A Motivation Perspective on Achievement Appraisals, Emotions, and Performance in an Online Learning Environment

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Abstract:
Control-value theory (CVT) posits that cognitive appraisals and emotions govern motivation and learning in achievement settings. Within this framework, we used latent profile analysis to identify multifaceted motivation profiles involving academic control and value appraisals and achievement emotions (boredom, anxiety, enjoyment). Three motivation profiles were identified that comprised co-occurring appraisals and emotions at the start of a two-semester online university course: *high control-enjoyment, low control-boredom, low value-boredom*. These motivation profiles related to achievement perceptions and performance on six tests over the two-semester introductory psychology course. High control-enjoyment students reported greater success and expected better grades than low control-boredom and low value-boredom students, and outperformed low control-boredom students on all tests. These findings document the nature of adaptive (vs. maladaptive) CVT-related motivation profiles that predict academic attainment in an online course.

Keywords: control-value theory, perceived academic control, achievement emotions, motivation, academic performance.

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1. Introduction

Life course transitions such as moving to another city, starting a new job, getting married, having a first child, retiring, and age-onset disabilities entail motivation challenges and setbacks. Many are minor, several occur concurrently, and some are substantial and precipitous (e.g., Chipperfield et al., 2019; Hamm et al., 2019, 2020). School-to-college transitions typify one salient shift that creates formidable hurdles for students due to unaccustomed demands comprised of increased personal responsibility, frequent academic failure, new financial needs, unstable social networks, and critical career choices (Perry, 2003; Perry et al., 2005). Compounding these complexities are worldwide initiatives by postsecondary institutions to convert academic programs to remote delivery platforms in response to the COVID-19 pandemic. Though the debate is ongoing, online courses appear to have higher attrition rates than conventional face-to-face courses (e.g., Cochran et al., 2014; Lee & Choi, 2011), exceeding 90% for MOOCs in some cases (Daniels et al., 2016; Onah et al., 2014).

Our study draws on Control-Value Theory (CVT) to identify theory-derived patterns of cognitions and emotions students exhibit in online learning environments during the transition to college. CVT focuses on the interplay of academic control and value appraisals and emotions that influence motivation and performance in diverse achievement settings (Pekrun, 2006, 2019; Pekrun & Perry, 2014). CVT aligns with expectancy-value theory traditions that hypothesized cognitive and affective processes as precursors to motivation and performance over the decades (cf., Eccles & Wigfield, 2020; Gendolla & Wright, 2016, 2018; Koenka, 2020; Weiner, 2010). Within this context, we assessed the co-occurrence of CVT-related appraisals (control, value) and emotions (boredom, anxiety, enjoyment) to form multifaceted motivation profiles that predict achievement perceptions and performance in a two-semester online learning course.

2. Control-Value Theory and Achievement Appraisals and Emotions

CVT posits that perceived control and value appraisals are linked to emotions that contribute to motivation and performance in achievement settings (Pekrun, 2006, 2019; Pekrun et al., 2002, 2007; Pekrun & Perry, 2013, 2014). Control beliefs arise from individuals' subjective estimates concerning the degree to which they can influence or predict outcomes and events throughout the lifespan (e.g., Chipperfield et al., 2016; Morling & Evered, 2006; Perry, 1991, 2003). Value appraisals refer to the importance and interest individuals attach to tasks and activities (Pekrun, 2019; Wigfield & Eccles, 2020). Achievement emotions pertain to learning activities (studying, attending class, group projects, etc.), as well as to evaluative practices such as failing a test or mastering an assignment.

CVT differentiates three types of achievement emotions according to object focus: *retrospective* outcome emotions, *prospective* outcome emotions, and *activity* emotions. Retrospective outcome emotions follow an achievement outcome (e.g., failure); prospective outcome emotions relate to anticipated outcomes (future expectations); activity emotions are experienced in the context of the achievement activities (e.g., studying), rather than in the context of an outcome. CVT specifies that perceiving activities as controllable (vs. uncontrollable) and valued (vs. not valued) instigates discrete achievement emotions. For example, CVT posits that high levels of control and value promote enjoyment. Students who believe they can master the lecture material and value success are expected to enjoy themselves during achievement activities. Those who are uncertain that they can master the material (low control) are expected to feel anxious over the threat of future failure, especially if success is highly valued. In fact, CVT proposes that all emotions are amplified by perceived value, with the exception of boredom (Shao et al., 2020). Boredom is assumed to occur when students perceive achievement activities as irrelevant or unimportant (low value). Generally, high levels of perceived control and value predict higher levels of positive emotions (e.g., enjoyment, pride) and lower levels of negative emotions (e.g., hopelessness, anxiety; Elliot & Pekrun, 2007; Goetz et al., 2014).

Appraisals, Emotions, and Performance. Qualitative and quantitative studies in laboratory and field settings provide convergent support for linkages between control and value appraisals, emotions and performance. The link between control appraisals and performance is well-documented. For example, in a longitudinal study spanning a two-semester course, Perry et al. (2001) found that academic control predicted self-reported performance in semesters 1 and 2 (*r*s = .24, .26) and final course grades (*r* = .27). In a three-year follow-up, students with higher control had better GPAs in years 1, 2, and 3 and were less likely to withdraw from their courses or drop-out prematurely (Perry, Hladkyj et al., 2005). Robbins et al.'s (2004) meta-analysis of 109 studies found control-related constructs predicted college GPA and retention rates (*r*s = .50, .36) better than high school GPA, standardized achievement, or socio-economic status. Richardson et al.'s meta-analysis (2012) also showed control measures (e.g., academic self-efficacy; performance self-efficacy) predicted GPA (*r*s = .31, .59), surpassing associations between established psychosocial constructs and GPA (e.g., test anxiety, procrastination: *r*s = -.24, -.22). Finally, Schneider and Preckel's large-scale meta-analysis (2017; *n* = 38 meta-analyses) revealed that performance self-efficacy was the second strongest of 105 GPA predictors, greater than HSG (7^{th}) or ACT/SAT (10^{th}) measures.

The link between value appraisals and performance was not addressed in these meta-analyses, however studies do show that expectancy beliefs relate to actual achievement and that task value influences factors such as engaging in tasks and course enrolment (Eccles & Wigfield; 2002; Meyer et al., 2019). Further, Pintrich and de Groot (1990) reported a positive correlation between intrinsic value and final grades in middle school students. In college settings, Harackiewicz et al. (2002) also found course interest positively predicted course performance, but not overall long-term GPA. Pekrun et al. (2010) found no direct effect of course value in a model that included high school achievement, control, and boredom, but an indirect effect of value on performance mediated by boredom, suggesting that value may only exert indirect effects on performance through psychosocial mechanisms such as emotions, among others.

Higher levels of control and value appraisals are associated with more enjoyment (Goetz et al., 2006; 2019) and less boredom (Buhr et al., 2019; Pekrun et al., 2010). Consistent with CVT, Pekrun et al. (2010) found that the association between value and boredom exceeded that of control and boredom, as did Buhr et al. (2019). Several studies document a moderate to strong negative link between control appraisals and anxiety (e.g., Bieg et al., 2013; Goetz et al., 2019; Perry et al., 2001). In a structural model that included control and value appraisals, Stupnisky et al. (2013) demonstrated a negative link between control and anxiety that was larger than the one between self-esteem and anxiety. Studies have also found non-significant or positive links between value and anxiety. For example, Goetz et al. (2006) found a positive association between value appraisals and anxiety that appears to be qualified by intrinsic-extrinsic aspects of the appraisals (Goetz et al., 2019). Thus, empirical findings align with the patterns of control, value, and emotion proposed by CVT (e.g., Daniels et al., 2015; Linnenbrink-Garcia & Pekrun, 2011; Pekrun, 2019; Pekrun et al., 2010, 2011, 2014; Tze et al., 2013).

Considerable evidence supports associations between positive emotions and year-end performance (*r*s = .15 - .45; Daniels et al., 2008; Harackiewicz et al., 2000; Pekrun et al., 2017). For example, enjoyment predicts higher course grades and, in conjunction with high perceived control, better GPAs (e.g., Pekrun et al., 2002, 2011; Ruthig et al., 2008). In contrast, negative achievement emotions, such as boredom or anxiety, can hinder motivation and performance by interfering with attention processes and deeper processing of learning tasks (Pekrun et al., 2010, 2017). Test anxiety relates negatively to achievement in students from grade school to graduate school (Hembree, 1988; Ruthig et al., 2008; Schonwetter et al., 2002; Seipp, 1991; Zeidner, 1998, 2007). High levels of anxiety are associated with lower GPA and SAT scores in college students (Cassady & Johnson, 2002; Pekrun et al., 2011). Similarly, boredom negatively predicts achievement outcomes such as exam performance, college grades, and GPA (Daniels et al., 2008; Pekrun et al., 2009, 2010, 2014, 2017; Ruthig et al., 2008; Tze et al., 2016).

Evidence regarding these CVT relationships in online learning environments is lacking at a point in time when K-16 educational systems worldwide are converting academic programs to Internet-based, computer-assisted platforms. Online courses, including blended learning, a mix of Internet and face-to-face instruction, can create unstructured environments that have multiple distractions, such as social media, video gaming, and instant messaging, that, in turn, can impede motivation and cognitive engagement (Gaudreau et al., 2014; Moore & Kearsley, 2011; Wu, 2017). Hence, online learning environments can be seen as a double-edged sword offering both opportunities and obstacles for students (Lee & Choi, 2011). They are also likely to impact students' perceived control, since online settings provide and require more autonomy over the learning process and increased responsibility. Notably, in a recent systematic review, the key issues for students in a blended-online learning environment were challenges related to motivation involving self-regulation and using technology (Rasheed et al., 2020). These challenges were highlighted in 18 of the 30 studies found for the review and comprised issues such as procrastination, online help-seeking challenges, and poor time management.

Research on achievement emotions has largely focused on traditional, face-to-face classroom settings, with relatively few studies examining such emotions in online settings (cf., Artino, 2012; Buhr et al., 2019). One online study found enjoyment related positively, and boredom negatively, to how often students reviewed and attempted practice tests (Tempelaar et al., 2012). Another study found enjoyment was a positive predictor of motivated (self-regulatory) behaviours in an online course (Artino & Jones, 2012). Since CVT research on control-value appraisals and emotions (e.g., enjoyment, boredom) points to important relationships with motivated behaviors and achievement (Pekrun et al., 2002, 2009), these linkages are worth considering in online achievement settings where there is a stronger demand, and more challenges involved, for students to stay motivated in their learning environments (Artino & Jones, 2012; Rasheed, 2020). Furthermore, research is needed that considers how academic appraisals and emotions operate in online settings, given their potential limitations regarding quality of instruction, classroom discourse, and academic engagement.

3. Cognitive Appraisals and Emotions

Students can experience different cognitions and emotions in achievement settings that are interwoven closely in time as they complete their academic tasks. Robinson et al. (2017) provide some support for this using cluster analysis whereby affective profiles related to engagement and performance, though they did not include control and value appraisals in their analysis. Although CVT posits a process whereby appraisals are antecedent to emotion, it specifies that cognitive appraisals do not occur in a vacuum as strictly 'cold' appraisals. Rather, they are transformed into 'hot' appraisals once integrated into an emotional experience (Pekrun, 2006). Accordingly, CVT acknowledges that students' psychological realities are represented by the integrated occurrence of cognition, emotion, and motivation (Pekrun, 2006, 2019; Pekrun & Perry, 2014). For this study, we sought to capture student profiles that reveal motivation states comprised of multiple emotions that are interwoven with value and control appraisals. This examination allowed us to assess what levels of appraisals and emotions exist in specific profiles of students at a given time. This synchronous interplay of appraisals and emotions may capture real-time snapshots of motivation precursors of engagement and performance. Mounting evidence supports the linkages proposed by CVT, but the co-occurrence of achievement appraisals and emotions in relation to academic engagement warrants further examination.

We adopted a person-centered approach to test whether co-occurring cognitive appraisals (control, value) and achievement emotions (boredom, anxiety, enjoyment) form consistent patterns of motivation profiles among students in online learning environments. Latent profile analysis (LPA) was used to specify motivation profile differences at the start of a two-semester course and to examine whether the profiles predicted achievement perceptions and performance thereafter. Thus, our LPA approach considers appraisals and emotions jointly in keeping with theoretical perspectives that posit cognitive and affective factors of motivational states (see Koenka, 2020). Identifying such profiles is strategic in pinpointing differences in students' motivation states that arise in the same achievement setting (e.g., Hattie et al., 2020). Furthermore, much of the previous research on CVT utilizes variable-centered approaches which does not adequately account for the psychological reality that beliefs and emotions co-occur in tandem to drive motivated behaviour. Thus, a person-centered approach addresses this complexity by identifying common combinations of these beliefs and emotions. In the current special issue of *Contemporary Education Psychology*, Koenka (2020) notes that using such person-centered approaches can contribute important insights into understanding motivation processes that operate simultaneously.

Our study adds to extant research by capturing a moment-in-time, multifaceted LPA snapshot of CVT appraisals and emotions in an online learning environment. It focuses on whether students' cognitive and affective experiences in online learning conditions form motivation profiles consistent with CVT. Following prior research (e.g., Lichtenfeld et al., 2012; Putwain et al., 2020), we focused on boredom, anxiety, and enjoyment emotions since these emotions are viewed as frequently experienced, ecologically-situated in achievement settings, and predict performance (e.g., Camacho-Morles et al., 2021; Csikszentmihalyi & Larson, 1987; Pekrun et al., 2000, 2002, 2011; Pekrun & Perry, 2014). From a CVT perspective, boredom, anxiety, and enjoyment represent a negative activity emotion, a negative outcome emotion, and a positive activity emotion, respectively.

Specifically, we sought to identify multifaceted motivation profiles made up of cognitive appraisals (control, value) and emotions (boredom, anxiety, enjoyment) and determine whether they predicted subjective (perceived success, expected grades) and objective achievement outcomes (test performance) in a two-semester online course. We used a person-centred approach involving latent profile analysis (LPA) to assess whether motivation profiles emerged that varied in control and value appraisals and emotions at the start of the course. We expected that profiles having higher control and value appraisals would experience more enjoyment and less boredom and anxiety at the start of the course would predict better achievement perceptions and test performance over the two-semester course. Profiles having lower control and value appraisals, less enjoyment, and more boredom and anxiety, were expected to be associated with less positive achievement perceptions and performance outcomes.

4. Method

4.1 Participants and Procedure

Participants (*N* = 327) were recruited from a two-semester, online introductory psychology course at a large mid-western research-1 Canadian university and received course credit for participation. Most were native English speakers (82%), between the ages of 17 and 20 (80%), in their first year of university (67%), and female (60%). The study design involved a four-phase protocol that spanned the two semesters.[1] In the third week of Semester 1 (September), a questionnaire was administered shortly after students received feedback on their first course test which was timed to occur near the start of the school-college transition process as an initial and meaningful academic experience. Students completed the online questionnaire using a secure survey website that included demographic (e.g., age, sex), cognitive (e.g., perceived academic control, course value), and affective (e.g., boredom, anxiety, enjoyment) measures.

In Semester 2 (March), a second questionnaire was administered which required students to rate their perceptions of their course performance (perceived success, expected grades). At the end of Semester 2 (May), the course instructor provided students' test scores for the six class-based tests written throughout the course (October, November, December, February, March, and April). The research study was approved by the institution's Psychology and Sociology Research Ethics Board and test scores were provided only for those students granting their permission.

4.2 Measures

4.2.1 Covariates. In Semester 1 (September), measures of age, high school grade, and sex were assessed as covariates. Age (1 = *17-18*, 10 = *older than 45*) and high school grade (1 $\geq$ *50%*; 10 = *91-100%*) were measured using 10-point scales; sex was a dummy-coded variable (1 = *female*; 2 = *male*). Self-reported high school grade was used as a proxy for achievement in high school. Self-report and actual high school

[1] Introductory courses that span two-semesters are not uncommon in Canada.

grades have been found to be strongly related (e.g., r = .84; Perry, Hall et al., 2005), and self-reported high school grade is a reliable predictor of college final grades (e.g., r = .40-.54) and grade point averages (r = .51-.54; Hamm et al., 2014, 2017; Perry et al., 2001, 2010; Perry, Hall et al., 2005). See Table 1 for a summary of variables.

4.2.2 Perceived Academic Control (PAC). In Semester 1 (September), Perry et al.'s (2001) eight-item perceived academic control (PAC) scale was used to assess students' perceived control over their course performance, e.g., "I have a great deal of control over my academic performance in my psychology course". The PAC scale was administered in an online questionnaire at the beginning of the first semester (1 = *strongly disagree*, 5 = *strongly agree*; Cronbach α = .82, M = 32.23, SD = 5.18, range = 17-40). Four items were worded negatively and reverse coded, and students' ratings summed so high scores indicated high PAC. PAC has been found to have acceptable psychometric properties in past studies: Cronbach αs = .77 to .80 (Pekrun et al., 2010; Perry et al., 2001; Ruthig et al., 2008; Stupnisky et al., 2008); test-retest reliability: r = .59 (Perry, Hladkyj et al., 2005); r = .66 (Stupnisky et al., 2008).

4.2.3 Course Value. In Semester 1 (September), a six-item value measure assessed perceived importance of the course based on an academic value scale developed by Pekrun and Meier, (2011, e.g., "In general, learning about the issues raised in this course is useful"; 1 = *strongly disagree*, 5 = *strongly agree*). Participants' value ratings were collected as part of the Semester 1 questionnaire and summed so that high scores indicated high course value (Cronbach α = .87, M = 21.66, SD = 4.5, range = 7-30). These statistics correspond to course value reliabilities measured in past studies: Cronbach αs = .69 to .80 (e.g., Pekrun et al., 2010, 2011).

4.2.4 Achievement Emotions. In Semester 1 (September), students responded to three course-related scales from Pekrun et al.'s (2002, 2011) Achievement Emotions Questionnaire (AEQ) that pertained to emotions elicited while students were engaged in course-related activities (1 = *strongly disagree*, 5 = *strongly agree*): an 8-item boredom measure (e.g., "Because I get bored, my mind begins to wander"); a 5-item anxiety scale (e.g., "I worry whether I'm able to complete all my work)"; a 6-item enjoyment scale (e.g., "I enjoy doing my assignments").

Boredom, anxiety, and enjoyment ratings were summed whereby high scores indicated high levels of each emotion (Cronbach αs = 88, .81, .72; Ms = 22.27, 16.22, 17.88; SDs = 6.95, 4.73, 4.03; ranges = 8-39, 5-25, 6-29, respectively). The scale properties were consistent with the psychometric integrity of the AEQ measures empirically demonstrated in past studies: Cronbach's αs = .89-.93 (Pekrun et al., 2002, 2010, 2011; Ruthig et al., 2008); test-retest reliabilities (rs = .62-.68, ps < .01; Ruthig et al., 2008).

4.2.5 Perceived Success. In Semester 2 (March), students' perceived success was assessed in a second-semester questionnaire using a single-item, e.g., "How successful do you feel you are in your Introductory Psychology course so far this year?" (1 = *very unsuccessful*, 10 = *very successful*; M = 6.28, SD = 2.21, range = 1-10). Several studies indicate perceived success and actual achievement are strongly correlated (e.g., r = .67, Daniels et al., 2008; r = .78, Hall et al., 2006; r = .70, Ruthig et al., 2007).

4.2.6 Expected Grades. In Semester 2 (March), students' expected performance was assessed in the second-semester questionnaire (March) using a single-item, e.g., "What percentage do you expect to obtain in your Introductory Psychology course at the end of the year?'' (1 = *50% or less*, 10 = *90-100%*; M = 7.09, SD = 2.09, range = 1-10). Past research reveals a moderate to strong relationship between expected and actual achievement (e.g., r = .82, Daniels et al., 2008; Svanum & Bigatti, 2006).

4.2.7 Course-based Class Tests (1-6). In Semesters 1 and 2, students wrote six tests at the beginning, middle, and end of each semester of their introductory psychology course. Each test was noncumulative so that only the course material preceding each test was assessed. Descriptive statistics for the six tests were: Test 1 (October) M = 66.80%, SD = 16.07, range = 27.5-100; Test 2 (November) M = 70.83%, SD = 17.51, range = 22.5-100; Test 3 (December) M = 71.88%, SD = 17.09, range = 27.50-100; Test 4 (February) M = 71.94%, SD = 15.82, range = 20-100; Test 5 (March) M = 67.47%, SD = 17.88, range = 12.50-100; Test 6 (April) M = 71.30%, SD = 16.69, range = 7.50-100 (inter-test correlations ranged from r = .67 to .76; see Table 1).

5. Results

5.1 Rationale for Analyses

We employed Latent Profile Analysis (LPA) to identify student motivation profiles at the beginning of Semester 1 in a two-semester, introductory psychology course. LPA is a type of mixture modelling that estimates the optimal number of latent (unobserved) subgroups based on responses to multiple indicator variables (Muthén & Muthén, 2007; Nylund et al., 2007). As a person-centered approach, LPA identifies subgroups of individuals who are similar to each other on the indicator variables, but different from those in other subgroups. This enabled us to estimate the optimal number of profile subgroups based on subjects' PAC, course value, and emotions ratings at the beginning of Semester 1. LPA models were assessed using M*plus* version 8 (Muthén & Muthén, 2007) and recommendations by Marsh et al. (2009) were used to estimate a range of profile numbers (i.e., up to six profiles). To prevent model convergence resulting from local maxima (Kam et al., 2016), we chose starting values of 500 random sets with 50 optimizations. For these analyses, M*plus* uses all available data to estimate the model with full information maximum likelihood.

5.1.1. Model Selection. LPA model selection was guided by CVT, profile interpretability, fit statistics, profile size, and classification quality (Infurna & Grimm, 2017; Marsh et al., 2009). Recommended fit statistics were considered, such as the Aikake Information Criterion (AIC), Bayesian Information Criterion (BIC), Sample-size Adjusted BIC (SABIC), the Vuong-Lo-Mendell-Rubin Likelihood Ratio Test (LRT), and the Bootstrapped Likelihood Ratio Test (BRLT) to select the best fitting class solution (Nylund et al., 2007).

The AIC, BIC, and SABIC tests are based on the log-likelihood function where lower values represent a better-fit model (Schwarz, 1978). Significant values generated by the LRT and BLRT support the tested model over a model with one fewer profiles (i.e., k vs. k-1; Lo et al., 2001). Entropy values can range from 0 to 1 where values approaching 1.0 indicate a clearer separation of participants into profiles (Infurna & Grimm, 2017; Jung & Wickrama, 2008; Nylund-Gibson et al., 2014). Finally, ideal models contain few profiles that comprise less than 5% of the total sample and are parsimonious in adequately accounting for complex patterns using the smallest number of profiles (DiStefano & Kamphaus, 2006; Jung & Wickrama, 2008; Samuelsen & Raczynski, 2013).

5.2 Zero-order Correlations

Semester 1 PAC, course value, and enjoyment measures correlated positively with each other and negatively with boredom. Anxiety correlated negatively with PAC and positively with boredom. PAC related positively to performance on Tests 1-6, whereas value was unrelated. Boredom correlated negatively with performance, enjoyment had no significant associations, and anxiety related negatively to performance on Tests 1 and 3. High school grade was positively associated with PAC, achievement perceptions, and performance on Tests 1-6. Finally, age related to high school grades and enjoyment, older students reported lower high school grades and higher course enjoyment.

5.3 Latent Profile Analysis

Latent Profile Analysis (LPA) indicated the values for all fit indices (AIC, BIC, SABIC) declined as the number of profiles (model complexity) increased. Marginal gains in model fit (AIC, BIC, SABIC) were relatively large up to the 3-profile solution. The LMRT test was significant for the 4-profile solution and the BLRT test for all 2-6 profiles (p range < .001 to .040). This finding is not surprising given that fit statistics are dependent on sample size and our sample was relatively large (Marsh et al., 2009). Entropy values supported the 3-profile and 4-profile solutions (.76 and .76, respectively). In considering the above criteria, we opted for the 3-profile solution since it had the greatest marginal improvement in fit across the AIC, BIC, and SABIC indices, significant LMRT and BLRT values, adequate entropy, no profiles with less than 5% of the total sample, and it was parsimonious (see Table 2 for LPA criteria information).

The LPA profiles were specified based on z-standardized scores for measures of the CVT Semester 1 appraisals (PAC, course value) and emotions (boredom, anxiety, enjoyment). For interpretation purposes, the magnitudes of the scores derived from these measures were classified as follows: low ($\leq$ -.50 SD); moderate (-.49 SD to +.49 SD); high ($\geq$ +.50 SD). These criteria resulted in three LPA profiles in which *Profile 1* was defined by high control, high value, low boredom, moderate anxiety, high enjoyment; *Profile 2*, by low control, moderate value, high boredom, high anxiety, moderate enjoyment; and *Profile 3*, by very low value, moderate control, very high boredom, moderate anxiety, very low enjoyment.

We selected profile labels based on low and high scores for the control and value appraisals, and the highest score for each emotion. For example, the label for the profile with the highest enjoyment score would include “enjoyment”. These standardized scores were interpreted relative to the other profile scores to aid in the interpretation of the profiles and in their meaningfulness. Profile 1 was labelled *high control-enjoyment* because it had the highest levels of control and enjoyment. Profile 2 was named *low control-boredom* because it had the lowest levels of control, paired with high boredom. Finally, we termed Profile 3 *low value-boredom* because of its combination of very low value and very high boredom.

These LPA profiles document multifaceted motivation states that arise from CVT-derived co-occurring cognitive appraisals and emotions. These profiles describe “motivation snapshots” of a moment in time experienced by students based on Semester 1 cross-sectional data. Figure 1 portrays the three profiles in a way that distinguishes the appraisals (Panel A) and emotions (Panel B) for explication purposes. It is not meant to imply causal linkages between the appraisals and emotions in these data, nor to imply they were analyzed separately. We expected the multifaceted profiles to relate to Semester 1 and 2 test performances. From a CVT perspective, students who had a high control-enjoyment profile were predicted to perceive and to expect more success and to have better performance than their peers having low control-boredom or low value-boredom profiles. It was less certain whether differences in achievement outcomes would emerge when comparing students having the low control-boredom and low value-boredom profiles.

5.4 Achievement Perceptions and Performance

We assessed relationships of the Semester 1 LPA profiles with Semester 2 achievement perceptions (perceived success, expected grades) and performance (Tests 1-6) using MANCOVAs, controlling for age, high school grades, and sex.[2] A significant MANCOVA profile main effect (Wilk's λ = .92, F = 5.51, p < .001) was followed up with ANCOVAs for the perceived success [$F(2, 245) = 10.70$, $p < .001$] and expected grades measures [$F(2, 245) = 7.96$, $p < .001$]. LPA profile pairwise t-test comparisons showed that high control-enjoyment students reported higher perceived success than low control-boredom (M_{diff} = 0.81, p = .003) or low value-boredom students (M_{diff} = 1.89, p < .001). High control-enjoyment students also reported higher expected grades than low control-boredom (M_{diff} = 0.65, p = .008) or low value-boredom students (M_{diff} = 1.49, p < .001). Low control-boredom and low value-boredom students did not differ in perceived success or expected grades.

For the six class tests, a MANCOVA revealed a significant LPA profile main effect (Wilk's λ = .90, F = 2.38, p = .005) that was probed using ANCOVAs, controlling for age, high school grades, and sex.[3,4] Significant profile effects for Tests 1-6 (Fs = 4.26 -7.46, p's = .001 - .015) were followed up with t-test comparisons that showed high control-enjoyment students outperformed low control-boredom students on all tests (M_{diff} = 5.25 - 8.25, ps < .001 - .004).

High control-enjoyment students achieved higher grades than low value-boredom students on Test 1 and Test 3 (M_{diff} = 5.68, p = .031; M_{diff} = 8.19, p = .005, respectively), achievement differences on the other four tests showed the same trend but did not reach statistical significance. Low value-boredom students' performance did not differ from low control-boredom students on any test (see Table 4 for means and standard deviations of perceived success, expected grades, and Tests 1 to 6). Figure 2 depicts the six test scores for the three student motivation profiles.[5]

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[2] Additional ANOVAs were conducted to assess LPA profile differences in relation to demographic information (age, high school grades, and sex). LPA profile comprised the independent variable and age, high school grades, and sex comprised the dependent variables. Results revealed a significant univariate LPA profile difference for high school grades only [$F(2, 324) = 7.63$, $p = .001$]. Pairwise t-tests for high school grades showed both high control-enjoyment students (M = 7.98; SD = 1.73) and low value-boredom students (M = 8.09, SD = 1.56) reported better grades than low control-boredom students (M = 7.19, SD = 1.85); high control-enjoyment students and low value-boredom students did not differ. No differences were found between high control-enjoyment, low control-boredom, and low value-boredom students for age (Ms = 1.90, 1.90, 1.50, respectively) or sex (Ms = 1.41, 1.38, 1.38, respectively). See Table 3 for details.

[3] Extreme outliers were identified in Tests 4, 5, and 6. The results remain consistent in the analyses when extreme outliers are removed.

[4] Levene's tests of equality variances were non-significant (p range = .326 to .751) indicating the error variance of all six tests, as well as perceived success and expected grades, were equal across the profiles.

[5] In a supplemental analysis, we assessed LPA profile comparisons based on the six course-based test performances using M*plus*'s Auxiliary (BCH) function (Asparouhov & Muthén, 2014; Vermunt,

6. Discussion

School-to-college transitions entail unexpected academic and personal setbacks marked by unfamiliar pedagogical practices and newly emerging online learning environments. Our study documents real-time snapshots of multifaceted motivation profiles formed by patterns of cognitions and emotions consistent with CVT. These profiles predicted achievement perceptions (perceived success, expected performance) and performance on six tests in a two-semester online course. The three latent profiles identified were as follows: *high control-enjoyment*; *low control-boredom*; *low value-boredom*. These profiles point to CVT-related cognitive and affective processes that may underpin complex aspects of motivation states activated in online learning conditions.

6.1 Profiles of Control-Value Appraisals and Emotions

High control-enjoyment students (n = 184; 56.26%) made up the largest profile denoted by high PAC and value appraisals, paired with low boredom, moderate anxiety, and high enjoyment. This combination of cognitive appraisals and emotions fosters an adaptive profile in educational settings according to CVT since the theory posits individuals experience positive emotions when they have control over achievement activities or outcomes that they highly value (Pekrun, 2006, 2007, 2016; Pekrun & Perry, 2014). In contrast, low control-boredom students (n =109; 33.33%) had a maladaptive profile characterized by low PAC, high boredom and anxiety, and moderate value appraisals and enjoyment. Levels of control appraisals in Profile 2 were appreciably lower than for the entire sample (PAC *M*s = 26.84 vs. 32.23, d = 1.11). Fewest in number, low value-boredom students (n = 34; 10.40%) exhibited a motivation profile characterized by very low value appraisals, very high boredom, and very low enjoyment, with moderate levels of PAC and anxiety.

The three LPA motivation profiles align with CVT's predicted patterns of appraisals and emotions. For example, the high control-enjoyment profile represents students who believe they are in control of their course-related activities, positively value them, and experience higher enjoyment and lower boredom as they engage with learning materials (Pekrun, 2006). Consistent with CVT, high levels of control and value coincided with moderate anxiety in this profile. Assigning value to academic success amplifies the threat of failure, thus instigating anxiety. However, high perceived control over success lessens anxiety to an extent that it does not substantially interfere with engagement and achievement.

The low control-boredom profile similarly aligns with CVT. This profile represents students who value success but believe they have little control over achieving success or avoiding failure. In accordance with CVT, the strongest emotion exhibited by this profile was boredom, with some anxiety and little enjoyment. The third profile of low value-boredom students is in keeping with CVT's proposition that boredom is primarily instigated by low

2010). The Auxiliary (BCH) function estimates mean differences between the latent profiles and the continuous outcome variables while accounting for missing data using FIML (Marsh et al., 2009; Wang et al., 2016). These analyses were consistent with the traditional two-step process used in the main analyses. Replicating the results, profile differences on tests 1-6 showed that high control-enjoyment students had higher test scores than the low control-boredom; Test range 1-6: χ^2 (1, n = 293) = 13.45 – 26.20, all ps < .001. Moreover, high control-enjoyment students had significantly higher test scores than low value-boredom students on Tests 2 and 3: χ^2 (1, n = 218) = 4.60, 4.50, ps = .031, .034; and low value-boredom outperformed low control-boredom students on Tests 5 and 6: χ^2 (1, n = 143) = 12.30, 15.40, ps < .001, .002.

perceived value of academic activities and outcomes. This profile could potentially reflect students who find the demands of the course activities too easy (e.g., monotonous activity, high competence). CVT asserts boredom can also be experienced when possessing little positive value for, but having control over, the course activities (Pekrun et al., 2007).

6.2 Appraisal-Emotion Profiles and Achievement Perceptions and Performance

High control-enjoyment versus low control-boredom students differed in achievement perceptions and performance over two semesters of the online course. High control-enjoyment students perceived greater success in the course and expected their successes to continue. They also outperformed low control-boredom students on each of the six tests individually (Table 4), and aggregated across Semesters 1 and 2 (Total overall *M*s = 73.31 vs. 66.37). These results amount to a letter-grade difference in the grade distribution used by the course instructor (C+ vs. B), and hence have appreciable practical relevance for students. The low-control boredom students demonstrated the lowest achievement among the three groups, suggesting that feelings of boredom in conjunction with low control hindered their course engagement and learning.

CVT posits high appraisals of control over one's performance strengthen expectations of success and achievement behaviors in pursuing academic success (Pekrun & Perry, 2014), which may be one explanation for why high control-enjoyment students perceived themselves to be more successful and had better performance across the six tests than low control-boredom students. High control-enjoyment students also had the most adaptive levels of achievement emotions compared to the other two profiles, which according to CVT, influences academic attainment (Pekrun et al., 2006). Thus, performance results for the high control-enjoyment and low control-boredom profiles make meaningful and empirical contributions in support of CVT. Moreover, these performance results align with findings from extant studies that have demonstrated the relevance of control and value appraisals and emotions for academic attainment (e.g., Perry et al., 2001, 2008; Perry, Hladkyj et al., 2005; Respondek et al., 2017, 2019).

Low value-boredom students had an ambiguous motivation profile as depicted by very low value appraisals, very high boredom, and very low enjoyment, coupled with moderate control appraisals and anxiety. This combination suggests an emotionally-disengaged motivation state (high boredom, low enjoyment), offset by more adaptive control appraisals. Students with this ill-defined motivation profile had achievement perceptions and performance outcomes that were between those for high control-enjoyment and low-control boredom students. In Semester 1, low value-boredom students also did more poorly than high control-enjoyment students in their overall semester average (*M*s = 67.37 vs 73.40, p = .014) which is one letter grade worse based on the marking distribution used by the course instructor.

By Semester 2, low value-boredom students continued to do worse than the high control-enjoyment students in their overall semester average, but not statistically so (*M*s = 73.22 vs. 69.82; p = .110). Though these differences are smaller than between the high control-enjoyment versus low control-boredom students, in conjunction with the achievement perceptions, they imply a second maladaptive motivation state different from that of the low control-boredom students. Notable is that the low value-boredom profile's combination of low value appraisals, very high boredom, and low enjoyment is consistent with a CVT maladaptive motivation state.

But the low value-boredom profile also implies some motivation ambiguity in its moderate control appraisals and anxiety levels, both pointing to potential adaptive motivation tendencies. The low value-boredom profile's ambiguity is apparent when comparing the low value-boredom and low control-boredom students' achievement perceptions and performances over Semesters 1 and 2. Though the achievement perceptions are comparable for both profiles, a small, but discernible, difference exists in Semester 1 test performances (*M*s = 67.37 vs. 66.32) and Semester 2 (*M*s = 69.82 vs. 66.42), though not significant. In further support, the supplemental M*plus* auxiliary BCH function analysis suggests that low value-boredom students performed better than low control-boredom students on Semester 2 tests 5 and 6.

A plausible explanation for why low value-boredom students may have had some advantage in performance over the low control-boredom students in Semester 2 could be their moderate levels of control appraisals and anxiety. These were more similar to high control-enjoyment students' levels of control and anxiety than to low control-boredom students' very low levels of control appraisals and high levels of anxiety. Hence, the low control-boredom students' moderate control appraisals and anxiety may have buffered the negative consequences of their boredom. Research evidence supports this in that perceived control is among the strongest predictors of academic performance as documented by meta-analytic studies (e.g., Richardson et al., 2012; Schneider & Preckel, 2017), and moderate anxiety levels can be conducive to learning and performance (Zeidner, 1998, 2007). Another possibility is that these students' low value appraisals allow them to disengage more easily from the psychological impediments of anxiety.

As low value-boredom students become sensitized to school-college transition differences, their moderate control appraisals, coupled with discernible performance increases, may reduce their maladaptive motivation state over time. Since college differs from high school in affording more self-regulated learning opportunities, their moderate control appraisals may be a strategic resource to offset their low value appraisals and maladaptive motivation state. However, because value-disengaged students are fewest in number (*n* ~ 10%), these speculations should be viewed with caution

6.3 Maladaptive Profiles, Treatment Interventions, and Online Learning Conditions

Low control-boredom and low value-boredom students' profiles differed in their control-value appraisals and emotions. The low control-boredom maladaptive profile (very low control appraisals, high boredom and anxiety) predicted adverse achievement perceptions and performance. The low value-boredom profile was ambiguous inasmuch that it exhibited a maladaptive emotion profile, but predicted achievement perceptions and performance outcomes that do not necessarily suggest they are motivationally at-risk. In addition, although both of these groups are boredom, the low value-boredom students reported higher high school grades (see Table 3). Such findings replicate existing evidence showing low perceived control hinders academic performance (Perry et al., 2001; Respondek et al., 2017) and implies low control can be a greater academic risk factor than low value in some situations. The current study findings are in line with this reasoning. Despite similar levels of boredom, and even when high school grades are controlled, low control-boredom students had worse performance. Thus, our study offers an important contribution to the literature by documenting a distinction between these two critical CVT constructs that, to our knowledge, has not yet been documented in the achievement literature.

Notably, 44% of incoming college students in our study exhibited a maladaptive psychosocial profile (low control-boredom; low value-boredom) that corresponds to motivation and well-being deficits studied by researchers for decades (e.g., Gendolla, 2016, 2018; Koenka, 2020; Weiner, 2010). The frequency of these profiles also may, in part, reflect the unfamiliar and unpredictable nature of online learning environments. Since enjoyment has been found to relate to self-motivated behaviours instrumental to success in online courses (Artino & Jones, 2012), students with lower levels of enjoyment may be less motivated to navigate the complexities of online instruction, thereby impacting their achievement striving.

In an era in which educational institutions worldwide are converting their academic programs to online platforms in response to the COVID pandemic, the numbers of students who have such motivational deficits will likely increase beyond the 44% observed in this study and their academic engagement and perseverance will become inexorably more maladaptive. Both maladaptive profiles identified here pose serious threats to the academic attainment of incoming college students and raise serious questions about remedial actions to rectify the situation. In response to these circumstances, postsecondary institutions will need to implement interventions that are responsive to these maladaptive motivation states, underpinned by strong theory, and empirically efficacious.

For low control-boredom students, control-enhancing motivation interventions such as attributional retraining (AR) may be effective (Perry et al., 1994, 2005, 2010, 2014, 2017). Based on Weiner's attribution theory of motivation and emotion (1979; 1985, 2000, 2014, 2018), AR is designed to help students cognitively reframe academic setbacks in adaptive ways. For example, following failure on a test, AR encourages students to ascribe their academic failures to controllable causes (e.g., insufficient effort, poor study strategies, lack of note-taking), rather than uncontrollable causes (e.g., lack of aptitude, difficult test, inadequate teaching). Decades of research from laboratory and field studies show that AR interventions have sizable effects on academic motivation and goal attainment mediated by cognitive and affective processes and contextual conditions (e.g., Hamm et al., 2017; Parker, Perry, Chipperfield, Hamm, & Pekrun, 2018; Parker, Perry, Hamm et al., 2018; Perry & Penner, 1990; Perry et al., 2010).

For example, students who receive AR attained GPAs that corresponded to B grades relative to non-AR recipients' C to C+ grades (Haynes et al., 2006; 2008; Ruthig et al., 2004; Perry et al., 2010). AR treatments reduce course withdrawals as well, so AR recipients complete more courses in their first year and are less likely to leave college, and hence are more likely to graduate than those who do not receive AR (e.g., Haynes-Stewart et al., 2011; Ruthig et al., 2004; Wilson & Linville, 1982). In an eight-year randomized treatment study, Hamm, Perry et al. (2020) administered AR (vs. no-AR) to first-year STEM students academically at risk and prone to withdraw prematurely from college. AR doubled the odds of failure-prone students graduating from their STEM programs over an eight-year period.

These studies demonstrate that AR affects performance through a recursive sequence of mediators that contribute to more enjoyment, hope, and pride, and less anger, boredom, and helplessness. Treatments such as AR might increase perceived control over achievement outcomes for low control-boredom students, thus reducing anxiety and potentially increasing their enjoyment and reducing boredom. Given that these students indicate moderate course value and enjoyment, it is plausible that AR could have motivation benefits in keeping with the research literature. For these students, reformulated, adaptive post-treatment control appraisals may then contribute to more positive achievement emotions and performance outcomes.

For low value-boredom students, utility-value interventions may be a viable option since they encourage student interest in the course and, in turn, academic performance (Canning et al., 2019; Harackiewicz & Hulleman, 2010; Rosenzweig et al., 2019). For these students, it may be easier to alter low value appraisals with a utility-value intervention than it would be to increase control appraisals with an AR treatment. Other options that target maladaptive motivation states could include goal-setting interventions that change course and related achievement goals (e.g., Morisano et al., 2010). It may also be strategic to alter contextual factors such as the course design and instructor to increase student engagement in and processing of the learning material (Garrison & Cleveland-Innes, 2005). Finally, a treatment "cocktail" combination that augments control (i.e., AR) and value (i.e., utility-value enhancement) aspects of the learning conditions may have benefits for the motivation profiles of both low control-boredom and low value-boredom students.

In sum, these findings contribute to the achievement motivation literature in that they unveil psychosocial profiles that arise in an online learning environment (e.g., Tze et al., 2017). The academic experiences of students in online learning settings that involve co-activated cognitive and affective processes have received little attention to date and the addition of online technology can bring further complexity to learning tasks (Daniels & Stupnisky, 2012). Because students in North American universities are enrolling in online courses in increasing numbers (Allen & Seaman, 2007, 2013; Allen et al., 2016), it is critical now, more so than ever in view of the Covid-19 pandemic, to examine the cognitive and affective processes that underpin students' multifaceted motivation states in online learning environments.

6.4 Strengths, Limitations, and Future Research

Several strengths and limitations are manifest in this study. One critical strength is the examination of CVT using a person-centred approach. Researchers have focused on variable-centered approaches to examine achievement appraisals and emotions (Goetz et al., 2010; Pekrun et al., 2002, 2009; Ruthig et al., 2008), with few studies adopting person-centred approaches. Robinson and colleagues (2017) note a drawback to variable-centered approaches is that they "can mask heterogeneity in the levels, array, and function of affect experienced, and misrepresent the experience of particular students and particular emotions" (p. 210). The latent CVT profiles uncovered in this study also correspond to adaptive and maladaptive motivation states documented in healthcare settings whereby the combination of control and (health) value appraisals predicted physician care and survival rates in older persons over a 12-year period (e.g., Chipperfield et al., 2016, 2017).

A second strength of this study is its focus on multifaceted motivation states comprised of co-occurring cognitive and affective processes that researchers have not examined in systematic ways. Relatively few studies have investigated control and value appraisals jointly or several emotions in combination (e.g., Bieg et al., 2013; Goetz et al., 2010; Putwain et al., 2018), but none explored appraisals and emotions in synchronicity. Our approach rested on the assumption that students experience more than one cognition or emotion in achievement settings and that these cognition-affect combinations jointly contribute to subsequent motivation and performance outcomes.

Another strength was the prospective design employed in our study that assessed achievement perceptions and performance at six time points over the two-semester course. These findings inform how temporally-sequenced subjective and objective outcomes are associated with the three motivation profiles. Finally, the study introduces a unique focus on CVT in online learning conditions and provides potentially strategic findings for educational systems converting their academic programs to online delivery platforms.

The two main limitations in the study pertain to the generalizability of our results and to conceptual issues. The generalizability of the results may be limited because our sample was comprised of college students in an online introductory psychology course. Though this criticism may be valid, our findings offer meaningful insights into the co-occurrence of cognitive and affective processes in the more common online learning conditions. Future research could target the motivation profiles of students in other subject areas (Mathematics, Sciences, Business, etc.), academic program levels (2nd year, 3rd year, etc.), and conventional face-to face lecture formats. Second, motivational goals are an important component of CVT and worthy of further consideration in relation to the motivation profiles documented herein. Third, the stability of the motivation profiles requires further examination given that the profiles in this study were momentary snapshots that begs the question of their stability over time.

6.4 Summary

Building on the control-value theory of achievement emotions, our study examined ecologically-situated configurations of control and value appraisals, course-related boredom, anxiety, and enjoyment that comprised adaptive and maladaptive motivation profiles in an online learning introductory psychology course. The three latent motivation profiles identified were examined in relation to subsequent achievement perceptions and performance outcomes over the two-semester course. The findings help to inform researchers and educators about students academically at-risk based on their motivation profiles in online learning environments.

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Table 1

Zero-Order Correlations Between Study Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Age[a]	–															
2. HSG[a]	-.23*	–														
3. Sex[a]	.02	-.14*	–													
4. PAC[a]	.02	.24*	.07	–												
5. Value[a]	.06	-.07	-.06	.15*	–											
6. Boredom[a]	-.08	-.07	.05	-.39*	-.51*	–										
7. Anxiety[a]	-.08	-.06	-.15*	-.33*	.06	.22*	–									
8. Enjoyment[a]	.20*	-.02	.01	.18*	.45*	-.31*	-.01	–								
9. PS[b]	.01	.33*	.08	.28*	.23*	-.28*	-.21*	.14*	–							
10. EG[b]	-.03	.42*	-.02	.22*	.14*	-.22*	-.13*	.10	.76*	–						
11. Test 1[a]	.01	.39*	.04	.29*	.08	-.18*	-.12*	.03	.63*	.74*	–					
12. Test 2[a]	-.05	.43*	.02*	.32*	.04	-.17*	-.09	.05	.62*	.75*	.75*	–				
13. Test 3[a]	-.01	.40*	.09	.29*	.14*	-.22*	-.12*	.04	.68*	.79*	.73*	.77*	–			
14. Test 4[b]	-.01	.38*	.03	.22*	.09	-.17*	-.07	.01	.69*	.82*	.69*	.71*	.76*	–		
15. Test 5[b]	-.11	.46*	.02	.31*	.03	-.19*	-.06	.01	.60*	.72*	.67*	.71*	.71*	.76*	–	
16. Test 6[b]	-.10	.39*	.01	.28*	.06	-.15*	-.11	-.01	.64*	.74*	.71*	.68*	.75*	.76*	.76*	–
Mean/%	1.84	7.71	59.9%	32.23	21.66	22.27	16.22	17.88	6.28	7.09	66.80	70.83	71.88	71.94	67.47	71.30
SD	1.34	1.80	–	5.18	4.85	6.95	4.73	4.03	2.21	2.09	16.07	17.51	17.09	15.82	17.88	16.69

Note. HSG = high school grade. PAC = perceived academic control. PS = perceived success. EG = expected grades.
[a]First-semester. [b]Second-semester. * $p \leq .05$ (two-tailed tests).

Table 2

Criteria Values for Latent Profile Analysis

No. of profiles	LL	Free par.	AIC	BIC	SABIC	BLRT	LMRT	Entropy	Profile size < 5%
1	-2294.76	10	4609.52	4647.42	4615.70	-	-	-	0
2	-2212.13	16	4456.26	4516.89	4466.14	.000	.006	.63	0
3	**-2173.32**	**22**	**4390.64**	**4474.02**	**4404.24**	**.000**	**.010**	**.76**	**0**
4	-2157.17	28	4370.34	4476.46	4387.64	.000	.037	.76	0
5	-2137.45	34	4342.90	4471.76	4363.91	.000	.192	.72	0
6	-2126.35	40	4332.69	4484.29	4357.41	.040	.264	.74	1

Note. Criteria values of the latent profile analysis when random starts = 500 50. LL = loglikelihood. Free par. = number of free parameters. AIC = Aikake information criterion. BIC = Bayesian information criterion. SABIC = sample-size adjusted BIC. LMRT = Vuong-Lo-Mendell-Rubin Likelihood Ratio Test and BLRT = Bootstrap Likelihood Ratio Test (values significant at $p < .05$). Profile size refers to number of profiles that contain < 5% of the sample. Bold font indicates the best fitting model selected.

Table 3

Demographic Variables and LPA Profiles

Outcomes	*Df*	*MS*	*F*	High Control-Enjoyment (1)		Low Control-Boredom (2)		Low Value-Boredom (3)	
				M	*SD*	*M*	*SD*	*M*	*SD*
Age	2, 324	2.45	1.33	1.90	1.39	1.90	1.35	1.50	1.21
HSG	2, 324	23.59	7.63[a]	7.98	1.73	7.19	1.85	8.09	1.56
Sex	2, 324	0.05	0.21	1.41	.49	1.38	.49	1.38	.49

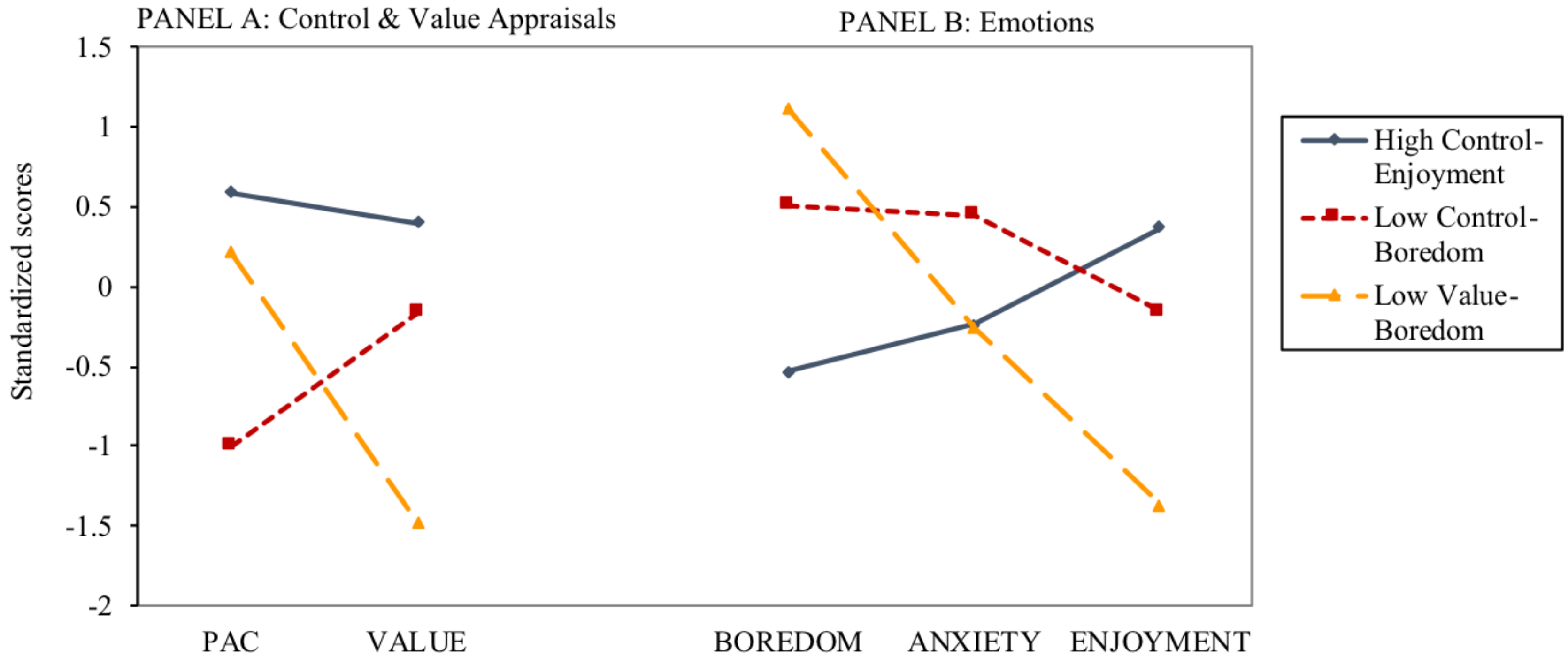
Note. [a]LPA profile differences are significant at $p \leq .05$. The sex variable was dummy-coded (1 = *female*; 2 = *male*). Students reported their age on a 10-point scale (1 = *17-18*, 2 = *19-20*, 3 = *21-22*, 4 = *23-24*, 5 = *25-26*, 6 = *27-30*, 7 = *31-35*, 8 = *36-40*, 9 = *41-45*, 10 = *older than 45*).

Table 4
LPA Profile effects and Pairwise Comparisons of Perceived Success, Expected Grades, and Test Performance

		LPA Profile Effect[a]		LPA Profile Test Means			Pairwise LPA profile comparisons[b]	Pairwise LPA profile comparison mean differences
Course Test	*Df*	*MS*	*F*	High Control-Enjoyment (1)	Low Control-Boredom (2)	Low Value-Boredom (3)		
					M (SE)			
Perceived success	245	42.34	10.70*	6.67 (.16)	5.86 (.24)	4.78 (.43)	1 > 2, 3	.81*, 1.89*
Expected grades	245	26.64	7.96*	7.41 (.15)	6.76 (.22)	5.92 (.39)	1 > 2, 3	.65*, 1.49*
Test 1	258	1516.72	7.46*	70.02 (1.14)	62.59 (1.62)	64.34 (2.80)	1 > 2, 3	7.43*, 5.68*
Test 2	258	1552.36	6.98*	74.72 (1.20)	66.96 (1.70)	70.49 (2.93)	1 > 2	7.76*
Test 3	258	1383.31	6.36*	75.48 (1.18)	69.40 (1.68)	67.29 (2.90)	1 > 2, 3	6.07*, 8.19*
Test 4	258	798.91	4.26*	74.74 (1.10)	69.49 (1.56)	70.07 (2.69)	1 > 2	5.25*
Test 5	258	1717.15	7.46*	70.77 (1.22)	62.53 (1.73)	68.53 (2.98)	1 > 2	8.25*
Test 6	258	1216.01	5.67*	74.15 (1.17)	67.24 (1.67)	70.87 (2.88)	1 > 2	6.91*

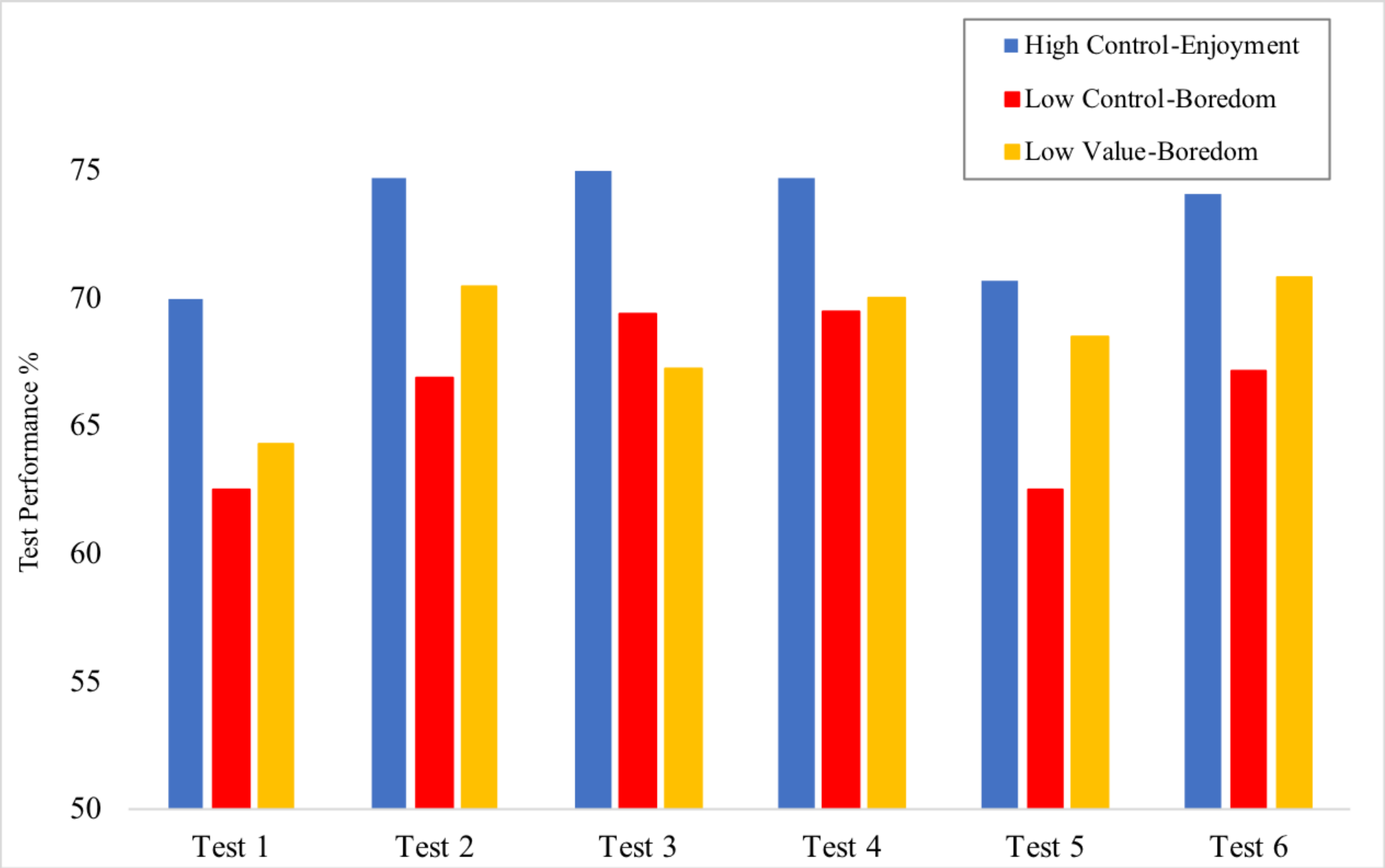
Note. [a]LPA profile test differences are significant at $p \leq .05$. [b]Pairwise LPA profile test performance comparisons are significant at $^{*}p \leq .05$. All analyses control for age, high school grade, and sex.

Figure 1



Note. Standardized scores of perceived academic control (PAC), course value, boredom, anxiety and enjoyment for high control-enjoyment, low control-boredom, and low value-boredom profiles. Note that the scores for each profile are standardized scores that represent deviations from the mean (i.e., zero). These profiles are visually separated by appraisals (Panel A) and emotions (Panel B) for ease of interpretation (the appraisals and cognitions were not analyzed separately).

Figure 2



Note. Test scores (1-6) are conveyed for the high control-enjoyment, low control-boredom, and low value-boredom profiles.