change in autonomous motivation (i.e., intrinsic, identified). From the elementary through high school years, there is a robust and systematic pattern of linear, average decline in levels of both intrinsic motivation (e.g., Corpus et al., 2009; Gottfried, Fleming, & Gottfried, 2001; Lepper, Corpus, & Iyengar, 2005; Otis et al., 2005) and identified regulation (e.g., Otis et al., 2005; Leroy & Bressoux, 2016). The transition from high school to college may be unique in that it is typically marked by greater opportunities for autonomy and independent decision-making, and of course a more autonomously motivated cohort of peers given that the least motivated students are less likely to pursue higher education. Accordingly, there is some evidence that intrinsic motivation increases from the end of high school to the first year of college (e.g., Kyndt et al., 2015; Ratelle et al., 2004).

The majority of studies conducted *during* the college years, however, suggest a pattern of loss to autonomous motivation that is more consistent with what has been observed with younger populations. When comparing two assessments taken during the first year, levels of both intrinsic motivation and identified regulation have been shown to decrease (Busse & Walter, 2013; Taylor et al., 2014), as have related constructs such as learning orientation (Kowalski, 2007) and interest value (Robinson, Lee, et al., 2019). When comparing assessments from freshman to sophomore year, a similar pattern of declining autonomous motivation is observed (Muller & Palekcic, 2005; Pan & Gauvain, 2012). Perhaps the most relevant evidence comes from a study of first-year Swiss business students that showed a pattern of declining intrinsic motivation over three measurement assessments with partial recovery on a fourth assessment after the end of their first year (Brahm et al., 2017). Although there are some examples of relative stability in autonomous motivation during the first year (Fazey & Fazey, 1998; Kyndt et al., 2015; Stage & Williams, 1990), the majority of evidence points to a pattern of motivational decline.

Patterns of change in controlled motivation (i.e., external, introjected). Far less is known about trajectories of change in the more controlled types of motivation (i.e., external, introjected). Limited research with younger populations has shown a pattern of declining levels of extrinsic and introjected regulation over elementary and high school (Corpus et al., 2009; Leroy & Bressoux, 2016; Otis et al., 2005), with some evidence of stabilization after age 12 (Gillet, Vallerand, & Lafreniere, 2012). One might imagine that the more extreme types of controlled motivation would decrease over the first year of college as authority figures and accountability systems generally become less salient, and the college admissions process no longer looms ahead. But the available evidence is both limited and mixed, characterized by varying conceptualizations of extrinsic motivation and diverse patterns of change over time: loss (Brahm et al., 2017; Ratelle et al., 2004; Taylor et al., 2014), stability (Fazey & Fazey, 1998; Kyndt et al., 2015; Muller & Palekcic, 2005), and even gain (Kowalski, 2007; Stage & Williams, 1990).

Patterns of change in amotivation. Amotivation is perhaps the least investigated among the various types of motivation. Research on younger populations is scant, with no consistent pattern emerging (see Gillet et al., 2012; Otis et al., 2005; Leroy & Bressoux, 2016). There seems to be a decline in amotivation as students make the transition from high school to college (Kyndt et al., 2015), when presumably they would be less likely to see their daily academic behaviors as futile and meaningless. The few studies that have mapped amotivation during the first year of college suggest relative stability, both when comparing two assessments taken during the first year (Kyndt et al., 2015) and when comparing assessments from freshman to sophomore year (Fazey & Fazey, 1998; Muller & Palekcic, 2005; Ratelle et al., 2004). One additional study of college students assessed twice during the first year appeared to show a pattern of increasing amotivation, although a formal statistical test of mean comparisons was not reported (Taylor et al., 2014, Study 3). Thus, it is very difficult to draw any firm conclusions about the typical trajectory of amotivation over the first year of college.

Assessing the full spectrum of motivation types. In the present study we sought to examine growth trajectories across the full spectrum of motivation types specified by SDT. Some studies adopt a less granular approach by focusing on the composite indicators of autonomous (i.e., intrinsic, identified) and controlled (i.e., external, introjected) motivations (e.g., Kyndt et al., 2015), or combining a range of motivation types together into a relative autonomy index (e.g., Pan & Gauvain, 2012). While this more global approach has the advantage of parsimony (Sheldon, Osin, Gordeeva, Suchkov, & Sychev, 2017), examining growth trajectories for the full range of motivation types is important because even those types of motivation that are closely related in the SDT continuum have distinct correlates and patterns of change (Assor, Vansteenkiste, & Kaplan, 2009; Burton, Lydon, D'Alessandro, & Koestner, 2006; Koestner & Losier, 2002; Ratelle et al., 2004). For example, whereas intrinsic motivation increased from the end of high school to the end of the first year in college, identified regulation decreased over that same period (Ratelle et al., 2004), and whereas intrinsic motivation predicted well-being, identified regulation predicted achievement (Burton et al., 2006). Considering the more controlled types of motivation, there is also an argument for separating introjection into more positive approach (i.e., seeking pride and self-worth) and more negative avoidance (i.e., avoiding guilt and shame) components. Assor and colleagues (2009) found that the avoidance form of introjected regulation was associated with more negative correlates than the approach form, and that both forms predicted lower levels of well-being and performance than did identified regulation, arguing for a clear empirical and conceptual distinction among these types of motivation. In the present study, therefore, we assessed the full range of SDT motivation types (i.e., intrinsic, identified, positive introjection, negative introjection, external, and amotivation) and used latent growth modeling to construct motivation trajectories for each. This approach paints an important descriptive picture of students' strengths and needs that can inform the design of learning contexts to more effectively support student motivation.

Looking across the full spectrum of SDT motivation types, no research to date has collected enough measurement points to capture both linear and non-linear trajectories of change over the first year of college. Considering all six SDT types of motivation in a single investigation allows for a comparison of their distinct patterns of change, in addition to a more absolute description of each type of motivation's individual trajectory. This holistic picture is essential for a comprehensive understanding of how motivation tends to manifest both at college entry and over the course of the first year, and assessing four time points is a promising starting point to fully considering non-linear trajectories of motivational change.

3. Motivational change and academic functioning

The second objective of the present study was to examine the implications of motivation trajectories for students' functioning, which we conceptualized as academic achievement and retention to sophomore year.

Initial states of motivation. The most typical approach in longitudinal research has been to examine how academic motivation assessed at one point in time predicts subsequent academic outcomes or a change in academic outcomes (e.g., Baker, 2003; Black & Deci, 2000; Brunet et al., 2015; Burton et al., 2006; Guay, Ratelle, Roy, & Litalien, 2010; Snyder et al., 2018; Taylor et al., 2014). Studies examining the effects of initial states of motivation have shown quite consistently that both intrinsic motivation and identified regulation predict positive achievement outcomes and retention in college populations (e.g., Brunet et al., 2015; Meens et al., 2018; Taylor et al., 2014; Vallerand & Bissonnette, 1992), with some evidence that identified regulation may be a particularly powerful predictor (Burton et al., 2006; Koestner & Losier, 2002).

By contrast, controlled motivation is thought to produce less optimal outcomes due to the feelings of coercion and distraction from task involvement that come from less autonomous sources of action. The data on initial states of controlled motivation, however, are somewhat mixed. While there is some evidence that it is a weak negative predictor of achievement (Brunet et al., 2015; Taylor et al., 2014), a number of studies show no significant relationship between controlled motivation and academic achievement or retention (e.g., Baker, 2003; Koestner & Losier, 2002; Vallerand & Bissonnette, 1992; Vanthournout, Gijbels, Coertjens, Donche, & Van Petegem, 2012), and yet others show controlled motivation to be a protective factor against dropout from both college (Meens et al., 2018) and high school (Otis et al., 2005; Vallerand, Fortier, & Guay, 1997). Distinct effects of external versus introjected regulation may explain some of this complexity. In an investigation of persistence among competitive swimmers, introjected regulation was a protective factor whereas external regulation was a risk factor (Pelletier, Fortier, Vallerand, & Briere, 2001). Dividing introjection into its positive and negative components may also reveal distinct effects on academic functioning among college students – a possibility that has not yet been explored to date but is examined in the present study (for related work with elite athletes and younger students see Assor et al., 2009). Taken together, the previous research does not paint a consistent picture of the relationship between controlled motivation and academic functioning in college student samples.

Although initial states of amotivation have been investigated far less frequently, the extant data offer clarity: At the college level, amotivation is a strong negative predictor of both achievement (Taylor et al., 2014) and retention (Vallerand & Bissonnette, 1992; Vanthournout et al., 2012). Similar patterns have been documented with younger populations (e.g., Leroy & Bressoux, 2016; Vallerand et al., 1997), which is perhaps not surprising given that amotivation represents a lack of volition or desire to act altogether. Additional research is needed to replicate and extend this work, focusing on how amotivation at the time of college entry may shape academic functioning by the end of the first year. The present study took up this charge.

Motivation trajectories. Given the motivational instability that characterizes the first year of college, it is critical to go beyond documenting students' initial levels of motivation to determine also how motivational change may predict outcomes over and above initial levels. To our knowledge, no research to date has examined how trajectories of change in the full spectrum of SDT motivation types predict achievement outcomes over the first year of college. However, small bodies of research on the impact of motivational change at other levels of schooling and using constructs in related traditions (e.g., expectancy-value, implicit theories) may provide some guidance. Considering autonomous motivation, growth in intrinsic motivation and especially identified regulation predicted both achievement and retention intentions among middle and high school populations (Gottfried et al., 2013; Leroy & Bressoux, 2016; Otis et al., 2005), as did growth in both interest and attainment value among engineering students in their first two years of college (Robinson, Lee, et al., 2019), and growth in a malleable view of ability among introductory biology students (Dai & Cromley, 2014) Changes in controlled motivation did not predict achievement over the transition to middle school (Leroy & Bressoux, 2016), but were positive predictors over the transition to high school such that growth in both external and introjected regulation predicted lower dropout intentions and more positive adjustment (Otis et al., 2005). In other words, growth in controlled motivation served a protective function in this research. Finally, the slope of change in amotivation was the strongest predictor of achievement in Leroy and Bressoux's (2016) study across the middle school transition, and a decrease in amotivation predicted lower dropout intentions and more positive adjustment in high school (Otis et al., 2005).

Overall, then, considering motivation trajectories alongside initial levels of motivation appears to be a promising and underexplored means of understanding academic functioning among first-year college students. Examining both initial levels and change trajectories of each motivation type in the same analysis reveals the unique contribution of each while controlling for the other – an important methodological advance that we have not yet seen in the literature with SDT constructs at the college level. Based on the limited data available, it appears that growth in autonomous motivation and a reduction in amotivation are likely to forecast positive achievement and retention. However, it is unclear if both initial levels and slopes relate independently to outcomes.

4. Present study

In summary, the present study aimed to (1) identify change trajectories of the full spectrum of SDT motivation types over the first year of college and (2) test the impact of these trajectories for academic functioning. We expected the more autonomous types of motivation (i.e., intrinsic, identified) to decrease over the first year of college based on evidence from studies using composite indicators or related variables (e.g., Brahm et al., 2017; Pan & Gauvain, 2012; Robinson, Lee, et al., 2019). Predictions for the more controlled types of motivation (introjected, external) and for amotivation were unclear given the scant and mixed evidence available. Likewise, formal hypotheses regarding the shape of change were not made because both linear and non-linear trajectories for each type of motivation were considered plausible.

In terms of achievement outcomes, we expected growth in intrinsic motivation and especially identified regulation to positively predict academic functioning based on the available evidence with younger populations (e.g., Leroy & Bressoux, 2016), composite indicators (e.g., Brunet et al., 2015), or static level predictors (e.g., Koestner & Losier, 2002). Predictions for the more controlled types of motivation were unclear given mixed evidence of risk and protective functions and numerous nonsignificant relationships. Growth in amotivation was expected to negatively predict both achievement and retention based on the limited evidence available with college student populations (e.g., Taylor et al., 2014, Vanthournout et al., 2012).

5. Method

5.1. Participants and procedure

All first-year students entering Reed College in Fall 2015, Fall 2016, and Fall 2017 were recruited during orientation for a larger study on the transition to college. Reed College is a primarily undergraduate institution in the liberal arts tradition characterized by a rigorous academic program, democratic learning environment, and focus on learning for learning's sake (Sheehy, 2013). Student work is returned with narrative evaluative comments rather than letter grades, although official letter grades are recorded with the institution. These mastery-oriented practices might seem to both select for and actively encourage autonomous motivation. At the same time, the intensity of the academic program and its accompanying stress culture may encourage some forms of controlled motivation (e.g., introjection) while discouraging others (e.g., external regulation).

Recruitment took place via announcements at required orientation sessions, an informational table outside the central dining hall, and prolific campus flyers. Across all three cohorts, 776 first-year students (69.9% response rate) agreed to participate by completing a survey reporting on their academic motivation in the days immediately prior to the start of classes (T1). Table 1 presents the number of participants by cohort and time point. Out of the 776 who consented to participate, 3 participants (2 from the Fall 2015 cohort, 1 from the Fall 2016 cohort) completed only a few survey items at T1 and so are not represented in the data for T1. However, these participants still

Table 1
Number of participants by cohort and time point.

	Fall 2015 *n*	Fall 2016 *n*	Fall 2017 *n*	Total *N*
Eligible for recruitment[1]	379	317	414	1,110
Time 1 (orientation)	268	218	290	776
Time 2 (end fall semester)	178	137	190	505
Time 3 (start spring semester)	–	149	184	333
Time 4 (end spring semester)	–	143	192	335

Note: The Fall 2015 cohort only participated in T1 and T2. For the Fall 2016 and Fall 2017 cohorts, the study was expanded to follow students throughout their entire first year of college.

[1] For the Fall 2015 and Fall 2016 cohorts, this includes all entering first-year students age 18 and older. For the Fall 2017 cohort, this includes all entering first-year students regardless of age. The more inclusive recruitment criteria in Fall 2017 was due to a change in the IRB approval such that a waiver of parental consent was granted for 17-year-old college students.

participated in subsequent survey waves and thus they are included in the overall data. Participants in the Fall 2015 cohort (n = 268) were invited to report on their academic motivation again at the end of the first semester (T2; n = 178; 66.4% retention), but were not followed thereafter because funding was not available. Participants in the Fall 2016 (n = 218) and Fall 2017 (n = 290) cohorts were also invited to report on their academic motivation at the end of the first semester (T2; 64.4% retention), and then again the first week of the spring semester (T3; 65.6% retention), and the end of the spring semester (T4; 65.9% retention). For the second, third, and fourth time points, participants received an invitation by email to complete the survey online and were given a one-week window to respond. See missing data analysis for additional information.

Demographic information (gender, race/ethnicity, first-generation status) was collected in the T1 survey. Of the 776 participants at T1, 49% identified as female, 45% as male, 4% as non-binary, and 1% as other or prefer not to respond. With regard to family background, 10.8% of students identified as first-generation college students. The racial/ethnic distribution of the sample was 74.5% White, 18.6% Asian/Asian American, 10.3% Hispanic/Latinx, and 4.1% Black/African American.

Academic outcomes were collected from institutional records with participants' consent. Data on first-year GPA were obtained for 704 students (91%) and data on registration status for sophomore year were obtained for 715 students (92%). The study was approved by the Institutional Review Board at the first author's institution.

5.2. Measures

Academic motivation. Academic motivation was assessed using the 16-item version of the Academic Self-Regulation Scale (Ryan & Connell, 1989) as adapted by Vansteenkiste, Sierens, Soenens, Luyckx, and Lens (2009). Students used a 5-point scale (1 = *completely not important*, 5 = *very important*) to rate the importance of a variety of reasons for engaging in their academic work, reflecting intrinsic motivation (e.g., "because I enjoy doing it"; 4 items), identified regulation (e.g., "because it is personally important to me"; 4 items), positive introjected regulation (e.g., "because I want others to think I'm smart"; 2 items), negative introjected regulation (e.g., "because I would feel ashamed if I didn't study"; 2 items), and external regulation (e.g., "because others oblige me to do so"; 4 items). In addition, the Academic Motivation Scale (Vallerand et al., 1992) was used to assess amotivation (e.g., "Honestly, I don't know; I really feel that I am wasting my time in school"; 4 items).

Following Assor et al. (2009) as well as Sheldon et al. (2017), we used a model of regulation that included each of the six separate constructs: intrinsic motivation, identified regulation, positive introjected regulation, negative introjected regulation, external regulation, and amotivation. After dropping one item from the identified subscale ("because I want to learn new things") and one from the external subscale ("because I'm supposed to do so"), each subscale demonstrated good internal consistency at each time point, with Cronbach's alphas ranging from 0.72 to 0.89. CFAs including all six constructs at each time point showed acceptable factor structure (CFI = 0.91 −0.94, RMSEA = 0.07 −0.09)[1]. Overall, confirmatory factor analyses provided evidence that students viewed these as six distinct constructs.

Academic outcomes. Academic achievement was indexed by first-year college GPA, with composite SAT/ACT scores used as an indicator of prior achievement. SAT scores were converted to the ACT scale. Retention was indexed by students' registration status (1 = enrolled, 0 = not enrolled) for sophomore year, collected at the end of their first year. All academic outcome data were obtained directly from institutional records with participants' consent.

5.3. Analytic plan

Preliminary analyses included an examination of missing data patterns, individual trajectory plots, and tests of longitudinal measurement invariance. Six separate second-order latent growth curve models (Ferrer, Balluerka, & Widaman, 2008; Hancock, Kuo, & Lawrence, 2001; McArdle, 1988) were used to examine the nature of change in each of the motivation constructs, which addressed our first research aim. Following the specification of unconditional latent growth curve models, academic outcomes (GPA and registration for sophomore year) were regressed on latent intercepts and slopes, with SAT/ACT scores added as a covariate, to address our second research question. Model fit was evaluated using the comparative fit index (CFI; values > = 0.90 for adequate fit; values > = 0.95 for excellent fit; Hu & Bentler, 1999) and root mean square error of approximation (RMSEA; values < 0.08 for adequate fit; values < 0.06 for excellent fit). Missing data analyses and correlations were conducted in SPSS Version 22, and the remaining analyses were conducted in Mplus version 8 (Muthén & Muthén, 1998–2018) using full information maximum likelihood (FIML) to handle missing data.

6. Results

6.1. Preliminary analyses

Correlations and descriptive statistics are presented in Table 2. As expected, repeated measures over time were positively correlated. Amotivation, external regulation, negative introjection, and positive introjection were positively – and in most cases significantly – correlated with one another. Identified and intrinsic were positively correlated with one another and negatively correlated with the other types of motivation. Means of amotivation, external, negative introjection, and positive introjection appeared to increase over time, while means of identified and intrinsic appeared to decline over time.

Missing data. Missing data showed a pattern of attrition primarily from T1 to T2, with response rates holding relatively stable from T2 to T4. The Fall 2015 cohort was not invited to participate at T3 and T4; accordingly, missing data rates are reported for all three cohorts at T1 and T2, and the Fall 2016 and Fall 2017 cohorts at T3 and T4. Among those who participated in at least one survey wave (n = 776), missing data ranged from 0.3 to 34.6% at the item level, with an average missing rate of 26.3% across all waves. The average item-level missing rate was 0.005% at T1, 35.1% at T2, 34.6% at T3, and 34.2% at T4.

We also examined potential correlates of missing data (i.e.., demographics, Time 1 study variables, achievement, and retention) by comparing students with complete data to those with any missing data. The missing data indicator was calculated to include both missing due

[1] Initial CFA results for T1 and T4 indicated suboptimal fit, with CFI slightly below 0.90 at T4 and RMSEA just above 0.10 at T1. We examined modification indices and considered any that would be consistent with theory. As a result, we included residual covariances for two sets of items at T1 and T4. These decisions were based on theory, with only residuals for items that are conceptually related to one another allowed to covary. They were also consistent at both T1 and T4. First, the item, "Because I am highly interested in doing this," from the intrinsic scale was allowed to covary with the item, "Because it is personally important to me," from the identified scale. The former item is slightly ambiguous in meaning compared to the other intrinsic items, as a student could be

(*footnote continued*)
interested in school either because it is inherently interesting or because they are interested in the resulting outcomes. Thus, the item might in some cases be interpreted to be similar to identified regulation, particularly the importance of school. Second, the item, "Because this is an important life goal to me," from the identified scale was allowed to covary with, "Because I want others to think I'm a good student," from the positive introjection scale. We believe students may connect these two ideas to some extent when their important life goals are closely tied to managing the perceptions of valued others.

Table 2
Correlations and descriptive statistics.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1.T1_Amot																								
2.T2_Amot	**0.41**																							
3.T3_Amot	**0.52**	**0.73**																						
4.T4_Amot	**0.44**	**0.60**	**0.70**																					
5.T1_Ext	**0.35**	**0.17**	**0.23**	**0.17**																				
6.T2_Ext	**0.21**	**0.31**	**0.20**	**0.22**	**0.57**																			
7.T3_Ext	**0.15**	**0.18**	**0.30**	**0.26**	**0.59**	**0.67**																		
8.T4_Ext	0.11	0.07	**0.14**	**0.19**	**0.54**	**0.57**	**0.71**																	
9.T1_NJect	**0.18**	0.05	0.09	0.01	**0.45**	**0.30**	**0.36**	**0.29**																
10.T2_NJect	0.04	**0.13**	0.06	0.01	**0.23**	**0.41**	**0.30**	**0.25**	**0.50**															
11.T3_NJect	0.03	0.03	0.07	0.01	**0.36**	**0.32**	**0.46**	**0.37**	**0.54**	**0.58**														
12.T4_NJect	0.03	0.04	0.11	**0.12**	**0.28**	**0.28**	**0.37**	**0.43**	**0.50**	**0.54**	**0.58**													
13.T1_PJect	**0.15**	0.06	0.06	0.00	**0.35**	**0.32**	**0.32**	**0.29**	**0.46**	**0.35**	**0.35**	**0.34**												
14.T2_PJect	0.03	0.08	0.03	0.02	**0.28**	**0.40**	**0.35**	**0.27**	**0.28**	**0.47**	**0.39**	**0.31**	**0.57**											
15.T3_PJect	0.01	0.00	0.05	0.00	**0.33**	**0.32**	**0.43**	**0.40**	**0.32**	**0.30**	**0.42**	**0.37**	**0.58**	**0.69**										
16.T4_PJect	0.00	0.01	0.05	-0.01	**0.26**	**0.32**	**0.39**	**0.44**	**0.33**	**0.33**	**0.41**	**0.50**	**0.56**	**0.61**	**0.71**									
17.T1_Iden	-0.31	**-0.21**	**-0.32**	**-0.31**	-0.03	-0.05	-0.07	0.00	**0.12**	**0.14**	**0.22**	0.10	**0.13**	**0.15**	**0.14**	**0.13**								
18.T2_Iden	-0.32	**-0.45**	**-0.45**	**-0.44**	-0.07	-0.03	-0.07	0.01	0.08	**0.25**	**0.22**	0.11	0.08	**0.25**	**0.15**	**0.13**	**0.57**							
19.T3_Iden	-0.30	**-0.43**	**-0.49**	**-0.42**	**-0.13**	-0.09	-0.06	-0.02	0.04	0.07	**0.21**	0.04	0.05	**0.15**	**0.15**	0.10	**0.58**	**0.64**						
20.T4_Iden	**-0.28**	**-0.40**	**-0.46**	**-0.48**	-0.10	**-0.12**	-0.09	0.00	0.07	0.08	0.08	**0.14**	0.05	0.09	**0.14**	**0.17**	**0.48**	**0.61**	**0.67**					
21.T1_Intr	**-0.25**	**-0.18**	**-0.20**	**-0.14**	**-0.11**	-0.10	-0.09	-0.10	**-0.12**	-0.02	0.06	-0.07	**-0.07**	-0.03	0.01	0.00	**0.50**	**0.33**	**0.41**	**0.34**				
22.T2_Intr	**-0.28**	**-0.38**	**-0.36**	**-0.33**	**-0.11**	-0.03	-0.05	-0.05	-0.05	0.03	0.06	-0.08	-0.02	**0.11**	0.07	0.01	**0.38**	**0.60**	**0.55**	**0.40**	**0.53**			
23.T3_Intr	**-0.22**	**-0.34**	**-0.41**	**-0.35**	-0.10	-0.07	-0.05	-0.08	-0.04	-0.06	0.02	**-0.16**	-0.08	0.05	0.03	-0.03	**0.35**	**0.39**	**0.57**	**0.44**	**0.52**	**0.73**		
24.T4_Intr	**-0.26**	**-0.38**	**-0.37**	**-0.41**	**-0.16**	**-0.19**	**-0.15**	-0.08	-0.05	-0.11	-0.04	-0.06	-0.06	-0.02	0.02	0.08	**0.35**	**0.43**	**0.52**	**0.68**	**0.53**	**0.65**	**0.71**	
N	771	505	333	335	774	505	333	335	773	502	330	335	769	497	331	331	774	505	333	335	774	505	333	335
M	1.37	1.69	1.63	1.62	2.14	2.28	2.20	2.23	2.77	3.28	3.17	3.19	2.52	2.73	2.66	2.70	4.22	4.09	4.08	4.06	4.01	3.55	3.58	3.54
S.D.	0.57	0.88	0.77	0.79	0.93	1.01	0.96	0.98	1.11	1.12	1.06	1.07	1.01	1.14	1.06	1.06	0.74	0.85	0.84	0.91	0.77	0.90	0.89	0.95
α	0.80	0.89	0.87	0.88	0.80	0.85	0.85	0.86	0.76	0.80	0.81	0.81	0.75	0.85	0.82	0.83	0.75	0.82	0.81	0.84	0.82	0.86	0.87	0.88

Note. **Bolded** correlation coefficients are significant at $p < .05$. Amot = Amotivation; Ext = External; Nject = Negative Introjection; Pject = Positive Introjection; Iden = Identified; Intr = Intrinsic.

to non-response and missing due to not being invited (i.e., the Fall 2015 cohort for waves 3 and 4). A multiple analysis of variance (MANOVA) comparing motivation types at Time 1 for those with complete data vs. those with any missing data was not significant, Wilks' λ (6, 761) = 0.996, p = .761, η^2 = 0.004, indicating that survey item missingness was not associated with initial levels of the study variables. A chi square analysis examining missing data by racial/ethnic group (person of color vs. not a person of color), χ^2 (1) = 0.99, p = .32, was not significant. However, a chi square analysis examining gender (female, male, or other), χ^2 (3) = 7.09, p = .03 was significant and indicated that women were the least likely to have missing data. Further, a *t*-test examining prior achievement (ACT/SAT scores) and cumulative GPA at the end of the year comparing those with missing (M_{ACT_SAT} = 31.07, M_{GPA} = 2.91) vs. complete data (M_{ACT_SAT} = 31.54, M_{GPA} = 3.18) was significant, Wilks' λ (2, 701) = 0.970, $p < .001$, η^2 = 0.03. This suggested that lower-performing students were more likely to have missing data. Further, a chi square analysis examining missing data by retention status indicated that students who did not enroll in classes the following year (n = 87) were more likely to have missing data, χ^2 (1) = 13.35, $p < .001$.

To examine whether the Fall 2015 cohort's missing data at T3 and T4 may have led to biased estimates due to systematic differences across cohorts, we compared T1 (i.e. orientation) motivation and prior achievement (ACT/SAT) across the cohorts. The MANOVA was not significant, Wilks' λ (14, 1406) = 0.98, p = .444, η^2 = 0.01, indicating that the cohorts appeared to be similar in terms of the study variables.

Overall, missing data analyses provided some evidence that the data were missing at random, with a substantial amount of missing being due to participants in the Fall 2015 cohort not being invited for certain waves (missing completely at random), and a further portion of missing data being at least partially accounted for by achievement differences. These indicators provided evidence supporting the assumptions for FIML estimation and increasing confidence that any bias in model estimates due to missing data would be minimal. Accordingly, we included gender, SAT/ACT scores, cumulative GPA, and retention status as auxiliary variables for missing data estimation in the unconditional latent growth curve models; gender was included as an auxiliary variable for missing data estimation in the conditional models.

Measurement invariance. To make inferences about change over time, it must first be established that each construct is being measured in the same way over time (Widaman, Ferrer, & Conger, 2010; Widaman & Reise, 1997). In this way, mean differences can be attributed to true change rather than measurement differences. To this end, we successively imposed configural, weak, strong, and strict invariance constraints across the four time points for the first-order common factor models (see Table 3). In the configural models, the factor structure was the same over time. In the weak invariance models, factor loadings were constrained to be equal over time. Next, strong invariance models additionally constrained the item intercepts to be equal over time, and lastly the strict invariance models involved constraining the item residual variances to be equal over time. Model comparisons resulted in a change in CFI that was less than or equal to 0.01 between models (Cheung & Rensvold, 2002; see Table 3), supporting strict or partial strict measurement invariance for each of the six constructs.

6.2. Unconditional latent growth models

To answer our first research question about the nature of change in the six types of motivation throughout the first year of college, we used second-order latent growth models. We compared no-growth, linear, and quadratic models for each construct, with additional exploration of a latent basis model when linear and quadratic models did not show adequate fit to the data (Ram & Grimm, 2007). Model selection was based on fit indices, with a change in CFI greater than 0.01 indicating significantly better fit (Cheung & Rensvold, 2002), and on significant vs. non-significant slope parameters. For example, when fit did not significantly differ between the no-growth and linear models, but the linear slope was significant, we selected the linear model because of our interest in describing change patterns and examining differences in change patterns. Fit indices for the unconditional latent growth models are presented in Table 4, and model parameters for the selected models are displayed in Table 5.

Overall, linear or quadratic models were selected as best fitting the data for all but amotivation (see Fig. 1), showing improved fit over the intercept-only models and/or slopes that were significantly different from 0. For amotivation, because all three models did not show acceptable fit when using FIML estimation, we additionally considered a latent basis model. Linear models were selected for the external and identified models. Quadratic models were deemed the best fit for the negative introjection, positive introjection, and intrinsic models. A latent-based model was selected for the amotivation model, with latent basis loadings of 0 for T1, 1 for T4, and freely estimated at T2 and T3. The latent basis model allowed us to examine non-linear change without being constrained to a quadratic trajectory (see Ram & Grimm, 2007). To address univariate and multivariate non-normality in the amotivation data, MLR estimation was adopted rather than FIML for the unconditional model.

Students reported high intrinsic and identified at T1 (> 4 on a 5-point scale) that declined slightly over time, with a slight increase in intrinsic between the final two time points. Positive and negative introjection showed a pattern of moderate initial levels (between 2.5 and 3 at T1) that increased from T1-T3, then leveled off and slightly decreased between the two final time points. External regulation started low (between 1.5 and 2) and very slightly increased over time, although it remained below 2 on the scale overall. Lastly, the overall slope for amotivation was 0.34, with latent basis loading estimates of 1.22 at T2 and 0.93 at T3. This indicates that amotivation began below a 1.5 on the scale, increased until T2, slightly decreased between T2 and T3, then appeared to level off, but overall remained rather low.

Confidence intervals around the intercepts indicated that initial levels of intrinsic (95% CI [4.34, 4.44]) and identified (95% CI [4.24, 4.34]) were significantly higher than initial levels of the other types of motivation, although they were not significantly different from one another. The intercept of positive introjection (95% CI [2.52, 2.66]) was significantly lower than the intercept of negative introjection (95% CI [2.69, 2.85]). Intercepts of both positive and negative introjection were significantly higher than intercepts of external regulation (95% CI [1.76, 1.88]) and amotivation (95% CI [1.43, 1.52]). Initial levels of external regulation were also significantly higher than those of amotivation.

The majority of intercepts and slopes showed significant variance, or between-person variation around the means, with the exception of the variances of the linear and quadratic slopes of negative introjection (see Table 5). It appeared, then, that some elements of the trajectories in negative introjection were relatively uniform in our sample compared to the other types of motivation.

6.3. Latent growth models predicting outcomes

Next, end-of-year GPA and college retention (registration for the following year) were added to the models as outcomes regressed on intercepts and slopes of the six constructs (see Table 6). Students' SAT/ACT scores were included in the models as a control variable, predicting intercepts, slopes, and outcomes.

Models examining outcomes fit the data well overall (RMSEAs = 0.03 to 0.04; CFIs = 0.91 to 0.98), although the negative introjection model did not converge to an interpretable solution, likely due to low variation in the slope, and so will not be presented here. Overall, only the amotivation, identified, and intrinsic models significantly predicted the two outcomes. First, the amotivation intercept negatively predicted both GPA (β = -0.13, S.E. = 0.04, $p < .001$) and retention (β = -0.24, S.E. = 0.07, $p < .001$, O.R. = 0.79), indicating

Table 3
Measurement invariance.

Amotivation	ChiSq	df	RMSEA	CFI	Delta CFI	TLI	SRMR
Configural	430.852	98	0.066	0.927		0.911	0.047
Weak	442.214	107	0.064	0.927	0.000	0.918	0.050
Strong	459.461	116	0.062	0.925	0.002	0.922	0.050
Strict	530.591	128	0.064	0.912	0.013	0.917	0.063
Strict partial	**468.428**	**127**	**0.059**	**0.925**	**0.000**	**0.929**	**0.051**
External							
Configural	229.824	48	0.07	0.943		0.922	0.042
Weak	234.444	54	0.066	0.944	−0.001	0.931	0.046
Strong	247.866	60	0.064	0.942	0.002	0.936	0.046
Strict	**275.907**	**69**	**0.062**	**0.936**	**0.006**	**0.938**	**0.049**
Negative introjection							
Configural	53.09	14	0.06	0.975		0.951	0.024
Weak	54.071	17	0.053	0.977	−0.002	0.961	0.026
Strong	60.682	20	0.051	0.974	0.003	0.964	0.028
Strict	**79.388**	**26**	**0.051**	**0.966**	**0.008**	**0.964**	**0.042**
Positive introjection							
Configural	72.805	14	0.074	0.969		0.938	0.026
Weak	75.868	17	0.067	0.969	0	0.949	0.03
Strong	76.447	20	0.06	0.97	−0.001	0.959	0.031
Strict	**94.584**	**26**	**0.058**	**0.964**	**0.006**	**0.961**	**0.036**
Identified							
Configural	210.916	48	0.066	0.936		0.913	0.045
Weak	214.579	54	0.062	0.937	−0.001	0.923	0.049
Strong	222.877	60	0.059	0.937	0	0.93	0.051
Strict	**243.487**	**69**	**0.057**	**0.932**	**0.005**	**0.935**	**0.067**
Intrinsic							
Configural	419.888	98	0.065	0.928		0.912	0.051
Weak	437.508	107	0.063	0.926	0.002	0.917	0.064
Strong	467.418	116	0.062	0.922	0.004	0.919	0.069
Strict	**498.668**	**128**	**0.061**	**0.917**	**0.005**	**0.923**	**0.086**

Note: The selected models are presented in **bold**.

Table 4
Fit indices for unconditional latent growth models.

Model	χ^2	df	RMSEA	CFI	TLI	SRMR
Amotivation						
Intercept Only	560.736	139	0.063	0.849	0.869	0.182
Linear	Did not converge to an interpretable solution					
Linear_a	516.158	138	0.059	0.864	0.882	0.183
Quadratic	379.566	132	0.049	0.911	0.919	0.086
Latent Basis	**349.434**	**134**	**0.046**	**0.923**	**0.931**	**0.074**
External						
Intercept only	328.499	80	0.063	0.922	0.936	0.072
Linear	**314.026**	**77**	**0.063**	**0.925**	**0.936**	**0.064**
Quadratic	297.016	73	0.063	0.930	0.936	0.060
Negative Introjection						
Intercept only	210.786	37	0.078	0.888	0.916	0.128
Linear	143.165	34	0.064	0.930	0.942	0.077
Quadratic	**103.102**	**30**	**0.056**	**0.953**	**0.956**	**0.055**
Positive introjection						
Intercept only	170.616	37	0.068	0.929	0.946	0.071
Linear	143.652	34	0.064	0.942	0.952	0.066
Quadratic	**122.464**	**30**	**0.063**	**0.951**	**0.954**	**0.051**
Identified						
Intercept only	327.111	80	0.063	0.903	0.920	0.152
Linear	**265.914**	**77**	**0.056**	**0.926**	**0.937**	**0.101**
Quadratic	Did not converge to an interpretable solution					
Quadratic_b	298.898	78	0.06	0.913	0.927	0.133
Intrinsic						
Intercept only	807.233	139	0.079	0.850	0.871	0.206
Linear	609.638	136	0.067	0.894	0.906	0.128
Quadratic	**532.521**	**132**	**0.063**	**0.910**	**0.918**	**0.111**

Note: For the Amotivation Linear_a model, the variance of the linear slope and the covariance between the intercept and slope were fixed to 0. For the Identified Quadratic_b model, the variances of the linear and quadratic slopes and the covariances among the slopes and intercept were fixed to 0. The selected models are presented in **bold**.

Table 5
Parameters for selected models.

Estimate	Intrinsic	Identified	Positive introjection	Negative introjection	External	Amotivation
Intercept mean	4.388	4.291	2.589	2.771	1.821	1.464
SE	0.024	0.026	0.037	0.042	0.031	0.026
p	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Intercept variance	0.175	0.258	0.621	0.700	0.392	0.152
SE	0.019	0.025	0.063	0.080	0.035	0.047
p	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	0.001
Linear/basis slope mean	−0.331	−0.058	0.187	0.484	0.033	0.337
SE	0.032	0.012	0.052	0.058	0.013	0.052
p	< 0.001	< 0.001	< 0.001	< 0.001	0.013	< 0.001
Linear/basis slope variance	0.149	0.017	0.270	0.132	0.013	0.197
SE	0.039	0.005	0.123	0.169	0.006	0.063
p	< 0.001	0.001	0.028	0.435	0.030	0.002
Quadratic slope mean	0.076		−0.044	−0.120		
SE	0.010		0.017	0.019		
p	< 0.001		0.011	< 0.001		
Quadratic slope variance	0.012		0.023	0.008		
SE	0.004		0.013	0.017		
p	0.003		0.070	0.636		
Intercept-linear covariance	< 0.001	0.011	0.050	−0.049	< 0.001	0.121
SE	0.019	0.009	0.061	0.082	0.011	0.040
p	0.985	0.202	0.413	0.555	0.966	0.003
Intercept-quadratic covariance	0.001		−0.017	0.007		
SE	0.006		0.018	0.024		
p	0.813		0.348	0.768		
Linear-quadratic covariance	−0.040		−0.076	−0.033		
SE	0.012		0.038	0.053		
p	0.001		0.046	0.532		

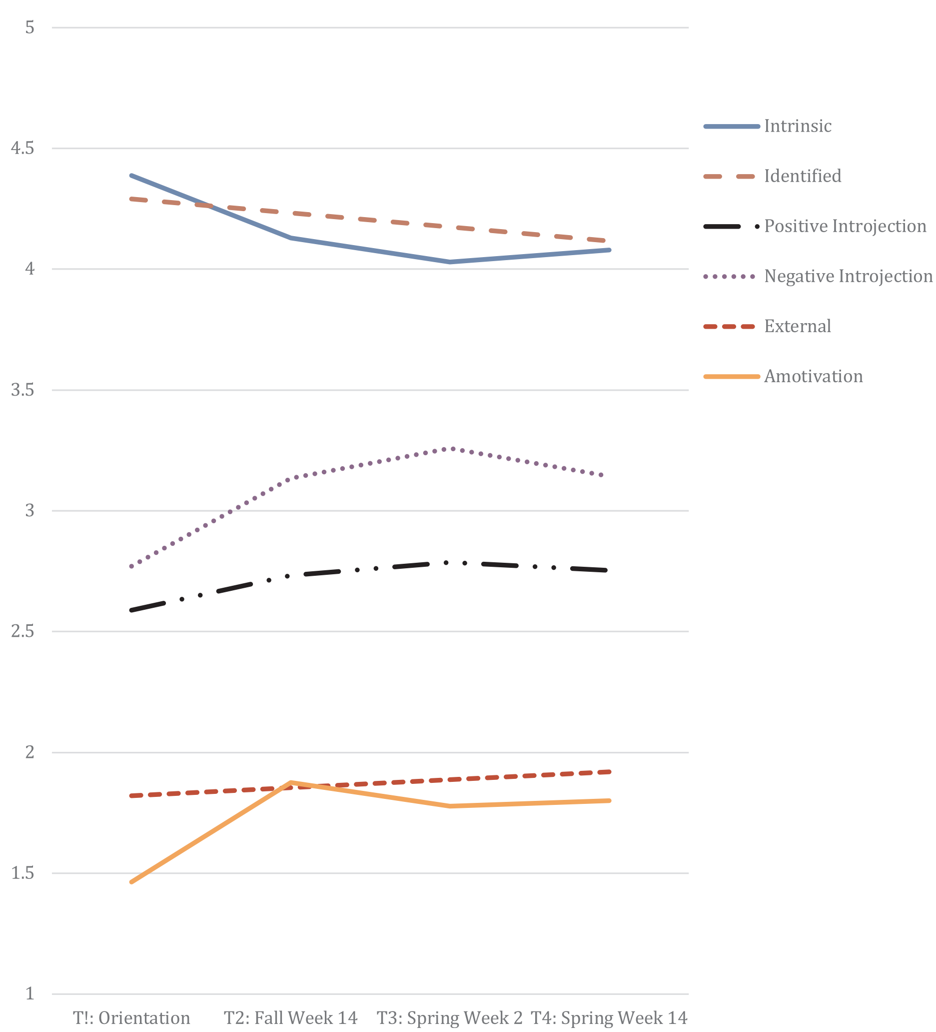

Fig. 1. Model implied trajectories for six types of motivation.

Table 6
Latent growth models predicting outcomes.

	GPA			Reg for Soph					
Predictor	beta	SE	*p*	beta	SE	*p*	RMSEA	CFI	TLI
Amotivation intercept	**−0.129**	**0.036**	**< 0.001**	**−0.240**	**0.064**	**< 0.001**	0.035	0.936	0.938
Amotivation basis slope	**−0.240**	**0.051**	**< 0.001**	**−0.234**	**0.094**	**0.012**			
External intercept	−0.078	0.052	0.131	−0.122	0.073	0.095			
External linear slope	−0.191	0.138	0.166	−0.124	0.208	0.553	0.027	0.952	0.953
Pos. introjection intercept	0.091	0.090	0.308	−0.028	0.091	0.761			
Pos. introjection linear slope	1.626	0.895	0.069	0.864	1.295	0.505	0.025	0.976	0.970
Pos. introjection quadratic slope	1.640	0.929	0.078	0.857	1.378	0.534			
Identified intercept	**0.161**	**0.045**	**< 0.001**	**0.183**	**0.070**	**0.009**			
Identified linear slope	**0.319**	**0.078**	**< 0.001**	0.266	0.144	0.066	0.028	0.962	0.963
Intrinsic intercept	0.071	0.060	0.233	0.044	0.115	0.699			
Intrinsic linear slope	**0.809**	**0.402**	**0.044**	**1.684**	**0.810**	**0.038**	0.036	0.914	0.914
Intrinsic quadratic slope	0.705	0.427	0.098	1.492	0.880	0.090			

Note: Bolded are significant at $p < .05$.

that students with higher amotivation at the beginning of their first year were less likely to achieve high grades and remain enrolled. Odds ratios indicated that students with initial amotivation that was one standard deviation above the mean were approximately 21% less likely to remain enrolled than students at the mean for initial amotivation. Similarly, the slope for amotivation negatively predicted GPA ($\beta = -0.24$, S.E. = 0.05, $p < .001$) and retention ($\beta = -0.23$, S.E. = 0.09, $p = .013$, O.R. = 0.79), indicating that greater increases in amotivation were associated with worse academic outcomes.

In the model for identified motivation, the identified intercept significantly predicted both GPA ($\beta = 0.16$, S.E. = 0.045, $p < .001$) and retention ($\beta = 0.18$, S.E. = 0.07, $p = .01$, O.R. = 1.20). As expected, this indicates that students beginning college with identified regulation one standard deviation above the mean attained higher GPAs and were 20% more likely to enroll for classes the following year than students at the mean. The linear slope of identified regulation also significantly predicted GPA ($\beta = 0.319$, S.E. = 0.05, $p < .001$, O.R. = 1.38), controlling for the effect of the intercept, but did not significantly predict retention ($\beta = 0.27$, S.E. = 0.14, $p = .07$). This indicates that students with more positive slopes in identified regulation showed higher GPA at the end of their first year, controlling for initial levels of identified regulation.

For intrinsic motivation, only the linear slope was associated with outcomes. The slope positively predicted both GPA ($\beta = 0.81$, S.E. = 0.40, $p = .04$) and retention ($\beta = 1.68$, S.E. = 0.81, $p = .04$, O.R. = 5.39), indicating that students with more positive trajectories of intrinsic motivation had higher GPA and were more than five times as likely to enroll for classes compared to peers at the average, regardless of their initial levels initial levels or quadratic slope.

7. Discussion

The first year of college is a time when new academic experiences shape students' beliefs about themselves, and academic decisions may have substantial consequences for life outcomes. The present study provided a holistic descriptive picture of motivational change during this period by considering how each type of motivation in the SDT continuum changes both in absolute terms and in comparison to the other types. Moreover, assessing motivation both at college entry and as it changes over time provided unique but complementary information on first-year students' motivational experiences, and how those experiences are associated with their academic achievement and decisions to remain enrolled in college. Results indicated that motivation changes in meaningful ways over the first year of college, with the six types of motivation showing distinct initial levels, patterns of development, and relations to academic functioning.

7.1. Initial levels and patterns of motivational change

The levels of motivation students reported at college entry appeared to be adaptive according to theory. Initial levels of intrinsic motivation and identified regulation were quite high, especially compared to students' moderate endorsement of positive and negative introjected regulation and relatively low endorsement of external regulation. Levels of amotivation were the lowest of all motivation types reported, and near the very bottom of the scale. In other words, students entered college with high-quality motivation as posited by SDT. These findings are perhaps not surprising for students entering an institution known for a focus on intrinsic motivation and mastery-based approaches to learning.

Average patterns of change over time, however, appeared to be less adaptive according to theory. Indeed, the loss over time to autonomous motivation and the growth observed in controlled motivation and amotivation paint a rather pessimistic picture of motivational change over the first year of college. The loss of intrinsic motivation and identified regulation is consistent with the robust literature on motivational change among younger populations (e.g., Gottfried, Marcoulides, Gottfried, Oliver, & Guerin, 2007; Lepper et al., 2005) and the limited work with collegiate samples (e.g., Busse & Walter, 2013; Hulleman, Godes, Hendricks, & Harackiewicz, 2010; Pan & Gauvain, 2012). Notably this pattern of decline in the more autonomous types of motivation was observed in a context that explicitly values learning for the sake of learning (e.g., through the de-emphasis on letter grades; Sheehy, 2013). This raises the interesting question of whether the loss to autonomous motivation over the first year of college may be a developmental as much as a contextual phenomenon, or perhaps a function of developmental mismatch with the broad experience of transitioning to higher education (see Eccles & Midgley, 1989; Seidman & French, 2004).

Considering the specific subtypes of autonomous motivation, identified regulation showed a gradual linear decline whereas intrinsic motivation evidenced a sharper drop-off followed by a partial recovery at the end of the first year. That identified regulation may be less subject to drastic change is consistent with conceptualizations of identity as being relatively stable once commitments are made, along with recent evidence that identity-related attainment value declines more gradually than other types of motivation during the first two years of college for engineering students (Robinson, Lee, et al., 2019) and remains stable throughout four years of college for the majority of science students (Robinson, Perez, Nuttall, Roseth, & Linnenbrink-Garcia, 2018). Although the college years are characterized by identity-based exploration (Arnett & Tanner, 2006), perhaps students' overall sense that they are driven to engage in personally meaningful academic pursuits remains relatively stable (see Eccles, 2009; Robinson et al., 2018).

The trajectory observed for intrinsic motivation echoes recent findings with STEM majors (Young et al., 2018) and first-year business students (Brahm et al., 2017), further hinting at the importance of considering non-linear patterns of change. It may be that some students enter college with unrealistic expectations around the intrinsic pursuit of knowledge and then are confronted with deadlines, exams, and experiences that disrupt their sense of competence, which may temporarily compromise their feelings of interest and enjoyment. Future research is needed to establish whether the partial recovery for intrinsic motivation at T4 replicates, whether it continues into sophomore year (see Kyndt et al., 2015), and what personal or contextual factors might be facilitative of such recovery patterns. Of course, it is important to remember that overall levels of autonomous motivation remained quite high even at T3, and were substantially higher than any of the other more controlled types of motivation.

Students' reports of controlled motivation were at low to moderate levels when beginning college, but then increased over the first year of college. This pattern diverges from the declining levels of extrinsic motivation over time observed among younger populations (e.g., Corpus et al., 2009; Leroy & Bressoux, 2016; Otis et al., 2005). Perhaps this is because authority figures generally become less compelling extrinsic forces of action over the primary and secondary years, but have a greater influence over the first year of college (see Stage & Williams, 1990). In addition, more internally regulated extrinsic motivators such as guilt and shame may increase in prominence at the collegiate level, as shown by the sharp rise in negative introjection observed in the present study. Perhaps the greater autonomy over daily living afforded by a collegiate environment brings with it a greater sense of responsibility for one's anticipated and actual failures. It is also possible that the rising trajectory of negative introjection may be specific to academic cultures of very high achieving students – an empirical question awaiting future research.

The trajectory for amotivation appeared to be non-linear in the present study, with students increasingly questioning the meaning of their academic work, especially over the first semester, with some recovery by the end of the first year. This pattern of growth in amotivation is interesting to consider within a sample simultaneously characterized by very high levels of autonomous motivation. Perhaps the curiosity-based engagement that exemplifies intrinsic motivation also leads to a broader questioning of the value and relevance of a liberal arts education itself. Although a pattern of growing amotivation over the first year of college has been observed in other samples (Taylor et al., 2014), it will be important to gather additional descriptive data on patterns of change from a broader range of populations.

Taken together, the trajectories observed in the present study contribute to our theoretical understanding of the complex, distinct patterns of change that are possible and perhaps typical over the first year of college. They also point to the value in considering each of the SDT motivation types separately rather than using composite indicators. The strongest case for this comes from the more controlled types of motivation, in that external regulation began at substantially lower levels than both positive and negative introjection and followed a linear rather than quadratic trajectory of growth. The two autonomous types of motivation also displayed distinct change trajectories, even while initial levels at the time of college entry were quite similar. Understanding the distinct developmental trajectories for each type of motivation may be particularly important for designing appropriately targeted pedagogical supports and interventions. For example, the present data could inform when best to intervene given a particular set of goals (e.g., preventing the decline of intrinsic motivation, targeting identity-based motivation, minimizing negative introjection, etc.) or which motivation type(s) might optimally be targeted at particular points during the first year of college.

7.2. Academic functioning

The present study advances the extant literature in that we examined initial levels of each motivation type alongside its change trajectory as predictors of academic functioning during the first year of college. Considering both initial levels and change trajectories simultaneously revealed the unique contribution of each for academic achievement and registration for sophomore year – a contribution to the literature on SDT.

As expected, the more autonomous types of motivation positively predicted academic functioning, consistent with the tenets of SDT (Ryan & Deci, 2017) and the available empirical evidence (e.g., Brunet et al., 2015; Taylor et al., 2014). When considering initial levels, however, only identified regulation predicted outcomes. Those students who began college with higher levels of identified regulation earned higher GPAs and were substantially more likely to persist, which is congruous with a small body of research showing that identity-based motivation may be a particularly powerful predictor of achievement outcomes (e.g., Burton et al., 2006; Koestner & Losier, 2002). At the same time, intrinsic motivation at college entry did not predict students' academic functioning while controlling for the effect of rates of change in intrinsic motivation. At first blush it might seem surprising that this quintessential type of autonomous motivation was not predictive given the substantial literature mapping initial or static levels of intrinsic motivation to achievement outcomes and college retention (e.g., Brunet et al., 2015; Meens et al., 2018; Taylor et al., 2014; Vallerand & Bissonnette, 1992). This body of work, however, has not generally controlled for rates of change in intrinsic motivation when examining its impact (for exceptions, see Gottfried et al., 2013; Leroy & Bressoux, 2016), which underscores the importance of considering both intercepts and slopes simultaneously for gaining a more complete picture of how motivation may predict academic functioning.

When considering change trajectories, on the other hand, intrinsic motivation was arguably the most impactful force. The slope of intrinsic motivation predicted both GPA and retention such that students on a more positive trajectory were more than five times as likely to register for sophomore year compared to their peers at the average. The slope of identified regulation also predicted GPA, but did not predict retention. Taken together, these findings extend our understanding of the effects of motivational change to a collegiate population, echoing findings with younger students that growth in autonomous types of motivation can be powerful predictors of academic functioning (Gottfried et al., 2013; Otis et al., 2005) but adding important nuance by showing that it is initial levels of identified regulation and change trajectories of intrinsic motivation that are most impactful.

That the more controlled types of motivation (i.e., positive introjection, external regulation) did not predict academic functioning is relatively unsurprising given the numerous nonsignificant relations in the literature (e.g., Koestner & Losier, 2002; Leroy & Bressoux, 2016; Taylor et al., 2014). It is notable that there was no distinction between the effects of external regulation and the positive form of introjection, though we were unable to examine the impact of negative introjection. Because of this, it would be premature to conclude that controlled types of motivation do not predict functioning at the college level or that there is no distinction among the various types of controlled motivation. Future research should continue to examine the potential impact of both initial states and rates of change in the various types of controlled motivation, particularly with additional outcomes that go beyond the two measures of the present study. There may, for example, be costs to well-being as a result of negative introjection (Assor et al., 2009), which could be particularly important to investigate given the sharp increase in negative introjection over the first year of college that was observed. Exploring students' affective experiences during the first year of college could be especially illuminating.

In line with our hypotheses, both initial levels and rates of change in amotivation predicted the academic correlates. This aligns with previous work showing a link between amotivation and both poor achievement and college dropout (e.g., Taylor et al., 2014; Vallerand & Bissonnette, 1992), and the powerful effect of amotivation trajectories on academic achievement among middle school students (Leroy & Bressoux, 2016). These findings add to the very few studies examining the impact of amotivation; indeed, those with college students have not simultaneously considered both initial levels and rates of change, and our findings show that each play a role in predicting outcomes, even when controlling for the other.

Although the descriptive data on motivation trajectories pointed to the value in examining each of the six distinct SDT motivation types, the findings related to academic outcomes paint a more complex picture. Intrinsic motivation versus identified regulation mapped on to academic functioning in somewhat distinct ways, but the relation to outcomes was similar for all types of controlled motivation, perhaps justifying a more global approach. Combining across motivation types to create autonomous and controlled composites or even creating a relative autonomy index (see Sheldon et al., 2017) may be appropriate depending on the focus of the inquiry. Because we examined only a limited set of outcomes, however, we would advocate for retaining the six SDT motivation types in subsequent research with additional outcomes before abandoning the more granular approach.

7.3. Implications for practice

Modeling the predictive value of both initial levels (i.e., intercepts) and change trajectories (i.e., slopes) for each type of motivation may provide important information for motivational interventions. In the present study, academic functioning was predicted not only by levels of identified regulation and amotivation at college entry but also by changes in amotivation, identified regulation, and intrinsic motivation. It may be essential, therefore, to focus our supports both prior to college entry (particularly regarding amotivation and identified regulation) and throughout the first year (particularly regarding amotivation and intrinsic motivation) in order to promote academic achievement and college retention. Supporting students' transition beyond a week of orientation events is consistent with a broader movement in the field of higher education to adopt longer transition strategies (e.g., Brooman & Darwent, 2014), and may be essential for buffering against the decline of autonomous motivation.

There is a flourishing body of intervention research focusing on motivational variables in the field of educational psychology (for summaries see Hulleman & Barron, 2016; Lazowski & Hulleman, 2016; Rosenzweig & Wigfield, 2016; Walton & Brady, 2017). Walton and Brady (2017), for example, describe a powerful set of intervention studies that effectively reduce belongingness uncertainty over the transition to college. Within the SDT tradition more specifically, there has been substantial development of intervention approaches focusing on building autonomous motivation and reducing amotivation, often by using autonomy-supportive instruction and emphasizing intrinsic goals (e.g., Cheon & Reeve, 2015; Patall, Cooper, & Wynn, 2010; Su & Reeve, 2011; Vansteenkiste, Simons, Lens, Sheldon, & Deci, 2004). Although much of this work focuses on relatively short-term change in laboratory contexts, Reeve and colleagues have developed an effective curriculum for teaching autonomy-supportive instructional practices in real-life educational contexts, often to teachers of physical education (e.g., Cheon & Reeve, 2015; Reeve, Jang, Carrell, Jeon, & Barch, 2004; Su & Reeve, 2011). They have documented teacher enthusiasm for the curriculum, high implementation fidelity, and a significant impact on student engagement and motivation. But, to our knowledge, such programs have not yet been implemented and assessed in higher education contexts. Before such programming can be developed and enacted, it is essential to understand the naturalistic pattern of change that can be leveraged or must be counteracted against. The fine-grained account of motivational change provided by the present study, then, is critical for developing interventions that are appropriately timed and targeted for first-year college students.

At a more local level, it could be quite useful for college faculty to know that autonomous motivation tends to decrease and controlled motivation tends to increase over the first year – and particularly the first semester – of college. Armed with this knowledge, faculty could consider how their particular course structure or pedagogical practices may impact motivational change. Faculty may be uniquely positioned to adapt their practices on a scale and during a timeframe that could have maximal impact. In addition to college-wide programming and targeted interventions, therefore, a clear descriptive account of fine-grained motivational change may be actionable by individual faculty within particular courses, especially those that serve as gateways to the major. The present data suggest that practices to sustain intrinsic motivation may be particularly fruitful.

7.4. Limitations and future directions

Data for the present study all came from one institution serving largely high achieving students who were attracted to a mastery-oriented collegiate learning environment. It is unclear whether these same trajectories would replicate in other populations and types of institutions, particularly those less marked by mastery-oriented approaches. At the same time, however, the patterns observed in the present study are consistent with the broader literature on motivation in higher education settings (e.g., Busse & Walter, 2013; Pan & Gauvain, 2012; Robinson, Lee, et al., 2019; Taylor et al., 2014), which suggests that they are not entirely unique to this particular context. Moreover, the inclusion of three separate cohorts, the high initial response rate, and high retention rate across time points speak to the validity of the patterns observed. Nonetheless it will be important for future research to examine whether these same trajectories replicate in other institutions, particularly those serving a greater diversity of achievement levels.

The longitudinal and correlational nature of the present study provides an important descriptive account of average motivational change, variation around the average trajectory, and correlates of motivational change. However, it cannot indicate causality. Intervention research could speak more clearly to the causal effects of particular trajectories of motivation. Further, it is possible that the change patterns and particularly the non-linear trajectories identified are artifacts of measurement, especially given the difficulty of capturing an unbiased snapshot of a dynamic and situated construct. Although this concern cannot be completely eliminated, we assessed motivation at a more global level rather than in the context of a specific class or task. This more trait-like assessment is less subject to minute fluctuations. Further, our findings align with prior research on motivation constructs finding average patterns of declines in positive forms of motivation and increases in less desirable forms of motivation during college (e.g., Kosovich et al., 2017; Robinson, Lee, et al., 2019). Again, however, the non-linear trajectories identified in the present study must be considered tentatively in light of the measurement error that comes from self-reported, longitudinal data, examining only four time points, and the less-than-excellent, although adequate, model fit indices for some models.

Moving beyond a description of the shape of change, it would also be useful for future research to examine the predictors of various motivational trajectories, whether they be dispositional factors students bring with them to college (e.g., mindset, goal orientation, contingent self-worth) or aspects of how the collegiate environment is experienced (e.g., belongingness, feedback on academic work). Moreover, the significant variability around both initial levels and motivation trajectories for all the motivation types except negative introjection indicates that not everybody experiences change in the same way. Examining heterogeneity in trajectories and the consequences and predictors of such individual differences will be another important direction for future research (e.g., Ratelle et al., 2004).

The present study examined each of the six SDT motivation types in separate models. This approach is valuable in that it allows for comparisons about trajectories and the absolute role of each motivation type in predicting outcomes. At the same time, at least some of the motivation types likely co-occur within individuals and/or differ in their salience to individuals over time. It could be illuminating to explore the effects of particular combinations of motives using a person-centered approach, which has been increasingly adopted in the SDT tradition in recent years (e.g., Boiché & Stephan, 2014; Vansteenkiste et al., 2009; Wang, Morin, Ryan, & Liu, 2016). Considering changes to profile membership over more than two timepoints using latent transition analysis would be particularly fruitful in future work with larger samples than that of the present study (for an example with two timepoints, see Gillet, Morin, & Reeve, 2017).

Finally, it would be interesting to consider an integrative model that tests all six motivation types jointly and examines the unique role of each type while controlling for others (e.g., Leroy & Bressoux, 2016). For the purposes of the present study, we tested separate models because of the high correlation across some of the motivation types (such that the remaining variance would become less meaningful) and the more practical reality that variables do not actually control for one another within real individuals moving through real-life contexts. The separate models approach, moreover, forms the empirical foundation for making decisions regarding the integration or separation of constructs in future work. Because the two different strategies address distinct research goals, both should ultimately be pursued in a comprehensive understanding of motivational change over the first year of college.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Anderman, E. M., & Midgley, C. (1997). Changes in achievement goal orientations, perceived academic competence, and grades across the transition to middle level schools. *Contemporary Educational Psychology, 22*, 269–298.
Arnett, J. J. (2000). Emerging adulthood: A theory of development from the late teens through the twenties. *American Psychologist, 55*, 469–480.
Arnett, J. H., & Tanner, J. L. (2006). *Emerging adults in America: Coming of age in the 21st century.* Washington, DC: American Psychological Association.
Assor, A., Vansteenkiste, M., & Kaplan, A. (2009). Identified versus introjected approach and introjected avoidance motivations in school and in sports: The limited benefit of self-worth strivings. *Journal of Educational Psychology, 101*, 482–497.
Baker, S. R. (2003). A prospective longitudinal investigation of social problem-solving appraisals on adjustment to university, stress, health, and academic motivation and performance. *Personality and Individual Differences, 35*, 569–591.
Baker, S. R. (2004). Intrinsic, extrinsic, and amotivational orientations: Their role in university adjustment, stress, well-being, and subsequent academic performance. *Current Psychology, 23*, 189–202.
Black, A. E., & Deci, E. L. (2000). The effects of instructors' autonomy support and students' autonomous motivation on learning organic chemistry: A self-determination theory perspective. *Science Education, 84*, 740–756.
Boiché, J., & Stephan, Y. (2014). Motivational profiles and achievement: A prospective study testing potential mediators. *Motivation and Emotion, 38*, 79–92.
Bong, M. (2005). Within-grade changes in Korean girls' motivation and perceptions of the learning environment across domains and achievement levels. *Journal of Educational Psychology, 97*, 656–672.
Brahm, T., Jenert, T., & Wagner, D. (2017). The crucial first year: A longitudinal study of students' motivational development at a Swiss Business School. *Higher Education, 73*, 459–478.
Broda, M., Yun, J., Schneider, B., Yeager, D. S., Walton, G. M., & Diemer, M. (2018). Reducing inequality in academic success for incoming college students: A randomized trial of growth mindset and belonging interventions. *Journal of Research on Educational Effectiveness, 11*, 317–338.
Brooman, S., & Darwent, S. (2014). Measuring the beginning: A quantitative study of the transition to higher education. *Studies in Higher Education, 39*, 1523–1541.
Brunet, J., Gunnell, K. E., Gaundrewau, P., & Sabiston, C. M. (2015). An integrative analytical framework for understanding the effects of autonomous and controlled motivation. *Personality and Individual Differences, 84*, 2–15.
Burton, K. D., Lydon, J. E., D'Alessandro, D. U., & Koestner, R. (2006). The differential effects of intrinsic and identified motivation on well-being and performance: Prospective, experimental, and implicit approaches to self-determination theory. *Journal of Personality and Social Psychology, 91*, 750–762.
Busse, V., & Walter, C. (2013). Foreign language learning motivation in higher education: A longitudinal study of motivational changes and their causes. *The Modern Language Journal, 97*, 435–456.
Cheon, S. H., & Reeve, J. (2015). A classroom-based intervention to help teachers decrease students' amotivation. *Contemporary Educational Psychology, 40*, 99–111.
Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling, 9*, 233–255. https://doi.org/10.1207/S15328007SEM0902_5.
Christie, H., Munro, M., & Fisher, T. (2004). Leaving university early: Exploring the differences between continuing and non-continuing students. *Studies in Higher Education, 29*, 617–636.
Conley, C. S., Kirsch, A. C., Dickson, D. A., & Bryant, F. B. (2014). Negotiating the transition to college: Developmental trajectories and gender differences in psychological functioning, cognitive-affective strategies, and social well-being. *Emerging Adulthood, 2*, 195–210.
Corpus, J. H., McClintic-Gilbert, M. S., & Hayenga, A. O. (2009). Within-year changes in children's intrinsic and extrinsic motivational orientations: Contextual predictors and academic outcomes. *Contemporary Educational Psychology, 34*, 154–166.
Dai, T., & Cromley, J. G. (2014). Changes in implicit theories of ability in biology and dropout from STEM majors: A latent growth curve approach. *Contemporary Educational Psychology, 39*, 233–247.
Eccles, J. (2009). Who am I and what am I going to do with my life? Personal and collective identities as motivators of action. *Educational Psychologist, 44*, 78–79. https://doi.org/10.1080/00461520902832368.
Eccles, J. S., & Midgley, C. (1989). Stage-environment fit: Developmentally appropriate classrooms for young adolescents. In R. E. Ames, & C. Ames (Eds.). *Research on motivation in education* (pp. 139–186). New York: Academic Press.
Fazey, D., & Fazey, J. (1998). Perspectives on motivation: The implications for effective learning in higher education. In S. Brown, S. Armstrong, & G. Thompson (Eds.). *Motivating students* (pp. 59–72). London: SEDA: Staff and Educational Development Series.
Ferrer, E., Balluerka, N., & Widaman, K. F. (2008). Factorial invariance and the specification of second-order latent growth models. *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences, 4*, 22–36.
Flanigan, A. E., Peteranetz, M. S., Shell, D. F., & Soh, L.-K. (2017). Implicit intelligence beliefs of computer science students: Exploring change across the semester. *Contemporary Educational Psychology, 48*, 179–196.
Gall, T. L., Evans, D. R., & Bellerose, S. (2000). Transition to first-year university: Patterns of change in adjustment across life domains and time. *Journal of Social and Clinical Psychology, 19*, 544–567.
Gillet, N., Morin, A. J. S., & Reeve, J. (2017). Stability, change, and implications of students' motivational profiles. A latent transition analysis. *Contemporary Educational Psychology, 51*, 222–239.
Gillet, N., Vallerand, R. J., & Lafreniere, M. K. (2012). Intrinsic and extrinsic school motivation as a function of age: The mediating role of autonomy support. *Social Psychology of Education, 15*, 77–95.
Gottfried, A. E., Fleming, J. S., & Gottfried, A. W. (2001). Continuity of academic intrinsic motivation from childhood through late adolescence: A longitudinal study. *Journal of Educational Psychology, 93*, 3–13.
Gottfried, A. E., Marcoulides, G. A., Gottfried, A. W., & Oliver, P. (2013). Longitudinal pathways from math intrinsic motivation and achievement to math course accomplishments and educational attainment. *Journal of Research on Educational Effectiveness, 6*, 68–92.
Gottfried, A. E., Marcoulides, G. A., Gottfried, A. W., Oliver, P., & Guerin, D. (2007). Multivariate latent change modeling of developmental decline in academic intrinsic mathematics motivation and achievement: Childhood through adolescence. *International Journal of Behavioral Development, 31*, 317–327.
Guay, F., Ratelle, C. F., Roy, A., & Litalien, D. (2010). Academic self-concept, autonomous academic motivation, and achievement: Mediating and additive effects. *Learning and Individual Differences, 20*, 644–653.
Guiffrida, D. A., Lynch, M. F., Wall, A. F., & Abel, D. S. (2013). Do reasons for attending college affect academic outcomes? A test of a motivational model from a Self-Determination Theory perspective. *Journal of College Student Development, 54*(2), 121–139.
Hancock, G. R., Kuo, W. L., & Lawrence, F. R. (2001). An illustration of second-order latent growth models. *Structural Equation Modeling, 8*, 470–489.
Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*, 1–55. https://doi.org/10.1080/10705519909540118.
Hulleman, C. S., & Barron, K. E. (2016). Motivation interventions in education: Bridging

theory, research, and practice. In E. Anderman, & L. Corno (Eds.). *Handbook of educational psychology* (pp. 160–171). (3rd ed.). New York, NY: Taylor & Francis.
Hulleman, C. S., Godes, O., Hendricks, B. L., & Harackiewicz, J. M. (2010). Enhancing interest and performance with a utility value intervention. *Journal of Educational Psychology, 102*, 880–893.
Kaplan, A., & Patrick, H. (2016). Learning environments and motivation. In K. Wentzel, & D. Miele (Eds.). *Handbook of motivation at school* (pp. 251–274). (2nd ed.). New York: Routlege.
Koestner, R., & Losier, G. F. (2002). Distinguishing three ways of being internally motivated: A closer look at introjection, identification, and intrinsic motivation. In E. L. Deci, & R. M. Ryan (Eds.). *Handbook of self-determination research* (pp. 101–121). Rochester, NY: The University of Rochester Press.
Kosovich, J. J., Flake, C. S., & Hulleman, C. S. (2017). Short-term motivation trajectories: A parallel process model of expectancy-value. *Contemporary Educational Psychology, 49*, 130–139.
Kowalski, P. (2007). Changes in students' motivation to learn during the first year of college. *Psychological Reports, 101*, 79–89.
Kroger, J. (2004). *Identity in adolescence: The balance between self and other* (3rd ed.). New York: Routledge.
Kyndt, E., Coertjens, L., van Daal, T., Donche, V., Gijbels, D., & van Petegem, P. (2015). The development of students' motivation in the transition from secondary to higher education: A longitudinal study. *Learning and Individual Differences, 39*, 114–123.
Larose, S., Ratelle, C. F., Guay, F., Senécal, C., & Harvey, M. (2006). Trajectories of science self-efficacy beliefs during the college transition and academic and vocational adjustment in science and technology programs. *Educational Research and Evaluation, 12*, 373–393.
Lazowski, R. A., & Hulleman, C. S. (2016). Motivation interventions in education: A meta-analytic review. *Review of Educational Research, 86*, 602–640.
Lepper, M. R., Corpus, J. H., & Iyengar, S. S. (2005). Intrinsic and extrinsic motivational orientation in the classroom: Age differences and academic correlates. *Journal of Educational Psychology, 97*, 184–196.
Leroy, N., & Bressoux, P. (2016). Does amotivation matter more than motivation in predicting mathematics learning gains? A longitudinal study of sixth-grade students in France. *Contemporary Educational Psychology, 44–45*, 41–53.
McArdle, J. J. (1988). Dynamic but structural equation modeling of repeated measures data. In J. R. Nesselroade, & R. B. Cattell (Eds.). *Handbook of multivariate experimental psychology* (pp. 561–614). New York: Plenum.
McArdle, J. J. (2009). Latent variable modeling of differences and changes with longitudinal data. Annual Review of Psychology, 60, 577–605. http://doi.org/10.1146/annurev.psych.60.110707.163612.
McFarland, J., Hussar, B., de Brey, C., Snyder, T., Wang, X., Wilkinson-Flicker, S., …, Hinz, S. (2017). The Condition of Education 2017 (NCES 2017- 144). U.S. Department of Education. Washington, DC: National Center for Education Statistics. Retrieved June 5, 2019, from https://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2017144.
Meens, E., Bakx, A., Klimstra, T., & Denissen, J. (2018). The association of identity and motivation with students' academic achievement in higher education. *Learning and Individual Differences, 64*, 54–70.
Middleton, M. J., Kaplan, A., & Midgley, C. (2004). The change in middle school students' achievement goals in mathematics over time. *Social Psychology of Education, 7*, 289–311.
Muller, F. H., & Palekcic, M. (2005). Continuity of motivation in higher education: A three-year follow-up study. *Review of Psychology, 12*, 31–43.
Musu-Gillette, L. E., Wigfield, A., Harring, J. R., & Eccles, J. S. (2015). Trajectories of change in students' self-concepts of ability and values in math and college major choice. *Educational Research and Evaluation, 21*, 343–370.
Muthén, L. K., & Muthén, B. O. (1998 –2018). Mplus user's guide, 8th edition. Los Angeles, CA: Muthén & Muthén.
National Student Clearinghouse (2019). Snapshot report: First-year persistence and retention. Retrieved from https://nscresearchcenter.org/wp-content/uploads/SnapshotReport35.pdf.
Otis, N., Grouzet, F. M. E., & Pelletier, L. G. (2005). Latent motivational change in an academic setting: A longitudinal study. *Journal of Educational Psychology, 97*, 170–183.
Pan, Y., & Gauvain, M. (2012). The continuity of college students' autonomous learning motivation and its predictors: A three-year longitudinal study. *Learning and Individual Differences, 22*, 92–99.
Paunesku, D., Walton, G. M., Romero, C., Smith, E. N., Yeager, D. S., & Dweck, C. S. (2015). Mind-set interventions are a scalable treatment for academic underachievement. *Psychological Science, 26*, 784–793.
Patall, E. A., Cooper, H., & Wynn, S. R. (2010). The effectiveness and relative importance of choice in the classroom. *Journal of Educational Psychology, 102*, 896–915.
Pelletier, L. G., Fortier, M. S., Vallerand, R. J., & Briere, N. M. (2001). Associations among perceived autonomy support, forms of self-regulation, and persistence: A prospective study. *Motivation and Emotion, 25*, 279–306.
Perry, R. P., Hladkyj, S., Pekrun, R. H., & Pelletier, S. T. (2001). Academic control and action control in the achievement of college students: A longitudinal field study. *Journal of Educational Psychology, 93*, 776–789.
Pisarik, C. (2009). Motivational orientation and burnout among undergraduate college students. *College Student Journal, 43*, 1238–1252.
Ram, N., & Grimm, K. (2007). Using simple and complex growth models to articulate developmental change: Matching theory to method. *International Journal of Behavioral Development, 31*, 303–316.
Ratelle, C. F., Guay, F., Larose, S., & Senécal, C. (2004). Family correlates of trajectories of academic motivation during a school transition: A semiparametric group-based approach. *Journal of Educational Psychology, 96*, 743–754.
Ratelle, C. F., Guay, F., Vallerand, R. J., Larose, S., & Senécal, C. (2007). Autonomous, controlled, and amotivated types of academic motivation: A person-oriented analysis. *Journal of Educational Psychology, 99*, 734–746.
Reeve, J., Jang, H., Carrell, D., Jeon, S., & Barch, J. (2004). Enhancing students' engagement by increasing teachers' autonomy support. *Motivation and Emotion, 28*, 147–169.
Robbins, S. B., Lauver, K., Le, H., Davis, D., Langley, R., & Carlstrom, A. (2004). Do psychosocial and study skill factors predict college outcomes? A meta-analysis. *Psychological Bulletin, 130*, 261–288.
Robinson, K. A., Lee, Y.-K., Bovee, E. A., Perez, T., Walton, S. P., Briedis, D., & Linnenbrink-Garcia, L. (2019). Motivation in transition: Development and roles of expectancy, task values, and costs in early college engineering. *Journal of Educational Psychology, 111*, 1081–1102. https://doi.org/10.1037/edu0000331.
Robinson, K. A., Perez, T., Carmel, J. H., & Linnenbrink-Garcia, L. (2019). Science identity development trajectories in a gateway college chemistry course: Predictors and relations to achievement and STEM pursuit. *Contemporary Educational Psychology, 56*, 180–192.
Robinson, K. A., Perez, T., Nuttall, A. K., Roseth, C. J., & Linnenbrink-Garcia, L. (2018). From science student to scientist: Predictors and outcomes of heterogeneous science identity trajectories in college. *Developmental Psychology, 54*, 1977–1992. https://doi.org/10.1037/dev0000567.
Roisman, G. I., Masten, A. S., Coatsworth, J. D., & Tellegen, A. (2004). Salient and emerging developmental tasks in the transition to adulthood. *Child Development, 75*, 123–133.
Rosenzweig, E. Q., & Wigfield, A. (2016). STEM motivation interventions for adolescents. A promising start, but further to go. *Educational Psychologist, 51*, 146–163.
Ryan, R. M., & Connell, J. P. (1989). Perceived locus of causality and internalization: Examining reasons for acting in two domains. *Journal of Personality and Social Psychology, 57*, 749–761.
Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*, 68–78.
Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness.* New York: Guilford Press.
Seidman, E., & French, S. E. (2004). Developmental trajectories and ecological transitions: A two-step procedure to aid in the choice of prevention and promotion interventions. *Development and Psychopathology, 16*, 1141–1159.
Sheehy, J. (2013, June). Going through the fire. Reed magazine. Retrieved from https://www.reed.edu/reed_magazine/june2013/articles/features/oralhistory/oralhistory1.html.
Sheldon, K. M., Osin, E. N., Gordeeva, T. O., Suchkov, D. D., & Sychev, O. A. (2017). Evaluating the dimensionality of self-determination theory's relative autonomy continuum. *Personality and Social Psychology Bulletin, 43*, 1215–1238.
Snyder, K. E., Barr, S. M., Honken, N. B., Pittard, C. M., & Ralston, P. A. S. (2018). Navigating the first semester: An exploration of short-term changes in motivational beliefs among engineering undergraduates. *Journal of Engineering Education, 107*, 11–29.
Stage, F. K., & Williams, P. D. (1990). Students' motivation and changes in motivation during the first year of college. *Journal of College Student Development, 31*, 516–522.
Su, Y.-L., & Reeve, J. (2011). A meta-analysis of the effectiveness of intervention programs designed to support autonomy. *Educational Psychology Review, 23*, 159–188.
Taylor, G., Jungert, T., Mageau, G. A., Schattke, K., Dedic, H., Rosenfield, S., & Koestner, R. (2014). A self-determination theory approach to predicting school achievement over time: The unique role of intrinsic motivation. *Contemporary Educational Psychology, 39*, 342–358.
Tinto, V. (1993). *Leaving college: Rethinking the causes and cures of student attrition* (2nd ed.). Chicago, IL: University of Chicago Press.
Towbes, L. C., & Cohen, L. H. (1996). Chronic stress in the lives of college students: Scale development and prospective prediction of distress. *Journal of Youth and Adolescence, 25*, 199–203.
Urdan, T., & Midgley, C. (2003). Changes in the perceived classroom goal structure and pattern of adaptive learning during early adolescence. *Contemporary Educational Psychology, 28*, 524–551.
Vallerand, R. J., & Bissonnette, R. (1992). Intrinsic, extrinsic, and amotivational styles as predictors of behavior: A prospective study. *Journal of Personality, 60*, 599–620.
Vallerand, R. J., Fortier, M. S., & Guay, F. (1997). Self-determination and persistence in a real-life setting: Toward a motivational model of high school dropout. *Journal of Personality and Social Psychology, 72*, 1161–1176.
Vallerand, R. J., Pelletier, L. G., Blais, M. R., Briere, N. M., Senecal, C. B., & Vallieres, E. F. (1992). The academic motivation scale: A measure of intrinsic, extrinsic, and amotivation in education. *Educational and Psychological Measurement, 52*, 1003–1017.
Vansteenkiste, M., Sierens, E., Soenens, B., Luyckx, K., & Lens, W. (2009). Motivational profiles from a self-determination perspective. The quality of motivation matters. *Journal of Educational Psychology, 101*, 671–688.
Vansteenkiste, M., Simons, J., Lens, W., Sheldon, K. M., & Deci, E. L. (2004). Motivating learning, performance, and persistence: The synergistic effects of intrinsic goal contents and autonomy-supportive contexts. *Journal of Personality and Social Psychology, 87*, 246–260.
Vanthournout, G., Gijbels, D., Coertjens, L., Donche, V., & Van Petegem, P. (2012). Students' persistence and academic success in a first-year professional bachelor program: The influence of students' learning strategies and academic motivation. *Education Research International*. https://doi.org/10.1155/2012/152747.
Walton, G. M., & Brady, S. T. (2017). The many questions of belonging. In A. J. Elliot, C. S. Dweck, & D. S. Yaeger (Eds.). *Handbook of competence and motivation* (pp. 272–293). (2nd ed.). New York: Guilford.
Wang, J. C. K., Morin, A. J., Ryan, R. M., & Liu, W. C. (2016). Students' motivational

profiles in the physical education context. *Journal of Sport & Exercise Psychology, 38*, 612–630.

Widaman, K. F., Ferrer, E., & Conger, R. D. (2010). Factorial invariance with longitudinal structural equation models: Measuring the same construct across time. *Child Development Perspectives, 4*, 10–18. https://doi.org/10.1111/j.1750-8606.2009.00110.x.

Widaman, K. F., & Reise, S. P. (1997). Exploring the measurement invariance of psychological instruments: Applications in the substance abuse domain. In: Bryant, K. J., Windle, M., & West, S. G. (Eds.), The science of prevention: Methodological advances from alcohol and substance abuse research (pp. 281–324). http://dx.doi.org/10.1037/10222-009.

Wu, Z. (2019). Academic motivation, engagement, and achievement among college students. *College Student Journal, 53*, 99–112.

Yeager, D. S., & Walton, G. M. (2011). Social-psychological interventions in education: They're not magic. *Review of Educational Research, 81*, 267–301.

Young, A. M., Wendel, P. J., Esson, J. M., & Plank, K. M. (2018). Motivational decline and recovery in higher education STEM courses. *International Journal of Science Education, 40*, 1016–1033.

Zusho, A., & Pintrich, P. R. (2003). Skill and will: The role of motivation and cognition in the learning of college chemistry. *International Journal of Science Education, 25*, 1081–1094.