Stability and change in the achievement emotion profiles of university students

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Abstract

This study used latent transition analysis (LTA) to examine stability and change in the emotion profiles of university students during a two-semester course. Three positive emotions (i.e., hope, pride, and happiness) and five negative emotions (i.e., guilt, helplessness, anger, shame, and regret) derived from Weiner's attribution theory of emotion (1985, 2007, 2018a, 2018b) were used to identify the emotion profiles of university students at the beginning (Time 1) and end (Time 2) of a two-semester course. We also examined changes in emotion profile memberships over time. Results showed 81% of participants remained in their Time 1 profiles at Time 2, with the majority classified in profiles defined by stable positive emotions or mixed emotions. ANCOVAs indicated that students in the stable positive emotion profile achieved better overall course performance than those with a stable mixed profile or a stable negative emotion profile. An ascending emotion transition profile (Time 1 mixed-to-Time 2 positive) performed better than a stable mixed emotion profile. The present findings extend our current understanding of multifaceted profiles of student emotion that can change over time.

Keywords: emotions, profiles, achievement, university students, latent transition analysis

The emotional toll of higher education can be high. While many students experience positive emotions like enjoyment and hope; others struggle with boredom or even anger (e.g., Helmich, Bolhuis, Prins, Laan, & Koopmans, 2011; Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011; Pekrun, Goetz, Titz, & Perry, 2002; Robinson, Rancellucci, Lee, Wormington, Roseth, & Linnenbrink-Gracia, 2017). Never before have post-secondary institutions dealt with as complex an emotional landscape of their learners (Divecha & Stern, 2016; Stoltzfus, 2015). Specifically, Denovan, Dagnall, Macaskill and Papageorgiou (2020) revealed that first year undergraduate students' general positive emotions declined in the first three months, whereas general negative emotions were relatively stable across a 6-month period among first year undergraduates (Denovan & Macaskill, 2017). This is of particular importance as these newly admitted undergraduate students are just embarking on their post-secondary education journey.

Recognizing the complex emotion journey, researchers (e.g., Jarrell, Harely, & Lajoie, 2016; Jarrell, Harely, Lajoie, & Naismith, 2017; Robinson et al., 2017) are focusing on students' experiences of *multiple emotions* specific to their learning process. Multiple emotions and changes in combinations of those emotions may have different effects on achievement than the generally recorded direct effect of single course-specific emotions on achievement (e.g., Pekrun, Lichenfeld, Marsh, Murayama, & Goetz, 2017). Because multiple course-specific emotions are a truer representation of students' feelings in post-secondary, research in this area represents a critical new perspective in higher education. Furthermore, as was recently discussed by Koenka (2020), using new data analytical techniques (e.g., person-centered analyses) helps a discovery of important processes in learning. Hence, to further advance this field, we asked the following two research questions: First, do students' experiences of multiple course-specific emotions change over a two-semester course? Second, how does stability or change in the experience of multiple course-specific emotions predict students' final course grades?

Theoretical Perspectives of Emotions

Appraisal perspective. In Weiner's attributional theory (1979, 1985, 2018a, 2018b), cognitive appraisals of a situation give rise to emotional experiences (e.g., Posner, Russell, & Peterson, 2005). For post-secondary students, one of the most emotion-provoking situations in higher education is receiving marks/grades during the course (e.g., term paper and tests) as well as final letter grades. Weiner posits that these emotions arise as a function of students' interpretation of their successes or failures based on the combination of three appraisal dimensions: 1) locus of causality (internal vs. external locus); 2) stability (stable vs. unstable); 3) controllability (controllable vs. uncontrollable). For instance, pride is experienced when a person appraises that an outcome is positive and due to an internal cause, such as his/her ability or effort invested into attaining the desirable outcome (Hareli & Weiner, 2002). Therefore, pride is considered an emotion related to the locus dimension and is experienced due to the appraisal of an internal cause. By contrast, feelings of hopelessness can be conceptualized as a function of appraising failure due to a stable cause (e.g., an ongoing hardship), and hence hopelessness is related to the stability dimension (Hareli & Weiner, 2002). To illustrate the controllability dimension, guilt is experienced when one attributes failure to a controllable cause (e.g., low effort), while shame is experienced when one attributes failure to an uncontrollable cause (e.g., low aptitude). Commonly examined emotions in Weiner's theory include: pride, hopefulness, helplessness/hopelessness, shame, guilt, regret, anger, and regret (1985, 2018b). As an attribution is specific to a particular situation (e.g., laboratory work in Biology), the use of Weiner's theory thus sheds light on the stability of course-specific attribution emotions among students in higher education.

Hierarchical structure of emotions. While Weiner's theory helps us to understand why students feel a specific emotion, such as pride, it is also important to understand the structure and relationships between different emotions: the organization of discrete emotions. Weiner's theory does not address the co-occurrence of multiple emotions experienced either briefly or over a protracted period of time. It is also silent on which emotion-driven attributional dimensions would dominate a combination and whether such combinations may fluctuate. Specifically, in this regard, Watson and Stanton (2017) proposed a two-level hierarchical structure of emotion, in which the bottom level comprises of discrete emotion categories (e.g., fear includes nervous and frightened, and joviality includes cheerful and happy) while the top level comprises more general affect: positive vs negative valence. While each emotion category at the lower level represents a coherent set of experiences, the authors argued that this two-level hierarchical structure is appropriate because almost all emotions can be systematically categorized into either a positive or negative dimension. Although the hierarchical structure was developed based on emotions in general, it is arguably applicable to course-specific emotions, whereby the bottom level consists of discrete emotions (e.g., pride and shame) experienced in a particular course (e.g., Computer Science) and the top level consists of general positive and negative emotionality toward the same course.

Antecedents of performance. Although discrete and general emotions can be triggered by cognitive appraisals of achievement outcomes, it is critical to acknowledge that emotions are also theorized to influence grades. In addition to Weiner (1985) and Watson and Stanton (2017), Pekrun's (2006) control-value theory has pioneered research on understanding the impact of emotions on achievement, particularly grades. Positive emotions are generally associated with favorable outcomes including academic achievement measured by grades (e.g., Villavicencio & Bernardo, 2013; Giannakos, 2013;). For instance, Villavicencio and Bernardo (2013) found that pride felt in the trigonometry course was positively correlated with final grades in the course. Regarding negative emotions, Pekrun et al. (2011), for example, found an inverse relationship between shame and performance (*r*s ranged from -.18 to -.37) among university students. Most of these studies, however, relied on a variable-centered approach, which fails to account for the nuances of multiple emotions (Robinson et al., 2017). For example, Kim, Park and Cozart (2014) used a stepwise regression to identify to what extent each discrete emotion significantly predicted achievement. Among the six emotions in the regression, only boredom, enjoyment and anger emerged as significant predictors, despite the fact that the remaining three emotions—anxiety, shame and pride—demonstrated medium effect sizes (*r*s = -.33, -.37, and .30 respectively). By pitting emotions against each other rather than considering their multiple impact, researchers may be too narrowly focused.

Co-occurrence of multiple emotions

To date, few studies have examined the co-occurrence of multiple discrete emotions. Watson and Stanton (2017) observed that individuals often experience multiple emotions having the same valence at the same time (e.g., sadness, anger and disgust). The authors found that experiencing multiple positive emotions was (27%) more common than experiencing several negative emotions (3%), and that the majority of their participants (42%) reported experiencing low intensity of a wide range of positive and negative emotions (e.g., fear, sadness, and joviality). Furthermore, Larsen, Coles, and Jordan (2017) proposed that people can simultaneously experience combinations of negative and positive emotions. This proposition gained preliminary support in Watson and Stanton's (2017) study in which 5% of the observations fell into this category. With Watson and Stanton's work indicating the presence of co-occurrence of multiple general emotions, it is possible that the co-occurrence of multiple course-specific emotions would be applicable among students.

Jarrell and colleagues (2016) used cluster analysis to identify the unique patterns among seven discrete emotions: enjoyment, pride, hope, anxiety, hopelessness, shame and anger toward a specific computer-based learning environment. They found three different emotional patterns—positive, negative, and low emotion. Students in the first cluster reported mostly above average enjoyment and hope, with low anxiety, hopelessness, and shame. Students in the second cluster reported above average levels on all negative emotions and low enjoyment and hope. These clusters are consistent with the upper level of structure described by Watson and Stanton (2017). Students in the low emotion cluster reported low levels of all seven emotions. One major drawback in Jarrell et al. (2016) was the very small sample size in each resulting cluster. There were seven students in the first cluster (positive emotion), five students in the second cluster (negative emotion), and 13 students in the third cluster (low emotion). The three emotion patterns were replicated, using data from 30 medical professional students, in Jarrell et al.'s (2017) study. Although the emotions examined were different, they were specific to the same learning platform, in particular regarding emotions experienced after receiving feedback provided by the computer learning platform. In Jarrell et al. (2017), five discrete emotions—shame, pride, joy, anger, and relief—were included in the cluster analysis.

While Jarrell et al. (2016, 2017) found three unique emotion profiles, when working with a larger sample of 278 students Robinson et al. (2017) identified four different profiles (i.e., positive, negative, deactivated, and moderate-low) toward anatomy lectures. The deactivated emotion cluster in Robinson et al. (2017) could be considered an additional profile relative to what has been identified thus far in the emotion profile literature. This cluster revealed an emotion profile which comprised students who reported moderate positive and negative deactivating emotions which include at ease, relaxed, calm, exhausted, worn out, and tired (Robinson et al., 2017). Despite this new profile, the positive, negative, and moderate-low emotion profiles were replicated, with the use of different emotion items, across studies focus on different disciplines.

Emotion profiles identified in Jarrell et al. (2016, 2017) and Robinson et al. (2017) appear to align with Watson and Stanton's two-level hierarchical structure of emotions. Specifically, multiple discrete emotions at the lower level make up a unique emotion profile and with a dominant focus on either positive or negative valence when experienced in combination. In addition, the emotion profiles, to some extent, also adhere to Weiner's attribution theory such that the positive profiles feature a strong internal and unstable attribution (e.g., high hopefulness) while maintaining a mild controllable attribution on negative emotions (e.g., low shame) and negative profiles feature a strong stable (e.g., hopelessness) and external other-directed controllable attribution (e.g., anger).

With only a handful of studies starting to examine the co-occurrence of multiple emotions toward a course or a learning platform, it indicates the importance to advance this research direction by evaluating not only the co-occurrence of multiple course-specific emotions in another discipline (e.g., Psychology), but also addressing small sample size issues identified in two of the previous studies.

Emotion profiles: Stable versus transitional. Students' emotions are likely to change based on their educational experiences. Recently, Authors et al. (2017) identified different patterns of change for discrete emotions. The authors examined four emotions (i.e., anxiety, boredom, guilt, and relief) over the four-month duration of a Massive Open Online Course (MOOC). Students in the MOOC showed different patterns of change over time in their experience of each discrete emotion. For instance, Authors et al. reported that the majority of students (91%) experienced low levels of guilt over time, whereas a small group of students (9%) indicated an ever-increasing level of guilt that plateaued toward the end of the MOOC. When examining anxiety in the same group of students, the authors found three unique patterns over time: 77% showing low-grade anxiety over four time points, 14% demonstrating a moderately fluctuating level of anxiety over the entire course, and 6% reporting heightened anxiety at the beginning of the MOOC which was sustained throughout the course. Authors et al.'s study revealed the importance of tracking students' emotional experiences over time; however, it did not involve the examination of the co-occurrence of emotions with a person-centered approach.

In addition to Authors et al.'s (2017) study, Hou and Cheng (2012) examined stability and change over time in multiple emotions. Specifically, they tracked the emotional changes among students participating in online peer assessment. Participants used a 9-point pictorial scale to report valence of their emotional responses toward online peer assessment. Utilizing lag sequential analysis, Hou and Cheng found the stability of positive emotions and neutral emotions, while a transfer from a neutral emotion to a negative emotion was also evident. One major limitation in this study was the small sample size, which consisted of 65 students. Based on Hou and Cheng's study, it indicates that students' emotional experience can remain relatively stable and be transitional. By extension, the occurrence of multiple course-specific emotion may show stable and transitional patterns.

Relationships between multiple emotions and achievement. Jarrell et al. (2016, 2017) and Robinson et al. (2017) conducted the first few studies that evaluated how emotion profiles, which consisted of multiple positive and negative emotions, differed in terms of students' performance. In particular, Robinson et al. found that the students in the positive emotion profile performed similarly to students in the deactivated profile, who experienced multiple course-specific positive and negative deactivating emotions. More studies based on person-centered approaches are needed to better reflect the ecological realities of complex combinations of emotions experienced in higher education and their relationship with performance.

The Present Study

Given that students can experience multiple course-specific emotions while in higher education and that this experience of multiple emotions can change over time, it is important to identify both the number of unique combinations of emotion profiles and stability and change in these profiles over time. Latent transition analysis (Velicer, Martin & Collins, 1996), a person-centered approach with a time dimension, is the most appropriate analytical strategy to meet this objective. Moreover, both profile membership as well as change over time may have important implications for performance that need to be tested. In particular, we had two specific research objectives and hypotheses to address in this study.

Our first objective was to examine how many latent transition emotion profiles emerged in a university student sample at the start and end of the academic year. Specially, we examined latent transition emotion profiles among students taking an Introductory Psychology course. Based on the previous studies, we expected to find three unique emotion profiles at Time 1 (T1)—positive, negative and mixed profiles—similar to those obtained in Jarrell et al. (2016, 2017). We also expected that the same three emotional profiles would be found at Time 2 (T2).

Because students' experiences of multiple emotions can change over time, we also expected students might shift to a different profile or remain in the same profile over the semesters (from T1 to T2). In total, we expected nine unique emotion trajectories from T1 to T2 (3 x 3), as shown in Figure 1.

Our second objective was to assess the extent to which students in different latent transition emotion profiles differ in their course performance. Based on previous literature, we expected that students with a stable profile featuring predominantly positive emotions would perform better than their peers with stable profiles involving mixed or largely negative emotions. In addition, we aimed to identify differences in academic achievement among students who changed their emotion profile memberships during the course.

Method

Participants

In this study, we utilized quantitative and longitudinal data from university students (Total $N = 994$; $n_{\text{female}} = 590$, $n_{\text{male}} = 391$, and $n_{\text{missing}} = 13$) enrolled in a two-semester introductory psychology course at research-1 Canadian university. Participants completed self-reported questionnaire involving psychosocial and academic measures twice during the academic year: T1 (October) and T2 (March). The majority of these participants (80%) reported English as their first language.

Measures

Emotions. Based on Weiner's attribution theory of emotion (1985, 2014, 2018a, 2018b) three positive emotions (hope, pride, and happy) and five negative emotions (guilt, helpless, anger, shame, and regret) were assessed at two time points during the course. With the exception of happy (outcome-related), all items were attribution dimension-related and were preceded by the stem: "Indicate the extent to which each of the following describe how you feel about your performance in Introductory Psychology." All scores were converted to z-scores for latent transition analysis.

Academic performance. On the consent form, students indicated whether they allowed the researchers to obtain their final course grades from their instructors or not. Consenting students' final grades (M = 69.27, SD = 17.41) in their introductory psychology course were collected directly from the instructors at the end of academic year. Participants' high school grade was self-reported on the T1 questionnaire. We measured high school grade on a 10-point scale[1]: 1 = 50% or less, 2 = 51-55%, 3 = 56-60%, 4 = 61-65%, 5 = 66-70%, 6 = 71-75%, 7 = 76-80%, 8 = 81-85%, 9 = 86-90%, 10 = 91-100%.

Plan of Analysis

Latent Transition Analysis (LTA). LTA was conducted in Mplus 8 (Muthén & Muthén, 1998-2018) and was used to examine whether students in a given latent emotion profile at T1 either remained in the same profile or moved to another emotion profile at T2 (Asparouhov & Muthén, 2015). First, a measurement invariant LTA model was estimated, and in this invariant model, all parameters, such as means and variances, are set to be equal at both time points. In order to compare whether a measurement invariant LTA model was the most optimal model, a non-invariant LTA model was estimated. The restrictions on the equality of means and standard deviations in each profile were removed in the measurement non-invariant LTA model. Measurement invariant and non-invariant LTA models were compared based on information-based indices to see which model fit better (as described below).

Second, LTA with different numbers of profiles were compared based on the information-based indices. Three information-based indices are used to guide model selection:

Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and sample-size adjusted BIC (ABIC). Nylund, Asparouhov and Muthén (2007) showed that BIC is the best information-based indicator, however, all three information-based indices were reported for comparison (e.g., Gillet, Morin, & Reeve, 2017). In addition, the entropy value was used in the selection of the optimal number of latent profiles (Jung & Wickrama, 2008; Zhao & Karypic, 2004). Based on Clark's (2010) simulation study, when latent profiles were treated as discrete categories, an Entropy value of 0.6, coupled with a large sample size is sufficient to protect against Type I error, while maintaining enough power to detect group mean differences. A smaller BIC value and an entropy value nearer 1.0 (Lo et al., 2001; Zhao & Karypic, 2004), coupled with theoretical support, prior empirical evidence, and interpretability of results, are used to select the best fitting model (e.g., Bauer & Curran, 2003, Marsh. Lüdtke, Trautwein, & Morin, 2009, Muthén, 2003).

Analysis of covariance (ANCOVA)[2]. We conducted an ANCOVA comparing all LTA emotion profiles against one another on their final percentage obtained in the course, controlling for pre-existing differences in self-reported high school grades. Bonferroni adjustment was used to protect against inflated Type I error for multiple comparisons.

Results

Descriptive and Preliminary Analyses

Table S1 provides correlations for all variables used in this study. Positive emotions at both time points were significantly correlated with objective achievement: *r*s ranged between .28 and .49 (*p*s < .01). Similarly, all negative emotions were negatively associated with academic performance (*r*s range from -.22 to -.44, *p*s < .01). Results of preliminary latent profile analyses (LPA) are summarized in Tables S2-S3 and showed that three latent profiles emerged as the optimal number of profiles at both time points. We thus assessed our main study hypotheses using the latent transition analyses described below.

LTA Results and Model Selection

Results from the LTAs are shown in Table 1. The information-based index values (AIC, BIC, and ABIC) were smaller among measurement non-invariant models, whereas the entropy values were similar between measurement invariant and non-invariant models. Hence, non-invariant models were selected for subsequent analyses. This indicates that mean and standard deviation of each emotion item were allowed to vary within profiles, instead of assuming equality over time.

Information-based indices continued to decrease when the number of profiles examined increased, suggesting that model fit improved with more profiles. However, Marsh et al. (2009) noted, this could be related to our large sample size given the sample-size dependence of these fit statistics. Balancing the findings and interpretability, the three-profile solution was chosen based on an adequate entropy value of .72, its largest marginal gain in AIC, BIC and ABIC when comparing between *k* and *k-1* model, and its consistency with our preliminary LPA findings and previous research (Jarrell et al., 2016, 2017). The three profiles identified at T1 and T2 were similar to each other in terms of the pattern of the eight emotions. With 3 (T1) x 3 (T2) profiles, nine unique transition patterns were observed: three transition profiles featuring stable emotion trajectories over time that involved (i) stable positive, ii) stable negative, and iii) stable mixed and six transition profiles featuring a shift to a different emotion category involving (iv) positive-to-negative, v) positive-to-mixed, vi) negative-to-positive, vii) negative-to-mixed, viii) mixed-to-positive, and ix) mixed-to-negative.

Stable LTA profiles. Figure 2 shows nine distinct patterns and Table 2 shows the number of students in each emotion profile. Emotion stability was common in our sample, such that most students (*n* = 804) remained in their initial profiles: Specifically, 81% of students (*n* = 339) were in the ***Stable Mixed*** profile, meaning that they were classified in the Mixed profile at both T1 and T2. These students maintained a low intensity of both positive and negative emotions over the course, aside from a slight fluctuation in their feelings of hope (T1 = -.65 and T2 = .15) and regret (T1 = -.11 and T2 = .38). Next, 83% (*n* = 289) were in the ***Stable Positive*** profile, meaning they were classified to the Positive profile at both time points. Among those who remained in the *Stable Positive* profile, the intensity of pride (T1 = .55 and T2 = .99) and hope (T1 = .88 and T2 = 1.28) grew over time, paralleled by a very low level of guilt (T1 = -.59 and T2 = -1.01). These students maintained an overall positive emotionality and had a low intensity of negative emotions. Finally, 77% (*n* = 176) were in the ***Stable Negative*** profile, meaning they were classified to the negative profile at both times. Students in the *Stable Negative* profile had sustained high levels of helplessness, anger, shame, and regret, over the semesters despite the fact a negligible level of feeling hopefulness emerged.

Transitional LTA profiles. In addition to students who remained in their initial profiles, 19% of the total sample (*n* = 190) who were classified in a given profile at T1 switched to a different emotion profile at T2. Figure 2 (Panel 2) shows that 10% of students (*n* = 42) who were classified in the Mixed profile at T1 moved to the Positive profile at T2 (i.e., *Mixed-to-Positive* profile) and 9% (*n* = 36) who were classified in the Mixed profile at T1 transitioned to the Negative profile at T2 (i.e., *Mixed-to-Negative* profile).

Among students in the Positive profile at T1 (Figure 2 Panel 3), 12% (*n* = 40) transitioned to the Mixed profile at T2 (i.e., *Positive-to-Mixed* profile) and a small portion (5%, *n*

= 18) experienced a major negative change in emotions as they transitioned to the Negative profile at T2 (i.e., *Positive-to-Negative* profile). As shown in Figure 2 (Panel 4), for students initially in the Negative profile at T1, 20% ($n = 47$) experienced less extreme negative emotions and shifted to the Mixed profile at T2 (i.e., *Negative-to-Mixed* profile). A handful of students (3%, $n = 7$) who belonged to the Negative profile at T1 switched to the Positive profile at T2 (i.e., *Negative-to-Positive* profile).

Results of ANCOVA

After controlling for high school grades, there was significant difference in final course performance among the emotion profiles, $p < .001$. Figure 3 shows the adjusted means for the nine profiles on final course performance. Pair-wise comparisons, using Bonferroni adjustment to minimize Type 1 error, revealed that students in the *Stable Positive* profile outperformed students in both the *Stable Mixed* and *Stable Negative* profiles, ps < .001, and students in the *Stable Mixed* profile obtained a higher score in the course than the *Stable Negative* profile, $p = .007$.

Pair-wise comparison results also indicated that students in the *Mixed-to-Positive* profile did significantly better than students in the *Mixed-to-Negative* profile, $p = .044$. However, there were non-significant differences between students in the *Positive-to-Mixed* and *Positive-to-Negative* profiles and between students in the *Negative-to-Positive* and *Negative-to-Mixed* profiles.

In addition, students belonging to the *Mixed-to-Positive* did significantly better than students in *Stable Mixed* and *Stable Negative* profiles, ps < .001. Similarly, students in the *Negative-to-Mixed* profile did better than those in *Stable Negative* profile, $p = .002$. While it was expected to see that students in the *Mixed-to-Negative* profile performed significantly worse than students in *Stable Positive* profile, $p = .012$, students who belonged to the *Positive-to-Mixed* profile did better than those in *Stable Mixed* ($p = .011$) and *Negative* profiles ($p < .01$).

Discussion

Replicating earlier researcher, our study sought to identify how post-secondary students' course-specific positive and negative emotions, in combination, form unique profiles that represent multiple emotions. Extending previous research, we also evaluated whether students' profile memberships remained stable over time and differences in academic performance of students belonging to different emotion transition profiles.

Stable Emotion Profiles

The three stable LTA emotion profiles (*Stable Positive*, *Stable Negative*, and *Stable Mixed*) were similar to those identified in Jarrell et al. (2016, 2017). The *Stable Positive* profile exhibited high levels of all positive emotions in combination with a low level of negative emotions, corresponding to Jarrell et al.'s (2016, 2017) and Robinson et al.'s (2017) Positive Emotion Cluster. Similarly, our *Stable Negative* profile had elevated levels of negative emotions coupled with reduced emphasis on positive emotions, corresponding to Jarrell et al.'s and Robinson et al.'s Negative Emotion Cluster. Furthermore, not only did the *Stable Mixed* profile correspond to Jarrell et al.'s (2016, 2017) findings, but this profile also highlighted the experience of multiple positive and negative emotions with mild intensity.

More importantly, we extended Jarrell et al.'s and Robinson et al.'s investigations by testing the stability of these profiles over the two-semester course. Our results showed that the majority of students stayed in their initial emotion profiles throughout the entire course: *Stable Positive* (83%), *Stable Negative* (81%), or *Stable Mixed* (77%) profiles. In other words, students' emotional momentum was set early in the course and for many would continue as such through the term. This highlights the importance of instructors supporting students' emotional experiences early in the term.

In spite of the stability of patterns, there was fluctuation in the intensity of each emotion over time. Not only did students in the *Stable Positive* profile maintain a positive outlook toward their learning, but the sense of being hopeful, happy, and proud also intensified over time while almost all negative emotions reduced over time. This result is also consistent with the research on upward spiral effect of positive emotions (Fredrickson & Joiner, 2002). Although students in the *Stable Negative* profile maintained elevated negative emotions throughout the course, a substantial reduction in the levels of guilt and a greater sense of hope and pride was observed toward the end of the semester. A possible explanation for this phenomenon could be students seeing the light at the end of the tunnel; surviving the course may be sufficient enough to slightly elevate positive emotions (e.g., Kidwell, 2005).

By contrast, the *Stable Mixed* profile demonstrated greater variability in the intensity of specific emotional experiences across time, although no fluctuation was sufficient to change the overall profile. Their sense of having mixed feelings seemed to become stronger as the feeling of a positive emotion (hopefulness) was slightly more intense while the feeling of a negative emotion (regret) also grew in intensity over the same time. This could be partly due to students acknowledging their personal control and responsibility in their course, which might elicit regret. Regret may translate into a sense of hope given that they might be more aware of how to improve their future performance. Weiner (2007) argued that "regret is experienced when it is realized an outcome could have been more positive if better choices had been made" (p. 84). By making better choices, future success would become possible, with the accompanying feeling of hopefulness (Weiner, 2014).

Impact on achievement. In the discrete emotion literature, positive emotions are generally related to favorable learning outcomes and negative emotions are more likely to be associated with adverse achievement performance (e.g., Authors et al., 2017; Lindström, Hamberg, & Johansson, 2011; Pekrun, Elliot, & Maier, 2009; Pekrun et al., 2017; Snyder, Shorev, Cheavens, Pulvers, Adams III, & Wiklund, 2002; You & Kang, 2014). Our results not only contribute to this general pattern but also expand our current understanding regarding differences in achievement. As expected, students in the *Stable Positive* profile outperform those in the *Stable Mixed* and *Stable Negative* profiles. This suggests, in addition to helping students build positive emotional experiences early in the course, instructors need to help students maintain them throughout the course.

Transition Emotion Profiles

Approximately one fifth of the total participants demonstrated a change in their emotion profiles over time. Some students initially in the *Mixed* profile, characterized by a mild intensity in both positive and negative emotions at the beginning of the course, moved to the *Positive* profile (4% of total sample in the *Mixed-to-Positive* profile); whereas others moved to the *Negative* profile (i.e., 4% of total sample in the *Mixed-to-Negative*). The switch in profile membership could be a result of these students consolidating their feelings towards the class: they became either more positive or more negative in their experience. This fine tuning of their feelings over the course of the semester resulted in these students being moved into a different emotion profile category from their initial ones. For instance, Rowe, Fitness and Wood (2015) suggest that when students enjoy and are happy about their learning, they also feel proud of their work. Similarly, when they view learning as exciting, it becomes a source of enjoyment and happiness in their learning process (Rowe et al., 2015). This is also applicable for those who experience more negative emotions. When students experienced disappointment in learning, they also felt more stressed and their levels of frustration and anger also intensified (e.g., Bang & Goodyear, 2014). However, students also moved in such a way that their emotions became more ambiguous. Specifically, 4% of students who began the semester feeling predominantly positive and 5% of students who felt predominantly negative later moved to the emotion profile reporting a mix of both positive and negative emotions toward the end of the course.

We conceptualize the transition emotion profiles into two distinct themes: ascending and descending patterns based on Anttila, Pyhältö, Soini, and Pietarinen's (2017) categorization. The *Mixed-to-Positive* and *Negative-to-Mixed* profiles revealed a small incremental increase in positive emotions, thereby creating an ascending pattern even though the resultant levels of positive emotions differed. *By* contrast, the *Mixed-to-Negative* profile and the *Positive-to-Mixed* profile involved a gradual increase of negativity or reduction in positivity of emotions, and hence created descending patterns.

Finally, in contrast to Hou and Cheng's (2012) findings, our results revealed the possibility of ascending and descending change between the two extremes of transition emotion profiles: The *Positive-to-Negative* profile and the *Negative-to-Positive* profile. They represented the smallest number of students (2% and 1%, respectively) in the resulting LTA profiles, indicating the occurrence of this more extreme oscillation is rare. Although small, these groups are theoretically and practically important because they suggest students can experience quite major ascending or descending emotion transitions over the course. Future research may want to further explore the experiences of students who have such dramatic changes in their emotions to identify if a particular learning experience prompted the change.

Impact on achievement. While there were approximately similar proportions of students who initially were classified in the Mixed profile, and subsequently switched to either Positive or Negative profiles, these two groups of students showed a substantial 12% difference in their overall course performance, even after adjusting for prior high school achievement. One possible explanation for this could be related to how these students evaluated their early performance in the course. For example, previous research suggests students experienced increased negative emotions (anxiety and shame) following poor exam scores and increased positive emotions (relief, hope and pride) following positive exam scores (Daniels & Gierl, 2017). These emotion transitions may be linked to earlier performance that then carries through the course. Future research needs to identify the learning events that trigger shifts in emotions for better or worse.

Despite the non-significant difference in course performance between the *Positive-to-Mixed* and *Positive-to-Negative* profiles, the result was reassuring and in line with expectation regarding the importance of having a higher level of positive emotions in an emotion profile. Being initially classified in the Positive profile, students in these two profiles might have a stronger positive appraisal of their learning experience as well as their performance (e.g., Villavicencio & Bernardo, 2013). The positive cognition therefore might have buffered the possible adverse impact on achievement as they moved the mixed or negative emotion profiles later in the course.

At the first glance, students in the *Negative-to-Mixed* and *Negative-to-Positive* profiles should demonstrate, at least, poor academic performance, even though there was a non-significant difference revealed. However, an interesting pattern emerged in which both profiles had higher than 70% on the adjusted mean score. At first, this result might seem counterintuitive. However, Satterfield, Monahan and Seligman (1998) found similar results showing that pessimistic university students attained higher grade point averages. The authors explained that such pessimistic attitudes might help students to be more vigilant and attentive to how they approached their study. Therefore, the *Negative-to-Mixed* and *Negative-to-Positive* profiles identified in our study might also be more emotionally vigilant in assessing how they felt, thereby they might not report an initial positive emotion profile.

Differences in Academic Performance between Stable and Transition profiles

Unless students are in the *Stable Positive* profile, it seems that transition is better for grades than stability. Hence, it is expected to see that students in the *Stable* Positive profile did better academically than those in a descending transition—*Mixed-to-Negative*. However, students in both the *Stable Mixed* and *Stable Negative* profiles scored below the class mean and worse than all transition profiles – including descending transitions in terms of ranked adjusted mean. In particular, students in the *Stable Mixed* profile performed worse than those in the descending the *Positive-to-Mixed* profile. This could possibly be due to initial positive emotions serving as a buffer for these students to continue optimizing their academic achievement over the course. Furthermore, students in ascending transitions (*Mixed-to-Positive* and *Negative-to-Mixed*) outperformed those in the *Stable Negative* profile and the former also did better than those in the *Stable Mixed* profile. The movement could be indicative of students' engagement in their academic and emotion connectedness to their learning environment, whereas those who are emotionally stable at *Mixed* or *Negative* profiles may not be paying attention to learning events that should trigger upward emotional movement. The ascending trajectories are also related to functional theories of emotion arguing that each emotion has adaptive value when experienced in the right context (e.g., Ekman, 1999; Frijda, 1986; Lazarus, 1991). Negative emotions, such as guilt, anger and regret, may be adaptive in motivating students, who recognize themselves doing poorly early in the academic year, to rectify the problem by changing their academic behaviours. Furthermore, according to Weiner (2014), guilt and anger can be motivating emotions contributing to positive achievement.

Limitations

Two study limitations are worth noting and deserve attention in future studies in this field. First, our study focused on university students who were enrolled in an Introductory Psychology course which could limit the generalizability of our findings. However, we were able to identify the same three emotion profiles revealed in the literature (Jarrell et al., 2016, 2017; Robinson et al., 2017) using latent transition analysis, which examined how emotion profiles change at two time points, thereby increasing our confidence that our results might be replicated. Future research could investigate the generalizability of these emotion profiles, both stable and transitional, across multiple disciplines, such as Sciences, Engineering, and Business. In addition to studying course-specific and discipline-specific emotion profiles, future research may also consider evaluating students' general emotion profiles toward university. Second, we used only eight different emotions (three positive and five negative) to measure students' emotional experiences toward their performance, which might limit the number of LTA emotion profiles identified and the size of some resulting transitional profiles (e.g., *Negative-to-Positive* profile: $n = 7$). Hence, the comparative results between the *Negative-to-Positive* profile and other profiles should be interpreted with caution given the very small sample size of participants in this emotion profile.

Future Research Directions and Implications

A person-centered approach to investigate emotions represents a new direction to examine complex emotional experience. This approach acknowledges that people experience more than one emotion in a given situation. More importantly, our results revealed that some students' emotion profile membership did change over time, and the transitional emotion profiles may be a sign of engagement in learning. As Pekrun and Linnenbrink-Garcia (2012) discussed, when students are cognitively involved in their learning, epistemic emotions, such as anxiety or enjoyment would be induced. When students feel what there are learning, they may be more engaged in learning, as engagement is considered mediating the relationship between emotion and performance (Pekrun & Linnenbrink-Garcia, 2012).

In addition, our results showed that most students remained in the same emotion profile, even though this was not always beneficial for their performance. While researchers have discussed the challenges in post-secondary studies (e.g., Morosanu, Handley, & O'Donovan, 2010), our results further highlight different emotion profiles and associated performance. The most concerning pattern was the *Stable Negative* profile who maintained a negative emotionality with little hope, pride, or happiness and who had lowest overall course performance. Future research needs to clarify how prior and/or concurrent academic hardship impacts students' attribution emotions.

Future research should also continue to pursue how emotion theories, such as Pekrun's control-value theory of achievement emotions (2006) and Weiner's attribution theory of emotion, can be suited to study the complex multiple emotions in achievement settings. Our findings suggest that students in the transition emotion profiles may be emotionally engaged in their learning (Fredricks, Blumenfeld, & Paris, 2004). Even though there are moments at which their emotions are descending (e.g., in the *Positive-to-Mixed* and *Mixed-to-Negative* profiles), they are still, at least, experiencing an emotional connection to the course, which is an important part in their learning. For instance, transient frustration can be a natural part of learning process

(Baker, D'Mello, Rodrigo, & Graesser, 2014) and may be a good learning experience when being managed effectively. Future research should look into how changes in different negative emotions may serve to motivate students as they encounter success and failure during their academic careers.

Footnote

[1] There were multiple categories for students to enroll in undergraduate programs, in addition to direct entry from high school. In light of this, we asked students to self-report their overall percentage in their last year of high school and used this as a control variable to account for prior academic performance on their Introductory Psychology course. Students reported a wide range of possible high school GPAs, including less than 60%.

[2]Three participants had invalid scores on academic measures and hence they were not included in the ANCOVA.

Declaration Statement

The authors declare that they have no conflict of interest. The research procedures have adhered to the Declaration of Helsinki and received approval from the University Research Ethics Board. Informed consent was obtained from all individual participants included in the studies.

Data Availability Statement

Students in our study did not consent to the data being made publicly available. In addition, the data also contain confidential student records.

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Table 1
Latent Transition Analysis Results

	2 Profiles (Trajectories) (2 x 2)		3 Profiles (Trajectories) (3 x 3)		4 Profiles (Trajectories) (4 x 4)		5 Profiles ((5
	Invariant	Non-invariant	Invariant	Non-invariant	Invariant	Non-invariant	Invariant
df	35.00	51.00	48.00	72.00	63.00	95.00	80.00
Log likelihood							
Value	-16049.92	-15853.19	-15408.30	-15199.55	-15104.55	-14900.31	-14949.52
AIC	32169.84	31808.37	30912.59	30543.10	30335.10	29990.61	30059.05
BIC	32341.40	32058.36	31147.88	30896.03	30643.91	30456.28	30451.19
Adjusted BIC	32230.24	31896.38	30995.43	30667.35	30443.82	30154.55	30197.10
Entropy	0.73	0.73	0.71	0.72	0.72	0.72	0.73

Table 2
Number of students in each LTA profile

	Time 1			
Time 2	Positive	Mixed	Negative	Total
Positive	289 (83%)	40 (12%)	18 (5%)	347
Mixed	42 (10%)	339 (81%)	36 (9%)	417
Negative	7 (3%)	47 (20%)	176 (77%)	230

Figure 1. Conceptual Model

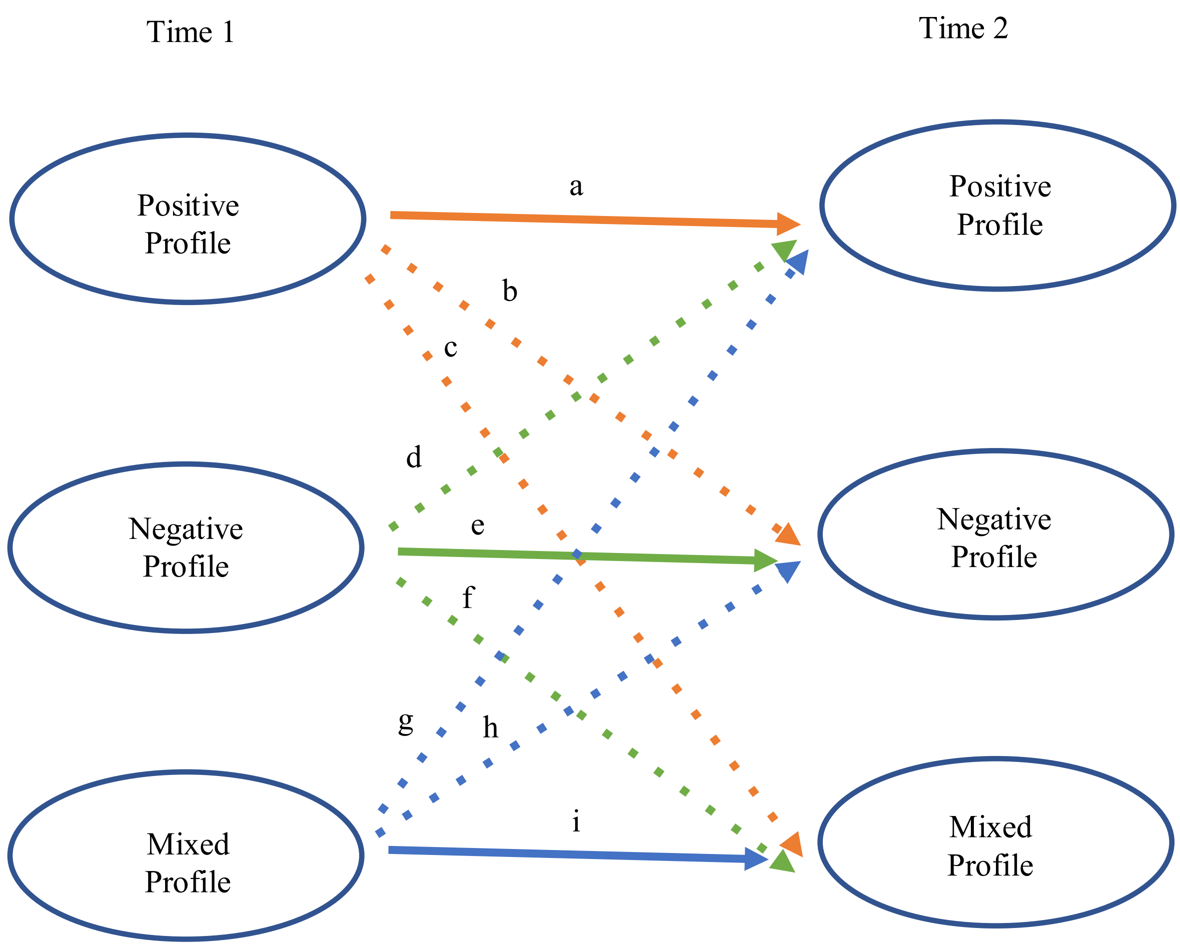

Figure X. A conceptual model of the latent transition profile analysis. Three profiles, positive, negative and mixed, were expected to find at both Time 1 (T1) and Time 2 (T2). With students in each profile can either remain in the initial T1 profile or move to other profiles at T2, these would result in nine transition patterns. Solid lines (a, e, & i) represent three stable transition profiles and dotted lines (b, c, d, f, g, & h) represent six change profiles

Figure 2. LTA Stable and Transition Emotion Profiles

Figure X. Panel 1 shows the z-scores of students classified in the stable profiles on the eight emotions at Time 1 (T1) and Time 2 (T2). Panels 2 to 4 shows the z-scores of students who belong to same profile at the beginning of the semester (T1) and subsequently moved to a different profile at T2.

Figure 3. Course Performance among LTA profiles

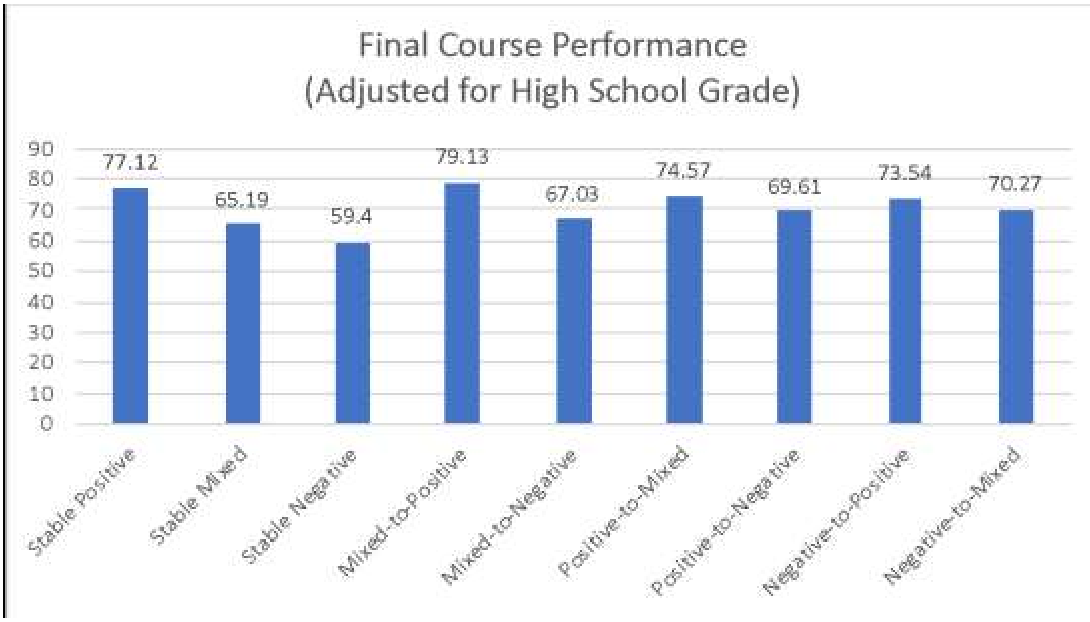

Figure X. A bar chart showing the adjusted final course percentage of each LTA profile.

Table S1. Zero-order Correlations

	Hopefulnes s (T1)	Pride (T1)	Happiness (T1)	Guilt (T1)	Helplessnes s (T1)	Anger (T1)	Sha (T
Hopefulness (T1)	1	.476**	.491**	-.136**	-.263**	-.177**	-.17
Pride (T1)		1	.705**	-.350**	-.331**	-.286**	-.35
Happiness (T1)			1	-.312**	-.288**	-.364**	-.37
Guilt (T1)				1	.481**	.488**	.60
Helplessness (T1)					1	.502**	.51
Anger (T1)						1	.59
Shame (T1)							1
Regret (T1)							

	Hopefulness (T2)	Pride (T2)	Happiness (T2)	Guilt (T2)	Helplessnes s (T2)	Anger (T2)	Shame (T2)
Hopefulness (T1)	.246**	.213**	.258**	-.090*	-.170**	-.171**	-.183**
Pride (T1)	.218**	.415**	.386**	-.223**	-.215**	-.248**	-.275**
Happiness (T1)	.200**	.353**	.414**	-.256**	-.227**	-.299**	-.310**
Guilt (T1)	-.103*	-.240**	-.244**	.382**	.312**	.315**	.400**
Helplessness (T1)	-.163**	-.234**	-.199**	.278**	.434**	.319**	.365**
Anger (T1)	-.114**	-.235**	-.245**	.342**	.365**	.444**	.382**
Shame (T1)	-.118**	-.251**	-.301**	.411**	.411**	.387**	.481**
Regret (T1)	-.110**	-.260**	-.251**	.385**	.284**	.294**	.385**

	Hopefulness (T2)	Pride (T2)	Happiness (T2)	Guilt (T2)	Helplessness (T2)	Anger (T2)	Shame (T2)
Hopefulness (T2)	1	.657**	.514**	-.268**	-.336**	-.262**	-.320**
Pride (T2)		1	.727**	-.437**	-.416**	-.330**	-.434**
Happiness (T2)			1	-.371**	-.402**	-.405**	-.432**
Guilt (T2)				1	.502**	.477**	.621**
Helplessness (T2)					1	.631**	.606**
Anger (T2)						1	.663**
Shame (T2)							1
Regret (T2)							
Percent							

Note. all rs *ps* < .01; T1 = Time 1 and T2 = Time 2.

Table S2. Latent Profile Analysis Results (Time 1)

	Time 1				
	2 Profiles	3 Profiles	4 Profiles	5 Profiles	6 Profiles
df	25	34	43	52	61
Log likelihood	-9834.38	-9458.32	-9285.99	-9178.92	*-9116.31*
AIC	19718.76	18984.64	18657.98	18461.83	*18354.62*
BIC	19840.30	19149.94	18867.04	18714.64	*18651.19*
Adjusted BIC	19760.90	19041.96	18730.47	18549.49	*18457.45*
Entropy	0.88	0.84	0.84	0.87	*0.85*
Luong-Lo-Mendell-Rubin (*p*-value)	0	0	0.0084	0.03	*0.5309*
Adjusted LMR (*p*-value)	0	0	0.0091	0.0314	*0.5358*
BLRT (*p*-value)	0	0	0	0	*0*

Note. Values italicized indicated the model was not trustworthy due to local maxima.

Table S3. Latent Profile Analysis Results (Time 2)

	Time 2				
	2 Profiles	3 Profiles	4 Profiles	5 Profiles	6 Profiles
Df	25	34	43	52	61
Log likelihood	-6071.74	-5841.90	-5714.09	-5645.22	-5582.92
AIC	12193.48	11751.80	11514.17	11394.44	11287.84

BIC	12303.89	11901.97	11704.09	11624.11	11557.56
Adjusted BIC	12224.52	11794.02	11567.58	11459.02	11363.59
Entropy	0.87	0.84	0.87	0.86	0.85
Luong-Lo-Mendell-Rubin (*p*-value)	0	0.0514	0.0137	0.4404	0.1207
Adjusted LMR (*p*-value)	0	0.0535	0.0146	0.4457	0.1226
BLRT (*p*-value)	0	0	0	0	0