How do students' achievement goals relate to learning from well-designed instructional videos and subsequent exam performance?

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Abstract

Well-designed instructional videos are powerful tools for helping students learn and prompting students to use generative strategies while learning from videos further bolsters their effectiveness. However, little is known about how individual differences in motivational factors, such as achievement goals, relate to how students learn within multimedia environments that include instructional videos and generative strategies. Therefore, in this study, we explored how achievement goals predicted undergraduate students' behaviors when learning with instructional videos that required students to answer practice questions between videos, as well as how those activities predicted subsequent unit exam performance one week later. Additionally, we tested the best measurement models for modeling achievement goals between traditional confirmatory factor analysis and bifactor confirmatory factor analysis. The bifactor model fit our data best and was used for all subsequent analyses. Results indicated that stronger mastery goal endorsement predicted performance on the practice questions in the multimedia learning environment, which in turn positively predicted unit exam performance. In addition, students' time spent watching videos positively predicted practice question performance. Taken together, this research emphasizes the availing role of adaptive motivations, like mastery goals, in learning from instructional videos that prompt the use of generative learning strategies.

Keywords: multimedia learning, instructional videos, achievement goals, generative strategies, bifactor confirmatory factor analysis

How do students' achievement goals relate to learning from well-designed instructional videos and subsequent exam performance?

College instructors are more frequently using online instructional videos as resources in their courses (Noetel et al., 2021). Accordingly, the research exploring the effectiveness of learning from instructional videos has also increased (see Mayer, 2021 for a review). This research has overwhelmingly supported that integrating narrated verbal and animated visual information in instructional videos is effective for learning when videos are designed in alignment with evidence-based design principles, such as those grounded in the cognitive theory of multimedia learning (Mayer, 2021). One such design principle is the *generative activity principle* (Mayer, 2021), which suggests prompting students to use generative strategies while learning from videos enhances learning (e.g., see Fiorella et al., 2020). However, to achieve their full effects, well-designed instructional videos require students to initiate and sustain their learning while watching videos and generatively, rather than passively, use strategies.

There has been extensive research establishing the efficacy of multimedia design principles and generative strategies, but much less research regarding what kind of achievement goals motivate students to initiate and sustain their learning with well-designed instructional videos and generative strategies (Pintrich, 1999). Findings from research conducted by Ozan and Ozarslan (2016) suggested students use surface-level video characteristics (e.g., video length) to decide how much time to spend watching instructional videos and often skip through video content. One potential explanation for these findings is that students need adaptive achievement goals motivating them to sustain their learning while watching videos. However, to our knowledge there has been no research involving the direct measurement of how students' motivation is related to how they watch videos and how those behaviors are ultimately related to learning. Furthermore, Fiorella and Mayer (2016) suggested generative strategies are most effective for learning when students are motivated to put in effort toward making sense of the material; however, again, little of the research on generative learning strategies has involved direct tests of how student motivation is related to performance and subsequent learning with such strategies. Thus, in this study, we investigated whether and how students' achievement goals predicted how long students sustained their learning with videos in a multimedia learning environment, their performance on questions requiring generative processing, and in turn whether time spent watching videos and question performance predicted future exam performance. An auxiliary purpose of this research was to test different methods for modeling achievement goals (i.e., specific factor vs. bifactor models; Reise, 2012), which is necessary to best understand how motivation relates to subsequent behaviors and learning. Our findings have implications for the use of instructional videos that adhere to evidence-based design principles and require optimal motivations for learning from those videos.

Well-Designed Instructional Videos and Generative Strategies Support Learning

Instructional videos are effective for learning because integrating verbal and visual representations supports the construction of a coherent mental model (cognitive theory of multimedia learning; Mayer, 2021). Furthermore, instructional videos help students to *select* relevant information from the learning material, *organize* that material into something meaningful, and *integrate* that knowledge with prior knowledge (SOI; Mayer, 2021). Generative cognitive processes, like organizing and integrating, help students to learn the material more meaningfully. For example, findings from a meta-analysis of 105 studies exploring the effects of learning from instructional videos in higher education supported that adding instructional videos to current teaching practices led to strong learning benefits for students (g = .80; Noetel et al., 2021).

Importantly, instructional videos are more likely to help students engage in generative cognitive processes when they are designed according to evidence-based design principles that adhere to the cognitive theory of multimedia learning (Mayer, 2021). One such evidence-based design feature is prompting students to use generative strategies within multimedia learning environments (i.e., *the generative activity principle*: Chi & Wylie, 2014; Fiorella & Mayer, 2015, 2016; Mayer, 2021). For example, Fiorella and colleagues (2020) conducted a study in which all students watched instructional videos about the function of the human kidney and some of those students were randomly assigned to explain what they learned in writing (i.e., generative strategy) after watching the videos, while other students re-watched the videos. Results indicated students who watched instructional videos and then explained what they learned in writing had significantly improved posttest performance over those students who only watched instructional videos. Other research (Eitel, 2016) supports that prompting students to use generative strategies via completing practice questions between studying multimedia lesson pages enhances learning; however, the same is not true for pages that only include text. Thus, prior research supports that students learn better from multimedia materials, such as instructional videos, when students are prompted to use generative strategies after watching videos, like writing summaries or answering questions. However, few researchers have explored whether and how motivation initiates and sustains student learning with well-designed instructional videos that prompt generative strategy-use via practice questions, nor how motivation affects performance on such questions.

Achievement Goals Initiate and Sustain Students' Learning Behaviors

Motivation is the driving force that initiates and sustains students' learning behaviors, and this is particularly important in media-rich multimedia environments where there are many different demands on students' attention and opportunities for students to engage with content

(Moreno, 2005; Moos & Azevedo, 2006, 2008, 2009). Achievement goals are an important motivation construct that determine how students will initiate and sustain their learning behaviors, based off their desired level of competence, like being motivated to master a skill or meaningfully learn the material (Elliot & Dweck, 2005). Other students are motivated by simply not appearing incompetent and therefore set goals that focus on a standard of performance, such as appearing equivalent to or better than their peers. As such, achievement goal theory establishes four goal constructs that measure how students are guided toward mastering content or performing well with content (e.g., mastery or performance) and how students are guided toward a need for achievement or a fear of failure (e.g., approach or avoidance; Urdan & Kaplan, 2020).

Mastery approach-oriented students set goals toward developing competence and mastering content, meaning mastery goals motivate students to actively construct meaning from the learning materials (Anderman, 2010). Thus, mastery approach goals are typically related to more adaptive outcomes, such as greater self-efficacy and positive affect for learning tasks, more persistence and self-regulation during learning (Kaplan & Maehr, 2007), and subsequent learning and achievement (Hulleman et al., 2010; Linnenbrink-Garcia et al., 2012). Performance goals orient students toward showing a desired level of competence in comparison to their peers. These goals motivate students to focus on their performance, and not mastering the material, therefore performance goals are less likely to help students actively construct meaning from the learning materials and are typically considered to be less adaptive than mastery goals (Pintrich, 2000).

Different types of performance goals have been shown to be adaptive for different student outcomes. Performance approach goals orient students toward demonstrating ability and *performing better* than their peers, which can be positively related to productive learning behaviors and achievement (Hulleman et al., 2010; Linnenbrink-Garcia et al., 2012). For example, performance approach goals have been related to improved behavioral and cognitive engagement, interest, and achievement (e.g., Elliot et al., 1999; Senko & Harackiewicz, 2005; Krou et al., 2021; Yeh et al., 2019). However, performance approach goals have also been related to a range of maladaptive outcomes, such as cheating and avoiding help-seeking (Tas & Tekkaya, 2010; Karabenick, 2004). On the other hand, performance avoidance goals focus on simply *not demonstrating poor performance* and are typically related to maladaptive student outcomes. For example, performance avoidance goals have been related to lower intrinsic motivation, academic self-efficacy, behavioral and cognitive engagement, and achievement (e.g., Church et al., 2001; Middleton & Midgley, 1997; Pajares et al., 2000; Pekrun et al., 2009). Last, students with mastery avoidance goals are focused on maintaining skills or ideas in which they have previously mastered and, thus, are not explored in the current study because they are irrelevant when students are acquiring new knowledge (Elliot & Murayama, 2008).

Beyond the theoretical and predictive similarities between achievement goals (e.g., mastery and performance approach sometimes support adaptive learning behaviors; performance approach and avoidance sometimes support maladaptive learning behaviors), there are also measurement similarities between goal constructs. For example, students' endorsements of individual achievement goal constructs are often correlated with each other (Barron & Harackiewicz, 2001). Further, in their review of the literature, Linnenbrink-Garcia and colleagues (2012) found students' achievement goals were only modestly correlated with enhanced learning. Such findings have prompted researchers to explore multiple methods of modeling motivation constructs, including methods that allow for both general and specific motivation constructs.

Measuring Achievement Goals with Bifactor Models

The measurement similarities, inconsistencies across findings, and overall modest relations between achievement goals and outcomes have led some researchers to pursue alternative conceptualizations and measurement models of achievement goals. Researchers have suggested students use multiple goals to motivate their learning behaviors and that endorsing multiple goals, like mastery and performance approach goals, is likely more adaptive for learning than endorsing only one or the other (i.e., *multiple goals perspective*; Barron & Harackiewicz, 2001; Harackiewicz et al., 1998; García & Pintrich, 1991). However, most of the prior research has measured and modeled achievement goals as individual constructs (e.g., mastery approach, performance approach, performance avoidance) without accounting for more general goal pursuit. As such, there is reason to measure goal pursuit more generally, along with each goal construct individually. Until now, the research examining the measurement of these constructs both separately and together has been mixed and primarily focused on only measuring performance constructs as a general factor (i.e., approach and avoidance), rather than looking at general goal pursuit as a factor across all three constructs (see Kaplan et al., 2002; Murayama & Elliot, 2009; Zusho et al., 2011). For example, Murayama and colleagues (2011) used a broad factor-analytic approach to examine the separability of just the two performance constructs and, across five studies, found strong evidence for separating the two constructs. On the other hand, in a study by Linnenbrink-Garcia and colleagues (2011), the researchers found that performance approach and avoidance constructs loaded on a single factor in an exploratory factor analysis.

One potential approach to measuring the multidimensionality of students' general goal pursuit is to employ bifactor modeling (Reise, 2012), which parses a general factor representative of an overarching construct (e.g., general goal pursuit) from more specific factors that represent precise components (e.g., mastery approach, performance approach, performance avoidance). Bifactor modeling has previously been employed with other motivation constructs, such as Situated Expectancy Value Theory (Eccles & Wigfield, 2020), to successfully partition the general subjective task value that learners perceive when they engage in an academic task from their more specific perceptions of values (i.e., attainment, intrinsic, and utility) and costs (i.e., effort, opportunity, and psychological; Part et al., 2020), resulting in better data-model fit than when modeling only the specific value and cost factors. In addition, general volition (i.e., desire to pursue a task) and specific reasons to pursue a task, separate components of self-determination theory (SDT: Deci & Ryan, 2016; Ryan & Deci, 2017), have been successfully modeled using a bifactor approach (Lohbeck et al., 2022). Modeling SDT in this way resulted in better model fit indices than traditional confirmatory factor analyses and produced factor loadings that better matched SDT's theoretical continuum structure of motivation.

This parsing of general and specific aspects of a motivational construct may be similarly advantageous for the measurement of achievement goals, in that it can capture the degree to which students endorse specific achievement goals, defined by their orientation to mastery approach, performance approach, and performance avoidance, as well as students' general goal pursuit, as the general factor. The generality (i.e., a general factor capturing the responses from all subscales that reflect student's general pursuit of goals) captured by the bifactor accounts for multidimensionality that exists simultaneously with the specific (i.e., specific factors that capture how much or little students endorse each type of goal that cannot be explained by the general factor) constructs. This distinction lowers the covariance between each of the specific factors and allows for greater dissociation of the specific mastery approach, performance approach, and performance avoidance factors. Greater dissociation between the specific factors allows the valence of each factor to make a more distinct contribution to the model, which then results in a clearer interpretation of that factor. Ultimately, a bifactor approach to modeling achievement goals allows us to measure students' general motivation for achievement goal pursuit with the general factor, while the specific factors measure more nuanced aspects of achievement goal pursuit (i.e., mastery approach, performance approach, performance avoidance). Given the promise of this technique, we compared traditional and bifactor models of students' achievement goals to determine which was a better fit to our data, and then used that model to understand how achievement goals predict students' learning with videos, performance on generative strategies, and exam performance.

Achievement Goals Sustain Learning with Videos and Enhance Performance on Practice Questions that Prompt Generative Processing

The adoption of adaptive achievement goals motivates how students approach a learning task, deploy strategies, and engage in productive learning behaviors, which then fosters future performance (Authors, Date; Duffy & Azevedo, 2015). Thus, students' endorsement of achievement goals likely predicts how they will sustain successful learning behaviors within multimedia learning environments, such as how long they spend watching videos and generatively process the learning material when prompted to use strategies, which ultimately affects their learning. Mastery approach-oriented students might spend more time watching instructional videos because they are motivated by a desire to meaningfully learn the material and master the content or skills, which requires that they watch and learn from videos in their entirety. Although there is no research, to our knowledge, that explores whether and how mastery goals sustain video-watching behaviors, Song and colleagues (2016) found mastery approach goals do support learning from instructional videos. Specifically, the researchers examined how medical students' achievement goals were related to their self-regulation and learning from instructional videos that taught about carotid artery disease in a complex multimedia environment. Findings suggested self-reported mastery approach and performance avoidance goals were positively related to performance on a post-test, whereas performance approach goals were negatively related to performance on a post-test. This research supports that mastery approach goals likely help students learn from videos in multimedia environments and the relationship between performance goals and learning from videos is potentially contrary to more common findings regarding performance approach and avoidance goals. Furthermore, students with mastery approach goals are more likely to effortfully use strategies to generatively process the learning materials, such as by completing strategies without the learning material in front of them. Indeed, research by Graabraek Nielsen (2008) suggests students who endorse mastery goals report greater use of effective learning strategies and other research by Heo and colleagues (2018) suggests increased endorsement of mastery approach goals is related to increased use of self-regulated learning (SRL; Authors, Date) strategies, such as reflection. Importantly, the prior research only explores the correlational relationships between achievement goals and self-reported strategy-use or only tests the effect of SRL strategies on performance, rather than directly exploring performance on cognitive strategies (i.e., generative strategies), respectively.

How performance approach and avoidance goals are related to learning in multimedia environments is difficult to hypothesize because of the lack of research exploring this topic and mixed findings in other research exploring how performance approach and avoidance goals are generally related to behaviors and learning. Theoretically, performance-oriented students might be mostly focused on using generative strategies to accurately complete a product (e.g., a finished practice test or complete written summary), rather than using strategies to help them actively make sense of the material in a multimedia learning environment. Therefore, performance-oriented students might spend less time watching videos because they are scrubbing through the videos to find accurate responses for completing a product, rather than *generatively* enacting the strategy. As discussed above, research by Song and colleagues (2016) indicated contrary findings between each type of performance goal and learning in a multimedia environment. Specifically, the researchers found that performance avoidance goals might benefit, whereas performance approach goals might not benefit learning from videos; however, these findings are misaligned with most of the prior research that suggests performance approach goals are sometimes helpful for learning behaviors and achievement, whereas performance avoidance goals are primarily maladaptive for learning behaviors and achievement. For example, Authors (Date) examined how students' achievement goals and strategy-use predicted learning from hypertext in a technology-enhanced environment. Results indicated students' endorsement of performance avoidance goals was negatively related to notetaking (i.e., strategy-use), information-seeking (i.e., sustained learning of the material), and performance on learning outcomes. Meanwhile, there were no statistically significant relationships between endorsement of performance approach goals and learning behaviors or outcomes. Considering the prior research by Song et al (2016) and Authors (Date), it is unclear whether performance approach and avoidance goals help, hurt, or do not relate to productive behaviors and enhanced learning in a multimedia environment.

The counterintuitive and mixed findings in the prior research on students' achievement goals (e.g., Song et al., 2016) may be due to issues with the measurement of achievement goals, such as failure to measure general goal pursuit using a bifactor model. Due to the lack of research modeling achievement goals with bifactor models, it is unclear how bifactor conceptualization of students' general goal pursuit relates to learning in a multimedia environment. On the one hand, it seems possible that the pursuit of goals at all (i.e., general goal pursuit) will benefit learning, at least beyond students with limited or no goals (i.e., amotivation). However, theories of self-regulation suggest that simply having a goal or goals is not enough for students to enact successful learning behaviors toward achieving that goal; instead, students must actively pursue cognitive strategies and update their strategies in accordance with their individual goal pursuit (Winne & Hadwin, 2008). Taken together, research is needed regarding how specific achievement goals and general goal pursuit predict sustained learning with instructional videos and generative processing when prompted to use strategies via practice questions, as well as how those learning behaviors predict future learning.

The Current Study

Learning from well-designed instructional videos that prompt generative strategy-use via completing practice questions can be effective for learning, dependent upon whether and how students are motivated by achievement goals to initiate and sustain their learning with videos and generatively process the learning material using strategies. Thus, in the current study, we used structural equation modeling to test how self-reported achievement goals motivate students in introductory biology courses to sustain their learning behaviors in a multimedia environment and how such behaviors predicted performance on a unit exam. We sought to address two gaps in the literature with the current research. First, we compared measurement models of students' achievement goals between a specific-factors-only model, using a traditional confirmatory factor analysis with three specific factors (i.e., mastery approach, performance approach, performance avoidance) and a bifactor model, which incorporates specific factors and a general factor to measure general goal pursuit. These findings can help us identify the best model for measuring achievement goals, which in turn will help us to estimate the relationships more accurately between achievement goal factors and students' behaviors and learning. Second, we sought to clarify how achievement goals predict students' learning behaviors in a multimedia environment that includes videos and prompts generative strategy-use, and how such goals and behaviors relate to later exam performance.

We measured students' learning behaviors within the multimedia learning environment with the time students spent watching well-designed instructional videos and their performance on practice questions. Although motivation, time spent watching videos, and performance on practice questions in a multimedia environment are the primary foci of the study, we also recognize that prior knowledge plays an important role in the relationships among these factors and future performance. As such, in alignment with other research (Authors, Date), we included prior knowledge as an additional predictor in our analyses. We made four hypotheses regarding (1) the best model for measuring achievement goals and (2) how achievement goals will predict time spent watching videos and performance on practice questions within the multimedia learning environment, (3) how time spent watching videos and performance on practice questions within the multimedia learning environment predict unit exam performance, and (4) how achievement goals will indirectly predict unit exam performance through time spent watching videos and performance on practice questions within the multimedia environment (see Figure 1 for our hypothesized model).

Hypothesis 1: Bifactor vs. Specific-Factor Achievement Goal Models

We hypothesized a bifactor model with three specific achievement goal factors (mastery approach, performance approach, performance avoidance) and one general factor (i.e., general goal pursuit) will have better data-model fit indices than a specific-factors-model that includes just the three specific achievement goal factors (mastery approach, performance approach, performance avoidance). We committed to using the model with better data-model fit indices in all subsequent analyses.

Hypothesis 2: Achievement Goals Predict Time Spent Watching Videos and Performance on Practice Questions

Hypothesis 2a: In line with prior research supporting that mastery approach goals motivate productive learning behaviors (Heo et al., 2018; Graabraek Nielsen, 2008), we expected the endorsement of mastery approach goals to have a positive relationship with time spent watching videos and performance on practice questions when accounting for the relationship between prior knowledge and performance on practice questions.

Hypothesis 2b: In line with prior research supporting that performance approach goals motivate students towards performing well or appearing competent on learning tasks (Yeh et al., 2019), but do not necessarily motivate students toward productive learning behaviors that foster long-term learning (Authors, Date; Song et al., 2016), we expected the endorsement of performance approach goals would negatively relate to time spent watching videos (i.e., productive behaviors that foster long-term learning) and positively relate to performance on practice questions (i.e., an outcome connected to appearing competent/performance) when accounting for the relationship between prior knowledge and performance on practice questions.

Hypothesis 2c: In line with prior research showing performance avoidance goals are typically detrimental to productive behaviors and learning (Authors, Date), we expected the endorsement of performance avoidance goals would negatively relate to time spent watching videos and performance on practice questions when accounting for the relationship between prior knowledge and performance on practice questions.

Hypothesis 3: Relationships Among Time Spent Watching Videos, Performance on Practice Questions, and Unit Exam Performance

Hypothesis 3a: We expected the time students spent watching videos would positively predict practice question performance when accounting for the relationship between prior knowledge and performance on practice questions.

Hypothesis 3b: In line with prior research supporting retrieval-based learning as a generative strategy that supports meaningful learning (Eitel, 2016; Johnson & Mayer, 2009; Roediger & Karpicke, 2006), we expected that time spent watching videos and performance on practice questions in the multimedia learning environment would positively predict unit exam performance when accounting for the relationship between prior knowledge and performance on practice questions.

Hypothesis 4: Achievement Goals Indirectly Predict Unit Exam Performance through Time Spent Watching Videos and Performance on Practice Questions

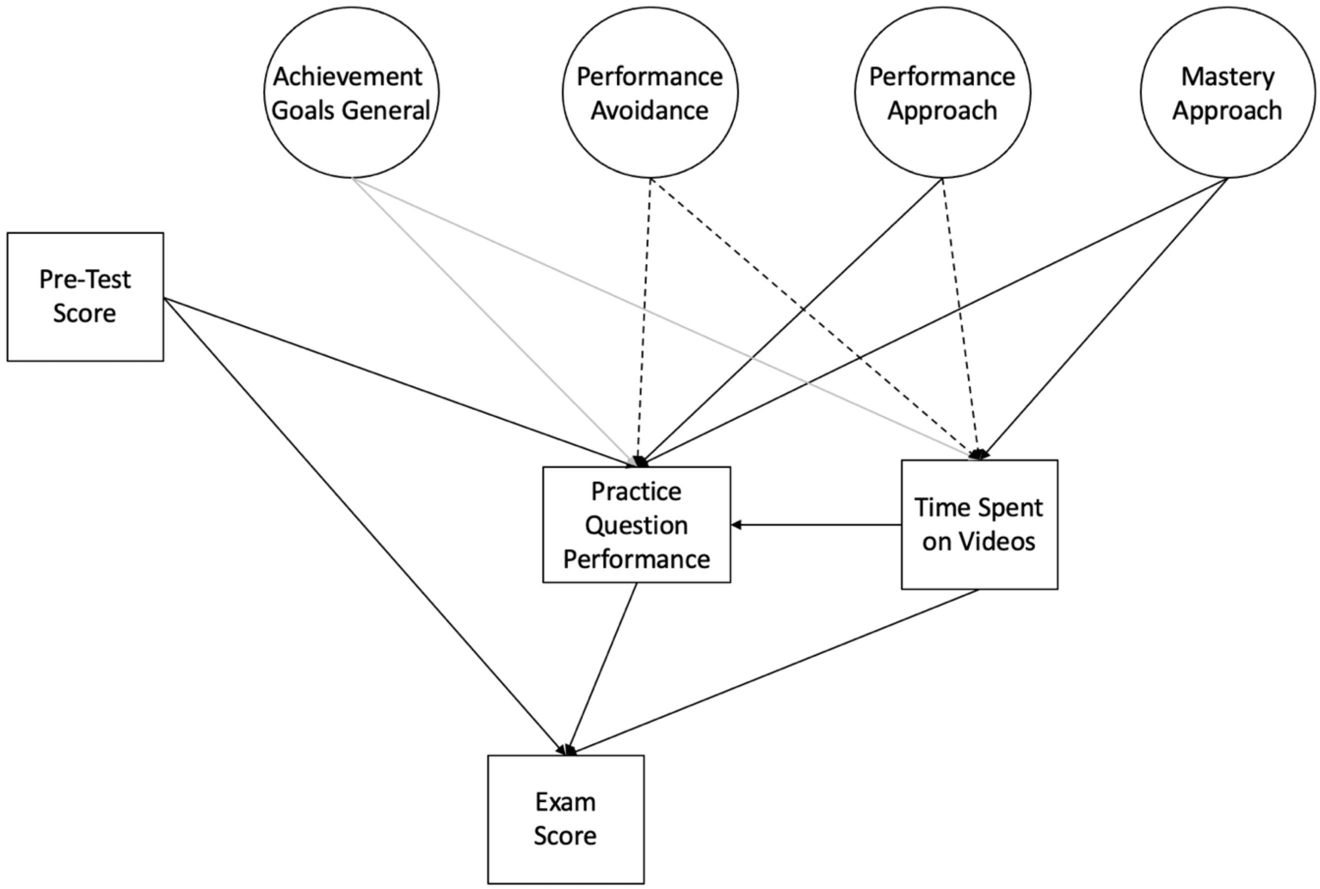
Hypothesis 4a: We expected there would be a positive indirect effect of the endorsement of mastery approach goals on unit exam performance through time spent watching videos and performance on practice questions.

Hypothesis 4b: Alternatively, we posited there would be no indirect effect of performance approach goals on unit exam performance through practice question performance because the benefit of such goals on immediate performance (i.e., practice questions in the environment) is not likely to transfer to delayed performance on a unit exam.

Hypothesis 4c: Finally, we expected there would be a negative indirect effect of performance approach goals on unit exam performance through time spent watching videos and a negative indirect effect of performance avoidance goals on unit exam performance through both, time spent watching videos and performance on practice questions.

Note that due to the lack of research testing the potential predictive effects of general goal pursuit, as measured with a bifactor, we did not make any a priori predictions regarding how students' endorsement of general goal pursuit would directly predict time spent watching videos and performance on practice questions or indirectly predict unit exam performance, but we estimated paths between this general factor, practice question performance, and time spent on videos, parallel to the paths for the specific factors .

Figure 1
Hypothesized model



Note. Solid lines represent positive relationships, dashed lines represent negative relationships, gray lines represent estimations without a priori hypotheses.

Method

Participants and Context

Participants were 166 undergraduate students from two sections of an introductory biology course at a large university in the southeastern United States. The mean age of students was 19.24 years (*SD* = .91), and 70.0% percent of the students were Female, 34.4% of the students listed biology as a primary major, 20.0% were first generation college students, and 30.3% were members of an underrepresented minority group. On average, students started the course with low prior knowledge of the course content, $M = 47.81\%$ out of 100% ($SD = 15.16$), as assessed by a pre-test. This study was approved and conducted in accordance with the ethical guidelines of the author's Institutional Review Board.

The introductory biology course was intended for majors and nonmajors and taught across two sections, using the same syllabus and active learning pedagogy. The courses were taught entirely online and engaged students in learning tasks across three clear phases during one learning cycle (i.e., one lesson taught over one week). The phases included (1) before-class activities, in which students read the textbook and completed preparatory assignments that provided immediate feedback; (2) during-class activities, in which students watched a lecture that required them to intermittently answer formative assessment questions; and (3) after-class activities, in which students learned with their peers through online discussion forums and peer-mentoring sessions. This study included data from the start of the course through the first course exam (i.e., Unit 1).

Learning Task

All consented students completed a multimedia learning environment that taught biology concepts with well-designed instructional videos and required students to complete practice questions about what they learned from the videos. The instructional videos were selected based off their alignment with evidence-based multimedia design principles (CTML; Mayer, 2021). Answering practice questions was considered a generative strategy because practice questions require students to activate and retrieve knowledge, then organize and integrate the learning material by strengthening existing connections and building new connections between new material and prior knowledge (Fiorella & Mayer, 2016). Students were told that completing the multimedia environment would help them prepare for the first course exam. The multimedia environment was provided through Qualtrics and designed in collaboration with biology instructors to be a truncated learning cycle that is ecologically valid to the learning students experience during one week of their biology course

The multimedia learning environment included three units that covered content taught during the first three weeks of class, and students completed the learning environment at their own pace. Unit one included concepts on the scientific method, unit two included concepts on the major themes of biology, and unit three included concepts on systems and processes (e.g., lipids, hydrogen bonds, the endomembrane system, and osmosis). Open-source online instructional videos were used to teach the prior concepts and were carefully selected for quality of content and delivery (by biology instructors) and alignment with multimedia design principles (by one of the authors). When completing the multimedia learning environment, students received directions, watched instructional videos on biology concepts, and answered practice questions about what they learned from the videos then received feedback on their responses. After answering each question, students were shown a table that compared their response to a model answer and were asked to evaluate their answer in comparison to the model answer. In total, there were 12 biology content videos (see Figure 2 for an example of the multimedia learning environment).

Measures

Measures included the Achievement Goals Questionnaire-Revised, a course pre-test, the time students spent watching videos, practice questions in the multimedia learning environment, and a course unit exam.

Achievement Goals

The Achievement Goals Questionnaire-Revised (Elliot & Murayama, 2008) measures students' goal endorsement and includes three task-relevant subscales (e.g., mastery approach, performance approach, and performance avoidance) comprising three items each, with a 7-point Likert response scale. Mastery avoidance items were not included in the survey, as they were not relevant to this novel task. Mastery approach items included, "My aim is to completely master the material presented in this class", "My goal is to learn as much as possible", and "I am striving to understand the content in this course as thoroughly as possible." Performance approach items included, "I am striving to do well in comparison to other students", "My aim is to perform well relative to others", and "My goal is to perform better than the other students." Performance avoidance items included, "My goal is to avoid performing poorly compared to others", "I am striving to avoid performing worse than others", and "My aim is to avoid doing worse than other students." Data from the achievement goals survey was analyzed across specific-factor and bifactor confirmatory factor analyses. Findings from these analyses are in the Results section below.

Course Pre-Test

The pre-test included 15 multiple choice items developed by the biology course instructors and it covered material that would be taught throughout the entire semester. All items were multiple choice in design; however, the questions themselves required students to answer a variety of question types such as reading graphs, true or false, and word problems. Example questions included, "Which of the following studies is <u>least likely</u> to contain a confounding factor in its design?" and "What likely caused populations of parrot fishes having different mouth shapes and sizes to become distinct species distributed on various coral reefs in the South

Pacific Ocean?". The pre-tests were scored by the biology course instructors and had marginal internal reliability (α = .500). Given the marginal internal reliability of the pre-test, it is important to note that knowledge assessments that intentionally include multiple topics tested at multiple levels of understanding are often not intended to be fully internally consistent (Cogliano et al., 2019).

Time Spent Watching Videos and Performance on Practice Questions

Time spent watching videos was recorded by analytics software in Qualtrics as students completed the multimedia learning environment. Videos were presented on individual pages within Qualtrics and the analytics software recorded, in real-time, the amount of time in seconds that students spent watching the video on each page.

Thirty-one biology content questions were developed in collaboration with the biology instructors to test what students learned in each of the videos. The types of practice questions varied throughout the environment, and included a range of multiple choice, fill-in-the-blank, short answer, and matching questions (see Table 1 for an example of each type). Practice questions in the multimedia learning environment were scored for accuracy, in which students received one point for an accurate response and zero points for an inaccurate response. Some questions included multiple parts, in which each part was worth one point and students could score more than one point for the whole question. For example, the question "Many biological molecules are made-up of similar elemental and molecular building blocks. Which atoms did the video suggest are the most common in biological molecules?" was scored from 0-5, in which students needed to include all atoms to receive the full five points: carbon, hydrogen, oxygen, nitrogen, and phosphorous. Each item could receive a score between 0-6 points and the practice questions altogether were worth a total of 63 points. The scoring rubric was developed by the biology instructors and questions were scored by one rater given items either matched exactly with the rubric (i.e., accurate) or not (i.e., inaccurate).

Unit Exam

The exam was a 38-item multiple choice test developed by the biology course instructors. The unit exam was the first exam of the semester in the biology course and covered material taught in the first four weeks of class, which was also the same material taught with instructional videos in the learning task. All items were multiple choice in design; however, the question stems required students to think through a variety of question types such as fill-in-the-blank, reading graphs and diagrams, true or false, and word problems. Example questions included, "ATP synthesis moves _____ via _____.", "Complete the analogy. Excessive growth is to chemotherapy (anti-cancer) drugs as _____ is to antibiotic.", and "Sosa does an experiment to study oxidative phosphorylation. She isolates mitochondria from cells and puts them in a solution that contains H+, NADH, oxygen, ADP, and P. Which statement is TRUE?". Individual exam items were weighted, based off their difficulty. Items were worth between 1-5 points, in which more simple items were worth 1 point and more difficult items were worth 5 points – students received 0 points for entirely inaccurate responses. The exam items altogether were worth a total of 100 points. The exams were scored by the biology course instructors and had acceptable internal reliability (αs > .720).

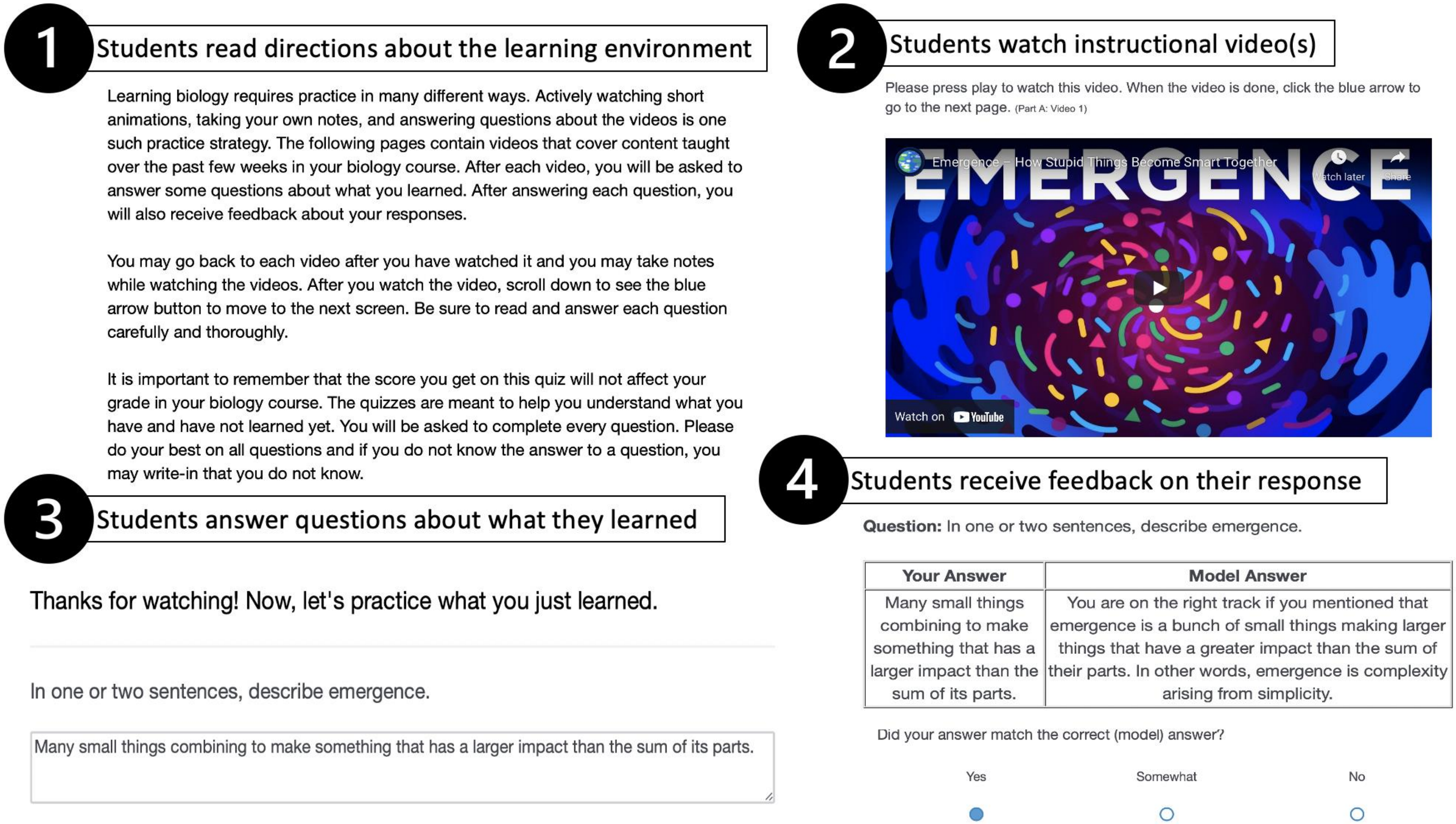
Table 1.

Examples of each type of practice question in the multimedia learning environment.

Question Type	Unit and Concept	Question	Model Answer
Fill-in-the-Blank	Unit 3: Hydrogen Bonds	Hydrogen bonds that exist between molecules with unequal charge distributions are called _______ molecules.	Polar
Multiple Choice	Unit 2: Protein Shapes & Folding	To aid proteins in the folding process, proteins can:	(A) Enter Chaperonins (C) Maturation after four structures
Short Answer	Unit 3: Lipids	The four groups of lipids include:	Triglycerides, phospholipids, waxes, steroids
Match/Sort	Unit 1: Experimental Design	<u>Sort:</u> *variable that is being measured*, *variable that remains consistent between the groups*, *variable that is manipulated* <u>Into categories:</u> **Independent Variable**, **Dependent Variable**, **Controlled Variable**	**Independent** = *variable that is manipulated* **Dependent** = *variable that is being measured* **Controlled** = *variable that remains consistent between the groups*

Figure 2.

Examples of each phase that students engaged in during the multimedia learning environment.



Procedures

Students completed consent forms online during the first week of class, and consented students continued to complete the study across three phases, (1) pre-surveys, (2) multimedia learning environment, and (3) unit exam. The achievement goal survey was administered during the pre-survey phase via Qualtrics in the second week of class. The multimedia learning environment phase started in the third week of class and occurred over the following ten days. During that time, students completed the multimedia learning environment via Qualtrics individually, at their own pace. Although students completed the multimedia environment at their own pace, they were asked to complete an entire unit in one session and could choose whether they completed one unit in separate, shorter sessions, or all three units in one long session. Completing one unit required that students watch a video, answer practice questions about what they learned, and review feedback on their response; then they would proceed onto the next video and repeat the same process until the unit was finished. Each unit took about 30 minutes to complete. Finally, students took a unit exam in the course exam phase, which occurred approximately one week after completing the multimedia environment. All students took the exam online during their designated biology course time.

Results

Missing Data

Missing values analysis revealed that 8.4% of the data were missing. Missing values were primarily due to students missing scores on the motivation instruments or missing data from the multimedia learning environment, but not both. No missingness mechanism was discernable. As such, all our models were estimated in MPlus 8.7 with full-information maximum likelihood.

Confirmatory Factor Analyses of Bifactor and Specific-Factor Achievement Goal Models (Hypothesis 1)

Descriptive statistics for each of the variables in the model can be found in Table 3 and a matrix of correlations between all variables in the model can be found in Table 4. We used confirmatory factor analysis to test the hypothesized factor structure of the achievement goal scales. Two models were estimated that compared specific factor structures to bifactor models with a general factor (Reise, 2012). A Satorra-Bentler scaled chi-square difference test was used to compare the fit indices across each model. As hypothesized, the model with an achievement goal general factor, $X^2(4) = 18.140$, $p < .01$, had better data-model fit than the model without a general factor (see Table 2)[1]. Therefore, we utilized the model shown in Figure 3, which included a general factor that reflects a degree of general achievement goal pursuit and three individual factors that included the performance avoidance, performance approach, and mastery approach latent factors. All items loaded on hypothesized factors and all but one loading were statistically significant. In addition, latent factor correlations aligned with theory and most had acceptable maximum reliability (Table 4). This measurement model was used in the subsequent structural equation model we used to test the remaining hypotheses.

[1] Of note, to achieve convergence of the bifactor model, two item residual variances had to be set to zero.

Table 2

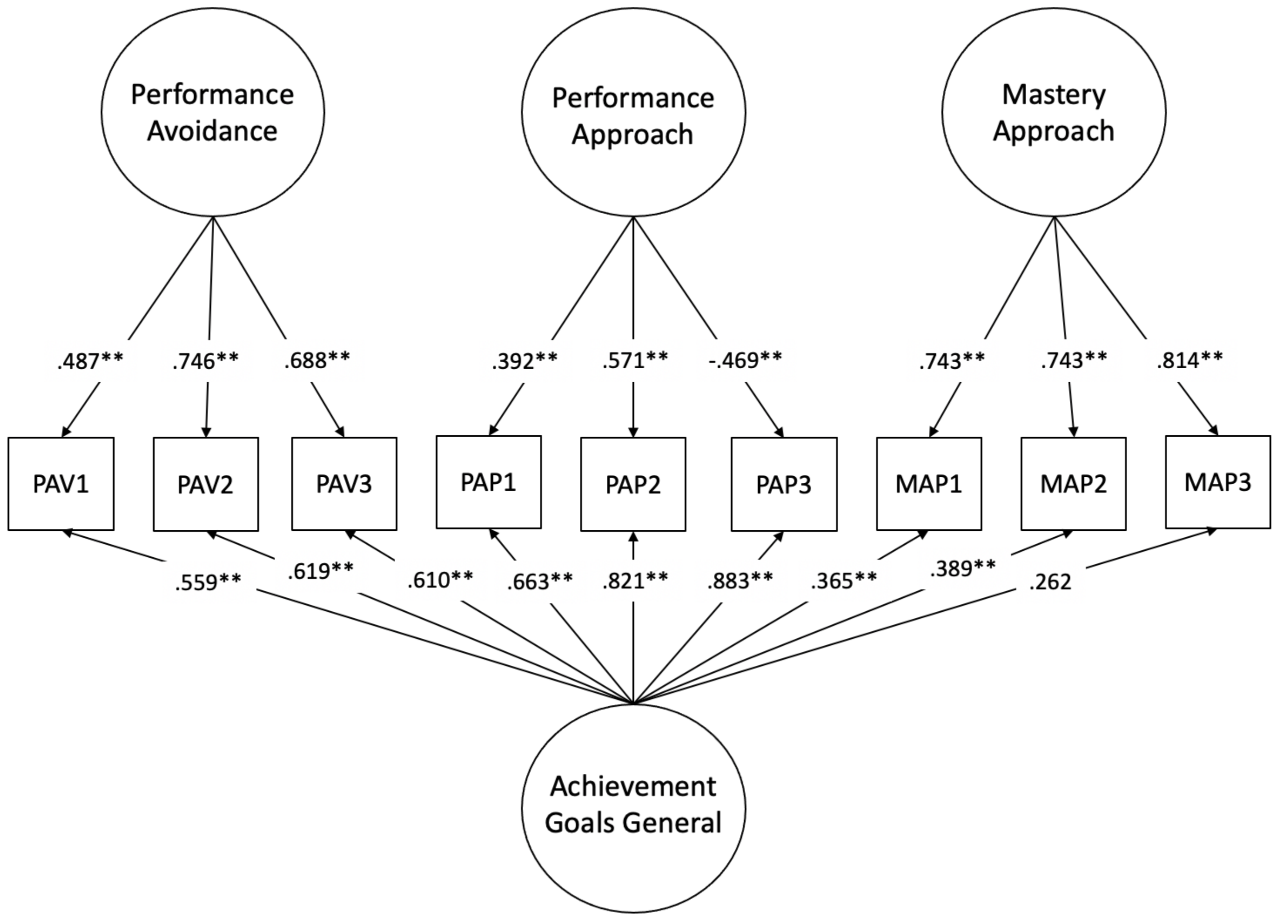
Confirmatory Factor Analyses of Specific and General Bifactor Models.

Model	Chi-square value/df	RMSEA (90% confidence interval)	CFI	SRMR
Specific Achievement Goal factors only	66.921/24*	.110 (.079, .142)	.933	.080
Specific Achievement Goal factors and Achievement Goals general factor	48.567/20*	.098 (.063, .134)	.955	.087

*$p < .001$

Figure 3

Confirmatory Factor Analysis of Achievement Goal Items Using Bifactor Model.



Note. PAV = performance avoidance item; PAP = performance approach item; MAP = mastery approach item

** $p < 0.001$

Achievement Goals Predict Time Spent Watching Videos and Practice Question Performance (Hypothesis 2)

First, we conducted an analysis for outliers to remove students who were likely doing tasks other than watching the videos. Individual video times ranged from 2:00 to 9:00 minutes (M = 4:47 minutes) and the total video watching time was 60 minutes (3,600 seconds). Initially, the mean time students spent watching all videos was 12,257.70 seconds (SD = 48,491.73) and there was a maximum time spent watching all videos of 434,571 seconds, which is about 120 hours. This and similar extreme outliers suggest students left the learning environment open without consistent interaction within the environment for several days. Thus, students with video-watching times one standard deviation above the mean were removed from the data (n = 25) for all analyses. The video watching times of the remaining students had a mean of 3385.30 seconds (SD = 2720.00) and a maximum of 14,747.70 seconds. This suggests students were spending 57 minutes, on average, to watch about 60 minutes of videos.

The Shapiro-Wilk's test of normality was statistically significant (p's < .001); therefore, robust maximum likelihood estimation was used to adjust for normality violations. Model fit indices suggested a good fit with the data, χ^2 (49) = 79.888, p = 0.004 (CFI = 0.960, SRMR = 0.078, RMSEA = 0.062, 90% CI [.036, .086]), and yielded the final solution shown with standardized coefficients in Figure 4.

In partial support of hypothesis 2a, mastery approach scores were positively, statistically significantly related to performance on practice questions in the multimedia learning environment (β = .232, p < .001); however, we did not detect a statistically significant relationship between mastery approach scores and how much time students spent watching instructional videos. Hypothesis 2b and 2c were not supported, as there were no statistically significant relationships between performance approach or performance avoidance scores and time spent watching instructional videos or performance on practice questions in the multimedia learning environment. Last, there was no statistically significant relationship between general goal pursuit (i.e., the general achievement goal factor) and time spent watching instructional videos or performance on practice questions in the multimedia learning environment. These findings suggest mastery approach goals are related to students' use of generative strategies, but do not necessarily relate directly to sustained motivation (as measured with time spent on videos) when students watch instructional videos.

Relationships Among Time Spent Watching Videos, Performance on Practice Questions, and Unit Exam Performance (Hypothesis 3)

In support of hypothesis 3a, there was a statistically significant positive path from time spent watching videos to performance on practice questions in the multimedia learning environment ($\beta = .160$, $p = .017$). In partial support of hypothesis 3b, there was a statistically significant positive relationship between performance on practice questions in the multimedia learning environment and unit exam scores ($\beta = .306$, $p < .001$). However, we did not find a statistically significant relationship between time spent watching videos and unit exam scores. Findings from hypothesis 2 suggest achievement goals are not related to time spent watching videos, but findings from hypothesis 3 suggest that this time did nonetheless predict performance on the practice questions. Furthermore, as expected, practice question performance positively predicted delayed learning on a unit exam.

Achievement Goals Indirectly Predict Unit Exam Performance through Time Spent Watching Videos and Performance on Practice Questions (Hypothesis 4)

Finally, in partial support of hypothesis 4a, practice question performance was a statistically significant mediator in the relationship between mastery approach scores and unit exam performance (β = .071, $p = .020$); however, there was no statistically significant indirect effect of mastery approach scores on the unit exam through time spent watching videos. In addition, there was a statistically significant positive total effect of mastery approach scores, performance on the practice questions, and time spent watching videos on unit exam scores (β = .068, $p = .032$). There were no statistically significant indirect effects of performance approach or avoidance scores on unit exam performance (hypotheses 4b and 4c).

Table 3

Descriptive Statistics

	M	*SD*
Course Pre-test	47.81	15.16
Time spent watching videos (in seconds)	3385.30	2720.00
Practice Question Performance	41.30	5.80
Course Exam Scores	80.20	11.40
Mastery approach item 1	6.189	.952
Mastery approach item 2	6.502	.859
Mastery approach item 3	6.383	.820
Performance approach item 1	5.972	1.075
Performance approach item 2	5.892	1.071
Performance approach item 3	4.747	1.431
Performance avoidance item 1	5.395	1.510
Performance avoidance item 2	5.213	1.622
Performance avoidance item 3	5.246	1.548

Table 4.

Correlation Matrix

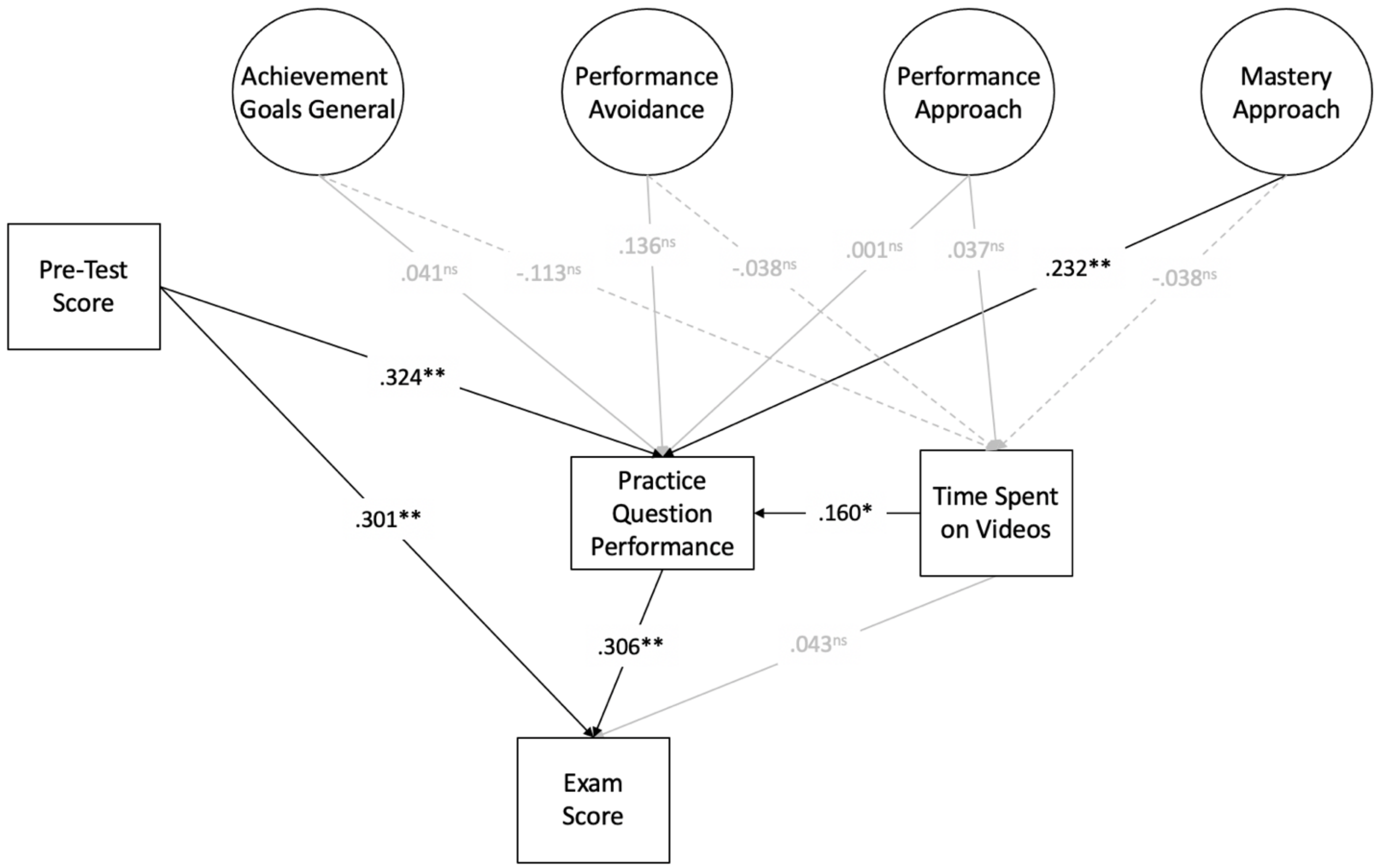
	Achievement Goals - General	Performance Approach	Performance Avoidance	Mastery Approach	Time spent watching video	Practice Question Performance	Course Exam
Achievement Goals - General	ω = .894						
Performance Approach	.850**	ω = .490					
Performance Avoidance	.932**	.600**	ω = .711				
Mastery Approach	.264**	.456**	.087	ω = .816			
Time spent watching video	-.101	-.155	-.048	-.057	1		
Practice Question Performance	.133	.104	.131	.227**	.145	1	
Course Exam	.070	.127	.020	.145	.090	.399**	1

*$p < .05$, ** $p < .01$

Note. Maximum reliability is reported on the diagonal, using McDonald's omega for each latent factor.

Figure 4

Final structural model



Note. Black lines represent statistically significant relationships, solid lines represent positive relationships, dashed lines represent negative relationships.
* $p < .05$
** $p < .001$
ns non-significant

Discussion

Instructional videos are a popular and powerful mechanism for fostering meaningful learning, particularly when students are prompted to use generative strategies in-between watching videos. However, learning effectively from instructional videos and generatively processing the learning material using strategies requires students to be motivated by productive achievement goals to initiate and sustain their learning. We explored how students' achievement goals related to learning within a multimedia environment that teaches biology concepts with well-designed instructional videos and requires students to answer questions about what they learned (i.e., generative strategy use). First, we investigated the optimal measurement model for our motivation factors, finding that a bifactor model was superior to a traditional CFA specific factor model (Lohbeck et al., 2022; Part et al., 2020). This finding supports other research indicating the value of modeling both general goal pursuit and specific achievement goal factors (Murayama et al., 2011), but extends that work by finding that a single general factor for all three specific achievement goal factors is warranted.

Using this bifactor approach to modeling achievement goals, we found endorsement of mastery approach goals was positively related to performance on the practice questions. Interestingly, we did not detect any statistically significant relationships between endorsement of performance approach, avoidance, or general goal pursuit and performance on the practice questions. These findings align to prior research on achievement goals by Authors (Date) that find mastery goals are more consistently related to adaptive learning behaviors that predict achievement than performance-oriented goals. The finding that general goal pursuit is not related to performance on the practice questions contributes new information to research on achievement goal theory and aligns with research on self-regulated learning that suggests having a goal(s) is not necessarily enough to motivate students to enact successful learning behaviors toward achieving that goal (Winne & Hadwin, 2008). Instead, our results suggest that students' endorsement of mastery goals are important for motivating successful learning behaviors, such as engaging in generative strategies.

Next, results indicated the time students spent watching instructional videos was positively related to performance on the practice questions, which supports prior meta-analyses (Noetel, 2021) suggesting how students engage with instructional videos (e.g., time spent watching) is related to how well they will learn from videos (e.g., performance on practice questions). It was somewhat surprising there were no statistically significant relations among the motivation factors and time spent watching the videos. This finding suggests that simple process measures of learning with digital tools (e.g., time spent with a video) may not be sensitive to important individual characteristics, suggesting the need for more nuanced measures (e.g., engagement through interaction; Martin & Borup, 2022).

Last, we found that performance on the practice questions was positively related to better unit exam performance, which supports prior research suggesting students learn better when they use generative strategies in addition to watching instructional videos (Fiorella et al., 2020). Furthermore, we found that performance on the practice questions was a significant mediator in the relationship between mastery approach goals and exam scores, and there was a total effect of mastery approach goals, time spent watching videos, and performance on the practice questions on unit exam performance. Taken together, these findings suggest that capturing the relationships between multiple phenomena, such as motivation, generative processing via strategy-use with instructional technologies, and learning, increases the understanding of how each of these processes work individually and in tandem with each other (Authors, Date).

Theoretical and Practical Contributions

Designing instructional videos in alignment with evidence-based design principles, such as the generative activity principle, fosters generative cognitive processing (Mayer, 2021). However, instructors must consider individual learner differences beyond cognitive processing with instructional videos, such as whether students will be motivated to watch instructional videos and generatively process the material when using adjunct strategies. This research suggests motivational factors, like learners' achievement goals, do influence how students learn from such multimedia environments. Mastery approach-oriented students are likely to benefit from learning in a multimedia environment that includes instructional videos and prompts strategy-use; however, the same benefit might not necessarily exist for performance-oriented students. Thus, researchers and practitioners must consider how to engage more performance-oriented students in generative processing when designing and implementing instructional videos that prompt generative strategy-use. For example, providing students with task-relevant feedback (i.e., feedback that is specific to individual student performance compared to a set standard) after completing a generative strategy might encourage more performance-oriented students to sustain their learning in multimedia environments (see Anseel et al., 2011).

Interestingly, there were no statistically significant relationships between achievement goals and time spent watching videos; however, time spent watching videos did predict increased performance on the practice questions and contributed to the significant total effect on exam performance, which suggests these videos did play a role in meaningful learning. One potential explanation for these findings is that the videos were relatively short overall (M = 4:47 minutes), and many students watched all the videos in their entirety (i.e., the average total time spent watching videos was 57 minutes out of a possible 60 minutes), thus rendering potential differences across students' achievement goals less relevant for sustained learning with videos. This is potentially good news for the use of instructional videos in the classroom, in that, regardless of adaptive or maladaptive achievement goals, students are motivated to watch instructional videos when they are relatively short. Thus, instructors should work to deliver content in instructional videos that is meaningful, yet also concise.

Finally, this study adds to the growing corpus of literature that suggests conceptual models of motivation may need to incorporate both a general factor and specific factors (e.g., Lohbeck et al., 2022; Part et al., 2020). Further iterations between empirical findings and theory, in addition to those in this study, are needed to provide sufficient evidence to substantiate change to theories of motivation, such as achievement goal theory (Authors, Date[2]).

Limitations and Future Directions

One limitation of this research is the moderate reliability of the performance approach factor. However, the maximum reliability score attained through structural equation modeling in the current research is a more accurate representation of performance approach than much of the research measuring achievement goals that primarily used summed scores. In addition, measuring performance approach in a bifactor model was shown to have better data-model fit than typical models that only measure achievement goal constructs separately. Also, this finding aligns with research that has produced mixed results on measuring achievement goals with both traditional confirmatory factor analysis and bifactor models (Kaplan et al., 2002; Murayama & Elliot, 2009; Zusho et al., 2011).

Another limitation of this research is measuring students' adaptive learning behaviors with time spent watching videos. Using time spent watching videos does not necessarily confirm that students were spending all that time generatively processing what they were learning.

However, the instructional videos used in this research were carefully selected based off their alignment with multimedia design principles (Mayer, 2021), which have consistently been shown to help students organize the learning material and integrate it with prior knowledge, leading to more meaningful learning outcomes (Fiorella et al., 2020; Mayer & Chandler, 2001; Mayer & Moreno, 2002; Pociask & Morrison, 2008). Future research could use more active measures of generative processing, such as self-explanation or think aloud protocols, to measure if and how students are working to actively organize and integrate the material during learning.

Finally, future work could also use other forms of multimodal data, such as digital trace data to better understand how students generatively process the material taught in videos. For example, digital traces collected from how students watch videos in a learning management system would indicate how often students use video-interface tools, such as play, pause, and scrubbing forward and backward throughout the video. Measuring these behaviors would help us better understand how endorsement of certain achievement goals relates to different behaviors when watching instructional videos, like pausing to take notes or scrubbing through the material to complete a graded assignment.

Conclusion

Overall, the present study explored how motivational factors, like achievement goals, were related to productive learning behaviors in a multimedia environment and how such behaviors were, in turn, related to learning. Productive learning behaviors within the multimedia learning environment were measured using the time students spent watching well-designed instructional videos and how they performed on generative strategies. Ultimately, findings suggested that productive motivations, such as mastery goals, were positively related to learning both within the multimedia environment and on a unit exam that was taken one week after completing the multimedia environment. Taken together, these findings suggest well-designed instructional videos and generative strategies might not always be enough to help students learn meaningfully, and students need productive achievement goals to help them initiate and sustain their learning in a multimedia environment.

References

Authors (Date).

Authors (Date[2]).

Anderman, E. M. (2010). Reflections on Wittrock's generative model of learning: A motivation perspective. *Educational Psychologist, 45*(1), 55-60. https://doi.org/10.1080/00461520903433620

Anseel, F., Van Yperen, N.W., Janssen, O. and Duyck, W. (2011), Feedback type as a moderator of the relationship between achievement goals and feedback reactions. *Journal of Occupational and Organizational Psychology, 84,* 703-722. https://doi-org.libproxy.lib.unc.edu/10.1348/096317910X516372

Barron, K. E., & Harackiewicz, J. M. (2001). Achievement goals and optimal motivation: testing multiple goal models. *Journal of Personality and Social Psychology, 80*(5), 706-722. https://doi.org/10.1016/B978-012619070-0/50031-3

Chi, M. T., & Wylie, R. (2014). The ICAP framework: Linking cognitive engagement to active learning outcomes. *Educational Psychologist*, *49*(4), 219-243. https://doi.org/10.1080/00461520.2014.965823

Church, M. A. et al., (2001). Perceptions of classroom environment, achievement goals, and achievement outcomes. *Journal of Educational Psychology, 93*(1), 43. https://doi.org/10.1037/0022-0663.93.1.43

Cogliano, M.C., Kardash, C. A., & Bernacki, M.L. (2019). the effects of retrieval practice and prior topic knowledge on test performance and confidence judgments. *Contemporary Educational Psychology, 56,* 117-129. https://doi.org/10.1016/j.cedpsych.2018.12.001

Deci, E. L., & Ryan, R. M. (2012). Self-determination theory. In P. A. M. Van Lange, A. W. Kruglanski, & E. T. Higgins (Eds.), *Handbook of theories of social psychology* (pp. 416–436). Sage Publications Ltd. https://doi.org/10.4135/9781446249215.n21

Duffy, M. C., & Azevedo, R. (2015). Motivation matters: Interactions between achievement goals and agent scaffolding for self-regulated learning within an intelligent tutoring system. *Computers in Human Behavior*, *52*, 338-348. https://doi.org/10.1016/j.chb.2015.05.041

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology*, *61*, 101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Eitel, A. (2016). How repeated studying and testing affects multimedia learning: Evidence for adaptation to task demands. *Learning and Instruction*, *41*, 70-84. https://doi.org/10.1016/j.learninstruc.2015.10.003

Elliot, A. J., & Dweck, C. S. (2005). *Handbook of competence and motivation*. Guilford Press.

Elliot, A. J., McGregor, H. A., & Gable, S. (1999). Achievement goals, study strategies, and exam performance: a mediational analysis. *Journal of Educational Psychology, 91*(3), 549. https://doi.org/10.1037/0022-0663.91.3.549

Elliot, A. J., & Murayama, K. (2008). On the measurement of achievement goals: critique, illustration, and application. *Journal of Educational Psychology*, *100*(3), 613. https://doi.org/10.1037/0022-0663.100.3.613

Fiorella, L., & Mayer, R. E. (2015). *Learning as a generative activity*. Cambridge University Press. https://doi.org/10.1017/CBO9781107707085

Fiorella, L., & Mayer, R. E. (2016). Eight ways to promote generative learning. *Educational Psychology Review*, *28*(4), 717-741. https://doi.org/10.1007/s10648-015-9348-9

Fiorella, L., Stull, A. T., Kuhlmann, S., & Mayer, R. E. (2020). Fostering generative learning from video lessons: Benefits of instructor-generated drawings and learner-generated explanations. *Journal of Educational Psychology*, *112*(5), 895. https://doi.org/10.1037/edu0000408

García, T., & Pintrich, P. R. (1991, April). *Student Motivation and Self-Regulated Learning: A LISREL Model.* Paper presented at the annual meeting of the American Educational Research Association, Chicago, IL.

Graabraek Nielsen, S. (2008). Achievement goals, learning strategies and instrumental performance. *Music Education Research*, *10*(2), 235-247. https://doi.org/10.1080/14613800802079106

Harackiewicz, J. M., Barron, K. E., & Elliot, A. J. (1998). Rethinking achievement goals: When are they adaptive for college students and why?. *Educational psychologist*, *33*(1), 1-21. https://doi.org/10.1207/s15326985ep3301_1

Heo, D., Anwar, S., & Menekse, M. (2018). The relationship between engineering students' achievement goals, reflection behaviors, and learning outcomes. *International Journal of Engineering Education*, *34*(5), 1634-1643.

Hulleman, C. S., Schrager, S. M., Bodmann, S. M., & Harackiewicz, J. M. (2010). A meta-analytic review of achievement goal measures: Different labels for the same constructs or different constructs with similar labels?. *Psychological Bulletin, 136*(3), 422-449. https://doi.org/10.1037/a0018947

Johnson, C. I., & Mayer, R. E. (2009). A testing effect with multimedia learning. *Journal of Educational Psychology*, *101*(3), 621. https://doi.org/10.1037/a0015183

Kaplan, A., Middleton, M. J., Urdan, T., & Midgley, C. (2002). Achievement goals and goal structures. *Goals, Goal Structures, and Patterns of Adaptive Learning*, *13*, 21-53.

Kaplan, A., & Maehr, M. L. (2007). The contributions and prospects of goal orientation theory. *Educational Psychology Review*, *19*(2), 141-184. https://doi.org/10.1007/s10648-006-9012-5

Karabenick, S. A. (2004). Perceived achievement goal structure and college student help seeking. *Journal of Educational Psychology, 96*(3), 569. https://doi.org/10.1037/0022-0663.96.3.569

Karabenick, S. A., Woolley, M. E., Friedel, J. M., Ammon, B. V., Blazevski, J., Bonney, C. R., De Groot, E., Gilbert, M. C., Musu, L. E., Kelly, K., Kempler, T. M. (2007). Cognitive processing of self-report items in educational research: Do they think what we mean? Establishing the cognitive validity of motivation-related assessments. *Educational Psychologist, 42*, 139-151. https://doi.org/10.1080/00461520701416231

Krou, M. R., Fong, C. J., & Hoff, M. A. (2021). Achievement motivation and academic dishonesty: A meta-analytic investigation. *Educational Psychology Review, 33*, 427-458. https://doi.org/10.1007/s10648-020-09557-7

Linnenbrink-Garcia, L., Middleton, M. J., Ciani, K. D., Easter, M. A., & O'Keefe, P. (2011, April). *The strength of the relation between performance-approach and performance-avoidance goal orientations: Theoretical, practical, and methodological implications*. Paper presented at the annual meeting of the American Educational Research Association, New Orleans, LA.

Linnenbrink-Garcia, L., Middleton, M. J., Ciani, K. D., Easter, M. A., O'Keefe, P. A., & Zusho, A. (2012). The strength of the relation between performance-approach and performance-avoidance goal orientations: Theoretical, methodological, and instructional implications. *Educational Psychologist, 47*(4), 281-301. https://doi.org/10.1080/00461520.2012.722515

Lohbeck, A., Tóth-Király, I., & Morin, A. J. (2022). Disentangling the associations of academic motivation with self-concept and academic achievement using the bifactor exploratory structural equation modeling framework. *Contemporary Educational Psychology*, *69*, 102069. https://doi.org/10.1016/j.cedpsych.2022.102069

Martin, F., & Borup, J. (2022). Online learner engagement: Conceptual definition, research themes, and supportive practices. *Educational Psychologist, 57*(3), 162-177. https://doi.org/10.1080/00461520.2022.2089147

Mayer, R. E. (2021). Evidence-based principles for how to design effective instructional videos. *Journal of Applied Research in Memory and Cognition, 10*(2), 229-240. https://doi.org/10.1016/j.jarmac.2021.03.007

Mayer, R. E. (2021). *Multimedia learning: 3rd edition.* New York: Cambridge University Press.

Mayer, R. E., & Chandler, P. (2001). When learning is just a click away: Does simple user interaction foster deeper understanding of multimedia messages?. *Journal of Educational Psychology, 93*(2), 390. https://doi.org/10.1037/0022-0663.93.2.390

Mayer, R. E., & Moreno, R. (2002). Aids to computer-based multimedia learning. *Learning and Instruction, 12*(1), 107-119. https://doi.org/10.1016/S0079-7421(02)80005-6

Middleton, M. J., & Midgley, C. (1997). Avoiding the demonstration of lack of ability: An underexplored aspect of goal theory. *Journal of Educational Psychology, 89*(4), 710. https://doi.org/10.1037/0022-0663.89.4.710

Moreno, R. (2005). Multimedia Learning with Animated Pedagogical Agents. In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning* (pp. 507–523). Cambridge University Press. https://doi.org/10.1017/CBO9780511816819.032

Moos, D., & Azevedo, R. (2006). The role of goal structure in undergraduates' use of self-regulatory variables in two hypermedia learning tasks. *Journal of Educational Multimedia and Hypermedia*, *15*(1), 49-86.

Moos, D. C., & Azevedo, R. (2008). Self-regulated learning with hypermedia: The role of prior domain knowledge. *Contemporary Educational Psychology*, *33*(2), 270-298. https://doi.org/10.1016/j.cedpsych.2007.03.001

Moos, D. C., & Azevedo, R. (2009). Learning with computer-based learning environments: A literature review of computer self-efficacy. *Review of Educational Research*, *79*(2), 576-600. https://doi.org/10.3102/0034654308326083

Murayama, K., & Elliot, A. J. (2009). The joint influence of personal achievement goals and classroom goal structures on achievement-relevant outcomes. *Journal of Educational Psychology, 101*(2), 432. https://doi.org/10.1037/a0014221

Murayama, K. Elliot, A. J., & Yamagata, S. (2011). Separation of performance-approach and performance-avoidance achievement goals: A broader analysis. *Journal of Educational Psychology, 103*(1), 238. https://doi.org/10.1037/a0021948

Noetel, M., Griffith, S., Delaney, O., Sanders, T., Parker, P., del Pozo Cruz, B., & Lonsdale, C. (2021). Video improves learning in higher education: A systematic review. *Review of Educational Research*, *91*(2), 204-236. https://doi.org/10.3102/0034654321990713

Ozan, O., & Ozarslan, Y. (2016). Video lecture watching behaviors of learners in online courses. *Educational Media International*, *53*(1), 27-41. https://doi.org/10.1080/09523987.2016.1189255

Pajares, F., Britner, S. L., & Valiante, G. (2000). Relation between achievement goals and self-beliefs of middle school students in writing and science. *Contemporary Educational Psychology, 25*(4), 406-422. https://doi.org/10.1006/ceps.1999.1027

Part, R., Perera, H. N., Marchand, G. C., & Bernacki, M. L. (2020). Revisiting the dimensionality of subjective task value: Towards clarification of competing perspectives. *Contemporary Educational Psychology*, *62*, 101875. https://doi.org/10.1016/j.cedpsych.2020.101875

Pekrun, R., Elliot, A. J., & Maier, M. A. (2009). Achievement goals and achievement emotions: Testing a model of their joint relations with academic performance. *Journal of Educational Psychology, 101*(1), 115. https://doi.org/10.1037/a0013383

Pintrich, P. R. (1999). The role of motivation in promoting and sustaining self-regulated learning. *International Journal of Educational Research, 31*(6), 459-470. https://doi.org/10.1016/S0883-0355(99)00015-4

Pintrich, P. R. (2000). Multiple goals, multiple pathways: The role of goal orientation in learning and achievement. *Journal of Educational Psychology, 92*(3), 544. https://doi.org/10.1016/B978-012109890-2/50043-3

Pociask, F. D., & Morrison, G. R. (2008). Controlling split attention and redundancy in physical therapy instruction. *Educational Technology Research and Development, 56*(4), 379-399. https://doi.org/10.1007/s11423-007-9062-5

Reise, S. P. (2012). The rediscovery of bifactor measurement models. *Multivariate Behavioral Research, 47*, 667-696. https://doi.org/10.1080/00273171.2012.715555

Roediger, H. L., & Karpicke, J. D. (2006). Test enhanced learning: Taking memory tests improves long-term retention. *Psychological Science, 17*, 249-255. https://doi.org/10.1111/j.1467-9280.2006.01693.x

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. Guilford Publications.

Senko, C., & Harackiewicz, J. M. (2005). Achievement goals, task performance, and interest: Why perceived goal difficulty matters. *Personality and Social Psychology Bulletin, 31*(12), 1739-1753. https://doi.org/10.1037/e633942013-732

Senko, C., & Tropiano, K. L. (2016). Comparing three models of achievement goals: Goal orientations, goal standards, and goal complexes. *Journal of Educational Psychology*, *108*(8), 1178. https://doi.org/10.1037/edu0000114

Song, H. S., Kalet, A. L., & Plass, J. L. (2016). Interplay of prior knowledge, self-regulation and motivation in complex multimedia learning environments. *Journal of Computer Assisted Learning*, *32*(1), 31-50. https://doi.org/10.1111/jcal.12117

Tas, Y., & Tekkaya, C. (2010). Personal and contextual factors associated with students' cheating in science. *The Journal of Experimental Education, 78*(4), 440-463. https://doi.org/10.1080/00220970903548046

Urdan, T., & Kaplan, A. (2020). The origins, evolution, and future directions of achievement goal theory. *Contemporary Educational Psychology*, *61*, 101862. https://doi.org/10.1016/j.cedpsych.2020.101862

Winne, P. H., & Hadwin, A. F. (2008). The weave of motivation and self-regulated learning. *Motivation and self-regulated learning: Theory, research, and applications*, *2*, 297-314.

Yeh, Y. C., Kwok, O. M., Chien, H. Y., Sweany, N. W., Baek, E., & McIntosh, W. A. (2019). How college students' achievement goal orientations predict their expected online learning outcome: The mediation roles of self-regulated learning strategies and supportive online learning behaviors. *Online Learning*, *23*(4), 23-41. https://doi.org/10.24059/olj.v23i4.2076

Zusho, A., & Clayton, K. (2011). Culturalizing achievement goal theory and research. *Educational Psychologist, 46*(4), 239-260. https://doi.org/10.1080/00461520.2011.614526