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# The limited role of expectancy-value beliefs, self-efficacy, and perceived attentional control in predicting online learning outcomes in a general education course

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**Introduction:** Researchers have expended enormous effort on understanding how college students' intrapersonal beliefs contribute to their academic success.

**Methods:** This study used structural equation modeling to examine factors associated with course outcomes of students enrolled in an online general education course at a non-selective public college (16 sections, $N$ = 940).

**Results:** Structural models linked students' expectancy-value beliefs with academic self-efficacy, which in turn correlated with reading comprehension and self-reported attentional control. Both reading comprehension and self-reported attentional control predicted course outcomes whereas students' expectancy-value beliefs and academic self-efficacy had no direct influence. Despite adequate model fit, students' intrapersonal beliefs and skills collectively accounted for only 6.6% of the variance in course outcomes.

**Conclusions:** Individual-level variables may lack explanatory value in accounting for online learning outcomes, indicating the need to increase emphasis in educational psychology research on social and systemic factors affecting student success. Instructors should also recognize that factors besides intrapersonal beliefs and skills influence students' persistence in online coursework and the need to support students at risk of dropping out.

KEYWORDS

**academic motivation, self-efficacy, expectancy-value, higher education, introductory psychology, online courses**

## Introduction

The notion that the capacity to change one's personal circumstances is entirely intrinsic is deeply embedded in U.S. lore ––"if you believe it you can achieve it," goes the cliché. That narrative is propagated by institutions, systems, and people of influence throughout society with regard to students' educational and professional achievements, and is exemplified by emphasis placed on intrapersonal attributes, such as motivation (Eccles and Wigfield, 2020; Wigfield and Eccles, 2000), self-efficacy (Bandura, 1977, 1994), self-regulation (Schunk and Zimmerman, 2023) in explaining student success. Being accepted into college and graduating are cast as momentous individual accomplishments, representing the culmination of arduous personal effort through years-long schooling, and willing oneself through hardship. In this context, the present study aimed to evaluate the extent to which intrapersonal beliefs influenced student success at the start of their college careers, with a specific focus on students taking an online general education course at a non-selective minority-serving public institution.

Learning online became globally ubiquitous during the COVID-19 pandemic with the temporary cessation of in-person instruction (Gallagher and Palmer, 2020). Once dominated by non-traditional, private, for-profit educators in the 2010's, online coursework has become increasingly available across public and private institutions and often preferred by students at all levels (Wood, 2022). The benefit of providing classes that can be accessed via the Internet anywhere in the world extends institutional reach and provides scheduling convenience and flexibility for otherwise-engaged students. However, those advantages come with a price, including decreased social engagement and Zoom fatigue––the mental and physical stress linked to extensive videoconferencing that limits one's ability to focus on academic tasks (Greenhow et al., 2022; Luebstorf et al., 2023). The sudden and traumatic transition from face-to-face learning, in which students physically attended classes and interacted with their teachers and classmates, to online learning in which students were permanently at home indoors and separated from their peers, exacerbated challenges that high school students faced when preparing for college. Consequently, many students entering college were less academically prepared than previous cohorts (Irwin et al., 2022; Kuhfeld et al., 2022). Academic underpreparedness is associated with heightened attrition, with 24% of full-time freshmen and 58% of their part-time and non-traditional counterparts dropping out of college after their first year (Hanson, 2022). These are troubling trends for U.S. society (National Center for Education Statistics, 2023).

These concerns indicate the need to identify factors associated with student persistence and success in online coursework, particularly at open-enrollment institutions serving increasingly diverse student populations. Hence, the present study examined student learning outcomes in an online Introductory Psychology course taken by mostly first-year students at a nonselective public institution. Introductory Psychology is arguably the most popular general education course in the United States, taken by approximately 40% of all first-year college students (Adelman, 2004), and as many as 1.6 million undergraduates annually (Gurung et al., 2016). Using the composite persistence model as an organizational framework (Rovai, 2003), we explored factors associated with online course outcomes. Building on prior research on student retention (Bean and Metzner, 1985; Gravelle et al., 2023, 2024; Tinto, 1975), we hypothesized that students' intrapersonal beliefs as well as reading comprehension (i.e., an objective measure of students' academic skills) would be predictive of course outcomes (i.e., quiz scores, test scores, homework completion).

## Intrapersonal beliefs as predictors of course outcomes

Online learning involves students attending classes remotely either synchronously via videoconferencing platforms or asynchronously via online learning management systems. Regardless of the specific online learning environment, students need to have reasonably high expectations of their ability to complete academic work online, a sense of current and future value in undertaking the work, and not view it as insurmountable or too costly in effort required. These factors align with the subconstructs of the expectancy-value theory, which posits that students will be more motivated to pursue goals if they perceive that the value outweighs the cost (Beymer et al., 2022; Wigfield et al., 2021).

Under the expectancy-value theory, expectancy is a person's belief in their ability to succeed in future tasks in a given domain (Eccles and Wigfield, 2020; Wigfield and Eccles, 2000). Value is a measure of their perception of the importance, enjoyment, and utility gained from engaging in specific tasks (Kosovich et al., 2015). Value and expectancy are positively related, domain-specific variables with multiplicative effects (Kosovich et al., 2015; Lauermann et al., 2017). However, their connection may diverge across education levels, e.g., weakening as academic difficulty increases, but strengthening in areas of preferred focus as students progress in their coursework (Loh, 2019). Cost, defined as one's perception of the price of engaging in a task (Beymer et al., 2022), is negatively associated with expectancy and value (Perez et al., 2019), and student outcomes (Flake et al., 2015). Future interest is the perceived long-term utility of engaging in and succeeding in a given task, which correlates positively with expectancy and value, but negatively with cost (Goldman et al., 2022). Undergraduates who do not perceive much value in taking a course tend to exert less effort than those placing higher value on the course (Cole et al., 2008). First-generation undergraduates tend to perceive higher cost than their non-first-generation counterparts and also show lower academic achievement, yet these two factors have not been causally linked (Goldman et al., 2022).

Other research has emphasized the importance of students' sense of self-efficacy in predicting their success in online coursework (Alqurashi, 2016). Academic self-efficacy is defined as beliefs in one's ability to organize, implement, and accomplish specific academic tasks (Bandura, 1994; Doménech-Betoret et al., 2017). As students achieve academic success, their perceptions of their abilities tend to increase (Schunk and DiBenedetto, 2020), which may lead to greater persistence and higher course grades (Wright et al., 2013). At the college level, academic self-efficacy has been linked with academic resilience (Cassidy, 2015; Stephen et al., 2020), especially in academic contexts that demand self-regulated study such as massive open online courses (Alamri, 2022). Expectancy-value beliefs and academic self-efficacy are related. Both refer to students' belief in their own ability; however, their conceptual definitions are different. Expectancy-value beliefs involve one's expectation of success in an upcoming task, while academic self-efficacy beliefs refers to one's ability to perform that task (Wigfield et al., 2021; Gao et al., 2008).

In the context of online coursework, it is also imperative for students to minimize distractions to remain focused and engaged in their studies (Greenhow et al., 2022; Salhab and Daher, 2023). Hence, the present study also examined students' self-reported ability to pay attention and maintain focus while doing academic work in relation to course outcomes. Attentional control plays a critical role in students' ability to self-regulate while studying, and it is positively associated with academic outcomes (Rueda et al., 2010). With regard to learning conditions, attentional control is thought to play a greater role in individualized, remote learning environments as compared to traditional, in-person instructional settings with enhanced social support for learning (Biwer et al., 2021; Nesher-Shoshan and Wehrt, 2022). To date, there is a paucity of research linking attentional control with expectancy-value beliefs and academic self-efficacy. However, university students report being less motivated and less able to regulate their attention when learning online compared to in person (Biwer et al., 2021), suggesting a positive association. Researchers using a proxy for attentional control (P3b, derived from electroencephalography) reported a significant positive association between students' self-efficacy and P3b amplitude, suggesting that students with higher self-efficacy showed higher levels of attentional control (Themanson and Rosen, 2015).

In addition to examining students' self-reported expectancy-value beliefs, academic self-efficacy, and self-reported attentional control in relation to course outcomes, we considered students' reading comprehension as a critical skill for online coursework. Reading is fundamental at all levels of education (Elleman and Oslund, 2019; Perin, 2013); however, according to the Nation's Report Card, it remains a grave problem. Since 1992, the average U. S. student has scored below proficiency in reading from elementary to secondary levels of education (National Assessment of Educational Progress, 2022). Alarmingly, fewer than half of U.S. adults between the ages of 16 and 74 demonstrate reading abilities above the 6th grade level (Rothwell, 2020). Though 62% of high school graduates enroll immediately in college (National Center for Education Statistics, 2023), 63% of them score below proficiency-levels in reading (National Assessment of Educational Progress, 2022). This is troubling because strong reading comprehension is necessary for college coursework and predictive of grades (Clinton-Lisell et al., 2022; Talwar et al., 2023). Undergraduates with a history of reading difficulties tend to have lower self-efficacy than their counterparts and earn lower grades (Bergey et al., 2018). More generally, less-skilled students tend to be outperformed by their peers, making it difficult for them to close the skills gap and elevating their risk of dropping out (Kalbfleisch et al., 2021; Pinkerton, 2010).

## Present study

The present study used the composite persistence model (Rovai, 2003) as a framework for identifying factors associated with learning outcomes in an online Introductory Psychology course. Course attrition and dropout rates tend to be highest among first-year students taking general education courses like Introductory Psychology, making this course suitable for examining academic persistence (Windham et al., 2014). Further, at the time of this study (Fall 2021), students were still experiencing the repercussions of the COVID-19 pandemic and its disruptive effect on education, specifically for high-school students making the transition to college. We used structural equation modeling (SEM) to explore factors associated with course outcomes in fully online course sections. Aligning with the composite persistence model, we focused on self-reported expectancy-value beliefs about the course, academic self-efficacy, and attentional control and assessed students' reading comprehension as predictors of their success in an online course. These factors have been linked to course outcomes in prior research (e.g., Gravelle et al., 2023, 2024; Gurung and Stone, 2023) but have yet to be considered jointly in a structural model.

# Method

## Course section and student characteristics

Course outcomes assessment data were collected from 16 sections of an online Introductory Psychology course taught at a non-selective, minority-serving public institution in the northeastern United States in Fall 2021 (Institutional Review Board classification: exempt). Following best practices for replicability, the following materials are publicly available in an Open Science Framework repository (Roberts et al., 2025): course syllabus, the Qualtrics online assignments (PDF and QSF file for implementation), a de-identified datafile, R analysis script, and Supplementary tables. For an updated course curriculum with deployable Qualtrics assignments, see Brooks et al. (2025) and Zapparrata et al. (2025).

Twelve course sections had regular enrollments ($M = 41.3$ students, $SD = 9.2$) and four had large enrollments ($M = 111.3$ students, SD = 9.7). All sections followed a uniform syllabus for a 15-week semester, with links to course materials posted to a learning management system. All sections held synchronous meetings once or twice weekly on Zoom. During the Zoom meetings, students were advised to turn cameras off to preserve Internet bandwidth, as per institutional policy. In contrast, instructors had cameras on at all times.

Asynchronous course features included a free online textbook (Diener Education Foundation, 2020), weekly multiple-choice quizzes and periodic multiple-choice tests on textbook modules, bi-weekly online assignments emphasizing psychology as a data science, a role-play activity and discussion board on research ethics, and rubric, template, and instructions for recorded student presentations on psychological disorders. The bi-weekly online assignments were developed using Qualtrics survey software to align with the textbook modules. The Qualtrics assignments included TED talks by prominent psychological scientists, instruction on using the college library website and Google Scholar to find empirical research articles, practice in reading scientific abstracts, and exercises in using Excel for data analysis and manipulation. Each assignment was designed to take approximately 1 hour to complete and included various open-response and multiple choice questions; the assignments are publically available in our Open Science Framework repository (Roberts et al., 2025).

Of the 1,090 enrolled students, 142 (13.0%) did not complete the first Qualtrics assignment containing the measures reported in this paper. An additional 8 students (0.7%) did not complete any of the course outcome measures apart from the first Qualtrics assignment; these students were dropped from the analytic sample. We have no further information about these students. Otherwise, students who completed the first Qualtrics assignment and at least some of the other course outcome measures were included in the sample. The final analytic sample comprised 940 students (*M age* = 19.3 years, *SD* = 3.9, *range* = 16–51). Of these students, 93 students (9.9%) withdrew at some point during the semester. Students self-reported their race/ethnicity using non-mutually exclusive categories; see Table 1. Most students (78%) were in their first semester of college. About half (46.4%) were among the first generation of their families to attend college.

TABLE 1 Student demographics ($N$ = 940).

| Characteristics | Frequency (%) |
|---|---|
| Gender | |
| Female | 566 (60.2%) |
| Male | 353 (37.6%) |
| Another Gender Identity/Prefer to Self-describe | 10 (1.0%) |
| Prefer not to Respond | 11 (1.2%) |
| Race/ethnicity (not mutually exclusive) | |
| White | 387 (40.8%) |
| Latinx, Chicanx, Hispanic, or Spanish origin | 247 (26.3%) |
| Black/African American | 205 (21.8%) |
| Asian/Asian American | 95 (10.1%) |
| Middle Eastern/North African | 88 (9.4%) |
| American Indian/Alaska Native | 10 (1.0%) |
| Native Hawaiian/Other Pacific Islander | 4 (0.4%) |
| Some other race | 20 (2.1%) |
| Prefer not to say/Unknown | 27 (2.9%) |
| Either parent attended college | 504 (53.6%) |
| First semester Student | 733 (78.0%) |

## Measures

Students completed measures of expectancy-value beliefs, academic self-efficacy, self-reported attentional control, and reading comprehension in the first Qualtrics assignment. As a data quality check that students were reading the items, we examined variability in responses for scales with reversed scored items (i.e., expectancy-value beliefs, academic self-efficacy). Students who failed to vary responses across all items had scores imputed using the *mice* package in *R* (van Buuren and Groothuis-Oudshoorn, 2011).

### Expectancy-value beliefs

To assess expectancy-value beliefs, the instructional team adapted 7-point Likert-scale items rating agreement (1 = *Strongly disagree* to 7 = *Strongly agree*) from existing scales (Beymer et al., 2022; Kosovich et al., 2015): expectancy (3 items; e.g., *I know I can learn the material in my PSY100 class*; $M$ = 6.30, $SD$ = 0.83, $\alpha$ = .89), value (3 items; e.g., *I value my PSY100 class*; $M$ = 6.32, $SD$ = 0.96, $\alpha$ = .88), future interest (3 items; e.g., *I look forward to learning more about psychology*; $M$ = 6.06, $SD$ = 1.08, $\alpha$ = .78), and cost (4 items; e.g., *My PSY100 class requires too much effort*; $M$ = 5.21, $SD$ = 1.47, $\alpha$ = .84). Note that scores for cost were reversed to align with the other measures (i.e., higher scores reflect lower cost associated with taking the course). Scores were imputed for 11 students (1.2%) who showed no response variability. Supplementary Table 1 provides item-level and summary statistics by subscale. Correlations between subscales were small-to-medium in magnitude, $r$'s(938) = .16 to .59, $p$'s < .001; see Supplementary Table 2.

### Academic self-efficacy

The Employable Skills Self-Efficacy Survey (ESSES) tool is a measure of self-efficacy designed for psychology students (Ciarocco and Strohmetz, 2018). The instructional team adapted four ESSES subscales relevant to the course. Each presented a series of items using a 6-point Likert-scale (1 = *Strongly disagree* to 6 = *Strongly agree*): reading (5 items; e.g., *I usually understand information that I read; M* = 4.86, $SD$ = 0.88, $\alpha$ = .60); research (5 items; e.g., *I have the analytical skills to work with data; M* = 4.19, $SD$ = 1.02, $\alpha$ = .69); technology (5 items; e.g., *I am comfortable learning to use new technology when working on a project; M* = 4.73, $SD$ = 1.03, $\alpha$ = .61); and information literacy (4 items; e.g., *I know where to find relevant information from good sources when I need it; M* = 4.47, $SD$ = 0.94, $\alpha$ = .66). Scores were imputed for 18 students (1.9%) who showed no response variability. Supplementary Table 3 provides item-level and summary statistics for each subscale. Correlations between the four subscales were small-to-medium in magnitude, $r$'s(938) = .42 to .60, $p$'s < .001; see Supplementary Table 4.

### Attentional control

Self-reported attentional control was assessed using four 5-point Likert-scale items (1 = *Strongly disagree*, 5 = *Strongly agree*) adapted from Ober et al. (2024). Items asked students whether they were able to focus or felt distracted while completing schoolwork online (e.g., *I can focus and remain on task while doing schoolwork online*; $M$ = 3.35, $SD$ = 0.79, $\alpha$ = .71); see Supplementary Table 5 for item-level statistics.

### Reading comprehension

Reading comprehension was assessed using a passage from a Regents English Language Arts examination, paired with six multiple-choice comprehension questions (New York State Education Department, 2019; $M$ = 70.6% correct, $SD$ = 24.8%, $\alpha$ = .56, $\omega$ = .65).

### Quizzes

Students were assigned 27 low-stakes multiple-choice quizzes, comprising four questions each. Each quiz was linked to a module in the online textbook covering foundational subfields of psychology (e.g., Social Psychology, Physiological Psychology, Developmental Psychology; Diener Education Foundation, 2020) and a quiz-bank containing eight quiz questions and possible answers (four multiple-choice options per question). Students were given three opportunities to attempt each quiz. The four quiz questions were selected randomly from the quiz bank on each attempt, with the highest score across attempts taken as the final score for that quiz. Quizzes were administered through the online learning management system. Overall, students earned an average of 89.5 out of 108 possible points on the quizzes ($SD$ = 24.9, *range* = 0 to 108). Note that a score of 0 indicates that the student did not attempt any of the quizzes.

### Tests

At regular intervals across the 15-week semester (i.e., 5 weeks), students completed an open-book multiple-choice test assessing their grasp of information from the online textbook modules and associated lectures. Each test comprised 25 multiple-choice questions with four options per question, and were administered through the online learning management system. Three of the tests covered ~9 modules each (*range* = 7 to 10). An optional cumulative final test was offered at the end of the semester to allow students to replace a low or missing test score. Students were given a single opportunity to complete each test within a time limit of 60 min. The three highest test scores were averaged together to create the final test grade. On average, students scored 75.7% correct on the tests ($SD$ = 23.6%, *range* = 0 to 100%). As with the quizzes, a score of 0% indicates that the student did not attempt any of the tests.

### Homework completion

Eight bi-weekly homework assignments were assigned throughout the semester through the Qualtrics online survey software, with links posted to the online learning management system. These homework assignments were graded based on completion. On average, students completed 6.5 homework assignments out of eight ($SD = 2.1$, *range* = 1 to 9).

## Results

We examined relations between self-reported expectancy-value beliefs, academic self-efficacy, perceived attentional control, and reading comprehension, and the extent to which these factors predicted online course outcomes through a series of confirmatory factor analyses and structural equation models (SEMs). Preliminary analyses indicated little clustering based on course section (intra-class correlations = .04 to .08), so we opted for simpler single-level, non-hierarchical modeling. Additionally, we investigated different ways to model expectancy-value beliefs. Based on model fit comparisons between the various models, we found that including expectancy-value as a latent factor in the SEM had the best fit to the data (see Supplementary Table 6 for alternative model comparisons). For the models presented in the main analyses, we assessed model fit indices using chi-square ($\chi^2$), comparative fit index (CFI), Tucker-Lewis fit index (TLI), root mean square error of approximation (RMSEA), and standardized root mean squared residual (SRMR). Models were considered acceptable if they approached the criteria of 0.90 for CFI and TLI (Bentler and Bonett, 1980) and 0.05 for RMSEA and SRMR (Browne and Cudeck, 1992).

As a first step, we constructed a measurement model to assess the validity of expectancy-value beliefs, academic self-efficacy, and course outcomes as latent variables. In order to identify initial relations between the latent variables, we allowed expectancy-value beliefs, academic self-efficacy, and course outcomes to covary. The latent variable for expectancy-value beliefs used composite scores from expectancy, value, future interest, and cost subscales. The latent variable for academic self-efficacy used composite scores from information literacy, reading, technology, and research subscales. We used the scaled quiz scores, test scores, and homeworks completed as observed variables to construct the latent variable for course outcomes. Note that due to their use of different scales, the three variables for course outcomes were scaled and centered. Correlations between quiz, test, and homework scores were positive and medium-to-large in magnitude, $r$'s$(938) = .65$ to $.75$, $p$'s $< .001$; see Supplementary Table 7.

Figure 1 presents the three-factor confirmatory factor analysis. Model fit indices were within an acceptable range; see Table 2. All observed variables loaded significantly onto their respective factors. Expectancy-value beliefs and academic self-efficacy had a significant positive covariance ($\beta = 0.59$, $SE = 0.03$, $p < .001$), as would be expected given that these constructs are conceptually related (Wigfield and Eccles, 2000). Outcomes had a non-significant covariance with academic self-efficacy ($\beta = 0.07$, $SE = 0.05$, $p = .064$), and a small but significant covariance with expectancy-value beliefs ($\beta = 0.08$, $SE = 0.05$, $p = .047$). Note that subscales for expectancy-value beliefs and academic self-efficacy were significantly correlated (see Supplementary Table 8). To account for these correlations,

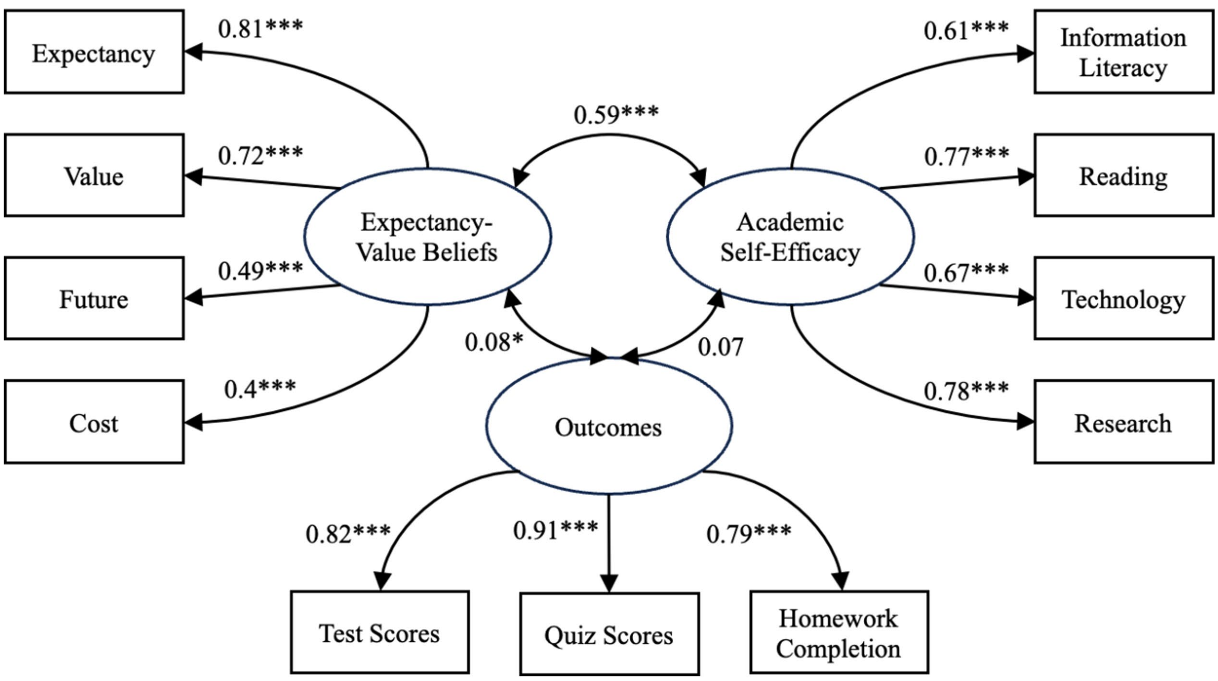


FIGURE 1
Three-factor confirmatory factor analysis ($N = 940$) Note. *$p < .05$, **$p < .01$, ***$p < .001$. Coefficients are standardized. Double sided arrows refer to covariances.

TABLE 2 Model fit indices ($N$ = 940).

| Model | $\chi^2$ | df | $p$ | CFI | TLI | RMSEA | SRMR |
|---|---|---|---|---|---|---|---|
| Confirmatory factor analysis (CFA) | | | | | | | |
| Three-Factor CFA | 132.39 | 41 | < .001 | 0.98 | 0.97 | 0.049 | 0.038 |
| Structural equation models (SEM) | | | | | | | |
| Beliefs and skills only | 181.80 | 31 | < .001 | 0.94 | 0.91 | 0.072 | 0.048 |
| Course outcomes | 215.23 | 57 | < .001 | 0.96 | 0.95 | 0.054 | 0.041 |

we explicitly modeled the covariance between expectancy-value and self-efficacy in all models.

Next, we constructed a series of structural equation models (SEM) to examine the extent to which intrapersonal beliefs and student skills predicted course outcomes. In building the SEM, we aimed to identify relations between expectancy-value beliefs, academic self-efficacy, attentional control, and reading comprehension; see Figure 2. Note that attentional control did not include any subscales, so we treated it as an observed variable. We did not consider directional effects to be appropriate for variables measured at the same time point (i.e., start of the semester), so all variables had covariances specified. The SEM had acceptable fit; see Table 2. Expectancy-value beliefs had a positive association with attentional control ($\beta = 0.25$, $SE = 0.03$, $p < .001$) and reading comprehension ($\beta = 0.12$, $SE = 0.01$, $p = .001$), and academic self-efficacy had a positive association with attentional control ($\beta = 0.39$, $SE = 0.03$. $p < .001$). Reading comprehension was not associated significantly with attentional control ($\beta = -0.02$, $SE = 0.01$, $p = .480$) or academic self-efficacy ($\beta = 0.02$, $SE = 0.01$, $p = .575$). Expectancy-value beliefs and academic self-efficacy retained their positive covariance ($\beta = 0.59$, $SE = 0.03$, $p < .001$). See Supplementary Table 9 for full path coefficients and statistics.

Figure 3 presents the SEM with the course outcomes latent variable added. Retaining the covariance pathways from the previous SEM, we added covariance pathways from each variable (expectancy-value beliefs, academic self-efficacy, attentional control, reading comprehension) regressing onto course outcomes. The model had acceptable model fit indices; see Table 2. For full reporting of pathway coefficients and statistics, see Supplementary Table 10. In addition to the significant associations from the previous model, reading comprehension significantly predicted course outcomes ($\beta = 0.24$, $SE = 0.14$, $p < .001$), as did attentional control ($\beta = 0.08$, $SE = 0.05$, $p = .034$). Notably, neither expectancy-value beliefs ($\beta = 0.02$, $SE = 0.05$, $p = .763$) nor academic self-efficacy ($\beta = 0.02$, $SE = 0.06$, $p = .656$) were significant in predicting course outcomes in the final SEM. Moreover, despite the significant directional effects between academic skills and course outcomes, the model explained a nominal 6.6% of the variance in the dependent variable ($R^2 = .066$).

# Discussion

This study examined factors associated with students' persistence in an online Introductory Psychology course taught at a non-selective public college. Introductory Psychology is an immensely popular general education course for first-year college students across a wide variety of majors (Gurung et al., 2016). Hence, the course provided an ideal context for assessing learning outcomes of a large, diverse sample of undergraduates at a minority-serving institution. Using SEM, we assessed the extent to which students' self-reported expectancy-value beliefs, academic self-efficacy, and attentional control, and a direct assessment of their reading comprehension predicted course outcomes. While the models generally supported hypotheses regarding the formation of latent variables and associations between predictors, the variables collectively did not account for much of the variance in course outcomes (i.e., quiz scores, test scores, homework completion).

## Roles of students' intrapersonal beliefs and skills

As an initial step in model-building, we constructed a measurement model to examine how the three latent variables (expectancy-value beliefs, academic self-efficacy, and course outcomes) fit together in a structural model. All three latent variables had excellent model fit indices, establishing their validity. Ratings taken at the start of the semester indicated that students generally held high expectations of success in the course, high perceptions of immediate and future interest in the course and believed that costs associated with the course were reasonably low. They also possessed generally high levels of academic self-efficacy, reporting moderate-to-strong beliefs in their reading, research, technology, and information literacy abilities. Expectancy-value beliefs and academic self-efficacy were positively correlated, which is appropriate given the connection between beliefs of success and future task performance (Wigfield and Eccles, 2000; Wigfield et al., 2021). Surprisingly, however, only expectancy-value beliefs were positively related to course outcomes, and the magnitude of the relation was small.

Regarding associations between intrapersonal beliefs and student skills, both expectancy-value beliefs and academic self-efficacy showed positive relations to self-reported attentional control, while only expectancy-value beliefs showed a positive relation to reading comprehension. These results align with prior research linking academic motivation in pre-college students with staying on task (Wu, 2019) and reading performance (Geng et al., 2023). The association between academic self-efficacy and perceived attentional control aligns with research identifying associations between self-efficacy and cognitive measures of attentional control in experimental tasks (e.g., flanker task; Themanson and Rosen, 2015). The finding that perceived attentional control exhibited stronger correlations with both belief variables than with reading comprehension might be attributed to the self-report nature of the former measures and students' generally optimistic views of their abilities at the start of the semester. While a cognitive measure of attentional control,

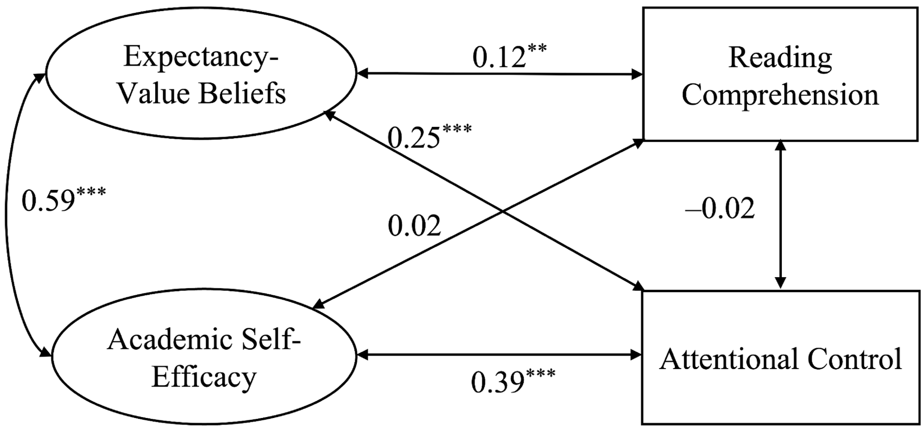


FIGURE 2
Structural model showing relations between internal factors ($N$ = 940). *$p$ < .05, **$p$ < .01, ***$p$ < .001; Coefficients are standardized. Double sided arrows refer to covariances.

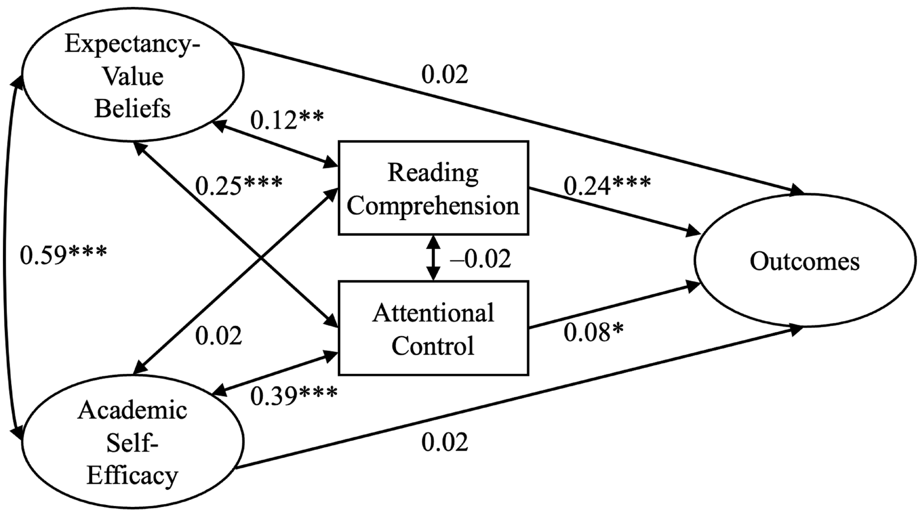


FIGURE 3
Structural model predicting passing the course−enrollment excluded ($N$ = 940). *$p$ < .05, **$p$ < .01, ***$p$ < .001; Coefficients are standardized. Double sided arrows refer to covariances.

such as the flanker task, may have produced different results, we considered a self-reported measure of students' perceived ability to pay attention while studying online to be more relevant in the context of online coursework.

Regarding the effects of intrapersonal beliefs and student skills on course outcomes, only student skills predicted course outcomes. Students' outcomes were twice as strongly associated with the performance-based reading comprehension test than with their self-reported attentional control. This difference might reflect students overestimating their ability to maintain attention while studying online over a 15-week semester. The finding that a performance-based measure was more predictive of course outcomes than any of the attitudinal measures is in keeping with other research findings. For example, Hood et al. (2012) reported that prior knowledge of course-related material (i.e., past performance) predicted over 20% of the variance in course grades in a psychology statistics course, whereas expectancy-value beliefs explained only 2% of additional variance. Similarly, Zapparrata et al. (2025) found that prior knowledge of statistical concepts predicted course outcomes in an Introductory Psychology course to a greater extent than academic self-efficacy, though the self-efficacy measure was statistically significant in some of their analyses (e.g., quiz scores). Here, the knowledge and attitudinal measures collectively accounted for 5.4–11.8% of the variance in course outcomes. Taken together, these and other findings (e.g., Zakariya, 2021) suggest strong continuities between past and future academic success, with attitudinal measures likely reflecting students' educational experiences rather than yielding a direct effect on future performance.

In the present study, the SEM explained a mere 6.6% of the variation in course outcomes. When we examined previous estimates from Gravelle et al. (2024), which included measures of academic self-efficacy, self-reported attentional control, and reading comprehension, we similarly found that these three

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factors alone explained just 2.1% of the variance in quiz scores, 4.4% of the variance in test scores, and 2.2% of the variance in Qualtric assignments completed; see Supplementary Table 11. Note that the Gravelle et al. (2024) dataset came from the same institution as the present study and examined Introductory Psychology course outcomes in Fall 2020 when classes were fully online due to the COVID-19 pandemic. Taken together with the present SEM analysis, the results suggest that individual factors, even when well-established, may account for relatively little variance in online course outcomes. Here it is important to note that the students may have been experiencing social isolation, health and mental issues, and other negative consequences of the pandemic (Filho et al., 2021). Though they seemed to be largely motivated, expressed confidence in their academic abilities, and seemed adequately skilled at the start of the semester, those factors seemed to play a limited role in determining their course performance. Student motivation tends to be higher at the beginning of the semester and declines as the semester progresses (Darby et al., 2013). In Fall 2021, this trend may have been more pronounced as the after-effects of the COVID-19 pandemic were still resonant, and the steady diet of classes via Zoom may have exacted an earlier toll on many students, with attention and zeal quickly giving way to boredom and fatigue.

## Limitations and future directions

The present study is representative of educational research examining effects of individual-level attributes on academic performance: Though many intrapersonal, non-cognitive factors may predict student outcomes, such as grades and GPA, previous models indicate that they collectively account for less than 20% of the variance in performance (Abdulwahid et al., 2022; Forjan, 2017; Gravelle et al., 2023). Looking forward, we must consider limitations to this study and how we can mitigate them in future research. Future work should consider how self-report measures of motivation, self-efficacy, and attentional control might change as the semester progresses. That is, administering measures more frequently instead of once at the start of the semester might catch students closer in time to when they are at risk of giving up. Unfortunately, however, as students withdraw from participating, it becomes increasingly difficult to obtain measures of their course-related attitudes. One potential approach is to adopt analytic approaches that allow researchers to estimate when students will stop participating or withdraw from the course (e.g., survival curve analyses; Ameri et al., 2016) to better understand factors influencing attrition.

Notably, in creating the SEMs for the present study, we had to drop 13% of the enrolled students because they failed to complete the first homework assignment containing the reported measures and an additional 1% who did not submit any quizzes, tests, or other assignments. Consequently, we cannot rule out the possibility that students' intrapersonal beliefs might play a greater role in determining their initial engagement in an online course as opposed to their sustained engagement throughout the semester. Relatedly, our students tended to have relatively high expectancy-value beliefs and academic self-efficacy at the start of the semester, and they tended to do quite well in the course overall. Significant effects of self-efficacy and expectancy-value beliefs on learning outcomes have been observed in mathematics and statistics courses (Cherney and Cooney, 2005; Hoegler and Nelson, 2018; Hood et al., 2012; Huang and Mayer, 2019). Thus, had we examined the performance of students in a more difficult science or math course with a wider grade distribution, we may have found intrapersonal beliefs to play a larger role in explaining online course outcomes. Additionally, research involving high school students has reported larger effects of expectancy-value beliefs on academic achievement than we observed (Doménech-Betoret et al., 2017), suggesting that effects may be attenuated in higher education settings where students self-select to enroll in specific courses.

Another concern is that we examined attentional control using a self-report measure, as opposed to using a behavioral measure. While students' perceptions of their ability to focus on school work predicted online learning outcomes in previous study (Gravelle et al., 2024), future research should attempt to measure attentional control in a more objective way. Similarly, by focusing specifically on expectancy-value and self-efficacy as intrapersonal constructs, we failed to consider whether other beliefs (e.g., growth mindset or mindfulness) might influence engagement and success in online coursework. Hence, we should be cautious about overstating our findings regarding the minimal effects of students' intrapersonal beliefs on online learning outcomes.

Emerging scholarship makes a more strenuous, compelling argument for psychologists to direct more of their efforts beyond the level of individual-level factors and focus more on systemic factors associated with educational outcomes and other social issues (Chater and Loewenstein, 2023; Thomas, 2021; Zengilowski et al., 2023). As evidence of the imbalance, researchers cite the preponderance of studies focusing on individual-level factors and the relatively small number exploring effects of social and systemic factors in relation to student success. This opens up an interesting line of inquiry, possibly more appropriately studied qualitatively at some future juncture. Along these lines, future work should consider how social-cultural and contextual factors (e.g., discrimination and social injustice, food and housing insecurity, and family and work obligations) influence students' sense of agency and efficacy at the undergraduate careers and, ultimately start of their undergraduate careers and, ultimately, their academic success (Osher et al., 2018; Stetsenko, 2017).

# Conclusion

In today's educational landscape, online instruction remains a popular option for college students, presenting opportunities for campuses and programs to boost enrollment. Yet, online courses often suffer from high rates of attrition, with students failing to engage with materials even from the start of the semester. The present study asked how college students' course-related beliefs and skills influenced their persistence in a fully online Introductory Psychology course. Students' expectancy-value beliefs about the course were strongly associated with their academic self-efficacy but only indirectly associated with course outcomes. Rather, outcomes were more strongly tied to student skills than with achievement motivation, in keeping with prior work (Gravelle et al., 2024; May and Elder, 2018). However, when considered together, these factors explained relatively little variance in course outcomes. To improve students' success in online coursework, college instructors and administrators may need to recognize that factors besides students' self-efficacy beliefs, academic self-efficacy, and perceived attentional control influence their persistence and find additional ways of supporting students at risk of dropping out.

## Data availability statement

The original contributions presented in the study are publicly available. This data can be found here: https://osf.io/r7xng/.

## Ethics statement

The studies involving humans were approved by CUNY Human Research Protection Program. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required from the participants or the participants' legal guardians/next of kin because the protocol was exempted due to it being part of educational outcomes assessments conducted by the college.

## Author contributions

RR: Data curation, Methodology, Formal analysis, Funding acquisition, Writing – review & editing, Writing – original draft. CG: Data curation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. EC: Investigation, Resources, Writing – review & editing. NZ: Methodology, Writing - original draft, Writing – review & editing. AL: Investigation, Resources, Writing – review & editing. PB: Conceptualization, Supervision, Writing - original draft, Writing – review & editing.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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## Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2025.1597898/full#supplementary-material

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