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Understanding and Supporting Academic Attribution in Online Learning Using Clickstream Data

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Understanding and Supporting Academic Attribution
in Online Learning Using Clickstream Data

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Education

by

Qiujie Li

Dissertation Committee:
Assistant Professor Rachel Baker, Chair
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2019

DEDICATION

To

my parents and husband,

who always picked me up on time

and encouraged me to go on every adventure,

especially this one

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ABSTRACT OF THE DISSERTATION

Understanding and Supporting Academic Attribution
in Online Learning Using Clickstream Data

By

Qiujie Li

Doctor of Philosophy in Education

University of California, Irvine, 2019

Assistant Professor Rachel Baker, Chair

Professor Mark Warschauer, Co-Chair

Colleges offer online courses as a cost effective way to enhance the accessibility of higher education. However, one major concern about online learning has been the lack of student engagement. Attribution theory proposes that students will encounter great difficulties maintaining their motivation and engagement when experiencing failures in a course and that the causal factors, such as insufficient effort versus low ability, that students use to interpret their failures may influence how much subsequent effort students will expend and what learning strategies they will use in the course. Some studies have applied attribution theory to online learning, but very few of them have considered the unique challenges that may prevent online students from adopting more adaptive attributions when experiencing poor performance. There is also a lack of studies that take advantage of the rich and nuanced clickstream data collected in online learning environments to understand the role of attribution and to support online students in the process of seeking reasons for their poor performance and making productive adjustments.

To address these gaps, this dissertation uses clickstream data collected from online learning platforms to explore the behavioral consequences of attributions and to develop and evaluate the effect of an attribution intervention. In Chapter 1, I attempted to identify valid clickstream measures of self-regulated learning behaviors, which can then be used to examine the behavioral consequences of attribution. In Chapter 2, I used these clickstream measures to investigate the relationships between students' attribution, expectancy, and changes in students' subsequent behavior and performance in online learning. Lastly, in Chapter 3, I used clickstream data to build an informational intervention that aimed to correct students' attributional biases and encourage students to attribute their performance to effort. I expect that my dissertation will lead to a deeper understanding of the role of attribution processes and provide guidance on the design of automatic and light touch attribution interventions in online learning. Moreover, my dissertation provides a novel example of and useful tools for using the clickstream data available in online learning environments to examine and support motivational processes, which is less feasible in in-person educational settings.

INTRODUCTION

In the past decade, colleges have sharply increased the number of online courses as online learning is considered to be more cost-effective and flexible than in-person courses. According to the National Center of Education Statistics, approximately 28% of undergraduate students took at least one online course in Fall 2016, a figure almost twice as large as that of 10 years ago (National Center for Education Statistics, 2018, Table 311.15). Despite the rapid growth of online learning in higher education, current research shows that a lack of student engagement is an ongoing problem associated with low course achievement and a high dropout rate in online courses (Finnegan, Morris, & Lee, 2008; Fritz, 2011; Macfadyen & Dawson, 2010; Morris, Finnegan, & Wu, 2005).

Research on the lack of student engagement in online courses typically focuses on academic motivation (e.g., Lee, Choi, & Kim, 2013; Street, 2010). It is possible that students who are less motivated are more likely to enroll in online courses than in in-person courses. Another concern is that it is more difficult for students to maintain their motivation, stay engaged, and persist in online courses (Lee & Choi, 2011). An increasing amount of causal evidence from large administrative datasets shows that students are more likely to withdraw from a class when taking it online versus in-person, suggesting that even starting with similar levels of motivation, students' motivation and engagement levels are more likely to decrease in online courses than in-person courses (e.g., Xu & Jaggars, 2011, 2013). Indeed, it has been found that a large percentage of online students experience a decreasing level of motivation and engagement and the pattern is associated with low performance and early dropout (Hershkovitz & Nachmias, 2011; Kim & Frick, 2011; Park, Denaro, Rodriguez, Smyth, & Warschauer, 2017; Xie, Debacker, & Ferguson, 2006). Problems like decreases in motivation and engagement are more salient in online settings because of the difficulty for instructors to quickly detect and react to these changes. Thus, it is imperative to identify critical moments when students have difficulties maintaining their motivation and engagement in online learning.

Attribution theory indicates that a challenging moment is when students experience a failure in a course. Such undesired outcomes may have differential effects on students' motivation and behavior depending on students' attributions or, in other words, the causal factors that they use to interpret their failures (Weiner, 1979). Previous research has mainly explored two causal factors of academic failures—ability and effort —and their relationships with students' expectancy (e.g., Henry & Stone, 2001; McMahan, 1973; Pancer & Eiser, 1977), effort (e.g., Haynes, Perry, Stupnisky, & Daniels, 2009; Weiner, 1979), use of self-regulation strategies (e.g., Ho, Salili, Biggs, & Kit-Tai, 1999), and performance (e.g., Perry & Penner, 1990; Perry, Stupnisky, Hall, Chipperfield, & Weiner, 2010).

In particular, if a student fails a prior task and believes that the failure is caused by her low ability, she would lack confidence to succeed in a subsequent task, and as a result, substantially decrease her effort level and use of self-regulation strategies and not perform as well as she could in the subsequent task (Weiner, 1979). On the contrary, if the student attributes the failure to insufficient effort, she may believe that she could still succeed if she puts in extra effort and adopt appropriate study strategies, which could encourage her to maintain or even increase her effort and use of self-regulation strategies and improve her performance in the subsequent task.

In spite of the positive role of effort attribution, researchers have found that some people tend to avoid making effort attributions when experiencing failures (e.g., Davis &

Davis, 1972; Federoff & Harvey, 1976; Fontaine, 1975). It has been identified that potential motivational and informational biases may prevent students from attributing failures to lack of effort (e.g., Mezulis, Abramson, Hyde, & Hankin, 2004; Miller & Ross, 1975). Attribution interventions targeting those biases have been proven to have positive effects on student persistence and performance (Haynes et al., 2009).

Although there is evidence that the attribution process plays an important role in learning across various types of academic contexts including online courses, more research is clearly needed to test the attribution model in the context of online learning and, more importantly, apply the verified model to support online learning processes. In order to do that, we need to fully take into account the characteristics of online courses as a learning environment and understand how these characteristics may relate to students' attribution processes. In addition, we need to take advantage of the detailed clickstream data uniquely available in technology-enhanced learning environments, including online courses, to enhance our understanding of and ability to support students' attribution processes.

Specifically, I explore two gaps in the literature of attribution. First, most previous work on attribution processes has focused on the relationships between attributions and students' psychological and performance outcomes, while few studies have examined the behavioral consequences of attributions. Therefore, there is no consensus on the behavioral mechanisms through which attributions drive performance. Part of the reason has been the lack of timely measurement methods for capturing students' behavior that can be scaled up for large sample sizes. Yet, online learning platforms log every click that students make, allowing for timely and fine-grained measures of behavior that can be automatically computed for a large number of students. In addition, attribution interventions have been limited to having students watch pre-designed videos that attempt to manipulate attributions (Haynes et al., 2009; Perry & Penner, 1990; Wilson & Linville, 1982), while very few studies have explored the potential of automatic and individualized interventions that are now feasible in online learning environments.

In this dissertation, I address these gaps by using the rich clickstream data in online learning environments to understand the behavioral consequences of attributions and to design attribution interventions. Specifically, in Chapter 1, I explored how to use clickstream data to measure students' use of self-regulation strategies in online courses. Using the clickstream measures developed in Chapter 1, I then examined how online students' attributions were related to the changes in their subsequent effort, self-regulation behaviors, and performance in Chapter 2. Furthermore, in Chapter 3, I used the clickstream data from an online homework system to develop an individualized attribution intervention and tested the effect of the intervention on student attributions, behaviors, and performance.

CHAPTER 1: Using Clickstream Data to Measure Self-Regulated Learning in an Online Course

Introduction

Online learning has been growing quickly in higher education as a promising method to increase the accessibility and decrease the costs of higher education. In 2016, more than thirty percent of college students were enrolled in at least one online course and around fifteen percent of college students were completing their degree entirely online (National Center for Education Statistics, 2018, Table 311.15). Despite the rapid growth of online learning in higher education, current research has found that low course performance is an ongoing problem in online courses (Finnegan et al., 2008; Fritz, 2011; Macfadyen & Dawson, 2010). Controlling for selection into online courses, students in online courses tend to have lower persistence rates and worse course grades as compared to their counterparts in in-person courses (Xu & Jaggars, 2011, 2013). Moreover, online performance gaps tend to be larger for some student subgroups who are traditionally at-risk in college environments, such as males, African-American students, and students with lower levels of academic preparation (Xu & Jaggars, 2014).

There are many factors at the course level that could contribute to the low academic performance in online learning, such as poorly organized course structure, limited social interaction, and lack of timely feedback (Sun, Tsai, Finger, Chen, & Yeh, 2008; Willging & Johnson, 2009). At the student level, the low performance in online learning is due, in part, to the fact that some students are not well prepared to study in unstructured online environments (Artino Jr & Stephens, 2009). As suggested by self-regulation theories and the online learning literature, online courses require a higher degree of self-regulation as compared to in-person courses (Broadbent & Poon, 2015; Yukselturk & Bulut, 2007). More so than in in-person courses, in which students receive constant supports such as instructors' supervision and individualized guidance, students in online courses have substantially greater responsibility to regulate their own learning by establishing their own study plans and monitoring and controlling their cognition, motivation, and behavior to implement and gradually and effectively adjust their study plans (Dabbagh & Kitsantas 2004; Roll & Winne, 2015). Indeed, extensive evidence has shown that students' skills in regulating their own learning, measured by self-report questionnaires or observation, are important predictors of student performance in online courses (Azevedo, 2005; Dabbagh & Bannan-Ritland, 2005; Dabbagh & Kitsantas, 2004). Students who are traditionally marginalized in higher education, such as first-generation students and ethnic minority students, tend to report lower self-regulated learning (SRL) skills than their peers, which may contribute to their relatively lower performance in online courses (Bembenutty, 2007; Williams & Hellman, 2004).

In light of the critical role that SRL skills play in success in online learning, it is essential to assess student SRL skills and identify students who are likely to struggle in online courses so that institutions and instructors can provide timely supports to those students before and during the course. Researchers and practitioners mainly rely on self-report questionnaires to identify students with low SRL skills (Broadbent & Poon, 2015; Winne, 2010). However, these self-report questionnaires are usually costly and time intensive to administers. Another, perhaps more serious problem is that students' self-report data are not always accurate and may not reflect or predict student actual behavior in the course.

These questionnaires often ask students, at the beginning or end of a course, to predict or to recall the frequency, intensity, or likelihood with which they carry out a self-regulated learning process, such as making study plans in advance (Winne, 2010). However, student self-reports before or after an online course often do not accurately predict or capture their actual behaviors in the course (Winne, Jamieson-Noel, & Muis, 2002; Winne & Perry, 2000). Student self-reporting after a course requires that students recall their past behaviors, and such recall is based on students' memories which are likely to be unrepresentative and abbreviated versions of past events (Gilbert & Wilson, 2007). Students' self-reporting before a course, usually based on their past experiences, to predict their SRL behaviors in the future can invite even more opportunities for misreporting, since students may omit contextual features of past events that may profoundly influence their reactions in the future (Loewenstein, O'Donoghue, & Rabin, 2003).

These concerns have given rise to new avenues into research on measuring SRL in online learning environments. Clickstream data, the frequently collected, detailed, and real-time record of students' observable interactions with online learning environments over the span of the learning episode, provide new opportunities to measure SRL (Greene & Azevedo, 2010; Roll & Winne, 2015; Winne, 2010). Past research has shown that clickstream data can be used to capture SRL more accurately and provide a more comprehensive understanding of students' behaviors than self-reporting (e.g., Cicchinelli, Veas, Pardo, Pammer-Schindler, Fessl, Barreiros, & Lindstädt, 2018; Winne & Jamieson-Noel, 2002). A growing body of research has in particular used clickstream data from learning management systems, a type of commonly used learning environment, to describe, interpret, and evaluate student SRL behaviors (Roll & Winne, 2015). These studies have identified a variety of behavioral patterns that can be used as indicators of SRL behaviors, such as submitting assignments before the deadline and logging in to the platforms regularly (e.g., Baker, Evans, Li, & Cung, 2018; Cicchinelli et al., 2018; Crossley, Paquette, Dascalu, McNamara, & Baker, 2016).

While there is cumulative evidence that some of these clickstream measures, such as the number of assignments submitted before deadlines, are predictive of student achievement, the extent to which the clickstream measures capture SRL as intended by researchers remains unclear. The development and interpretation of these clickstream measures are often not guided by educational theories (Gašević, Dawson, Rogers, & Gašević, 2016) nor are the clickstream measures triangulated with data from other instruments that have been previously evaluated. Additionally, although it has been argued that clickstream data have many advantages over self-report data, practitioners may question the benefits of exerting effort to collect and analyze clickstream data as people might prefer existing self-report instruments of SRL, which they are familiar with and which seem to be efficient. Therefore, more direct evidence is needed to determine the extent to which clickstream measures of SRL can meaningfully improve the prediction of student future performance.

To address these questions, this study used both a self-report questionnaire and clickstream data to measure two sub-constructs of SRL in an online course: time management and effort regulation. Specifically, I investigated 1) the extent to which clickstream measures could provide valid inferences about the constructs of time management and effort regulation and 2) whether the clickstream measures of time management and effort regulation could meaningfully improve the prediction of student performance. The results show that the clickstream measures of SRL may offer more insightful and valid information about students' actual SRL behaviors than do students' own predictions before the course. In addition, the clickstream measures significantly improved the prediction of student performance both in the current and subsequent courses.

Literature review

SRL and Its Role in Online Learning

There is a large body of literature on SRL with numerous definitions and models developed over the last two decades. Pulling from previous models of SRL, the theoretical framework proposed by Pintrich (2004), a comprehensive framework that is most widely cited in the SRL measurement literature, defines SRL as the process whereby students actively and constructively set goals for their learning, constantly adjust those goals, and regulate their cognition, motivation, and behaviors to achieve them. Along with other SRL models, Pintrich's framework suggests that students are active and constructive participants in their learning process and self-regulated students have high motivation and can appropriately apply effective learning strategies to improve learning effectiveness based on their personal needs and the characteristics of the learning environment (Pintrich, 1991; Zimmerman, 1994).

To better describe and measure SRL, Pintrich further divided it into three subcomponents: the use of cognitive strategies, the use of metacognitive strategies, and the management of resources (Pintrich, 1991; Pintrich & De Groot, 1990). In particular, deep cognitive strategies, such as elaboration and organization, can help students integrate new information with prior knowledge and facilitate long-term retention of target concepts, skills, and ideas (Pintrich, 2004). Metacognitive strategies, defined as students' awareness of and ability to control their cognitive activities, allow students to set study plans for themselves and monitor and adjust their cognitive activities actively and effectively (Pintrich, 1991). Finally, resource management strategies, including the management of time and study environment, effort regulation, peer learning, and help seeking, refer to students effectively using and manipulating personal resources (e.g., study time and effort level) and environmental resources (e.g., the amount of potential distraction, such as TV and cell-phone, in the learning environment) and seek support from instructors and peers in order to facilitate their learning (Pintrich, 1991).

The Measurement of SRL

Researchers have made considerable efforts in measuring SRL for better understanding the process, the determinants, and the consequences of SRL (Winne, 2010). Practitioners also rely on these established measures to identify students with low SRL skills and to offer them encouragement, learning strategy tutorials, and other academic supports (Schellings & Van Hout-Wolters, 2011). Previous researchers and practitioners in online learning have mainly used self-report questionnaires and some other methods (e.g., think aloud protocol and observations) to measure SRL (Schellings & Van Hout-Wolters, 2011; Winne, 2010). A growing number of studies, however, have suggested that it is possible to better measure SRL using the detailed clickstream data available in online learning platforms. In this section, I provide an overview of previous work on the measurement of SRL in online learning where I focus on two approaches of measuring SRL: self-report questionnaire and clickstream data. For both approaches, I summarize how they are used to measure SRL and then discuss the extent to which the measures predict students' performance.

Self-report Questionnaire and SRL.

Using self-report questionnaires to measure SRL. Self-report questionnaires, such as the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1993), the Learning and Study Strategies Inventory (LASSI; Weinstein, Schulte, & Hoy, 1987), and the Study Process Questionnaire (SPQ; Biggs, 1987), have been used to measure SRL, with MSLQ being the most widely used (Broadbent & Poon, 2015). These questionnaires usually instruct students to respond to several Likert scale statements either predicting their behaviors in an upcoming course or recalling their behaviors in a course that just ended. Most of the SRL questionnaires are designed for traditional in-person classroom settings and have high or acceptable reliability measured by Cronbach's alpha coefficients, a commonly used indicator of internal consistency within measures (e.g., Loong, 2012; Taylor, 2012; Yilmaz & Orhan, 2011). A large body of research has borrowed or adapted measures from previous questionnaires, mainly MSLQ, to capture student SRL in online learning and has also reported high Cronbach's alpha coefficients (e.g., Artino Jr. & Jones II, 2012; Cho & Shen, 2013; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Lynch & Dembo, 2004; Puzziferro, 2008; Wang, Shannon, & Ross, 2013; Yukselturk & Bulut, 2007).

Self-report measures of SRL predicting success in online learning. A great body of research has used self-report measures directly taken or adapted from MSLQ to predict student success in online learning. Despite the evidence for the high psychometric quality of self-reported SRL measures in these studies, the evidence concerning the relationships between self-reported SRL measures and academic outcomes is mixed, with some studies suggesting significant and positive relationships between self-reported SRL and online course performance outcomes (e.g., Chang, 2007; Cho & Shen, 2013; Puzziferro, 2008) and others suggesting no relationships at all (e.g., Bruso & Stefaniak, 2016; Cicchinelli et al., 2018; Klingsieck, Fries, Horz, & Hofer, 2012).

For instance, Broadbent and Poon (2015) conducted a meta-analysis on twelve studies that examined the relationships between self-report measures of SRL and academic achievement in online higher education settings and found significant and positive associations between students' online achievement and their overall SRL and the subscales of time management, effort regulation, and metacognition. In contrast, a small but notable number of studies failed to find significant correlations between academic outcomes and self-report measures of SRL overall (e.g., Cicchinelli et al., 2018; Pardo, Han, & Ellis, 2016) or the subscales of time management (e.g., Bruso & Stefaniak, 2016; Cazan, 2014; Klingsieck et al., 2012; Lynch & Dembo, 2004) and effort regulation (e.g., Bruso & Stefaniak, 2016; Dunnigan, 2018).

Some researchers argue that these mixed findings may be due to the fact that some of the SRL questionnaires used are designed for traditional in-person courses and have not been adapted and contextualized to online learning environments. However, even using instruments that are established in online learning environments, several studies failed to identify significant relationships between student course performance and self-report measures of time management and effort regulation (e.g., Cazan, 2014; Dunnigan, 2018). Other researchers question the accuracy of the self-report measures, especially when they are collected before the course (e.g., Bruso & Stefaniak, 2016; Klingsieck et al., 2012). Indeed, previous research suggests that there are substantial issues associated with using self-report data to capture past or predict future behaviors, and the same issues may also apply to the measurement of SRL in online learning (Gilbert & Wilson, 2007; Winne et al., 2002; Winne & Perry, 2000).

First, self-reporting one's SRL behaviors after a course mainly involves memory reconstruction that may not accurately capture one's actual experiences in the course (Bruso & Stefaniak, 2016). These responses may suffer from issues including response bias and memory deficiencies. Indeed, previous studies suggest that memories can sometimes be biased as people are more likely to remember recent events or extreme events than they are to remember a typical event (Kahneman, Fredrickson, Schreiber, & Redelmeier, 1993; Morewedge, Gilbert, & Wilson, 2005). In a study that directly compared students' perceived use and actual use of SRL strategies, Winne and Jamieson-Noel (2002) found that students were positively biased in reporting their use of SRL strategies (e.g., setting goals for studying).

Perhaps even more problematic is using self-report questionnaires before a course starts to predict student SRL behaviors later on, which is often how the early identification of students with low SRL skills is attempted. Self-reporting the probability of carrying out an SRL behavior, such as the ability to maintain one's effort when the coursework is not interesting, requires students to make predictions based on their memories of similar events in the past. In addition to the problem of memories being inaccurate, memories are aggregated recall over many events and thus may lack significant contextual features (Gilbert & Wilson, 2007). Such features, however, may profoundly influence students' SRL behaviors (e.g., the goals they would set and the learning strategies they would apply), since SRL behaviors depend on the current condition of the external environments (e.g., the nature of the task and help resources available) and the internal environments (e.g., one's knowledge, learning skills, and task value beliefs; Hadwin, Winne, Stockley, Nesbit, & Woszczyna, 2001). Existing literature suggests that at the beginning of the course, students may ignore the difficulties of carrying out SRL behaviors and tend to be overconfident in estimating their ability to carry out SRL behaviors (e.g., Bernard, Brauer, Abrami, & Surkes, 2004; DiBenedetto & Bembenutty 2013; Matuga, 2009).

Finally, predicting one's SRL behaviors in an upcoming online course may be especially challenging for students who lack prior experience with online learning. As noted above, past experience is necessary, though insufficient, for predicting future behaviors (Gilbert & Wilson, 2007). For students who have limited or no experience with formal online learning, their predictions of SRL behaviors in online courses may not be reliable because such predictions may largely rely on students' past experience in in-person classrooms, a learning environment that substantially differs from online courses. For instance, because online courses have relatively flexible course schedules, students who have only experienced in-person courses with fixed schedules might have a hard time reporting how they would manage their study time in online learning.

Clickstream data and SRL.

Using clickstream data to measure SRL. A growing body of literature has used clickstream data collected from online learning environments to obtain more objective information on SRL behaviors (e.g., Baker et al., 2018; Cicchinelli et al., 2018; Crossley et al., 2016; Winne & Jamieson-Noel, 2002). Clickstream data are a class of detailed, frequent, and unobtrusive records of various kinds of students' click behaviors in online learning environments, such as logging in to the learning platforms, pressing the play and pause buttons of the lecture videos, submitting assignments, posting in the discussion forum, and so on. While they are not direct measures of the underlying mental processes, they correspond to students' cognition and metacognition and therefore provide promising opportunities for tracing and measuring SRL (Winne, 2010).

Researchers argue that clickstream data have several advantages over self-report data as measures of SRL (Winne, 2010). First, clickstream data are collected in authentic learning settings while learning is happening and therefore can be used to measure student behavior more objectively and accurately than self-report data based on unreliable memories. More importantly, such data enable researchers to trace back to the specific contexts of a given behavior, such as the content covered on the frame of the video where the student pauses for five minutes and the difficulty of the assignments that the student is about to complete. This information allows for a more thorough and comprehensive interpretation of the behavior than do the decontextualized self-report measures collected before or after the learning event (Winne, 2010). Second, clickstream data are unobtrusive and do not require students' effort or attention. Thus, they can be collected without interrupting the learning processes (Greene & Azevedo, 2010; Sha, Looi, Chen, & Zhang, 2012). In contrast, self-report questionnaires may encourage students to reflect on their behaviors. This reflection may serve as an intervention that changes students' behavior and bias the results in an unpredictable manner (Greene & Azevedo, 2010). Finally, the automatically collected clickstream data can provide timely, frequent, and large-scale measures of student behavior, which are usually not feasible with self-report instruments.

An emerging literature has explored the use of clickstream data to measure SRL in technology-enhanced learning environments. While some studies focus on interactive learning environments that are designed to support and promote SRL using various SRL tools, such as information processing (e.g., note-taking window), goal-setting, reflection, and help-seeking tools (Nussbaumer, Steiner, & Albert, 2008; Perry & Winne, 2006; Winne & Jamieson-Noel, 2002), much of the work has been done with clickstream data from learning management systems (e.g., Blackboard and Canvas), which are commonly adopted in higher education contexts. Learning management systems, unlike the learning environments explicitly designed to promote SRL, provide the basic functions needed for teaching and learning online, including delivering learning materials (e.g., text, video, and audio), managing learning activities (e.g., quizzes, assignments, and discussion), and supporting different forms of evaluation (e.g., exams and gradebook systems; Lewis et al., 2005; Martin, 2008). Students usually interact with learning management systems by downloading course materials, watching video lectures, submitting assignments, completing quizzes, posting on the discussion forums, and so on, which are similar to the learning activities in typical in-person courses (Kljun, Vicic, Kavsek, & Kavcic, 2007; Lewis et al., 2005).

While most of the previous studies that used clickstream data in learning management systems mainly focused on measuring student general effort or engagement rather than SRL, a few studies have taken a step further to measure time management, a sub-construct of SRL (e.g., Baker et al., 2018; Cicchinelli et al., 2018; Crossley et al., 2016; Lim, 2016; Park, et al., 2017; You, 2016). Three types of behaviors related to time management have been measured: studying on time, studying in advance, and spacing.

Studying on time is defined as viewing course materials or completing assignments before the deadlines, and researchers have used measures such as the frequency with which students view resources pertaining to face-to-face meeting dates in blended courses (Cicchinelli et al., 2018; Park et. al., 2017) to capture the amount of course work that students study on time. Similarly, studying in advance is defined as studying early before the deadlines instead of postponing studying until it is close to deadlines (Baker et al., 2018). Researchers have used measures such as how far in advance students start work on/turn in assignments in fully online courses to measure to what extent students study in advance (Crossley et al., 2016; Kazerouni, Edwards, & Shaffer, 2017; Levy & Ramim, 2013). Spacing is defined as distributing study time over a long time period instead of finishing a lot of coursework during a short time period (Baker et al., 2018; Park et al., 2017). For instance, prior research has used how widely one's work sessions are distributed within a week to capture the behavior of spacing (e.g., Baker et al., 2018; Lim, 2016; Park et al., 2017; You, 2016).

Clickstream measures predicting success in online learning. There is emerging evidence showing that clickstream measures of SRL, mainly time management behaviors, are good predictors of success in online learning (Baker et al., 2018; Cicchinelli et al., 2018; Crossley et al., 2016; Kazerouni et al., 2017; Levy & Ramim, 2013; Lim, 2016; Park et al., 2017; You, 2016). First, studies in college-level online courses have found that the clickstream measures of studying on time, studying in advance, and spacing are consistently predictive of higher course performance. For instance, several studies found consistent evidence that the more assignments students finished on time and the earlier students attempted or completed assignments, the better they performed on quizzes and final exams (e.g., Baker et al., 2018; Crossley et al., 2016; Park et al., 2017). In an online course where students were required to watch a number of videos by the end of the week, Baker and colleagues (2018) also found that the behavior of spacing, measured by the standard deviation of the watch time for each of the course videos within a week, was significantly and positively associated with quiz performance and final course grade.

Moreover, there is evidence that clickstream measures have better predictive power over self-report measures collected before the course (e.g., Cicchinelli et al., 2018). In one study about student SRL in a blended course, Cicchinelli and colleagues (2018) used both self-report questionnaire and clickstream data to measure SRL in a blended course. They found that self-report data collected at the beginning of the course did not predict course performance. In contrast, they found that the average time until a student returns to the platform after each face-to-face class, a behavioral measure that is opposite to studying in advance, was significantly and negatively associated with quiz score and final exam score.

Summary

Identifying valid measures of SRL is important for researchers and practitioners in online learning. Recent studies argue that clickstream data collected in online learning environments provide novel and promising opportunities for timely, objective, and comprehensive measures of SRL at large scale (Roll & Winne, 2015). Prior research has mainly used clickstream data collected from learning management systems, the mostly widely used online learning environments in higher education, to measure the SRL behaviors of time management. These studies have shown consistent evidence that clickstream measures of time management are predictive of student online performance.

However, despite the promising evidence on the associations between clickstream measures and performance, there are three important gaps in knowledge. First, it is still not clear the extent to which these clickstream measures could provide valid inferences about the constructs of SRL. The interpretation of clickstream measures as measures of SRL are researchers' inferences about observable interaction between students and the learning management systems, which are usually not guided by SRL theories (Gašević et al., 2016). Moreover, very few of the prior studies have looked beyond the associations between clickstream measures and student performance to triangulate clickstream measures with other instruments that have been evaluated before, such as the MSLQ. Therefore, more research is needed to compare self-report and clickstream measures of SRL in order to examine the extent to which researchers' inferences about student behaviors align with student self-report data collected based on theory-driven instruments. Such evidence can provide empirical and theoretical support for the validity or, in other words, the accuracy of the interpretation of the clickstream measures.

Moreover, although previous studies have found significant relationships between clickstream measures and student performance, very few studies have examined the extent to which clickstream measures could significantly improve the prediction of outcomes over self-reported SRL alone. As self-report questionnaires have already been widely used in higher education to measure SRL, such evidence is needed to better inform practitioners in deciding whether to invest their effort in understanding and utilizing the clickstream data reports provided by learning management systems or even collecting and analyzing extra clickstream data themselves.

It is worth noting that although one study from Cicchinelli and colleagues (2018) found that clickstream measures had better predictive power over student performance compared to student self-reported SRL before the course started, it only included student performance in the current course as the outcome variable. The relationships between clickstream measures and student performance in the current course may be overestimated since the clickstream measures, such as completing homework on time, may sometimes directly or indirectly account for part of the course grade. Moreover, it remains unclear the predictive power of clickstream measures over long-term outcomes and the effectiveness of using clickstream measures for early identifications of at-risk students. Therefore, studies are needed to explore the relationships between clickstream measures of SRL and academic outcomes beyond current course performance.

Finally, there are relatively few studies using clickstream data in learning management systems to measure other sub-components of SRL beyond time management. This is partially due to the fact that the aspects of SRL behaviors that can be inferred using clickstream data collected from a learning environment largely depend on the types of interactions students can have within the learning environment. The features of learning management systems, however, are not set up to explicitly support or record SRL behaviors, such as the use of cognitive strategies (e.g., note-taking and highlighting). Therefore, more studies are needed to explore the potential of innovative approaches for using clickstream data from learning management systems to measure other sub-constructs of SRL, such as effort regulation.

The present study

To address these gaps, this study examined the following research questions: 1) to what extent do clickstream measures provide valid inferences about students' self-reported SRL after the course, 2) to what extent does students' self-reported SRL before the course reflect their actual behaviors in the course, and 3) to what extent do clickstream measures complement self-report measures in predicting student performance in the current and subsequent courses?

Method

Research context

Course. This study was conducted in the context of a 10-week fully online Chemistry course at a public university in Fall 2016. The course schedule is presented in Table 1.1. The course contained four modules. Each module was comprised of 9 to 14 small study units. Each study unit consisted of a lecture video, a summary note, example problems, and homework problems. All the materials were released at the beginning of the course and were available to students until the end of the course. In each module, students also needed to take a one-hour quiz. The instructor recommended that students finish one module (i.e., complete all the study units and the one-hour quiz in a given module) every two weeks. Therefore, the four module quizzes were due on the Sundays of the second, fourth, seventh, and ninth weeks (see Table 1.1). Students' course grades were comprised of the scores from homework assignments (15%), the module quiz scores (20%), the midterm exam score (20%), and the final exam score (45%). This course was the first course of a series of general chemistry courses offered to first year college students, and students needed to get a grade of C- or better in this course in order to enroll in the subsequent courses.

Participants. A total of 319 freshmen enrolled in this course, which was also their first college course. Of these, 238 completed both the pre- and post-course surveys and were used as the main analytic sample.[1] Using this sample allowed me to compare one type

[1] I also conducted the analysis using the full sample of 319 students and found similar relationships between clickstream measures and student achievement (see Appendix A Table A.1)

of students' self-reported SRL with clickstream measures of SRL. As noted above, this course was the first of a course series. Therefore, I followed a subset of students who continued to the next course and collected their course grades in the subsequent course. Although most students did follow the preferred course sequence to take the subsequent course in the following quarter, due to low course grades or other personal reasons, 18 students did not take the subsequent course in the following quarter. Therefore, my analytic sample for subsequent course outcome included 220 students. [2]

Table 1.1
Course Design

Week	Dates	Topics	Course Material
1-2	9/22 - 10/7	Numbers, Units and Conversions	Module 1 (9 Segments)
3-4	10/10 - 10/21	Atoms, Ions and Molecules	Module 2 (13 Segments)
5	10/24 - 10/28		Midterm (Modules 1 & 2)
6-7	10/31 - 11/11	Reaction Stoichiometry	Module 3 (14 Segments)
8-9	11/14 - 11/25	Chemical Reactions in Water	Module 4 (12 Segments)

Data

Demographic variables. The institution provided data on student prior achievement (e.g., high school GPA and SAT scores) and a variety of student demographics (e.g., gender, age, and race). Eight of the 238 students who completed the pre- and post-course surveys had missing data on one or two demographic variables. Table 1.2 presents summary statistics on student demographic characteristics for the 230 students. The sample was predominantly female (79%). Students were, on average, around 18 years old. The sample was 48 percent Hispanic, 34 percent Asian/Pacific Islander, 13 percent White, and 5 percent African American. More than half of the students were first generation students (defined as neither parent having a college degree). Around half of the students

[2] Among the 18 students who did not take the subsequent course in the following quarter, 5 of them (28%) got a course grade below C- in the current course.

were from low-income families. Students' average high school GPA and SAT Total score were 3.96 and 1619, respectively.

Table 1.2
Descriptive Statistics of Student Demographic Characteristics

	Mean	SD
Female	0.79	/
Age	18.37	0.4
Hispanic	0.48	/
Asian / Pacific Islander	0.34	/
White	0.13	/
African American	0.05	/
First generation	0.63	/
Low income	0.56	/
SAT score	1619	130.82
High school GPA	3.96	0.19
N	230	

Self-report measures. Self-report data were collected through pre- and post-course surveys launched during the first and last week of the course. Measures adapted from MSLQ were used both in the pre- and post-course surveys to measure two sub-constructs of SRL: time management and effort regulation.

Time management was measured by two statements ($\alpha = 0.69$): "I keep/kept a record of what my assignments are/were and when they are/were due" and "I plan/planned my work in advance so that I could turn in my assignments on time." Effort regulation was measured by four statements ($\alpha = 0.67$):: "I often feel so lazy or bored when I study that I quit before I finish what I planned to do" (reverse coded), "I work/worked hard to do well in courses even if I don't/didn't like what I am/was doing," "Even when course materials are/were dull and uninteresting, I manage/managed to keep working until I finish/finished," and "I am/was quick to catch up with coursework when I start/started falling behind." All the self-report questions were measured in a 5-point answer format ranging from 1 (strongly disagree) to 5 (strongly agree).

Clickstream measures. I generated three clickstream measures for time management and one clickstream measure for effort regulation. I drew on three sources to create these measures: the definitions of the two concepts, the key behaviors captured by the survey measures, and previous studies on clickstream data in learning management systems (Baker et al., 2018; Park et al., 2017; Pintrich, 1991).

Three clickstream measures were defined to measure time management. The two survey measures of time management mainly capture the behavior of getting coursework done on time, which is in agreement with past work on SRL and achievement that finds that students with higher levels of time management skills are likely to study more materials before the deadline. Since the study units in a module contained all the learning material that students needed to learn before the deadline of the module, I created a clickstream measure of *studying on time* based on the proportion of units studied before the deadline. The behavior of studying a unit on time is defined as a student having visited unit page i of a give module j before the deadline of the final quiz of module j. The proportion of units a student studied on time was calculated for each module (P_j) and the average value of the proportion of units studied on time in the four modules ($\frac{P_1+P_2+P_3+P_4}{4}$) was used as the measure of studying on time in the analysis.

In addition, previous studies suggest students with higher time management skills are more likely to study early and to space out their study time instead of procrastinating, cramming, and completing coursework right before the deadlines (Elvers, Polzella, & Graetz, 2003; Michinov, Brunot, Le Bohec, Juhel, & Delaval, 2011). Therefore, I included two additional clickstream measures—*studying in advance* and *spacing*—that have been commonly used in previous studies to measure time management (e.g., Baker et al., 2018;

Crossley et al., 2016; Park et al., 2017). The behavior of studying in advance is defined as students studying a unit in advance of the deadlines. It can be captured by the time difference ($T_j - T_i$) between the deadline of the the final quiz of a given module j (T_j) and the timestamp of when a student visited the unit page i in module j for the first time (T_i). The average value of such time differences for each module was calculated ($\overline{T_j - T_i}$) and the average value across the four modules was used as a measure of studying in advance in the analysis ($\frac{\overline{T_1-T_i}+\overline{T_2-T_i}+\overline{T_3-T_i}+\overline{T_4-T_i}}{4}$).

Spacing is defined as spacing out one's study time and it is operationalized as the standard deviation of time difference ($std(T_j - T_i)$) between the deadline of the final quiz of a given module j (T_j) and the timestamp of when a student visited the unit page i in module j for the first time (T_i). Again, I used the average value of the standard deviations of the four modules in the analysis ($\frac{std(T_1-T_i)+std(T_2-T_i)+std(T_3-T_i)+std(T_4-T_i)}{4}$). I expect students with higher time management skills would study the units earlier in advance of the deadlines and have larger standard deviation values for the days before deadlines when students studied each unit than students with lower time management skills.

One clickstream measure was generated to capture effort regulation based on the definition of effort regulation. Effort regulation is defined as the extent to which students can maintain their effort level when they encounter difficulties (Pintrich, 1991). Based on this definition, one should measure the difference between student effort levels before and after they encounter some difficulties, such as uninteresting or difficult course materials. In online learning, students may encounter various kinds of difficulties, such as decreasing self-efficacy due to experiences of failure, growing confusion due to lack of timely support, and competing academic and non-academic tasks. Although it is difficult to identify specific moments when students experience difficulties, effort regulation could be approximately captured based on the overall trend of student effort level in the course. In previous studies on learning management systems, student effort level is usually measured by student time spent on the system, defined as time on task (Grabe & Sigler, 2002; Munk & Drlík, 2011). Therefore, I proposed to use the change in time on task during the course to measure effort regulation and capture this type of behavioral pattern. For each individual student, the change in time on task during the course was operationalized as the slope of a simple linear regression that regressed her time on task in a given module on the module number.[3] In order to estimate the slope for each individual student, I regressed module time on task against module number using a mixed model with random slope and intercept (i.e., $Time\ on\ task_{sj} = \beta_0 + \beta_{0s} + \beta_1 Module\ Number_{sj} + \beta_{1s} Module\ Number_{sj} + v_{sj}$). For each individual student, her unique slope was equal to the average slope of the whole sample plus her random slope (i.e., $\beta_1 + \beta_{1s}$). Results from the mixed model show that there was significant variation in the individual random slopes, supporting the use of the mixed model approach. Since students with higher effort regulation are better at maintaining their effort level, one would expect they also have larger slopes (i.e., more positive or less negative).

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[3] Time-on-task is usually measured based on the time interval between one click event and the subsequent click event, since students are assumed to be engaged in class-related activities (e.g., watching lectures and completing quizzes) between two click events (Kovanovic, GaĹˇevic, Dawson, Joksimovic, Baker, & Hatala, 2015). However, as previous studies pointed out, this approach can be problematic if students fall off-task and engage in other activities not related to learning between the two click events (Kovanovic et al., 2015). A commonly used technique to address this issue is to define a maximum value for the duration of an activity, such as 15 minutes (e.g., Grabe & Sigler, 2002; Munk & Drlík, 2011). If the time interval between the two click events is longer than the maximum value, it should be replaced by the maximum value. In this study, we measured time on task as the sum of the time differences between the click of one page and the click of the next page and set the maximum value to be one hour since module quizzes took one hour to complete.

Performance outcomes. I used student final exam scores and overall course grades in the current course as the performance outcomes to compare the predictive power between self-report and clickstream data. The final exam score and overall course grade were measured on a 100-point scale and 4-point scale, respectively. On average, students scored 64.99 out of the 100 available points on the final exam and received a course grade of 3.14 on a 4.0 scale (Table 1.3). I also included student course grades in the subsequent course to examine the predictive power of self-report and clickstream measures over long-term outcomes.

Analysis

Correlation analysis. To answer the first two research questions, I analyzed the relationships between self-report and clickstream measures of SRL. The analyses were conducted separately for time management and effort regulation. For each construct, I first examined the Pearson correlation coefficients between the clickstream measures and the pre-course survey measures. If the clickstream measures aligned with students' own prediction of their SRL behaviors, one would expect to see significantly positive correlation coefficients between the clickstream measures and the pre-course survey measures. Specifically, students who reported higher scores on the pre-course survey measures of time management would also score higher on the clickstream measures of studying on time, studying in advance, and spacing. Students who reported higher scores on effort regulation would also score higher on the clickstream measure on the change in time on task.

Table 1.3

Descriptive Statistics of Self-Report Measures, Clickstream Measures, and Course Performance

	M	SD	Min	Max	N
Pre-course self-report measures					
Time management					
Keeping record of assignments_PRE	4.07	0.93	1	5	238
Planning in advance_PRE	4.11	0.83	1	5	238
Effort regulation					
Quitting before finishing_PRE	3.73	0.86	1	5	238
Working hard to do well_PRE	4.2	0.83	1	5	238
Keeping working until finished_PRE	4	0.89	1	5	238
Catching up when falling behind_PRE	3.5	1.07	1	5	238
Post-course self-report measures					
Time management					
Keeping record of assignments_POST	3.84	1.05	1	5	238
Planning in advance_POST	3.51	1.06	1	5	238
Effort regulation					
Quitting before finishing_POST	3.55	1.02	1	5	238
Working hard to do well_POST	3.77	0.95	1	5	238
Keeping working until finished_POST	3.97	0.91	1	5	238
Catching up when falling behind_POST	3.64	1.05	1	5	238
Clickstream measures					
Time management					
Studying on time_CL	0.80	0.2	0.12	1	238
Studying in advance_CL	4.69	2.32	0.45	13.72	238
Spacing_CL	2.88	1.05	0.29	5.01	238
Effort regulation					
Change in time on task_CL	-0.84	0.54	-2.31	0.97	238
Course performance					
Current course final exam	64.99	17.78	2	99	238
Current course grade	3.14	0.73	1.00	4.00	238
Subsequent course grade	1.13	0.98	0.00	4.00	220

If I fail to find significant relationships between the clickstream measures and the pre-course survey measures, it could be that the clickstream measures could not capture SRL behaviors or that students could not accurately predict their future SRL behaviors in the course. Therefore, I also examined the Pearson correlation coefficients between the clickstream measures and the post-course survey measures, which were students' own retrospective perceptions or interpretations of their SRL behaviors in this specific course. If the clickstream data could to some extent measure SRL behaviors and students could fairly recall their SRL behaviors in the course, one would expect to see significantly positive correlation coefficients between the clickstream measures and the post-course survey measures.

Regression analysis. While the correlation analysis can be used to examine how similar the clickstream measures are to the well-established self-report measures, these analyses cannot provide evidence on if clickstream measures can enhance the utility of SRL measures. To answer this question, I regressed student performance outcomes on both the self-report and clickstream measures to compare the predictive power of clickstream measures and self-report measures. For each outcome variable, I conducted multiple regression analyses in five steps. The same regression analyses were conducted for pre- and post-course self-report measures separately as they may have different predictive power over course performance and the clickstream measures may complement the two types of self-report measures in different ways. The five regression models using pre-course surveys are written as:

$$y_i = \alpha + \sum_{k=0}^{2} \beta_{k0}\, TM_{PRE_{ki}} + \mu_i \tag{1}$$

$$y_i = \alpha + \sum_{k=0}^{2} \beta_{k1}\, TM_{PRE_{ki}} + \sum_{k=0}^{3} \beta_{k2}\, TM_{CL_{ki}} + \sum_{k=0}^{3} \beta_{k3}\, {TM_{CL_{ki}}}^2 + \mu_i \tag{2}$$

$$y_i = \alpha + \sum_{k=0}^{3} \beta_{k4}\, ER_{PRE_{ki}} + \mu_i \tag{3}$$

$$y_i = \alpha + \sum_{k=0}^{3} \beta_{k5}\, ER_{PRE_{ki}} + \beta_{k6} ER_{CL_i} + \beta_7 {ER_{CL_i}}^2 + \mu_i \tag{4}$$

$$y_i = \alpha + \sum_{k=0}^{2} \beta_{k1}\, TM_{PRE_{ki}} + \sum_{k=0}^{3} \beta_{k2}\, TM_{CL_{ki}} + \sum_{k=0}^{3} \beta_{k3}\, {TM_{CL_{ki}}}^2 + \sum_{k=0}^{3} \beta_{k5}\, ER_{PRE_{ki}} + \beta_{k6} ER_{CL_i} + \beta_7 {ER_{CL_i}}^2 + Student\_control_i + \mu_i \tag{5}$$

Model 1 regresses the outcome variable only on the two measures of self-reported time management, denoted as $TM_{PRE_{ki}}$. An F-test is conducted for the overall significance of the two self-report measures to test if they predict outcomes jointly. Model 2 adds the three clickstream measures of time management, denoted as $TM_{CL_{ki}}$. For each clickstream measure, a quadratic term, denoted as ${TM_{CL_{ki}}}^2$ is also included as previous research has found that the relationship between clickstream measures and performance tend to be nonlinear (Li, Kidzinski, Jermann, & Dillenbourg, 2015).[4] A partial F-test is conducted to test whether adding the three clickstream measures in Model 2 significantly improves model fit, or in other words, significantly improves the explanatory power of the regression. Model 3 regresses the outcome variable only on the four measures of self-reported effort regulation, denoted as $ER_{PRE_{ki}}$. Again, an F-test is conducted to test if the four self-report measures predict outcomes jointly. Model 4 adds the linear and quadratic terms of the clickstream measure of effort regulation, denoted as ER_{CL_i} and ${ER_{CL_i}}^2$. Again, a partial F-test is conducted for these two variables to test whether adding them significantly improves model fit. Finally, Model 5 regresses the outcome variable on the self-report and clickstream measures of both time management and effort regulation, controlling for all the demographic variables listed in Table 1.2, denoted as $Student\_control_i$.

Results

Descriptive statistics

The descriptive statistics for the self-reported time management and effort regulation before and after the course are presented in the first and second horizontal

[4] To determine whether the quadratic term is needed given that a linear term is already in the model, for the clickstream measure, I first regressed the outcome variable only on the linear and quadratic terms of the clickstream measure and examined if the quadratic term was significant. Finally, quadratic terms of studying in advance, spacing, and change in time on task were included.

panels of Table 1.3, respectively. In general, I found that students reported high levels of time management skills and effort regulation in the pre-course survey. Specifically, for both self-report measures of time management, the averages were higher than 4. For two out of the four self-report measures of effort regulation, the averages were also higher than 4. In the post course survey, however, students reported lower values on all of these measures compared to the pre-course survey except for the measure of catching up when falling behind. The decreases in self-reported time management and effort regulation from pre- to post-course surveys might suggest that the course had negative influences on students' SRL. However, as argued by previous studies with similar findings (Bernard et al., 2004; DiBenedetto & Bembenutty 2013; Matuga, 2009), the decreases may indicate that students tend to overestimate their SRL skills at the beginning of the course, especially for those who lack sufficient experience with online learning or college courses (e.g., the freshmen in my sample).

The descriptive statistics for clickstream measures are presented in the third panel of Table 1.3. On average, students studied 80% of the units in each module on time and studied the units in each module 4.69 days before the deadlines of the module quizzes. In addition, the behavior of spacing, measured by the standard deviation of days before deadlines when students studied each unit, ranged widely from 0.29 to 5.01. Finally, the negative value on the change in time on task indicates that students' effort level in this course, on average, tended to decrease over time. This finding may suggest the course required less effort over time. However, it may also suggest that students in this course, in general, encountered difficulties maintaining the effort necessary for the course since it usually requires more time instead of less to learn new materials as well as review previous materials as the course continues.

Correlation analysis

I then report the Pearson's correlation coefficients between clickstream measures and self-report measures. Table 1.4 presents the results for time management and Table 1.5 presents the results for effort regulation. Interestingly, I found that there were differences in the extent to which clickstream measures were related to pre- and post-course survey measures. For both time management and effort regulation, while there were, in general, moderate, positive, and significant correlations between clickstream measures and post-course survey measures, the correlations between clickstream measures and pre-course survey measures were, in general, small and insignificant.

Results in Table 1.4 showed that there were moderate, positive, and significant correlations between the two time management measures in the post-course survey and the clickstream measures of studying on time, studying in advance, and spacing. For instance, the clickstream measure of studying in advance was positively associated with student self-report of keeping record of assignments, $r(238) = 0.22$, $p < .001$, and planning in advance, $r(238) = 0.35$, $p < .001$, in the post-course survey. The clickstream measure of spacing was significantly correlated with the self-report measure of keeping record of assignment, $r(238) = 0.20$, $p < .05$, and planning in advance, $r(238)= .13$, $p < .05$, in the post-course survey. Yet, for the pre-course survey measure, only the measure of planning in advance was significantly correlated with the clickstream measure of studying in advance, $r(238) = .17$, $p < .05$.

I found similar results for effort regulation. Results in Table 1.5 showed that all the effort regulation measures in the post-course survey were positively and significantly correlated with the change in time on task. In contrast, only the self-report measure of quitting before finishing in the pre-course survey was positively and significantly correlated with this clickstream measure, r(238) = .22, $p < .001$. For instance, the change in time on task was positively and significantly associated with the self-report measure of keeping working until finished in the post-course survey, r(238)= .30, $p < .001$, and not with the same self-report measure in the pre-course survey, $r(238) = .10$, $p = .113$.

These significant correlations between clickstream measures and post-course survey measures show the alignment between the clickstream measures and students' own interpretations of their SRL behaviors and provide evidence for the validity of using clickstream measures to infer students' SRL. Additionally, the lack of significant correlations between pre-course survey measures and clickstream measures, which aligns with the results from previous studies (Gilbert & Wilson, 2007), suggests that students' anticipated behaviors or predictions made before the course may not reflect their actual behaviors in the course.

Table 1.4

Correlations Between Self-Report and Clickstream Measures of Time Management and Course Performance

	K_PRE	P_PRE	K_POST	P_POST	SOT_CL	SA_CL	SP_CL	CFE	CCG
Keeping record of assignments_PRE	1								
Planning in advance_PRE	0.53***	1							
Keeping record of assignments_POST	0.31***	0.30***	1						
Planning in advance_POST	0.31***	0.37***	0.56***	1					
Studying on time_CL	0.08	0.07	0.22***	0.27***	1				
Studying in advance_CL	0.02	0.17*	0.22***	0.35***	0.33***	1			
Spacing_CL	0.04	0.10	0.20*	0.13*	0.54***	0.49***	1		
Current course final exam score	-0.09	0.00	0.15*	0.16	0.47***	0.36***	0.33***	1	
Current course grade	-0.07	0.02	0.14*	0.16*	0.50***	0.36***	0.32***	0.94***	1

Note. * p<0.05 ** p<0.010 *** p<0.001

Table 1.5

Correlations for Self-Report and Clickstream Measures of Effort Regulation and Course Performance

	Q_PRE	W_PRE	K_PRE	C_PRE	Q_POST	W_POST	K_POST	C_POST	CT_CL	CFE	CCG
Quitting before finishing_PRE	1										
Working hard to do well_PRE	0.23***	1									
Keeping working until finished_PRE	0.32***	0.43***	1								
Catching up when falling behind_PRE	0.25***	0.34***	0.41***	1							
Quitting before finishing_POST	0.35***	0.03	0.25***	0.08	1						
Working hard to do well_POST	0.19**	0.2**	0.34***	0.07	0.32***	1					
Keeping working until finished_POST	0.22***	0.04	0.27***	0.12	0.42***	0.44***	1				
Catching up when falling behind_POST	0.29***	0.08	0.29***	0.17*	0.34***	0.35***	0.46***	1			
Change in time on task_CL	0.22***	0.00	0.10	-0.05	0.21**	0.26***	0.30***	0.28***	1		
Current course final exam score	0.07	0.08	0.01	-0.07	0.17**	0.18*	0.30***	0.23***	0.41***	1	
Current course grade	0.05	0.09	0.03	-0.05	0.20**	0.21**	0.32***	0.29***	0.42***	0.94***	1

Note. * p<0.05 ** p<0.010 *** p<0.001

Regression results

While the bivariate correlations indicate that the clickstream measures were associated with student self-reported self-regulation after the course, the question remains to what extent these clickstream measures could provide additional information than the survey data and whether they can be used to improve the prediction of student performance. Therefore, I used regression analysis to examine the predictive power of self-report measures and clickstream measures on students' course performance. Table 1.6 presents the results of using clickstream measures along with self-report measures in the pre-course survey to predict course performance, and Table 1.7 presents results from the same regression analyses using self-report measures in the post-course survey.

In each table, two outcomes in the current course—course grade and final exam score—were used. For each performance outcome, five regression models were tested. Model 1 regresses course performance on self-reported time management and Model 2 adds the clickstream measures (Equations 1 and 2). Similarly, Model 3 regresses course performance on self-reported effort regulation and Model 4 adds the clickstream measure (Equations 3 and 4). Finally, Model 5 regresses course performance outcomes on all self-report measures, clickstream measures, and student controls (Equation 5).

Predicting performance in the current course using pre-course survey and clickstream measures. Results from Model 1 and Model 3 in Table 1.6 reveal that students' self-reported time management and effort regulation before the course did not predict student performance in the current course. First, the joint F test for the overall significance of Model 1 revealed that neither of the coefficients on the two time management measures were statistically significant for course grade, $F(2, 235) = 1.10$, $p =$

.35, or final exam score, $F(2, 235) = 1.24$, $p = .29$. Similarly, the joint F test for the four self-report measures of effort regulation in Model 3 show that none of the coefficients was significantly different from zero for course grade, $F(4, 233) = 1.09$, $p = .36$, or final exam score, $F(4, 233) = 1.30$, $p = .27$. Overall, these results imply that pre-course survey measures of time management and effort regulation were not significantly predictive of student performance in the current course.

In contrast, I found that both the clickstream measures of time management and effort regulation significantly improved the prediction of both course grades and final exam scores in the current course. First, the partial F test for the clickstream measures of time management in Model 2 shows that adding the clickstream measures of time management significantly increased the explanatory power of the regression models for both course grades, $F(5, 230) = 19.24$, $p < .001$ and final exam scores, $F(5, 230) = 17.55$, $p < .001$. In particular, after controlling for students' self-reported time management, the clickstream measures of studying on time and studying in advance were predictive of higher course grade and final exam score, although no significant relationships were found for spacing (see Table 1.6 Model 2). For instance, a one standard deviation increase in studying on time was associated with around a 0.4 of a standard deviation increase in course grade and final exam score.

Similar results were found for effort regulation. After controlling for self-reported effort regulation in Model 4, the partial F test for the linear and quadratic terms of the change in time on task measure indicates that adding these two variables significantly increased the explanatory power of the regression models for both course grades, $F(2, 231) = 41.22$, $p < .001$ and final exam score, $F(2, 231) = 32.85$, $p < .001$. The change in time on task showed a significantly positive linear relationship and a significantly negative quadratic relationship with both course grade and final exam score. For instance, the change in time on task had a significantly positive linear relationship, ($ß$ = .449, $p < .001$), and a significantly negative quadratic relationship, ($ß$ = -.193, $p < .001$), with course grade. These results suggest that an increase in time on task was associated with better performance; however, the relationship became weaker as the students' levels of change in time on task increased.

Finally, the clickstream measure of studying on time, studying in advance, and the change in time on task were significant predictors of course performance even after controlling for a variety of student background characteristics (e.g., gender, race, and prior performance) (see Table 1.6 Model 5). For instance, a one standard deviation increase in studying on time was associated with around a 0.16 of a standard deviation increase in course grade and final exam score. Again, after controlling for student background characteristics, there was a positive relationship between change in time on task and course grade, ($ß$ = .245, $p < .001$), while the relationship decreased as students' change in time on task increased, ($ß$ = -.115, $p < .01$).

Table 1.6

Pre-Course Self-Report and Clickstream Measures of Self-Regulation Predicting Performance

	Course Grade					Final Exam Score				
	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
Time management										
Keeping record of assignments_PRE	-0.111	-0.116+			-0.070	-0.121	-0.122+			-0.089
	(0.08)	(0.07)			(0.06)	(0.08)	(0.07)			(0.06)
Planning in advance_PRE	0.081	0.017			0.078	0.064	-0.004			0.055
	(0.08)	(0.07)			(0.06)	(0.08)	(0.07)			(0.06)
Studying on time_CL		0.441***			0.160*		0.395***			0.161+
		(0.07)			(0.08)		(0.07)			(0.08)
Studying in advance_CL		0.238**			0.143*		0.258***			0.155*
		(0.07)			(0.07)		(0.08)			(0.07)
Studying in advance_CL^2		-0.019			-0.005		-0.042			-0.028
		(0.04)			(0.04)		(0.04)			(0.04)
Spacing_CL		-0.028			0.003		0.001			0.033
		(0.07)			(0.07)		(0.07)			(0.07)
Spacing_CL^2		0.004			0.004		0.015			0.013
		(0.05)			(0.04)		(0.05)			(0.05)
Effort regulation										
Quitting before finishing_PRE			0.050	-0.031	-0.048			0.075	-0.005	-0.017
			(0.07)	(0.06)	(0.06)			(0.07)	(0.06)	(0.06)
Working hard to do well_PRE			0.114	0.137*	0.148**			0.109	0.131*	0.146*
			(0.07)	(0.06)	(0.06)			(0.07)	(0.07)	(0.06)
Keeping working until finished_PRE			0.007	-0.057	-0.066			-0.008	-0.067	-0.070
			(0.08)	(0.07)	(0.06)			(0.08)	(0.07)	(0.06)
Catching up when falling behind_PRE			-0.103	-0.027	-0.030			-0.119	-0.049	-0.050
			(0.07)	(0.06)	(0.06)			(0.07)	(0.07)	(0.06)
Change in time on task_CL				0.449***	0.245***				0.428***	0.206**
				(0.06)	(0.07)				(0.06)	(0.08)
Change in time on task_CL^2				-0.193***	-0.115**				-0.159***	-0.080*
				(0.04)	(0.04)				(0.04)	(0.04)
Student controls					X					X
Self-reported time management	1.10					1.24				
Clickstream measures of time management		19.24***					17.55***			
Self-reported effort regulation			1.09					1.30		
Clickstream measure of effort regulation				41.22***					32.85***	
N	238	238	238	238	230	238	238	238	238	230

Note. All coefficients are standardized. +p<0.1 * p<0.05 ** p<0.010 *** p<0.001

Predicting performance in the current course using post-course survey and clickstream measures. I then repeated the same analyses using self-report measures in the post-course survey and clickstream measures. The results are presented in Table 1.7. First, results from Model 1 and Model 3 suggest that, unlike self-report measures in the pre-course survey, the measures in the post-course survey were predictive of student performance in the current course. The joint F test of the overall significance of Model 1 shows that the two time management measures combined were significantly associated with course grades, $F(2, 235) = 3.58$, $p < .05$, and final exam score, $F(2, 235) = 3.62$, $p < .05$, although results in Model 1 indicate that neither of the coefficients on the two time management measures in Model 1 was significant at the 0.1 level for course grade or final exam score.

For effort regulation, the joint F test of Model 3 reveals that the four self-report measures of effort regulation combined were significantly associated with course grade, $F(4, 233) = 8.87$, $p < .001$, and final exam score, $F(4, 233) = 6.70$, $p < .001$. In particular, results in Model 3 showed that the self-report measure of keeping working until finished was predictive of higher course grade ($ß = .202$, $p < .01$) and final exam score ($ß = .224$, $p < .01$), and the self-report measure of catching up when falling behind was predictive of higher course grade, ($ß = .166$, $p < .05$), though not final exam score. These significant relationships between course performance and student self-reported SRL after the course may suggest that students were more accurate at reporting their SRL after they had experienced online courses. However, these findings may also suggest that, when asked to report one's SRL after the course, students might rely on their current performance in the course to answer the survey.

In spite of the good predictive power of self-report measures in the post-course survey, I found that adding clickstream measures still improved the prediction of student performance in the current course. The partial F test for all the clickstream measures of time management in Model 2 showed that adding the clickstream measures of time management significantly increased the explanatory power of the regression models for both course grade, $F(5, 230) = 17.06$, $p < .001$, and final exam score, $F(5, 230) = 15.22$, $p < .001$. Specifically, there were large, positive, and significant relationships between course performance and the measures of studying on time and studying in advance. For instance, the clickstream measure of studying on time was significantly associated with higher course grade ($ß = .439$, $p < .001$) and final exam score, ($ß = .391$, $p < .001$), even after controlling for self-reported time management in the post-course survey. Similarly, results in Model 4 showed that adding the linear and quadratic terms of the change in time on task significantly increased the prediction of course grade, $F(2, 231) = 26.50$, $p < .001$, and final exam score, $F(2, 231) = 22.02$, $p < .001$, after controlling for self-reported effort regulation in the post-course survey.

After further combining all self-report and clickstream measures and controlling for student background characteristics in Model 5, the clickstream measures of studying in advance and studying on time were still predictive of higher final exam score, though not course grade. Again, there were significantly positive relationships between the measure of change in time on task for both course grade and final exam score, however, the positive relationships decreased as the change in time on task increased.

Table 1.7

Post-Course Self-Report and Clickstream Measures of Self-Regulation Predicting Performance

	Course Grade					Final Exam Score				
	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
Time management										
Keeping record of assignments_POST	0.075	0.031			-0.005	0.091	0.044			0.012
	(0.08)	(0.07)			(0.06)	(0.08)	(0.07)			(0.06)
Planning in advance_POST	0.118	-0.059			-0.066	0.104	-0.065			-0.046
	(0.08)	(0.07)			(0.07)	(0.08)	(0.07)			(0.07)
Studying on time_CL		0.439***			0.127		0.391***			0.141+
		(0.07)			(0.08)		(0.07)			(0.08)
Studying in advance_CL		0.260**			0.108		0.276***			0.133+
		(0.08)			(0.07)		(0.08)			(0.08)
Studying in advance_CL^2		-0.021			0.011		-0.043			-0.013
		(0.04)			(0.04)		(0.04)			(0.04)
Spacing_CL		-0.041			0.020		-0.015			0.033
		(0.08)			(0.07)		(0.08)			(0.07)
Spacing_CL^2		-0.003			0.002		0.006			0.016
		(0.05)			(0.04)		(0.05)			(0.05)
Effort regulation										
Quitting before finishing_POST			0.047	0.040	0.056			0.029	0.020	0.037
			(0.07)	(0.06)	(0.06)			(0.07)	(0.06)	(0.06)
Working hard to do well_POST			0.047	0.025	0.048			0.027	0.001	0.021
			(0.07)	(0.06)	(0.06)			(0.07)	(0.07)	(0.06)
Keeping working until finished_POST			0.202**	0.105	0.100			0.224**	0.134+	0.117+
			(0.08)	(0.07)	(0.06)			(0.08)	(0.07)	(0.07)
Catching up when falling behind_POST			0.166*	0.084	0.044			0.113	0.036	-0.013
			(0.07)	(0.07)	(0.06)			(0.07)	(0.07)	(0.07)
Change in time on task_CL				0.367***	0.219**				0.367***	0.186*
				(0.06)	(0.07)				(0.06)	(0.08)
Change in time on task_CL^2				-0.172***	-0.111**				-0.140***	-0.078*
				(0.04)	(0.04)				(0.04)	(0.04)
Student controls					X					X
Self-reported time management	3.58*					3.62*				
Clickstream measures of time management		17.06***					15.22***			
Self-reported effort regulation			8.87***					6.70***		
Clickstream measure of effort regulation				26.50***					22.02***	
N	238	238	238	238	230	238	238	238	238	230

Note. All coefficients are standardized. +*p*<0.1 * *p*<0.05 ** *p*<0.010 *** *p*<0.001

Predicting performance in the subsequent course using post-course survey and clickstream data. The results above reveal that clickstream measures could significantly improve the prediction of student performance in the current course over self-report data regardless of whether the self-report data were collected before or after the course. However, as noted above, the relationships between clickstream measures and student performance in the current course may be overestimated since the behaviors captured by the clickstream measures may, directly or indirectly, account for part of the course grade. For instance, students who studied more units before the deadlines were also more likely to be those who completed the module quiz on time, which accounted for 20% of the course grade. Thus, it is useful to include measures of performance in the subsequent course as outcome variables to reduce potential bias from specific course grading scales. In addition, including subsequent course outcomes allows me to examine whether clickstream measures could be used to predict long-term outcomes and identify at-risk students early on. Therefore, I examined whether the clickstream measures could improve the prediction of subsequent course outcomes over self-report measures in the post course survey.

First, to make sure that any difference that I observed in the subsequent course outcome analysis was not due to the change in the student sample, I regressed student grades in the current course on clickstream measures and self-report measures in the post-course survey only for the subset of students who enrolled in the subsequent course (N = 220). The results are presented in the first five columns in Table 1.8. Most of the regression coefficients were similar in sizes and directions to those in Table 1.7. It is worth noting that, perhaps due to the reduced sample size, some of the coefficients on the clickstream measures in Model 5, such as the linear term of the measure of change in time on task, were not significant.

I then conducted the same analysis using student grade in the subsequent course for the same subset of students. The results are presented in the last five columns in Table 1.8. In general, I found evidence that clickstream measures of time management and effort regulation could improve the prediction of students' subsequent course grades over self-report measures on the post-course survey. In Models 2 and 4, the partial F tests show that, while the self-report measures were predictive of subsequent course performance, adding the clickstream measures of time management, $F(5, 212) = 11.10$, $p < .001$, and effort regulation, $F(2, 213) = 8.61$, $p < .001$, significantly improved the prediction of subsequent course grades. Finally, results from Model 5 indicate that, after further controlling for students' background characteristics and current course grade, there was still a significant and positive relationship between students' subsequent course grades and the clickstream measure of studying in advance ($ß = .130$, $p < .1$), although not the clickstream measures of studying on time or the change in time on task.

Table 1.8

Post-Course Report and Clickstream Measures of Self-Regulation Predicting Subsequent Course Grade

	Current Course Grade					Subsequent Course Grade				
	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
Time management										
Keeping record of assignments_POST	0.002	-0.013			-0.017	-0.086	-0.101			-0.080
	(0.07)	(0.07)			(0.07)	(0.08)	(0.07)			(0.06)
Planning in advance_POST	0.118	-0.040			-0.048	0.283***	0.126			0.166*
	(0.07)	(0.08)			(0.07)	(0.08)	(0.08)			(0.07)
Studying on time_CL		0.373***			0.163*		0.288***			0.125
		(0.07)			(0.08)		(0.07)			(0.08)
Studying in advance_CL		0.312***			0.163*		0.298***			0.130+
		(0.08)			(0.08)		(0.08)			(0.07)
Studying in advance_CL^2		-0.030			-0.000		0.005			0.008
		(0.04)			(0.04)		(0.04)			(0.04)
Spacing_CL		-0.076			-0.013		-0.035			-0.010
		(0.08)			(0.07)		(0.08)			(0.07)
Spacing_CL^2		-0.029			-0.004		-0.032			-0.018
		(0.05)			(0.05)		(0.05)			(0.04)
Effort regulation										
Quitting before finishing_POST			0.019	0.033	0.055			-0.013	-0.002	-0.059
			(0.07)	(0.07)	(0.06)			(0.07)	(0.07)	(0.06)
Working hard to do well_POST			0.007	-0.032	0.006			0.086	0.051	0.085
			(0.07)	(0.07)	(0.06)			(0.08)	(0.07)	(0.06)
Keeping working until finished_POST			0.244**	0.159*	0.139*			0.130	0.057	-0.068
			(0.08)	(0.08)	(0.07)			(0.08)	(0.08)	(0.07)
Catching up when falling behind_POST			0.154*	0.118+	0.060			0.120	0.088	-0.049
			(0.07)	(0.07)	(0.07)			(0.08)	(0.07)	(0.06)
Change in time on task_CL				0.290***	0.123				0.252***	-0.063
				(0.07)	(0.08)				(0.07)	(0.08)
Change in time on task_CL^2				-0.140***	-0.078*				-0.121**	-0.017
				(0.04)	(0.04)				(0.04)	(0.04)
Student controls/+ Current course grade					X					X
Self-reported time management	2.02					6.95**				
Clickstream measures of time management		13.50***					11.10***			
Self-reported effort regulation			7.56***					3.74**		
Clickstream measure of effort regulation				12.65***					8.61***	
N	220	220	220	220	213	220	220	220	220	213

Note. All coefficients are standardized. +*p*<0.1 * *p*<0.05 ** *p<0*.010 *** *p*<0.001

Discussion

Key findings

In contrast to traditional learning, where students' learning activities are managed mainly by the instructors, online courses require students to independently plan, monitor, and adjust their learning process by themselves. Therefore, success in online courses heavily relies on students' SRL skills, such as time management and effort regulation skills (Broadbent & Poon, 2015). Appropriately measuring SRL is essential to the research and practice aimed at understanding and facilitating SRL in online courses. While most previous studies measure SRL with self-report questionnaires, self-report data may not accurately predict or reflect students' actual SRL behaviors since they are mainly based on biased and decontextualized memories (Gilbert & Wilson, 2007; Winne, 2010). In contrast, a growing number of scholars have argued that clickstream data collected from online learning platforms can be used to measure SRL objectively, unobtrusively, and frequently at scale (Winne, 2010).

Previous studies have explored the relationships between clickstream measures and student performance in online courses. However, very few of the clickstream measures are theoretically grounded (Gašević et al., 2016) or triangulated with well-established instruments. In this study, I used both a self-report questionnaire and clickstream data from the learning management platform to measure students' time management and effort regulation in an online course and compared the two types of measures. Specifically, I triangulated clickstream measures with student self-report data before and after the course. Unlike previous studies, this study provides direct empirical evidence on the extent to which these clickstream measures align with self-report measures. In addition, I used regression analyses to examine whether adding clickstream measures could improve the prediction of current and subsequent course outcomes over self-report measures. These results provide a useful guide to wisely choose SRL measures to trace the student learning process and effectively identify online students who are at-risk of low performance. Specifically, these results indicate that the clickstream measure of studying in advance is a particularly strong predictor of students' performance in both the current and subsequent courses, providing promising opportunities for the identification of at-risk students early in the learning process.

For self-report data, I found that measures in the pre-course survey were not correlated with students' clickstream behaviors later in the course nor predictive of students' current and subsequent course performance. Unlike the data from the pre-course survey, students' self-report measures of SRL on the post-course survey were correlated with the clickstream behaviors and were predictive of current and subsequent course performance outcomes. As suggested by previous studies, one potential reason for the lack of significant relationships for pre-course survey measures is that students tend to be overconfident at the beginning of the course and therefore cannot accurately predict their behaviors in the course (DiBenedetto & Bembenutty 2013; Gilbert & Wilson, 2007). This may be extremely problematic in my research setting where students were in their first year of college and had little to no prior experience with online learning. Indeed, I found students' self-reported time management and effort regulation both decreased from the beginning to the end of the course.

For clickstream data, as noted above, I found that the measures of studying on time, studying in advance, and spacing were significantly correlated with students' self-reported time management after the course and the measure of the change in time on task was significantly correlated with students' self-reported effort regulation after the course. Additionally, these clickstream measures significantly improved the prediction of both current and subsequent course performance outcomes over self-report measures in the post-course survey.

Collectively, these findings have important implications for future research and practice regarding SRL in online learning environments. First, the evidence for the validity of these fine-grained and unobtrusive clickstream measures would allow researchers to use them in future studies to extend our understanding of the dynamics of SRL at a more micro-level. In particular, along with longitudinal analysis methods, these measures could be used to track how SRL gradually and dynamically unfolds in authentic learning environments and to examine the different changing trajectories of student SRL behaviors. Furthermore, using these detailed clickstream measures, researchers could explore how personal and environmental factors (e.g., students' interest in the course content, the difficulty of the assignments, and the academic and social resources available) shape students' SRL behaviors dynamically by tracing back to the contexts of a given SRL behavior and analyzing the temporary factors associated with SRL behaviors.

In addition, these findings deepen our understanding of and provide guidance for using self-report questionnaires to identify at-risk students in online learning. Practitioners mainly rely on self-report measures of SRL as tools to identify students who are likely to suffer in online courses due to lack of SRL skills. Such identification is often followed by reaching out to at-risk students and offering academic supports, such as academic consultant services and study skills tutorials. Therefore, the effectiveness and efficiency of the identification of at-risk students and the subsequent academic supports largely rely on the predictive power of these SRL measures. However, my results suggest that self-report data before the course may not be reliable and therefore raise important concerns about the usefulness of the self-report measures of SRL, especially when they are used on students who have little online learning experience and at the same time, may need the most help.

Finally, this study identified several clickstream measures of time management and effort regulation that can be used to complement self-report measures in predicting student course performance. These measures are generated from data that are commonly recorded in learning management systems widely used by higher education institutions. Therefore, real-time reports based on these clickstream measures can be automatically generated at the student, classroom, department, and institution level and can inform education decision-making by students, instructors, and administrators. For instance, these reports can help instructors effectively target at-risk students and provide them with timely and tailored supports. Students can also refer to these reports to reflect on and adjust their own learning processes.

Limitations

There are a few limitations to my study. First, while the clickstream measure of the change in time on task could complement self-reported effort regulation in predicting current and subsequent course performance, attention should be devoted to potential ceiling and floor effects of this measure. This measure may be less sensitive for students who start with very low or very high levels of time on task and thus do not have much room to decrease or increase their time on task during the course, which may undermine its predictive power over performance. In this study, I conducted regression analyses to explicitly test if the change in time on task predicted performance differently for students who started with different levels of time on task in the first module (see Appendix A Table A2). I found that the clickstream measure of change in time on task had similar significant relationships with current course performance for students who started with different levels of time on task, suggesting there were no ceiling or floor effects. However, I found the clickstream measures of time management had better predictive power over course performance than the clickstream measure of change in time on task within students who started with similar levels of time on task in module 1. The finding indicates that the predictive power of the clickstream measure of change in time on task is limited within students who started with similar levels of time on task.

Additionally, I observed some interesting differences in the ways that self-report measures predict course performance in the current and subsequent courses. For instance, while the post-course survey measure of planning in advance was not predictive of current course performance, it was associated with significantly higher subsequent course performance. One potential explanation for the difference is that most of the students (99.97%) in the subsequent course analysis were enrolled in the in-person section, which may require different types of skills. Therefore, future research is needed to examine how student self-report and clickstream measures of SRL collected in online courses may differentially predict students' performance in different types of subsequent courses.

Conclusion

This study provides a methodological foundation and practical guidance for the use of clickstream data to measure SRL and contributes to the development of valid SRL measures. Using the clickstream measures that have been verified in this study, future research can track student SRL behaviors and explore the antecedents and consequences associated with SRL behaviors, which may help with the development of comprehensive frameworks of how student behaviors interact with personal and environmental factors dynamically. Additionally, this study raises important concerns regarding the use of self-report questionnaires to measure SRL and identify at-risk students. Since the memories that students use to reflect or predict their past or future SRL behaviors are not always representative of past events, relying solely on self-report data may lead to inaccurate measures of SRL and under- or over-identification of at-risk students. Finally, this study highlights the unique and significant contributions of clickstream data in the identification of at-risk students. Clickstream data can be used to automatically identify at-risk students in online courses so that students, instructors, and institutions can make more timely and informed decisions.

CHAPTER 2: Dealing with Failures in Online Learning: The Role of Effort Attribution Versus Ability Attribution

Introduction

Despite the rapid growth of online learning in higher education, there has been great concern about the problem of disengagement and low course performance in college online courses (Fritz, 2011; Xu & Jaggars, 2011). Previous studies have documented that in online courses, students' effort levels tend to decrease as the course continues (Hershkovitz & Nachmias, 2011; Kim & Frick, 2011; Park et al., 2017; Xie et al., 2006). This down spiral trend in students' effort could be explained by many reasons at both the student and course level, such as students' low motivation and poor time management skills, a lack of timely support from the instructor, and so on (Fryer, Bovee, & Nakao, 2014; Muilenburg & Berge, 2005; Song, Singleton, Hill, & Koh, 2004). Extensive studies in online learning have explored the issue of disengagement from the perspective of motivation, and some studies have applied attribution theory of academic motivation to understand how the experience of failures may negatively influence students' motivation and subsequent behavior (e.g., Fryer et al., 2014; Lee et al., 2013; Street, 2010).

In attribution theory, Weiner (1979) argued that students encounter great challenges in maintaining their expectancy for succeeding in future tasks, engagement, and performance when they experience failures in a course, and the direction and the extent to which students' expectancy, engagement, and performance may change partially depends on the specific causal factor that students attribute their failures to. Specifically, he suggested that ability and effort, two commonly used causal factors, have different effects on students' expectancy and subsequent behaviors. When students attribute failures to low ability, a stable and uncontrollable causal factor, they tend to believe that they cannot improve their performance, work less hard, and thus perform poorly on the subsequent task (Weiner, 1979). On the contrary, when students attribute failures to insufficient effort, an unstable and controllable causal factor, they tend to believe they can get a better outcome next time if they try harder, maintain or even increase their effort level, and thus perform well on the subsequent task (Weiner, 1979). These hypotheses have been supported mainly by laboratory research and field studies conducted in in-person classroom settings (Haynes, Perry, Stupnisky, & Daniels, 2009; Henry & Stone, 2001; Ho et al., 1999) with some supportive evidence from the context of online courses (e.g., Langford & Reeves 1998; Miltiadou & Savenye, 2003; Rakes, Dunn, & Rakes 2013; Rozell & Gardner III, 2000; Wang Peng, Huang, Hou, & Wang 2008).

However, limitations persist in the attribution literature. First, existing literature on the consequences of attributions has mainly focused on expectancy and performance, and much less research has been done to examine the relationships between the attribution process and student behavior. Therefore, the behavioral mechanisms through which attributions may influence performance remain largely unexplored. This is partially due to the difficulty in collecting objective and rich data on student behavior in in-person courses. However, the rich and nuanced clickstream data available in online courses provide a novel opportunity to objectively measure students' interaction with the learning environments and explore the behavioral mechanisms through which motivation constructs, such as attribution, may influence behavior.

In addition, although many studies conducted in in-person educational settings have confirmed the associations between effort and ability attributions, expectancy, and performance, there are a few studies that identified only very small relationships between these concepts (e.g., Bernstein, Stephan, & Davis, 1979; Covington & Omelich, 1984). Researchers have tried to explain the lack of significant relationships based on the characteristics of the task, mainly how familiar the task is to the participants (Parsons, 1981; Schulz & Heckhausen, 1999), while how other personal factors may moderate attribution processes has been largely overlooked. The expectancy-value theory puts the attribution process into a larger and more comprehensive theoretical model along with other personal and environmental factors, suggesting that other personal factors, such as students' previous behavior and their goals, may moderate the relationships between attribution, expectancy, behavior, and performance (Eccles, 1983). Additional work is needed to uncover the circumstances under which attributing failures to effort rather than ability may relate to higher levels of subsequent behavior and performance.

In light of these limitations, this study examined the role of effort and ability attributions for failures in the context of online learning. In particular, I not only investigated how attributing failures to effort rather than ability relates to students' expected changes in performance and actual changes in performance, but also examined the relationships between the attribution process and the changes in students' subsequent behavior based on the clickstream data collected from an online learning management system. In addition, drawing on expectancy-value theory (Eccles, 1983), I argue that the role of the attribution process is moderated by other personal factors, including students' previous behavior and current goals. Specifically, I explored whether the levels of students' previous behavior could moderate the relationships between students' attributions and their expected changes in performance. Moreover, I examined whether students' previous behavior and current goals could moderate the relationships between students' expected changes in performance and their changes in subsequent behavior.

Literature Review

Attribution theory

In attribution theory, Weiner (1979) argues that when experiencing failures, students may lower their expectancy for succeeding in a similar subsequent task. Since people tend to avoid situations that they believe exceed their skills, students with lower expectancy may become less engaged and perform worse in the subsequent task (Eccles, 1983; Eccles & Wigfield, 2002). The direction and extent to which the student's expectancy for future success will change also depend on the specific factor she attributes her prior performance to (Weiner, 1979).

Weiner (1979) proposed that the impact of a perceived causal factor depends on its properties, which can be classified by a three-dimensional matrix: stability x controllability x locus of control. The stability dimension refers to whether a causal factor changes or remains relatively constant over time. The controllability dimension refers to the extent to which persons have volitional influence over a causal factor. The locus of control dimension differentiates causal factors that are internal versus external to the individual. Failures lead to larger decreases in expectancy when attributed to stable and uncontrollable factors rather than unstable and controllable factors (Weiner, 1979, 1986).

In the earliest work on academic attribution conducted in laboratories, Weiner and colleagues defined four important factors related to academic performance—ability, effort, task difficulty/ease, and luck—that differed in the properties of the three dimensions (Weiner & Kukla, 1970; Weiner, Russell, & Lerman, 1979). Among these causes relevant to academic achievement, the properties and effects of effort and ability attributions have received the most attention and support in the literature (e.g., Brownlow & Reasinger, 2000; Hall et al., 2007; Haynes et al., 2008; Mezulis et al., 2004). Effort is perceived as an internal, unstable, and controllable causal factor, which could potentially be increased on the will of the students (Weiner, 1979). On the contrary, ability is classified as an internal, stable, and uncontrollable causal factor as it is considered a personal attribute that can hardly be changed during a short period of time (Weiner, 1979). Therefore, the negative effects of experiencing failures may be mitigated by effort attribution whereas amplified by ability attribution. Specifically, when a student attributes her prior failure to insufficient effort rather than low ability, she may be able to maintain or even increase her expectancy, effort level, and use of self-regulation strategies, and thus improve her performance on the subsequent task.

Consequences of attributing failures to effort versus ability

Drawing on attribution theory, prior research has mainly explored the relationships between effort and ability attributions with three types of outcomes: expectancy, academic-related behaviors, and performance. First, the relationships between attributing failures to effort versus ability and students' expectancy have been documented by both experimental studies in laboratory settings (e.g., Clifford, 1986; Fontaine, 1975; Heilman & Guzzo, 1978; McMahan, 1973; Meyer, 1980; Pancer & Eiser, 1977) and field studies in college classroom settings (e.g., Bernstein et al., 1979; Covington & Omelich, 1984; Greene, 1985; Henry & Stone, 2001). For instance, experimental studies in laboratory settings found that college students who were induced to attribute a poor performance on a prior exam to insufficient effort had higher expectancy for a subsequent exam than their counterparts who were induced to attribute the poor prior performance to low ability (e.g., Meyer, 1980; Pancer & Eiser, 1977; Valle & Frieze, 1976). Several field studies conducted in college classrooms also found that attributing failures to ability was negatively associated with expectancy (e.g., Greene, 1985; Henry & Stone, 2001; McMahan, 1973).

By influencing students' expectancy for success, attributions may then direct students' subsequent behaviors, including their effort and use of self-regulation strategies. Previous research provides some, though limited, evidence on the relationships between effort and ability attributions and effort (Bar-Tal, 1978; Chapin & Dyck, 1976; Dweck, 1975; Dweck & Reppucci, 1973). For instance, previous laboratory studies of time limited tasks have found consistent correlational evidence that students who attributed a prior failure to low ability tended to exert less effort, measured by the speed of task completion, than students who attributed a prior failure to low effort (Dweck & Reppucci, 1973).

A few attribution studies have also investigated students' use of self-regulation strategies, suggesting positive relationships between effort attribution and better help-seeking strategies and time management behavior (e.g., Ho et al., 1999; Magnusson & Perry, 1992; Peterson & Barrett, 1987; Rakes et al., 2013; Tessler & Schwartz, 1972). For example, several studies found that students who attributed failures to effort were more likely to seek help for problem solving skills, while students who attributed failures to ability were more likely to seek solutions to the problems directly (e.g., Ames & Lau, 1982; Magnusson & Perry, 1992; Peterson & Barrett, 1987; Tessler & Schwartz, 1972). Effort and ability attributions may also differentially influence students' self-regulation behaviors related to time management (Cleary & Zimmerman, 2004). For instance, several studies found that, in college in-person classrooms, high procrastinators tended to attribute failures to low ability, while low procrastinators made more effort attributions (e.g., Brownlow & Reasinger, 2000; Gargari, Sabouri, & Norzad 2011). Rakes and colleagues (2013) reached similar conclusions in their study about an online course. They found that procrastination was negatively associated with effort attribution while positively associated with ability attribution.

Finally, the hypotheses regarding the relationships between attributing failures to effort versus ability and performance have been supported by prior research on attributional retraining interventions conducted in college settings (e.g., Haynes et al., 2009; Perry & Hamm, 2017; Perry, Chipperfield, Hladkyj, Pekrun, & Hamm 2014). Attributional retraining interventions are designed to counteract the maladaptive ways students might interpret academic failures by encouraging students to attribute failures to unstable and controllable factors, such as lack of effort or ineffective learning strategies, rather than stable and uncontrollable factors, such as ability (Perry et al., 2014; Perry & Hamm, 2017; Wilson & Linville, 1982). Results from randomized controlled trials and longitudinal quasi-experimental studies conducted on first year college students showed that these interventions consistently improved students' short-term as well as long-term academic outcomes, such as scores on GRE problems, grades in the current course, and persistence rates and overall GPA in the current and following semesters (e.g., Noel, Forsyth, & Kelley, 1987; Overwalle, Segebarth, & Goldchstein, 1989; Perry et al., 2014; Perry & Penner, 1990; Wilson & Linville, 1982).

Beyond attribution: factors that moderate the influence of attribution

Although most studies have confirmed the impacts of attribution on expectancy and performance, there are a few studies that identified only very small relationships between attributions and these outcomes (e.g., Bernstein et al., 1979; Covington & Omelich, 1984; Richardson, Abraham, & Bond, 2012). Researchers argue that the inconsistency in previous research about attribution may be due to differences in the features of the tasks examined in these studies and suggest that attributions play a more important role in the context of beginners completing novel tasks (Parsons, 1981; Schulz & Heckhausen, 1999). For instance, Parsons (1981) proposed that the attribution process may play a more salient role in tasks that students do not have much experience with than in tasks that students are familiar with. However, these arguments cannot fully explain the lack of significant findings in studies that examined students' attribution in college introductory courses (e.g., Bernstein et al., 1979) and in a meta-analysis that examined the relationship between attributions and university students' grade point average scores (Richardson et al., 2012). The inconsistency in prior research points to the need for further examination of other personal factors that may moderate the process of attribution affecting expectancy, behavior, and performance.

As pointed out by Bar-Tal (1978), the theoretical model of attribution has roots in expectancy-value theory of motivation (Atkinson, 1964), which argues that students' academic behavior and performance are not only determined by the extent to which they believe they can succeed in a task but also by how much they think the task is valuable and how costly it may be to succeed in the task (Eccles, 1983). The three components, namely expectancy, value, and cost, work jointly rather than individually to influence students' motivation and academic behavior. Specifically, when a student experiences a failure in a prior task, she may increase her effort to improve her performance in a subsequent task only if she believes that her performance could be improved by increasing effort, it is important for her to perform well, and it is not too costly to achieve a good performance. In other words, while attributing failures to insufficient effort rather than low ability may help students to maintain or increase their expectancy and thus their subsequent effort and self-regulation behaviors, this process may be moderated by students' cost beliefs and task values.

First, cost beliefs may moderate the relationship between attributions and expectancy. Cost is broadly conceptualized as the negative outcomes resulting from engaging in a task, which includes three components: effort cost (i.e., how much effort is needed to accomplish a task), opportunity cost (i.e., how much engaging in a task limits access to other valued activities), and emotional cost (i.e., negative emotions resulting from participating in a task; Eccles, 1983). Several studies have found students' perceptions of the effort required to do well to be negatively associated with expectancy (e.g., Eccles & Wigfield, 1995), suggesting students may lower their expectancy for succeeding in a future task when they believe that to succeed in the task requires too much effort. When perceiving high effort costs, students may also try to avoid the negative experience of failing a valued task by directly lowering their goals and the importance they attach to the task. For instance, it has been found that effort cost positively relates to performance-avoidance goals and negatively relates to achievement goals and task values (Conley, 2012; Safavian, Conley, & Karabenick, 2013).

In addition, previous studies have directly linked cost beliefs with maladaptive behavioral and achievement outcomes (Barron & Hulleman, 2015; Johnson & Safavian, 2016), suggesting cost beliefs may also moderate the positive relationship between expectancy and subsequent behavior and performance. Studies have found that increases in cost beliefs, especially effort cost and opportunity cost, are associated with decreases in students' intentions to persist, engagement, self-regulation behaviors, persistence rates, and academic achievement (Jiang, Rosenzweig, & Gaspard, 2018; Perez, Cromley, & Kaplan, 2014; Safavian et al., 2013). For instance, Jiang and colleagues (2018) found that cost beliefs were positively associated with students' avoidance intention and procrastination and negatively associated with achievement in math classrooms among 8th graders. Perez and colleagues (2014) found that for college students, the intention to drop a STEM major was significantly higher among those who tended to believe the major required more effort. Luttrell and colleges (2010) also identified a negative relationship between opportunity cost and college students' course-taking behaviors.

Finally, the relationship between expectancy and subsequent behavior and performance may also be moderated by students' subjective task values (Bar-Tal, 1978). In expectancy-value theory, Eccles (1983) argues that task value, defined as the incentive for being engaged in an academic activity, is an important determinant of students' academic behavior There is extensive evidence that students' subjective task values are strong predictors of students' intention for and actual behaviors of participating in academic activities (e.g., Eccles, Wigfield, Harold, & Blumenfeld 1993; Wigfield & Cambria, 2010; Wigfield & Guthrie, 1997). The moderating effect of task values on the attribution process is supported by early work that examined how attribution intervention may differentially affect the performance of individuals with high and low need for achievement. These studies found that the intervention that manipulated students to attribute their performance to effort and ability rather than ability only had positive effects on performance only for students with high need for achievement while no effects for students with low need for performance (Kukla, 1972; Weiner & Sierad, 1975).

Summary

As suggested by attribution theory, the change in behavior is an important outcome of attribution, serving as an intermediate between expectancy and performance in the attribution model. However, unlike expectancy and performance, remarkably few empirical studies have focused on the behavioral outcomes of attribution. It remains largely unexplored the extent to which attributions may lead to changes in behavior through the impact on expectancy. Similarly, it is not clear the behavioral mechanisms through which attributions may influence performance. To enhance our understanding of the motivational and behavioral processes proposed by attribution theory, much more research is needed to investigate the relationships between attributions and changes in behavior.

Part of the reason for the lack of evidence on behavioral consequences of attribution may be the difficulty of measuring students' behavior in in-person classrooms. Previous studies conducted in in-person classroom settings have mainly used two methods—self-report questionnaire and observation—to measure students' behavior. However, neither of the two methods can provide accurate, timely, and feasible measures of behavior for a large number of students. The clickstream data collected through online learning platforms may help to address the measurement issue. Using the clickstream data in online learning, researchers have identified various behavioral measures that are predictive of students' performance (e.g., Baker, Walonoski, Heffernan, Roll, Corbett, & Koedinger, 2008; Davis, Chen, Hauff, & Houben, 2016; Kovanovic et al., 2015). These behavioral measures provide novel and promising opportunities to explore influences of motivational processes, such as the attribution process, on behavior.

Another limitation of prior research on attribution is that it has infrequently considered other personal factors that may interact with the attribution process and thus moderate the effect of attribution. Drawing on expectancy-value theory (Eccles, 1983), students' cost beliefs and task values or factors related to them may moderate the relationships between attribution and expectancy and the relationships between expectancy and subsequent behavior. Further empirical evidence is needed to explore how these personal factors may moderate the attribution process, which can help build a more solid and comprehensive understanding of the attribution process.

The present study

To address these gaps, this study employed clickstream data collected from an online course to examine the relationships between students' attributions, expectancy, changes in students' behavior, and changes in performance. In addition, as suggested by expectancy-value theory (Eccles, 1983), the role of the attribution process is moderated by students' cost beliefs, task value, and factors related to them. Therefore, this study also examined whether the role of attributions would be moderated by students' prior behavior and desired score for a subsequent exam. Students' prior behavior, such as how much time they spent on the prior task, is an important source based on which students estimate the amount of effort required to succeed in the subsequent task. Students' desired score for the subsequent exam measures students' short-term academic goals, which is a main determinant of students' task value in the expectancy-value model (Eccles, 1983). In particular, this study examined two research questions: 1) how attributing a prior failure to effort rather than ability would relate to the extent to which students expected increases in their exam outcomes and 2) how students' expected changes in exam outcomes would relate to changes in their behavior and changes in their actual exam outcomes. Moreover, I investigated how these relationships may be moderated by students' prior behavior and desired scores for the subsequent exam.

Three hypotheses were tested in this study. First, I hypothesized that among students with low levels of prior behavior, the tendency of attributing failures to effort rather than ability would be positively associated with expected changes in exam outcomes. However, since high levels of prior behavior along with effort attribution may lead to high perceived effort cost and thus low expectancy and low future goals, I hypothesized that, among students with high levels of prior behavior, the tendency of attributing failures to effort rather than ability would be negatively associated with expected changes in exam outcomes and desired scores for the subsequent exam. Finally, since students' academic behavior is jointly determined by expectancy, task value, and cost beliefs, I hypothesized that expected changes in exam outcomes would be positively associated with changes in subsequent behavior and changes in actual exam outcomes only for students who had low levels of prior behavior and high levels of desired scores.

Method

Research context

Course. This study was conducted in a 10-week fully online course about biological and chemical principles related to food and cooking at a public university in Winter 2018. This course was highly structured and contained 18 lessons. In each week, students needed to complete one to two lessons, which included a reading guide, pre-lesson quizzes, video lectures, and participation assignments on a discussion board. At the end of each week, students needed to complete a review quiz, which contained questions about the lessons in that week. In addition to these weekly learning activities, there was a food experiment project that required students to apply concepts they learned in this course by conducting a food or cooking experiment at home. Finally, students took two midterm exams on the Wednesdays of weeks 4 and 8 and a final exam five days after the instruction ended. Students' course grades were comprised of the scores from survey participation (1%), discussion board assignments (4.5%), food experiment project (6%), pre-lesson quizzes (9%), weekly quizzes (4.5%), and exams (75%).

Participants. A total of 394 students enrolled in this course. To identify students who experienced failures in the course, for both midterm exams, I administered a post-midterm exam survey to students one day after they received their scores on the midterm exam. The one-day interval was chosen to make sure most students had checked their midterm scores before filling out the survey. The first question on these surveys asked students to report how well they did on the midterm exam. Following previous studies about attribution (e.g., Ames & Lau, 1982; Ho et al., 1999), students who reported that they did poorly or very poorly on the midterm exams were identified as students who experienced failures in the course.

Previous studies suggest that students may gradually develop more realistic perceptions about themselves and the learning environments as the course continues and students' self-reported motivational beliefs measured later in the course have higher correlations with each other and better predictive power over their behavior and performance (e.g., Gilovich, Kerr, & Medvec, 1993; Wicker, Turner, Reed, McCann, & Do, 2004). Therefore, this study focused on the survey data collected after the second midterm in the analysis. Among the 315 students who completed the second survey, 89 students reported that they performed poorly or very poorly on the second midterm and were therefore used as the analytic sample.

Data

This study collected four types of data: students' self-report data, clickstream data from the learning management system, students' course performance, and their demographic information. Multiple waves of data were collected. As mentioned above, there were in total three exams in this course, splitting the course into three time periods: Time 1 (before students took the first midterm exam: weeks 1, 2, and 3), Time 2 (after students took the first midterm exam and before students took the second midterm exam: weeks 5, 6, and 7), and Time 3 (after students took the second midterm and before students took the final exam: weeks 9 and 10). Two waves of self-report data were collected in the first weeks of Time 1 and Time 2. Three waves of clickstream data were collected during Time 1, Time 2, and Time 3.

Demographic variables. The institution provided data on student prior achievement (e.g., high school GPA and SAT scores) and a variety of students' demographics (e.g., gender, age, and race). Twelve of the 89 students in the analytic sample had missing data on one or two demographic variables. To maintain sample size, I kept students who had missing data on demographics and included indicators for missing data on these variables in the regression analysis. Table 2.1 presents the descriptive statistics on demographic characteristics for the 89 students. The sample was predominantly female (76%). Students were, on average, around 20 years old. The sample was 42 percent Asian, 33 percent

Hispanic, 12 percent White, 10 percent international students, and 3 percent other ethnic groups. More than half of the students were first generation students (defined as neither parent having a college degree). Around 40 percent of the students were from low-income families. Students' average high school GPA and SAT total score were 3.91 and 1722.56, respectively.

Table 2.1
Descriptive Statistics of Students' Demographic Characteristics

	Mean	SD	N
Female	0.76	/	88
Ethnicity		/	
Asian	0.42		86
Hispanic	0.33		86
White	0.12		86
International students	0.10		86
Other	0.03		86
First generation college student	0.54	/	87
Low income	0.38	/	89
Age	20.09	1.51	89
High school GPA	3.91	0.28	77
SAT score	1722.56	221.87	82

Note. A total of 89 students were included in the analytic sample.

Self-report measures. Students' self-evaluation of their performance on the second midterm, attributions for their midterm performance, expectancy for final exam, and desired score for final exam were measured in the second survey, which was launched in week 9 after students received their scores on the second midterm exam. The first panel in Table 2.2 presents the descriptive statistics for these measures.

Self-evaluation of exam performance. The first question on the survey asked students to evaluate their performance on the second midterm exam: "Please rate how well you think you did on the midterm exam." The response consisted of 5 options: 1 = very poorly, 2 = poorly, 3 = fairly, 4 = well, and 5 = very well. Since the analytic sample only included students who self-reported performing poorly or very poorly, the average score of self-evaluated exam performance was relatively low for the analytic sample (M = 1.64, SD = 0.48).

Attribution. Students were then asked to consider how important each of the causal factors, effort, ability, interest, and course difficulty, was in determining their performance on the midterm exam. These questions were adapted from previous attribution studies (e.g., Elig & Frieze, 1979) and were measured on a 5-point scale, ranging from 1 (very unimportant) to 5 (very important). Specifically, ability attribution was measured by two items (e.g., "the amount of talent you have in biology and chemistry", α = .67), effort attribution was measured by six items (e.g., "the amount of effort you put into this course", α = .91), interest attribution was measured by three items (e.g., "how much the course material interested you", α = .88), and course difficulty attribution was measured by three items (e.g., "the ease or the difficulty of the questions on the midterm", α = .78).[5]

Students in the analytic sample, on average, reported high values of effort attribution (M = 3.79, SD = 0.86) and relatively low values of ability attribution (M = 2.76, SD = 0.88). To directly capture students' tendency to attribute failures to effort rather than ability, the measure of *effort attribution relative to ability attribution* was calculated by subtracting ability attribution from effort attribution. Students in the analytic sample tended to attach more importance to effort than ability (M = 1.03, SD = 1.11).

[5] 24 items were used in the survey to measure eight causal factors. Finally, four factors were identified from a factor analysis, including effort, ability, interest, and course difficulty.

Expectancy. Two questions were used to capture students' expectancy for succeeding in the final exam. First, following the literature of expectancy (Eccles, 1983), students were asked to respond how well they expected to perform on the final exam on a 5-point scale, ranging from 1 (very poorly) to 5 (very well). In addition, students were directly asked what score they expected to get on the final exam. Given that the total score on the final was 250 points, the response format consisted of 5 options: 1"Less than 149 points (Less than 60%)", 2 "150-174 points (60-70%)", 3 "175-199 points (70-80%)", 4 "200-224 points (80-90%)", and 5 "More than 225 points (More than 90%)".

Based on the expectancy measures, two measures were calculated to capture to what extent students expected their performance would improve from the second midterm exam to the final exam. First, student *expected change in exam performance* was calculated as the difference between students' expected performance on the final exam and their self-evaluation of their midterm performance (M = 2.18, SD = 1.12). In addition, students' *expected change in exam scores* was calculated as the difference between their expected scores on the final exam and their actual scores on the second midterm exam (M = 1.73, SD = 1.05). The descriptive statistics for the two measures are also presented in Table 2.2. On average, students in the analytic sample tended to expect that their performance on the final exam would be better than their performance on the second midterm exam.

Desired score. One question was used to measure what score students desired to get on the final exam. The response format consisted of 5 options: 1"Less than 149 points (Less than 60%)", 2 "150-174 points (60-70%)", 3 "175-199 points (70-80%)", 4 "200-224 points (80-90%)", and 5 "More than 225 points (More than 90%)". On average, students in the analytic sample reported very high desired scores for the final exam (M = 4.31, SD = 0.78).

Clickstream measures. One clickstream measure, *time on task*, was used to capture students' effort levels in both Time 2 and Time 3, and two clickstream measures, *completing quizzes on time* and *watching lectures on time*, were used to capture students' positive time management behaviors in both Time 2 and Time 3. The descriptive statistics of the clickstream measures are presented in the second panel of Table 2.2.

Time on task. Following previous studies, I measured students' time on task by the sum of the time intervals between one click event and the subsequent click event (Grabe & Sigler, 2002; Kovanovic et al., 2015; Munk & Drlík, 2011). Moreover, since students may fall off-task and engage in other activities not related to learning between the two click events (Kovanovic et al., 2015), I set a maximum value to be half an hour and replaced the time interval between the two click events that was longer than half an hour to be half an hour. In particular, I calculated the average weekly hours that students spent on the course website during Time 2 and Time 3. Specifically, clickstream data collected from weeks 5, 6, and 7 were used to calculate students' time on task during Time 2. Clickstream data collected from only week 10 were used to calculate students' time on task during Time 3 to make sure that only clickstream data collected after students submitted the second survey contributed to behavioral measures in Time 3. On average, students in the analytic sample spent around 4.60 hours per week during Time 2 and around 5.23 hours per week during Time 3. The difference in students' time on task between Time 2 and Time 3 was calculated as the change in time on task (M = 0.08, SD = 2.33).

Time management behaviors. Since students' main learning activities in this course were completing quizzes and watching lectures, I created two measures, *completing quizzes on time* and *watching lectures on time*, to capture time management behaviors related to these two learning activities. The behavior of completing a quiz on time is defined as a student having submitted the quiz before the deadline. The percentage of quizzes completed on time for each week was calculated, based on which the average weekly percentage of quizzes completed on time in Time 2 and Time 3 were then calculated. On average, students in the analytic sample completed around 66% of the quizzes on time in both Time 2 and Time 3. The difference in the percentages of quizzes completed on time in Time 2 and Time 3 was then calculated and used in the analysis (M = 0.00, SD = 0.30).

The behavior of watching a lecture on time in a given week is defined as a student watching the lecture before the deadline of the review quiz of that week since to perform well on the review quiz required students to carefully watch the lectures and understand the content covered in the lectures. A simple way to decide whether a student watched a lecture before the deadline or not was to see whether the student opened the lecture before the deadline, which was recorded in the clickstream data. However, students might open a lecture accidently or just to check what the lecture was about without spending time watching it. To reduce potential noise in the clickstream data, the behavior of watching a lecture before the deadline was operationalized as students having opened the lecture and spent time longer than one-tenth of the length of the lecture before the deadline. Based on this operationalization, I calculated the percentage of lectures watched on time every week for each student and then students' average weekly percentage of lectures watched on time in Time 2 and Time 3. On average, students watched around 47% of the lectures on time in Time 2 and watched around 41% of the lectures on time in Time 3. The difference in students' percentages of lectures watched on time in Time 2 and Time 3 was then calculated (M = -0.06, SD = 0.32).

Performance. Students' scores on the second midterm exam and final exam were collected as performance measures. The difference between students' scores on the final exam and the second midterm exam was calculated to measure the actual change in students' exam scores from Time 2 to Time 3. The descriptive statistics of the performance measures are presented in the third panel of Table 2.2. On average, students in the analytic sample had higher scores on the final exam than the second midterm exam (M = 20.56, SD = 46.01).

Table 2.2
Descriptive Statistics of Students' Attribution, Expectancy, Goals, Behaviors, and Performance in Time 2 and Time 3

	Mean	SD	Median	N
Self-report measures				
Self-evaluation of exam performance	1.64	0.48	2.00	89
Effort attribution	3.79	0.86	4.00	89
Ability attribution	2.76	0.88	3.00	89
Interest attribution	3.00	0.95	3.00	89
Course difficulty attribution	3.61	0.86	3.67	89
Effort attribution relative to ability attribution	1.03	1.11	1.00	89
Expectancy for final exam	3.82	0.92	4.00	89
Expected change in exam performance	2.18	1.12	2.00	89
Expected final exam score	4.00	0.85	4.00	89
Expected change in exam scores	1.73	1.05	2.00	89
Desired score	4.31	0.78	4.00	89
Clickstream measures				
Time on task_T2	4.60	2.14	4.38	89
Time on task_T3	5.23	2.43	4.69	89
Change in time on task	0.08	2.33	-0.40	89
Completing quiz on time_T2	0.66	0.23	0.67	89
Completing quiz on time_T3	0.66	0.25	0.67	89
Change in completing quiz on time	0.00	0.30	0.00	89
Watching lecture on time_T2	0.47	0.27	0.42	89
Watching lecture on time_T3	0.41	0.31	0.25	89
Change in watching lecture on time	-0.06	0.32	-0.04	89
Performance measures				
Midterm score	165.62	25.49	170.00	89
Final exam score	186.18	51.07	200.00	89
Actual change in exam score	20.56	46.01	30.00	89

Analysis

The relationships between attribution, expected change in exam outcomes, and desired score. The first and second hypotheses concern whether effort attribution relative to ability attribution would differentially relate to expected changes in exam scores for students with different levels of prior behavior. Therefore, I first divided students into subgroups by their levels of behavior in Time 2. Then, within each subgroup, I compared the expected changes in exam outcomes between students who had high and low values of effort attribution relative to ability attribution. The second hypothesis also concerns whether effort attribution relative to ability attribution would differentially relate to desired scores for students with different levels of prior behavior. Therefore, within each subgroup, I also compared the desired scores between students who had high and low values of effort attribution relative to ability attribution. Below, I describe how I created subgroups and made the comparisons within these subgroups.

Grouping. In this study, the levels of students' prior behavior were captured by the three clickstream measures in Time 2. Based on each of the three clickstream measures in Time 2, students were divided into two subgroups using median split. For instance, using time on task measured in Time 2, students were divided into two subgroups with one group being students whose time on task in Time 2 was below the median and the other group being students whose time on task in Time 2 was equal to or above the median. Therefore, six subgroups in total were created.

Within-subgroup comparison. Within each of the subgroups, I first analyzed the raw differences in the outcomes between students with high and low levels of effort attribution relative to ability attribution defined by median split. Three outcomes were examined, including expected change in exam performance, expected change in exam scores, and desired score for the final exam. Moreover, regression analyses were conducted to examine whether the raw differences were statistically significant after controlling for a variety of covariates, including students' background characteristics listed in Table 2.1, scores on the second midterm exam, other attribution measures (e.g., interest attribution), and self-evaluation of exam performance.

The relationships between expected change in exam outcomes, changes in behaviors, and actual change in exam scores. The third hypothesis concerns whether the relationship between expected change in exam outcomes, changes in behaviors, and actual changes in exam scores differed by students' prior behavior levels and desired scores. Therefore, I first divided students into subgroups by students' prior behavior levels and desired scores. Then, within each subgroup, I compared the changes in behaviors and actual changes in exam scores between students who had high and low values of expected changes in exam scores.

Grouping. Based on each of the three clickstream measures in Time 2 and the measure of desired scores collected at the end of Time 2, students were divided into 2 by 2 subgroups using median split. For instance, using the clickstream measure of time on task in Time 2 and the measure of desired score, students were divided into four subgroups: 1) time on task in Time 2 below the median and desired score below the median, 2) time on task in Time 2 below the median and desired score equal to or above the median, 3) time on task in Time 2 equal to or above the median and desired score below the median, and 4) time on task in Time 2 equal to or above the median and desired score equal to or above the median. Therefore, twelve subgroups in total were created.

Within-subgroup comparison. Similarly, within each subgroup, I first examined the raw differences in the outcomes between students with high and low levels of expected change in exam scores defined by median split. Four outcome variables were used, including the changes in students' time on task, completing quizzes on time, and watching lectures on time from Time 2 to Time 3, and the actual changes in students' exam score from Time 2 to Time 3. Regression analyses were conducted to examine whether these differences were statistically significant, controlling for other covariates.

Results

Attribution and expected change in exam outcomes

I first examined the relationship between students' tendency to attribute failures to effort rather than ability and the extent to which students expected their exam outcomes would increase in the final exam by comparing the expected changes in exam outcomes between students who reported low and high levels of effort attribution relative to ability attribution. Since I hypothesized that the relationship would be moderated by students' prior behavior, the comparisons were conducted within six subgroups: students who had low or high levels of time on task in Time 2, low or high levels of percentage of quizzes completed on time in Time 2, or low or high levels of percentage of lectures watched on time in Time 2. For instance, I compared the expected changes in exam outcomes between those who reported low and high levels of effort attribution relative to ability attribution within the subgroup of students who had low levels of time on task in Time 2.

Table 2.3 presents the raw differences. Two outcomes were examined, including students' expected changes in exam performance and exam scores. In alignment with my hypothesis, among students with low levels of prior effort or positive time management behaviors (i.e., the first subgroup in each panel in Table 2.3), those who attached high levels of importance to effort relative to ability tended to expect higher increases in exam outcomes than those who attached low levels of importance to effort relative to ability. The pattern was consistent across behavioral measures. On the contrary, within subgroups of students who had high levels of prior effort or positive time management behaviors (i.e., the second subgroup in each panel in Table 2.3), the differences in expected change in exam outcomes between students with high and low levels of effort attribution relative to ability attribution were either in the opposite direction or close to zero. For instance, among students who had high levels of quizzes completed on time in Time 2 (i.e., the second subgroup in the second panel in Table 2.3), those who attached high levels of importance to effort relative to ability tended to expect lower increases in their exam outcomes as compared to those who attached low levels of importance to effort relative to ability.

Table 2.3
Raw Differences in Expected Change in Exam Outcomes and Desired Scores Between Students with High and Low Levels of Effort Attribution Relative to Ability Attribution

		Effort attribution relative to ability attribution		
		Low	High	Diff.
Subgroups				
Time on task_T2_Low	Expected change in exam performance	1.86	2.17	0.31
	Expected change in exam score	1.57	1.79	0.22
	Desired score	4.29	4.58	0.30
	N	21	24	
Time on task_T2_High	Expected change in exam performance	2.32	2.36	0.05
	Expected change in exam score	1.77	1.77	0.00
	Desired score	4.36	4.00	-0.36
	N	22	22	
Subgroups				
Completing quiz on time_T2_Low	Expected change in exam performance	1.76	2.43	0.67
	Expected change in exam score	1.32	2.00	0.68
	Desired score	4.32	4.48	0.16
	N	25	23	
Completing quiz on time_T2_High	Expected change in exam performance	2.56	2.09	-0.47
	Expected change in exam score	2.17	1.57	-0.60
	Desired score	4.33	4.13	-0.20
	N	18	23	
Subgroups				
Watching lecture on time_T2_Low	Expected change in exam performance	1.79	2.23	0.44
	Expected change in exam score	1.58	1.83	0.25
	Desired score	4.37	4.47	0.10
	N	19	30	
Watching lecture on time_T2_High	Expected change in exam performance	2.33	2.31	-0.02
	Expected change in exam score	1.75	1.69	-0.06
	Desired score	4.29	4.00	-0.29
	N	24	16	

Note. Time on task_T2_Low refers to students' time on task in Time 2 being below median and Time on task_T2_High refers to students' time on task in Time 2 being equal to or above median. Completing quizzes on time_T2_Low refers to students' percentages of quizzes completed on time in Time 2 being below median and Completing quizzes on time_T2_High refers to students' percentages of quizzes completed on time in Time 2 being equal to or above median. Watching lectures on time_T2_Low refers to students' percentages of lectures watched on time in Time 2 being below median and Watching lectures on time_T2_High refers to students' percentages of lectures watched on time in Time 2 being equal to or above median.

However, these results were purely descriptive and may partly reflect differences in students' demographic characteristics, prior performance, and other covariates. Therefore, Table 2.4 presents the regression-adjusted differences in these two outcomes between students with low and high levels of effort attribution relative to ability attribution, controlling for a variety of covariates. In each panel, the differences in students' expected changes in exam outcomes were examined for two subgroups: students with low levels of prior behavior (i.e., the coefficients on the dummy variable of high effort attribution relative to ability attribution for the first subgroup in models 1 and 2) and students with high levels of prior behavior (i.e., the coefficients on the dummy variable of high effort attribution relative to ability attribution for the second subgroup in models 3 and 4).

The regression-adjusted results in Table 2.4 generally echoed the patterns found in Table 2.3. First, for subgroups of students who had low levels of prior behavior, the differences in expected changes in exam outcomes between students with high and low levels of effort attribution relative to ability attribution were large and positive, with some of them being significant. For instance, for the subgroup of students who had low levels of quizzes completed on time in Time 2 (i.e., the first subgroup in the second panel), those who attached high levels of importance to effort relative to ability also reported significantly higher values of expected changes in exam performance and exam scores than those who attached low levels of importance to effort relative to ability by more than half of a standard deviation, after controlling for other covariates. On the contrary, no clear or consistent patterns were observed for subgroups of students with high levels of prior behavior. These results suggest that attributing a prior failure to effort rather than ability would positively affect students' expectancy for future success only if students did not work hard or use appropriate self-regulation strategies when completing the prior task and could adjust their behavior substantially to perform better on the subsequent task.

Attribution and goals for subsequent exam

Students' attributions may also relate to the goals students set up for subsequent tasks, and this relationship may also differ between students with high or low levels of prior behavior. Students' desired scores for the final exam were measured as students' goals for the subsequent exam. The raw differences in desired scores between students with low and high levels of effort attribution relative to ability attribution for each of the subgroups are presented in Table 2.3. First, for the subgroups of students who had low levels of time on task, quizzes completed on time, or lectures watched on time in Time 2 (i.e., the first subgroup in each panel), those who reported high levels of effort attribution relative to ability attribution reported higher desired scores for final exam as compared to those who reported low levels of effort attribution relative to ability attribution.

The opposite pattern was found for subgroups of students who had high levels of time on task, quizzes completed on time, or lectures watched on time in Time 2 (i.e., the second subgroup in each panel). Within these subgroups, those who reported high values of effort attribution relative to ability attribution consistently reported lower desired scores for final exam than those who reported low values of effort attribution relative to ability attribution. These results are in agreement with my hypothesis that students who tried very hard previously and still attributed failures to insufficient effort may lower their goals to avoid failures in the future.

The regression-adjusted differences in students' desired scores are also presented in Table 2.4. The results are consistent with the raw differences observed in Table 2.3. In general, for the subgroups of students who had low levels of prior behavior, there were large and positive differences between those with high and low levels of effort attribution relative to ability attribution after controlling for covariates. On the contrary, for the subgroups of students who had high levels of prior behavior, there were large and negative differences between those with high and low levels of effort attribution relative to ability attribution after controlling for covariates. For instance, within the subgroup of students had low levels of quizzes completed on time in Time 2 (i.e., the first subgroup in the second panel), those with high levels of effort attribution relative to ability attribution reported higher desired scores by 0.369 of a standard deviation than those with low levels of effort attribution relative to ability attribution, whereas within the subgroup of students who had high levels of quizzes completed on time in Time 2 (i.e., the second subgroup in the second panel), those with high levels of effort attribution relative to ability attribution reported lower desired scores by 0.442 of a standard deviation than those with low levels of effort attribution relative to ability attribution. However, probably due to the small sample size, none of the differences were statistically significant.

Overall, these results provide suggestive evidence that attributing failures to insufficient effort rather than ability may induce students to lower their goals for future tasks if they have previously tried very hard. One potential reason is that when a student works very hard for a prior task and still receives a low performance, attributing the low performance to insufficient effort may induce the student to think that it requires too much effort to achieve her original goal and therefore lower her goals for future tasks to avoid failures.

Table 2.4

Regression-Adjusted Differences in Expected Change in Exam Outcomes and Desired Scores Between Students with High and Low Levels of Effort Attribution Relative to Ability Attribution

		Expected change in performance				Expected change in exam score				Desired score			
		M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
Subgroups													
Time on task_T2 _Low	E-A_Low			-0.410	-0.236			-0.191	-0.221			-0.100	0.078
				(0.31)	(0.29)			(0.31)	(0.29)			(0.30)	(0.33)
	E-A_High	0.275	0.377	-0.135	0.141	0.209	0.401	0.018	0.180	0.383	0.233	0.283	0.311
		(0.30)	(0.29)	(0.30)	(0.29)	(0.30)	(0.28)	(0.30)	(0.29)	(0.29)	(0.32)	(0.29)	(0.32)
Time on task_T2 _High	E-A_Low	0.410	0.236			0.191	0.221			0.100	-0.078		
		(0.31)	(0.29)			(0.31)	(0.29)			(0.30)	(0.33)		
	E-A_High	0.451	0.462	0.040	0.226	0.191	0.113	-0.000	-0.108	-0.367	-0.369	-0.468	-0.291
		(0.31)	(0.29)	(0.30)	(0.31)	(0.31)	(0.29)	(0.31)	(0.30)	(0.30)	(0.32)	(0.30)	(0.34)
Controls		No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N		89	89	89	89	89	89	89	89	89	89	89	89
		Expected change in performance				Expected change in exam score				Desired score			
		M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
Subgroups													
Completing quizzes on time_T2 _Low	E-A_Low			-0.708*	-0.263			-0.506+	-0.013			-0.017	-0.355
				(0.30)	(0.29)			(0.28)	(0.24)			(0.31)	(0.32)
	E-A_High	0.600*	0.528+	-0.107	0.265	0.646*	0.571*	0.064	0.145	0.204	0.369	0.186	0.014
		(0.28)	(0.28)	(0.31)	(0.31)	(0.28)	(0.27)	(0.30)	(0.25)	(0.29)	(0.32)	(0.32)	(0.35)
Completing quizzes on time_T2 _High	E-A_Low	0.708*	0.263			0.804**	0.506+			0.017	0.355		
		(0.30)	(0.29)			(0.30)	(0.28)			(0.31)	(0.32)		
	E-A_High	0.291	0.297	-0.417	0.034	0.233	0.170	-0.337	-0.203	-0.244	-0.087	-0.261	-0.442
		(0.28)	(0.27)	(0.31)	(0.31)	(0.28)	(0.26)	(0.30)	(0.25)	(0.29)	(0.30)	(0.32)	(0.35)
Control		No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N		89	89	89	89	89	89	89	89	89	89	89	89

Table 2.4
Continued

		Expected change in performance				Expected change in exam score				Desired score			
		M1	M2	M3	M4	M1	M2	M3	M4	M1	M2	M3	M4
Subgroups													
Watching	E-A_Low			-0.544	-0.484			-0.162	-0.062			0.099	0.111
lectures on				(0.35)	(0.31)			(0.31)	(0.30)			(0.31)	(0.33)
time_T2	E-A_High	0.395	0.179	-0.100	-0.089	0.242	0.215	0.079	0.153	0.098	0.126	0.225	0.298
_Low		(0.29)	(0.29)	(0.31)	(0.27)	(0.30)	(0.29)	(0.28)	(0.28)	(0.23)	(0.29)	(0.27)	(0.30)
Watching	E-A_Low	0.484	-0.095			0.162	0.062			-0.077	-0.099		
lectures on		(0.31)	(0.30)			(0.31)	(0.30)			(0.24)	(0.31)		
time_T2	E-A_High	0.465	0.369	-0.021	-0.019	0.103	0.173	-0.059	0.111	-0.368	-0.474	-0.375	-0.352
_High		(0.34)	(0.31)	(0.36)	(0.32)	(0.34)	(0.32)	(0.33)	(0.31)	(0.26)	(0.34)	(0.32)	(0.34)
Control		No	Yes	No	No	No	Yes	No	Yes	No	No	No	Yes
N		89	89	89	89	89	89	89	89	89	89	89	89

Note. Time on task_T2_Low refers to students' time on task in Time 2 being below median and Time on task_T2_High refers to students' time on task in Time 2 being equal to or above median. Completing quizzes on time_T2_Low refers to students' percentages of quizzes completed on time in Time 2 being below median and Completing quizzes on time_T2_High refers to students' percentages of quizzes completed on time in Time 2 being equal to or above median. Watching lectures on time_T2_Low refers to students' percentages of lectures watched on time in Time 2 being below median and Watching lectures on time_T2_High refers to students' percentages of lectures watched on time in Time 2 being equal to or above median. E-A_Low refers to students' effort attribution relative to ability attribution being below median. E-A_High refers to students' effort attribution relative to ability attribution being equal to or above median. All coefficients are standardized. +p<0.1 * p<0.05 ** p<0.010 *** p<0.001

Expected changes in exam outcomes and changes in behavior

Having found that, for students with low levels of prior behavior, the tendency of attributing failures to effort rather than ability was positively associated with expected change in exam outcomes, I then examined whether expected change in exam outcomes was positively related to change in students' subsequent behavior. Specifically, I compared the changes in behavior between students with high and low levels of expected change in exam scores. As I hypothesized, the relationship between expected change in exam outcomes and change in subsequent behavior would be moderated by students' prior behavior and desired scores for the final exam. Therefore, for each behavioral measure, I conducted the comparison within four subgroups of students defined by their prior behavior and desire scores. For instance, for the behavioral measure of time on task, I examined the difference in the change in subsequent time on task between students with low and high levels of expected change in exam score for 1) the subgroup of students who had low levels of time on task in Time 2 and high desired scores for the final exam, 2) the subgroup of students who had low levels of time on task in Time 2 and low desired scores for the final exam, 3) the subgroup of students who had high levels of time on task in Time 2 and high desired scores for the final exam, and 4) the subgroup of students who had high levels of time on task in Time 2 and low desired scores for the final exam.

Table 2.5 shows the raw differences. I first examined the results for the first subgroup in each panel since I hypothesized that higher expected change in exam outcomes would relate to larger increases in a behavioral measure only for the subgroup of students who previously had low levels of this behavioral measure and high desired scores. In alignment with my hypothesis, for these subgroups, students who reported high values of expected change in exam scores tended to increase their time on task, quizzes completed on time, or watching lectures on time in Time 3 while students who reported low values of expected change in exam scores showed decreases in these behavioral measures in Time 3. For instance, among students who had low levels of time on task in Time 2 and high levels of desired score for final exam (i.e., the first subgroup in the first panel), those who reported high values of expected change in exam scores increased their weekly time on task by 1.04 hours in Time 3 while those who reported low values of expected change in exam scores decreased their weekly time on task by 0.38 hours in Time 3. Similarly, among students who had low levels of completing quizzes on time in Time 2 and high levels of desired score for final exam (i.e., the first subgroup in the second panel), those who reported high values of expected change in exam scores completed 13% more quizzes on time per week in Time 3 relative to Time 2, whereas students who reported low values of expected change in exam scores completed 9% fewer quizzes on time per week in Time 3 relative to Time 2.

For the other three subgroups in each panel, the differences in behavioral changes were either in the opposite direction or inconsistent across behavioral measures. For instance, for the subgroups of students with high levels of prior behavior and low levels of desired score (i.e., the fourth subgroups in each panel), those with high values of expected change in exam scores showed consistently larger decreases in their subsequent behavior as compared to those with low values of expected change in exam scores. Moreover, although the difference in changes in completing quizzes on time between students with high and low levels of expected change in exam scores was positive for the subgroup of students with high levels of completing quizzes on time in Time 2 and high levels of desired scores (i.e., the third subgroup in the second panel), the difference in changes in watching lectures on time between students with high and low levels of expected change in exam scores was negative and close to zero for the subgroup of students with high levels of watching lectures on time in Time 2 and high levels of desired scores (i.e., the third subgroup in the third panel).

Tables 2.6, 2.7, and 2.8 present the regression-adjusted differences for each of the three behavioral measures, respectively. In the first panel of each table, the differences in changes in behavior between students with high and low levels of expected change in exam scores were examined for four subgroups, including students with low levels of prior behavior and high levels of desired score (i.e., the coefficients on the dummy variable of high expected change in exam score for the first subgroup in models 1 and 2), low levels of prior behavior and low levels of desired score (i.e., the coefficients on the dummy variable of high expected change in exam scores for the second subgroup in models 3 and 4), high levels of prior behavior and high levels of desired score (i.e., the coefficients on the dummy variable of high expected change in exam scores for the third subgroup in models 5 and 6), and high levels of prior behavior and low levels of desired score (i.e., the coefficients on the dummy variable of high expected change in exam scores for the fourth subgroup in models 7 and 8).

The regression results further support the findings in Table 2.5. First, among students who had low levels of prior behavior and high levels of desired score, those who expected high increases in exam scores showed significantly larger increases in subsequent behavior than those who expected low increases in exam scores by around 1 standard deviation, after controlling for a variety of covariates. The pattern is consistent across behavioral measures. For instance, results in Table 2.6 show that among students with low levels of time on task in Time 2 and high levels of desired score for final exam, those who reported high levels of expected change in exam sore had significantly larger increases in their subsequent time on task than those who reported low levels of expected change in exam score by around 0.9 of a standard deviation. Moreover, no consistent evidence across behavioral measures was found for the other three subgroups.

Expected change in exam outcomes and actual change in exam scores

Having found that expected change in exam scores was positively associated with changes in subsequent behavior for the subgroups of students who had low levels of prior behavior and high levels of desired score, I then examined if expected change in exam scores was related to actual change in exam scores for these subgroups. In general, the relationships between students' expected change in exam scores and their actual change in exam performance were not consistent across behavioral measures for these subgroups. For instance, results in Table 2.5 show that the difference in actual change in exam scores between students with high and low levels of expected change in exam scores was positive (but small) for the subgroup of students with low levels of quizzes completed on time in Time 2 and high levels of desired score (i.e., the first subgroup in the second panel). On the contrary, the difference was negative for the subgroup of students with low levels of time on task in Time 2 and high levels of desired score (i.e., the first subgroup in the first panel).

Similarly, regression results show no significant associations between expected change and actual change in exam scores for these subgroups (see Tables 2.6, 2.7, and 2.8). In general, for these subgroups, students who had high levels of expected change in exam scores had lower increases or similar changes in their actual exam scores as compared to students who had low levels of expected change in exam scores, after controlling for other covariates. Furthermore, none of these differences were significant.

Table 2.5

Raw Differences in Changes in Behaviors and Actual Changes in Exam Performance Between Students with High and Low Levels of Expected Change in Exam Scores

			Expected change in exam scores		
			Low	High	Diff.
Subgroups					
Time on task_T2_Low	Desired score_High	Change in time on task	-0.38	1.04	1.43
		Actual change in exam scores	15.00	13.33	-1.67
		N	10	12	
	Desired score_Low	Change in time on task	0.83	0.24	-0.59
		Actual change in exam scores	-1.82	16.67	18.48
		N	11	12	
Time on task_T2_High	Desired score_High	Change in time on task	-0.90	1.08	1.98
		Actual change in exam scores	22.86	41.67	18.81
		N	7	12	
	Desired score_Low	Change in time on task	-0.47	-1.05	-0.58
		Actual change in exam performance	28.00	26.67	-1.33
		N	10	15	
Subgroups					
Completing quizzes on time_T2_Low	Desired score_High	Change in completing quiz on time	-0.09	0.13	0.21
		Actual change in exam scores	17.78	19.29	1.51
		N	9	14	
	Desired score_Low	Change in completing quiz on time	0.08	0.02	-0.06
		Actual change in exam scores	0.77	17.50	16.73
		N	13	12	
Completing quizzes on time_T2_High	Desired score_High	Change in completing quiz on time	-0.08	0.06	0.14
		Actual change in exam score	18.75	39.00	20.25
		N	8	10	
	Desired score_Low	Change in completing quiz on time	-0.01	-0.14	-0.13
		Actual change in exam scores	31.25	26.00	-5.25
		N	8	15	
Subgroups					
Watching lectures on time_T2_Low	Desired score_High	Change in watching lecture on time	-0.11	0.14	0.25
		Actual change in exam scores	16.25	16.43	0.18
		N	8	14	
	Desired score_Low	Change in watching lecture on time	-0.11	-0.03	0.09
		Actual change in exam scores	10.00	18.00	8.00
		N	12	15	
Watching lectures on time_T2_High	Desired score_High	Change in watching lecture on time	-0.04	-0.05	-0.01
		Actual change in exam scores	20.00	43.00	23.00
		N	9	10	
	Desired score_Low	Change in watching lecture on time	-0.05	-0.32	-0.27
		Actual change in exam scores	15.56	27.50	11.94
		N	9	12	

Note. Time on task_T2_Low refers to students' time on task in Time 2 being below median and Time on task_T2_High refers to students' time on task in Time 2 being equal to or above median. Completing quizzes on time_T2_Low refers to students' percentages of quizzes completed on time in Time 2 being below median and Completing quizzes on time_T2_High refers to students' percentages of quizzes completed on time in Time 2 being equal to or above median. Watching lectures on time_T2_Low refers to students' percentages of lectures watched on time in Time 2 being below median and Watching lectures on time_T2_High refers to students' percentages of lectures watched on time in Time 2 being equal to or above median. Desired score_Low refers to students' desired score being below median. Desired score_High refers to students' desired score being equal to or above median.

Table 2.6

Regression-Adjusted Differences in Changes in Time on Task and Actual Changes in Exam Performance Between Students with High and Low Levels of Expected Change in Exam Scores

		Change in time on task							
		M1	M2	M3	M4	M5	M6	M7	M8
Subgroups									
Time on task_T2_Low	Expected change_Low			-0.411	-0.876*	0.175	0.261	0.031	-0.259
+ Desired score_High				(0.34)	(0.40)	(0.38)	(0.43)	(0.35)	(0.39)
	Expected change_High	0.485	0.906*	0.073	0.030	0.660+	1.167*	0.515	0.647+
		(0.33)	(0.39)	(0.32)	(0.35)	(0.37)	(0.47)	(0.33)	(0.37)
Time on task_T2_Low	Expected change_Low	0.411	0.876*			0.587	1.137*	0.442	0.617
+ Desired score_Low		(0.34)	(0.40)			(0.37)	(0.48)	(0.34)	(0.37)
	Expected change_High	0.211	0.778+	-0.200	-0.099	0.387	1.039*	0.242	0.519
		(0.33)	(0.46)	(0.32)	(0.37)	(0.37)	(0.51)	(0.33)	(0.41)
Time on task_T2_High	Expected change_Low	-0.175	-0.261	-0.587	-1.137*			-0.145	-0.520
+ Desired score_High		(0.38)	(0.43)	(0.37)	(0.48)			(0.38)	(0.47)
	Expected change_High	0.497	0.735+	0.086	-0.141	0.672+	0.996*	0.528	0.476
		(0.33)	(0.41)	(0.32)	(0.36)	(0.37)	(0.45)	(0.33)	(0.39)
Time on task_T2_High	Expected change_Low	-0.031	0.259	-0.442	-0.617	0.145	0.520		
+ Desired score_Low		(0.35)	(0.39)	(0.34)	(0.37)	(0.38)	(0.47)		
	Expected change_High	-0.226	0.515	-0.638*	-0.361	-0.051	0.776	-0.196	0.256
		(0.32)	(0.46)	(0.31)	(0.35)	(0.35)	(0.53)	(0.32)	(0.41)
Control		No	Yes	No	Yes	No	Yes	No	Yes
N		89	89	89	89	89	89	89	89

Table 2.6
Continued

		Change on exam performance							
		M1	M2	M3	M4	M5	M6	M7	M8
Subgroups									
Time on task_T2_Low	Expected change_Low			0.480	0.635	-0.224	-0.264	-0.371	-0.465
+ Desired score_High				(0.58)	(0.62)	(0.65)	(0.67)	(0.59)	(0.60)
	Expected change_High	-0.048	-0.161	0.432	0.474	-0.272	-0.425	-0.418	-0.627
		(0.56)	(0.61)	(0.55)	(0.55)	(0.63)	(0.73)	(0.56)	(0.58)
Time on task_T2_Low	Expected change_Low	-0.480	-0.635			-0.704	-0.899	-0.850	-1.100+
+ Desired score_Low		(0.58)	(0.62)			(0.64)	(0.75)	(0.58)	(0.58)
	Expected change_High	0.048	0.102	0.527	0.736	-0.177	-0.162	-0.323	-0.364
		(0.56)	(0.71)	(0.55)	(0.57)	(0.63)	(0.80)	(0.56)	(0.64)
Time on task_T2_High	Expected change_Low	0.224	0.264	0.704	0.899			-0.147	-0.201
+ Desired score_High		(0.65)	(0.67)	(0.64)	(0.75)			(0.65)	(0.73)
	Expected change_High	0.760	0.611	1.240*	1.245*	0.536	0.347	0.390	0.145
		(0.56)	(0.64)	(0.55)	(0.56)	(0.63)	(0.71)	(0.56)	(0.61)
Time on task_T2_High	Expected change_Low	0.371	0.465	0.850	1.100+	0.147	0.201		
+ Desired score_Low		(0.59)	(0.60)	(0.58)	(0.58)	(0.65)	(0.73)		
	Expected change_High	0.333	0.104	0.812	0.738	0.109	-0.161	-0.038	-0.362
		(0.54)	(0.72)	(0.52)	(0.55)	(0.60)	(0.82)	(0.54)	(0.63)
Control		No	Yes	No	Yes	No	Yes	No	Yes
N		89	89	89	89	89	89	89	89

Note. Time on task_T2_Low refers to students' time on task in Time 2 being below median and Time on task_T2_High refers to students' time on task in Time 2 being equal to or above median. Desired score_Low refers to students' desired score being below median. Desired score_High refers to students' desired score being equal to or above median. Expected change_Low refers to students expected change in exam score being below median and Expected change_High refers to students expected change in exam score being equal to or above median. All coefficients are standardized. $+p<0.1$ $*\ p<0.05$ $**\ p<0.010$ $***\ p<0.001$

Table 2.7

Regression-Adjusted Differences in Changes in Completing Quizzes on Time and Actual Changes in Exam Performance Between Students with High and Low Levels of Expected Change in Exam Scores

		Change in completing quizzes on time							
		M1	M2	M3	M4	M5	M6	M7	M8
Subgroups									
Completing quizzes on time_T2_Low	Expected change_Low			-0.543	-0.816	-0.010	0.011	-0.241	-0.435
				(0.43)	(0.52)	(0.48)	(0.52)	(0.48)	(0.60)
+ Desired score_High	Expected change_High	0.709+	1.201*	0.166	0.385	0.699	1.212*	0.468	0.766
		(0.43)	(0.51)	(0.38)	(0.42)	(0.44)	(0.54)	(0.44)	(0.51)
Completing quizzes on time_T2_Low	Expected change_Low	0.543	0.816			0.532	0.827	0.302	0.381
		(0.43)	(0.52)			(0.45)	(0.53)	(0.45)	(0.52)
+ Desired score_Low	Expected change_High	0.349	0.908	-0.194	0.092	0.338	0.919	0.108	0.473
		(0.44)	(0.59)	(0.40)	(0.46)	(0.45)	(0.61)	(0.45)	(0.56)
Completing quizzes on time_T2_High	Expected change_Low	0.010	-0.011	-0.532	-0.827			-0.231	-0.446
		(0.48)	(0.52)	(0.45)	(0.53)			(0.50)	(0.60)
+ Desired score_High	Expected change_High	0.472	0.757	-0.071	-0.059	0.461	0.767	0.231	0.322
		(0.46)	(0.56)	(0.42)	(0.47)	(0.47)	(0.58)	(0.47)	(0.58)
Completing quizzes on time_T2_High	Expected change_Low	0.241	0.435	-0.302	-0.381	0.231	0.446		
		(0.48)	(0.60)	(0.45)	(0.52)	(0.50)	(0.60)		
+ Desired score_Low	Expected change_High	-0.180	0.612	-0.723+	-0.204	-0.191	0.623	-0.421	0.177
		(0.42)	(0.65)	(0.38)	(0.47)	(0.44)	(0.67)	(0.44)	(0.60)
Control		No	Yes	No	Yes	No	Yes	No	Yes
N		89	89	89	89	89	89	89	89

Table 2.7
Continued

		Change on exam performance							
		M1	M2	M3	M4	M5	M6	M7	M8
Subgroups									
Completing quizzes on	Expected change_Low			0.485	0.374	-0.028	0.004	-0.384	-0.368
time_T2_Low				(0.58)	(0.63)	(0.65)	(0.63)	(0.65)	(0.74)
+ Desired score_High	Expected change_High	0.043	0.052	0.528	0.426	0.015	0.056	-0.341	-0.317
		(0.57)	(0.63)	(0.51)	(0.52)	(0.59)	(0.66)	(0.59)	(0.62)
Completing quizzes on	Expected change_Low	-0.485	-0.374			-0.513	-0.371	-0.869	-0.743
time_T2_Low		(0.58)	(0.63)			(0.60)	(0.65)	(0.60)	(0.64)
+ Desired score_Low	Expected change_High	-0.008	0.170	0.477	0.545	-0.036	0.174	-0.392	-0.198
		(0.59)	(0.72)	(0.53)	(0.56)	(0.61)	(0.74)	(0.61)	(0.68)
Completing quizzes on	Expected change_Low	0.028	-0.004	0.513	0.371			-0.356	-0.372
time_T2_High		(0.65)	(0.63)	(0.60)	(0.65)			(0.66)	(0.73)
+ Desired score_High	Expected change_High	0.605	0.495	1.090+	0.869	0.577	0.499	0.221	0.126
		(0.61)	(0.68)	(0.56)	(0.57)	(0.63)	(0.71)	(0.63)	(0.71)
Completing quizzes on	Expected change_Low	0.384	0.368	0.869	0.743	0.356	0.372		
time_T2_High		(0.65)	(0.74)	(0.60)	(0.64)	(0.66)	(0.73)		
+ Desired score_Low	Expected change_High	0.234	0.121	0.719	0.495	0.207	0.125	-0.150	-0.247
		(0.56)	(0.79)	(0.50)	(0.57)	(0.58)	(0.82)	(0.58)	(0.74)
Control		No	Yes	No	Yes	No	Yes	No	Yes
N		89	89	89	89	89	89	89	89

Note. Completing quizzes on time_T2_Low refers to students' percentages of quizzes completed in Time 2 being below median and Time on task_T2_High refers to students' percentages of quizzes completed in Time 2 being equal to or above median. Desired score_Low refers to students' desired score being below median. Desired score_High refers to students' desired score being equal to or above median. Expected change_Low refers to students expected change in exam score being below median and Expected change_High refers to students expected change in exam score being equal to or above median. All coefficients are standardized. +p<0.1 * p<0.05 ** p<0.010 *** p<0.001

Table 2.8

Regression-Adjusted Differences in Changes in Watching Lectures on Time and Actual Changes in Exam Performance Between Students with High and Low Levels of Expected Change in Exam Scores

		Change in watching lectures on time							
		M1	M2	M3	M4	M5	M6	M7	M8
Subgroups									
Watching lectures on	Expected change_Low			0.019	-0.035	-0.247	0.044	-0.433	-0.535
time_T2_Low				(0.50)	(0.60)	(0.54)	(0.61)	(0.54)	(0.64)
+ Desired score_High	Expected change_High	0.910+	1.030+	0.929*	0.994+	0.662	1.073+	0.477	0.494
		(0.49)	(0.58)	(0.43)	(0.50)	(0.47)	(0.61)	(0.47)	(0.51)
Watching lectures on	Expected change_Low	-0.019	0.035			-0.266	0.079	-0.452	-0.500
time_T2_Low		(0.50)	(0.60)			(0.49)	(0.58)	(0.49)	(0.54)
+ Desired score_Low	Expected change_High	0.298	0.623	0.317	0.588	0.051	0.667	-0.135	0.088
		(0.48)	(0.67)	(0.43)	(0.56)	(0.47)	(0.70)	(0.47)	(0.51)
Watching lectures on	Expected change_Low	0.247	-0.044	0.266	-0.079			-0.186	-0.579
time_T2_High		(0.54)	(0.61)	(0.49)	(0.58)			(0.52)	(0.64)
+ Desired score_High	Expected change_High	0.217	0.313	0.236	0.278	-0.030	0.357	-0.216	-0.222
		(0.52)	(0.63)	(0.47)	(0.55)	(0.51)	(0.64)	(0.51)	(0.56)
Watching lectures on	Expected change_Low	0.433	0.535	0.452	0.500	0.186	0.579		
time_T2_High		(0.54)	(0.64)	(0.49)	(0.54)	(0.52)	(0.64)		
+ Desired score_Low	Expected change_High	-0.779	-0.473	-0.760+	-0.508	-1.026*	-0.429	-1.212*	-1.008+
		(0.50)	(0.71)	(0.45)	(0.60)	(0.49)	(0.76)	(0.49)	(0.56)
Control		No	Yes	No	Yes	No	Yes	No	Yes
N		89	89	89	89	89	89	89	89

Table 2.8
Continued

		Change on exam performance							
		M1	M2	M3	M4	M5	M6	M7	M8
Subgroups									
Watching lectures on	Expected change_Low			0.178	0.200	-0.107	0.161	0.020	0.202
time_T2_Low				(0.61)	(0.66)	(0.65)	(0.67)	(0.65)	(0.71)
+ Desired score_High	Expected change_High	0.005	-0.254	0.183	-0.054	-0.102	-0.093	0.025	-0.052
		(0.59)	(0.64)	(0.53)	(0.55)	(0.57)	(0.67)	(0.57)	(0.56)
Watching lectures on	Expected change_Low	-0.178	-0.200			-0.285	-0.039	-0.158	0.002
time_T2_Low		(0.61)	(0.66)			(0.59)	(0.64)	(0.59)	(0.59)
+ Desired score_Low	Expected change_High	0.050	0.083	0.228	0.283	-0.057	0.244	0.070	0.285
		(0.59)	(0.74)	(0.52)	(0.62)	(0.56)	(0.77)	(0.56)	(0.56)
Watching lectures on	Expected change_Low	0.107	-0.161	0.285	0.039			0.127	0.041
time_T2_High		(0.65)	(0.67)	(0.59)	(0.64)			(0.63)	(0.71)
+ Desired score_High	Expected change_High	0.763	0.778	0.941	0.977	0.656	0.939	0.783	0.979
		(0.64)	(0.70)	(0.57)	(0.61)	(0.62)	(0.71)	(0.62)	(0.62)
Watching lectures on	Expected change_Low	-0.020	-0.202	0.158	-0.002	-0.127	-0.041		
time_T2_High		(0.65)	(0.71)	(0.59)	(0.59)	(0.63)	(0.71)		
+ Desired score_Low	Expected change_High	0.321	0.131	0.499	0.330	0.214	0.292	0.341	0.332
		(0.61)	(0.78)	(0.55)	(0.66)	(0.59)	(0.83)	(0.59)	(0.62)
Control		No	Yes	No	Yes	No	Yes	No	Yes
N		89	89	89	89	89	89	89	89

Note. Watching lectures on time_T2_Low refers to students' percentages of lectures watched on time in Time 2 being below median and Time on task_T2_High refers to students' percentages of lectures watched on time in Time 2 being equal to or above median. Desired score_Low refers to students' desired score being below median. Desired score_High refers to students' desired score being equal to or above median. Expected change_Low refers to students expected change in exam score being below median and Expected change_High refers to students expected change in exam score being equal to or above median. All coefficients are standardized. +*p*<0.1 * *p*<0.05 ** *p*<0.010 *** *p*<0.001

Discussion

Key findings

Attribution theory suggests that attributing failures to insufficient effort rather than low ability can buffer students against the negative effect of experiencing failures on students' expectancy, behavior, and performance (Weiner, 1979). While the relationships between attributions, expectancy, and performance are well-researched, there is relatively less evidence on the relationships between attributions and behavior. Using clickstream data uniquely available in technology-enhanced learning environments, this study extends the current research of academic attribution by directly examining changes in students' behavior as a consequence of the attribution process. Furthermore, drawing on expectancy-value theory (Eccles, 1983), this study explores how students' prior behavior and their desired goals for a future task may moderate the role of attributions and expectancy, which shed light on other factors that may interact with the attribution process in determining students' motivation and behavior.

In support of my hypothesis, I found that the relationship between attribution and expected change in exam outcomes was moderated by students' prior behavior. Specifically, I found that attributing failures to effort rather than ability had a significant and positive relationship with expected change in exam outcomes for students with low levels of prior behavior and had no relationship with expected change in exam outcomes for students with high levels of prior behavior. These findings imply that attributing failures to effort rather than ability would help to maintain students' expectancy only if the student did not exert much effort previously and could potentially increase her effort for better performance. If a student studied hard for a previous task, failed the task, and attributed the failure to lack of effort, she may not necessarily expect to have a better performance in a subsequent task because she may believe that she could not put extra effort in the subsequent task or it is not worth the extra effort to improve her performance.

In addition, for students who previously worked very hard, attributing failures to insufficient effort rather than ability may even result in maladaptive psychological outcomes, such as lower goals for future tasks. For students who had high levels of prior behavior, I found suggestive evidence that attributing failures to effort rather than ability was associated with lower desired scores for the final exam. This is likely due to that these students may think it requires too much effort to achieve their original goals and thus lower their goals in order to avoid failing the subsequent task. However, lowering one's goals may not always be a bad thing. Previous research suggests that students may be unrealistically optimistic about their performance and tend to ignore how much effort is needed to achieve their goals (Wicker et al., 2004). When working on multiple tasks during the same time period, being able to accurately estimate the effort cost of each task and set up realistic goals for each task may help students to use their time more effectively and achieve better performance overall.

Thirdly, this study not only confirms the link between expectancy and behavior but also provides nuanced insights into how this link could be moderated by other personal factors, including students' prior behavior and goals for future tasks. Specifically, I found that expected change in exam scores was significantly associated with increases in behavior only among students with low levels of prior behavior and high levels of desired score. This finding, along with the findings about the relationships between attribution and expectancy, supports the claim that, under certain conditions, attributions could influence subsequent behavior through its impact on expectancy. More importantly, it underscores expectancy-value theory, which claims that expectancy, task value, and cost jointly determine students' academic behavior (Eccles, 1983).

Finally, although significant relationships were found between expectancy and changes in behavior, there was no relationship between expectancy and actual changes in exam performance. This may be due to the small sample size or the outliers in the measure of actual change in exam performance. I conducted regression analysis on students' actual change in exam scores after excluding seven outliers from the analytic sample and found that, in general, those who had high levels of expected change in exam scores also had higher increases in actual exam scores than those who had low levels of expected change in exam scores for the subgroups of students who had low levels of prior behavior and high levels of desired score (Appendix B Table B1). However, none of the differences were significant. Future studies with larger samples are needed to provide stronger evidence about the relationships between attributions and change in exam performance.

These findings have important theoretical and practical implications regarding academic attribution in online learning environments. First, these findings indicate that the motivational and behavioral processes proposed by attribution theory may be oversimplified in previous studies. By considering other personal factors, such as students' prior behavior and their goals, this study demonstrates that there are several boundary conditions for effort attribution to positively impact students' motivation and subsequent behavior. Future research is needed to test these boundary conditions in larger samples and explore how these personal factors may interact with other environmental factors, such as features of the academic tasks, in influencing the process and the consequences of attribution.

In addition, this study supports that under certain conditions, effort attribution may be able to buffer against the negative effects of experiencing failures in online learning. Therefore, instructors could help low-performing students in online courses by conducting timely interventions to encourage them to attribute their low performance to lack of effort rather than ability. However, this study also suggests that effort attribution is not the solution to all problems. For students who have tried their best but still are struggling, effort attribution may not only be unhelpful, it may be harmful. Researchers and practitioners should differentiate between the reasons why students fail a task and provide more individualized interventions tailored to the specific reasons.

Limitations

This study provides new insights into the role of effort attribution versus ability attribution in the context of online learning and the conditions under which effort attribution may be beneficial to students. Certain limitations in this study, however, should be kept in mind. First, previous studies have mainly used two types of measures to capture students' attribution for failures: neutral or negative statements about the causal factors (e.g., Ames & Lau, 1982; Elig & Frieze, 1979; Lefcourt, von Baeyer, Ware, & Cox, 1979; Lloyd, Walsh, & Yailagh, 2005; Wang et al., 2008; Watkins, 1985). For instance, the causal factor of effort could be either described using a neutral statement of "how hard you tried" (e.g., Watkins, 1985) or a negative statement of "you did not study enough" (e.g., Lloyd et al., 2005). Both types of measures have certain issues. In particular, the neutral statements of effort attribution do not directly capture to what extent students believe their failure is due to lack of effort, whereas the negative statements of effort attribution may hurt students' motivation and engagement by emphasizing the negative images of themselves. This study chose to use neutral statements due to the concern about the negative effects of the negatively worded questions. However, potential noise in the measures needs to be considered when interpreting the results.

In addition, this study suffers from the issue of small sample size. While 315 students participated in the survey in Time 2, only 89 students (28%) reported that they performed poorly or very poorly and thus might experience failures in the course. The small sample size may have occluded my ability to detect small relationships. The issue of small sample size is particularly challenging for my subgroup analysis, which further restricted the sample to even smaller subgroups for whom attribution may be effective. Therefore, it will be an intriguing avenue for future research to validate these findings in a larger population.

Conclusions

This study uses the rich and nuanced clickstream data from an online course to explore the motivational and behavioral processes of attribution. The results indicate that students accurately attributing their failures to lack of effort could buffer them against declines in motivation and engagement. It also suggests students' prior effort and future goals may moderate attribution processes. This study provides an example of using clickstream data to explore how motivational processes may shape students' behavior. In particular, these findings help to complement the theoretical model of attribution by more precisely clarifying the conditions under which attributions may influence expectancy, behavior, and performance. In addition, these findings provide guidance for practitioners to better employ attribution interventions and effectively target students who are struggling with low performance because of insufficient effort or inappropriate self-regulation strategies.

CHAPTER 3: The Effect of Informational Feedback on Students' Attribution, Effort, and Performance

Introduction

There is growing evidence that self-regulated learning skills are essential in online learning (Broadbent & Poon, 2015). Across various models of self-regulated learning, researchers emphasize the iterative nature of the self-regulation process where students actively set up goals and study plans, seek and receive feedback from the learning environment, and, consequently, make adjustments (e.g., Butler & Winne, 1995; Pintrich, 2000; Zimmerman, 2002). In this cyclical process, students constantly evaluate their performance and identify the reasons that contribute to their performance, which bridges their earlier experiences and subsequent goals, plans, and behaviors (Butler & Winne, 1995; Pintrich, 2000). The attempt by students to attribute their academic failures or successes to various personal and environmental factors, such as insufficient effort and course difficulty, has been investigated and referred to widely as academic attribution (Weiner, 1979).

Students' beliefs about what factors contribute to their performance can influence their subsequent behaviors (Weiner, 1979). There is theoretical and empirical evidence that effort attribution may facilitate subsequent effort, especially when students experience failures (Bar-Tal, 1978; Chapin & Dyck, 1976; Cleary & Zimmerman, 2004; Dweck & Reppucci, 1973; Haynes et al., 2008; Weiner, 1979). When experiencing failures, students tend to lower their expectancy for future success and reduce their effort. However, if they attribute failures to insufficient effort, which is an internal, unstable, and controllable factor, they may be able to maintain or even increase their expectancy for future success and expend more effort and perform better on subsequent tasks. On the contrary, if they attribute failures to external factors, such as task difficulty, or internal but stable and uncontrollable factors, such as low ability, their expectancy for future success is likely to decrease, which may have negative effects on their subsequent effort and performance.

Despite the positive effects of attributing failures to insufficient effort over other factors, previous literature on attribution bias suggests that, as compared to successes, people are less likely to attribute failures to their own behaviors. Instead, they tend to believe that failures are due to external factors, such as the task being too difficult (e.g., Davis & Davis, 1972; Federoff & Harvey, 1976; Fontaine, 1975). Such attribution bias is likely due to two types of informational bias. First, people tend to pay more attention to the co-occurrences of their behavior with positive outcomes and ignore the co-occurrences of their behavior with negative outcomes (Miller & Ross, 1975). This informational bias may then result in biased perceptions of the relationships between one's own behavior and different outcomes. Second, people may overestimate their own efforts, believing that they have exerted enough effort, and therefore, do not attribute failures to lack of effort.

Online learning environments, as compared to in-person classroom settings, may pose even greater challenges for students to make informed academic attributions due to more informational constraints. First, due to the absence of physically present peers in the virtual learning space, there is limited information on how much effort peers exert and what outcomes they achieve, which is the main information source for estimating the association between effort and performance. In addition, online students may have more difficulty tracking their own efforts since their study schedules are more flexible and can change constantly (Britt, Goon, & Timmerman, 2015). These informational constraints in online learning environments may thus undermine the tendency for students to attribute failures to lack of effort.

Prior research has taken advantage of the rich and real-time clickstream data available in online learning environments, digital records of students' interaction with the online platforms, to overcome these informational constraints. In particular, previous studies have provided students with data visualizations on various behaviors (e.g., the frequency of accessing course material) and with comparisons to different types of peers (e.g., all students or high-performing students from past or current courses; e.g., Chen, Chang, & Wang, 2008; Kim, Jo, & Park, 2016). There is limited but emerging evidence showing that being exposed to behavioral information had positive effects on online students' course behavior and performance (e.g., Chen et al., 2008; Kim et al., 2016), though at least one study found no effect of the intervention (e.g., Park & Jo, 2015).

Given the inconsistency of prior findings, more experimental research is needed to better understand what types of information online students need, how to visualize the information, and what types of social comparison to provide. Moreover, since previous studies have mainly focused on student performance outcomes, the mechanisms through which the information may influence student performance are not clear. To bridge these gaps, this study conducted a random-assignment experiment to investigate the influence of providing students with information on their own effort as well as the effort spent by relevant peers in a past course. In particular, I examined the effects of the informational feedback on students' attribution, subsequent effort, and performance.

Literature Review

The role of attribution in self-regulated learning

Since online learning, in general, has flexible instructional schedules and relies on individual learning with limited asynchronistic and synchronistic social interaction (Zhao, 2003), students in online courses have great freedom and responsibility for guiding and directing their own learning (Hung, Chou, Chen, & Own, 2010). Success in online learning, therefore, is heavily dependent on students appropriately self-regulating their learning processes (Broadbent & Poon, 2015). Researchers unanimously agree that one important characteristics of self-regulated learning is that it is a cyclical process in which students actively construct perceptions about their learning and, based on these perceptions, constantly change their cognition, motivation, and behaviors (Butler & Winne, 1995; Pintrich, 2000; Zimmerman, 2002).

Various models about self-regulated learning have captured its recursive nature (e.g., Butler & Winne, 1995; Pintrich, 2000; Zimmerman, 2002). For instance, Zimmerman views the structure of self-regulated learning in terms of three cyclical phases: 1) the forethought phase where students set goals and plan out their strategies, 2) the performance phase where students implement the strategies selected in the forethought phase and observe themselves during this process, and 3) the self-reflection phase where students evaluate their performance and identify the causes that contribute to their performance and make adjustments accordingly (Zimmerman, 2002). Similarly, Pintrich (2000) proposed a four-phase model including the forethought, planning, and activation phase; the monitoring phase; the control phase; and the reaction and reflection phase. This model views self-regulated learning as a recursive process in that the self-reflection students make in the last phase will then affect the subsequent forethought, planning, and activation phase and therefore affect future learning.

Although named differently, students' self-reflection plays an important role in the recursive process of self-regulated learning. One main component of students' self-reflection is academic attribution (Butler & Winne, 1995; Pintrich, 2000; Zimmerman, 2002), which is defined as students identifying the reasons that contribute to their failures or successes (Weiner, 1979). Weiner (1979) argued that people constantly pursue the question of why an event has occurred. The causal factors (e.g., effort, ability, interest, or task difficulty) that people use to explain their academic outcomes would determine their cognitive and motivational responses, which in turn influence future behavior and performance.

Attribution theory proposes that how a perceived causal factor influences a student's subsequent behavior and performance depends on both her perceptions on the academic outcome (i.e., whether the academic outcome, such as a midterm score, is a failure or a success) and the properties of the causal factor (Weiner, 1979). Of different causal factors, effort attribution has received the most attention as it could buffer students against the negative impacts of experiencing failures (e.g., Hall et al., 2007; Haynes et al., 2008; Mezulis et al., 2004). Attribution theory argues that, when students experience failures, they tend to lower their expectancy for succeeding on a similar subsequent task and therefore, work not as hard as they could and perform poorly on the subsequent task (Weiner, 1979). The extent to which students' expectancy for future success may decrease depends on what causal factors they attribute the failure to. Since effort is usually perceived as more internal, unstable, and controllable as compared to other factors (e.g., ability and task difficulty), failures attributed to lack of effort may lead to lower decreases in expectancy for future success and therefore lower decreases in subsequent effort and performance (Weiner, 1979).

The hypothesis has been verified experimentally in laboratory studies (e.g., Clifford, 1986; Heilman & Guzzo, 1978; Meyer, 1980; Pancer & Eiser, 1977) and supported by numerous studies in college classroom settings (e.g., Covington & Omelich, 1984; Greene, 1985; Henry & Stone, 2001). For instance, experimental studies in laboratory settings that manipulated college students' attributions for exam performance found that students expected a better performance in a subsequent exam when they were induced to attribute a poor prior exam performance to insufficient effort instead of low ability (e.g., Meyer, 1980; Pancer & Eiser, 1977; Valle & Frieze, 1976). Studies conducted on first-year college students found consistent evidence that attribution retraining programs, which were designed to promote effort attribution, had positive effects on students' persistence rates and college GPAs, especially for low performing students (Haynes et al., 2009; Perry & Hamm, 2017; Perry et al., 2014).

Attribution bias for failures

Although effort attribution may buffer against the negative effects of experiencing failures (Cleary & Zimmerman, 2004; Haynes et al., 2008; Ho et al., 1999; Magnusson & Perry, 1992), people tend to have bias interpreting the reasons that contribute to their failures versus successes and not attribute failures to insufficient effort (Miller & Ross, 1975; Tetlock & Levi, 1982). Specifically, it has been found that people are more likely to attribute failures to external factors, such as the characteristics of the task, while successes to internal factors, such as effort (e.g., Davis & Davis, 1972; Federoff & Harvey, 1976; Fontaine, 1975; Gilmor & Minton, 1974; Johnson, Feigenbaum, & Weiby, 1964; Simon &

Feather, 1973). For instance, an experimental study found that teachers tended to perceive themselves as responsible when students' performance improved, believing the improvement was due to their instruction, but perceive the students as responsible when students' performance remained constant (Johnson et al., 1964).

Some researchers argue that the phenomenon of attribution bias may reflect people's needs to maintain their self-esteem (Mezulis et al., 2004; Zuckerman, 1979). In the face of failure, people may avoid taking responsibility and attribute the failure to external factors to protect their self-esteem. The attribution retraining programs discussed above may help to target the attribution bias due to self-protection. These programs have been tested mainly on first-year college students, who are believed to be vulnerable to maladaptive attributions after entering a new environment (Haynes et al., 2009). In these studies, college students were presented with videos or handout materials emphasizing that it is common to encounter challenges at the beginning of college studies, and one can make great progress and succeed in the end by making more effort and changing learning strategies (e.g., Noel et al., 1987; Overwalle, Segebarth, & Goldchstein, 1989; Perry & Penner, 1990; Wilson & Linville, 1982). Results from previous studies showed that treatment students tended to have higher persistence rates and better course grades than control students (Haynes et al., 2009; Perry & Hamm, 2017; Perry et al., 2014).

Miller and Ross (1975), however, argued that attribution bias could be explained by various forms of informational bias. These informational biases may lead to biased perceptions of the relationships between one's behavior and different outcomes. For instance, Miller and Ross (1975) pointed out that in some studies where subjects were assigned to experience either improved performance outcomes or constant failures, the findings of attribution bias could be explained by the “co-variation principle”. Specifically, people tend to believe that their behaviors vary over time and are more likely to attribute outcomes that co-vary with their behaviors (e.g., improved performance outcomes in these studies) to their behaviors, while attributing constant outcomes (e.g., constant failures in these studies) to external factors (Kelley, 1971). Since the “co-variation principle” could not explain why people attributed constant successes to their own behaviors, Miller and Ross (1975) proposed another explanation that people tended to pay more attention to the co-occurrences of their behaviors with positive outcomes and ignore the co-occurrences of their behaviors with negative outcomes.

In addition, biases in people’s perceptions of their own effort could also lead to attribution bias. Specifically, people may be more likely to attribute successes to effort and failures to other factors if they tend to overestimate their effort and thus believe they have done enough to achieve their goals. Many studies have identified biases in self-estimated effort (Robinson, Martin, Glorieux, & Minnen, 2011; Seo, 2017). For instance, several studies have demonstrated that employees tend to overestimate their working hours when asked to estimate across days (Robinson et al., 2011). Winne and Jamieson-Noel (2002) also found that students were positively biased in estimating how often they used various learning strategies in a task even right after the task. In addition, studies that compared the attributions of actors and observers suggest that biases in the perceptions of one’s own effort may explain the biases in attribution (e.g., Monson & Snyder, 1977). These studies showed that actors tended to give themselves more credit for successes than observers. One mechanism could be that the information available to the actors and observers differed, and actors were more knowledgeable about their own behavior than observers

(Monson & Snyder, 1977). If so, these results may suggest that attribution bias is due to people's tendency to either overestimate their own effort or underestimate other people's effort (Beckman, 1970, 1973; Jones & Nisbett, 1971).

Informational constraints in online learning and an opportunity for intervention

The two forms of informational bias discussed above may be amplified in online learning environments where external information that can be used to objectively estimate the levels of both one's own and peers' effort is limited. First, it may be difficult for students to objectively estimate the relationships between effort and performance due to the absence of physically present peers. Students may assess the relationships between effort and performance and the amount of effort needed to achieve certain scores by comparing the effort of peers who receive different scores. However, the primary interactions in many online classes occur between individual students and the online learning platforms and most students have limited social interactions (Edgecombe, Barragan, & Rucks-Ahidiana, 2013). Therefore, it is challenging for students to collect enough information to develop a comprehensive understanding of the potential influences of effort on performance. It is particularly difficult for students to precisely estimate how much effort is needed to achieve their desired scores since it is difficult to identify desired role models from their peers and learn from them (Hodges, 2008).

Second, it is also more challenging for students to accurately track their effort spent on online versus in-person courses. First, when studying online, students will inevitably have access to other resources and activities on the Internet (e.g., Facebook messages and Youtube videos), which may distract their attention away from their academic work without full awareness (Hollis & Was, 2016; Winter, Cotton, Gavin, & Yorke, 2010).

Therefore, how much time students actually spend on studying tends to be overestimated. In addition, since in-person courses usually have fixed schedules with certain amount of contact hours on a weekly basis, students can use the course schedule as a reference to estimate their effort. In online courses, however, when to study and how much time to spend on coursework is often decided by the students and usually vary from time to time based on temporary personal and environmental factors, such as students' interest in the course content covered in a specific week and other academic and social commitments students have in that week. Finally, the fragmented nature of online learning may also make it more difficult for online students to track their study time. Online learning allows students to learn at anytime and anywhere as long as they have access to the Internet (Han & Shin, 2016; Jacob & Issac, 2008). Students could access the course materials and study in between other activities (e.g., watch a short lecture video or complete a quiz using mobile phones while waiting for buses), which may pose a challenge to accurately track how much time they spend on these small study sessions.

These informational constraints in online learning environments point to the need to provide online students with explicit informational feedback on their own and peers' behavior (Damgaard & Nielsen, 2018). The timely and rich clickstream data available in online learning provides a promising avenue for offering individualized and timely informational feedback on students' behavior, which may help to target attribution bias (e.g., Guglielmino & Guglielmino, 2002). Leveraging real time data on each interaction with the course management system from every student, instructors can provide students with the behavioral social comparisons and actionable suggestions necessary to promote self-monitoring, self-reflection, and productive behavior change.

Recently, there has been a growing interest in the use of real-time and rich clickstream data available in online learning environments to provide students with the informational feedback necessary for making appropriate and productive adjustments in their learning processes (e.g., Chen et al., 2008; Kim, Jo, & Park, 2016). Specifically, most prior research has presented students with one or more of four main types of information: the frequency of accessing course materials (e.g., Davis, Jivet, Kizilcec, Chen, Hauff, & Houben, 2017), time spent on these course materials (e.g., Park & Jo, 2015), timing of accessing course materials (e.g., Martinez, 2014; Park & Jo, 2015), or social interaction behaviors (Ali, Hatala, Gašević, & Jovanović, 2012; Dawson, Bakharia, & Heathcote, 2010). Moreover, social comparison is often included as an important component in the informational feedback provided by these studies. The type of students offered as comparisons has varied: all students from past classes, all peers in the current course, or high-performing students in a past or current course (e.g., telling students the number of times per day that students who earned As last year logged in; e.g., Auvinen, Hakulinen, & Malmi, 2015; Chen et al., 2008; Davis et al., 2017; Kim et al., 2016).

Although research in this area is fairly new, there is some early but promising evidence of the effectiveness of informational feedback interventions. Several studies revealed that being exposed to behavioral information significantly improved students' engagement and performance (e.g., Auvinen et al., 2015; Chen et al., 2008; Davis et al., 2017; Kim et al., 2016), though at least one study failed to confirm this effect (e.g., Park & Jo, 2015). The inconsistency of prior findings may be due to the great variety in the types of information given and how the information is provided, especially what types of social comparison is presented. Not all social comparisons are relevant to all students, as behavioral patterns are idiosyncratic and based on students' unique goals and background characteristics, such as prior knowledge and learning habits (Eccles, 1983). While most previous studies have compared students with the course average (e.g., Davis et al., 2017), studies on more nuanced comparisons, such as only comparing students to others who have similar academic histories, are needed.

In addition, most studies on informational feedback in online learning environments have focused on the outcomes of course performance (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). There is little evidence on the mechanisms through which the informational feedback changes performance. Based on the literature of self-regulated learning and academic attribution (Pintrich, 2000; Weiner, 1979), one potential mechanism could be that the informational feedback helps students to objectively assess the relationships between behavior and performance and evaluate their own behavior levels, which could then influence students' attribution and thus the cyclical process of self-regulated learning. Therefore, more research is needed to explore how informational feedback may influence psychological outcomes, such as attribution, to shed light on the psychological mechanisms underlying the positive effects.

The present study

In sum, there is inconsistency in the literature on the impact of informational feedback and limited understanding of how students engage with informational feedback psychologically. More experimental research is needed to better understand what types of information online students need and the psychological mechanisms through which informational feedback may change students' behavior and performance. To bridge these gaps, this study conducted a random-assignment experiment to investigate the influence of providing students with information on their own effort as well as effort spent by relevant peers in a past course.

Unlike previous studies that usually provide students with information on themselves and the course average, I provided students with social comparison information that is more relevant to them than the course average. In particular, for each student, I provided her with information on the amount of effort spent by herself as well as students who previously enrolled in the same course and had similar prior knowledge as her. In addition, for each student, I grouped her matched peers by their grades in the current course to help the student better estimate the relationships between effort and performance. Finally, I not only investigated the effect of informational feedback on behavior and performance, but also took a step further to examine the effect of informational feedback on effort, ability, and course difficulty attributions measured by self-report questions adapted from well-established survey instruments.

However, one concern was raised by including measures of attributions. The measures of attributions may induce students to reflect on their learning processes more consciously than they would have done without being exposed to these measures and may therefore influence students' subsequent behavior. Specifically, since some of the attribution measures were worded in negative or positive directions (discussed in detail in the method section below), they may have negative or positive effects on students' motivation, behavior, and performance. Therefore, I also investigated how inducing students to make attributions would influence their behavior and performance.

This study explores two main research questions: 1) What are the effects of inducing students to make attributions on students' effort and performance? and 2) What are the effects of informational feedback regarding the effort spent by oneself and relevant peers on students' attribution, effort, and performance? For the first research question, I hypothesized that the negatively and positively worded attribution questions would have negative and positive effects, respectively, on students' subsequent effort and performance. For the second research question, I hypothesized that the informational feedback would encourage students to attribute their performance to effort and would improve students' subsequent effort and performance. Moreover, I hypothesized that the effects of the informational feedback would be concentrated in students who self-reported performing poorly in the course for two reasons. First, based on the literature on attribution bias, students tend to have a bias towards not attributing failures to insufficient effort, which they may be able to correct with the informational feedback. In addition, students who self-reported performing poorly might have a strong desire to improve their performance and thus may be more likely to change their behavior based on their attribution.

Method

Experimental setting

Course. This study was conducted in a 5-week online undergraduate Chemistry course at a public 4-year university. Each week, students needed to complete online video assignments and assignments in an adaptive learning system, ALEKS, which together made up 20% of the final grade. ALEKS administered assessments to students who were then given homework problems personalized to their level of readiness. The midterm and final exams were held on the Tuesday of week 3 and the Tuesday of week 6, each making up 40% of the final grade.

Participants. A total of 300 students enrolled in the course. Ten of them did not participate in the study because they enrolled in the course after randomization, hence 290 students were randomly assigned. Four students who did not participate in the midterm exam were dropped from the analytic sample since students' midterm score served as an important variable for heterogeneity analysis. Since the intervention was conducted after the midterm exam, excluding students who did not participate in the midterm exam should not influence the balance in pre-treatment characteristics across treatment conditions. Indeed, results from the randomization check showed that there was no systematic relationship between students' pre-treatment characteristics and treatment assignment in the analytic sample (N = 286).

Experiment design

To examine both the effect of inducing attribution and the effect of providing informational feedback, a three-arm randomized controlled trial was conducted, including the following treatment conditions: 1) control condition, 2) attribution question only condition, and 3) attribution question with informational feedback condition. Students were randomly assigned to the control (N = 92), attribution question only (N = 101), or attribution question with informational feedback (N = 97) groups on the first day of week 2 since the deadline for making course changes was at the end of the first week of instruction. This study included two rounds of interventions. The interventions were delivered through two rounds of online surveys, each worth 5% extra credit toward the homework grade. The first round of intervention surveys was launched on the Wednesday of week 3, right after the instructor released students' midterm scores. The second round of intervention surveys was launched on the Sunday of week 5.

In these surveys, different questions were asked based on the treatment condition. Students in the control group were asked to respond to theoretically inert survey questions about their personality in the first round of intervention (e.g., “I see myself as someone who can be tense”) and about their college life in the second round of intervention (e.g., “Where do you now live during the school year”). In both rounds of intervention, students in the attribution question only group were first asked to evaluate how well they were doing in this course on a 5-point scale, ranging from 1 (very poorly) to 5 (very well). Then, they were asked to rate the importance of various reasons in contributing to their performance on a 5-point scale, ranging from 1 (not important at all) to 5 (extremely important). Finally, they were asked what grade they expected to get in the course. Students in the attribution question with informational feedback group received the same survey questions as students in the attribution question only group except that they were presented with a bar graph showing the number of hours per week he/she spent on ALEKS as well as the average hours spent by relevant peers (see Figure 3.1).

There are three important things to be noted about the informational feedback provided in the graph. First, students’ time spent on ALEKS was calculated based on data exported from ALEKS on a daily basis. In the first and second rounds of intervention, students’ average time spent on ALEKS in weeks 1 and 2 and in weeks 3 and 4 was calculated and presented respectively. Second, students were presented with information regarding both time spent by themselves and time spent by relevant peers. For a given student, her relevant peers were defined as previous students who enrolled in the same course last year and had similar prior knowledge as him or her. I measured students’ prior knowledge by their grade in a prerequisite course. Finally, for each student, I grouped her matched peers by their grades in the current course into three categories (i.e., students who earned As, Bs, or C+ and below) in order to help the student assess the relationship between time spent on ALEKS and overall course performance.

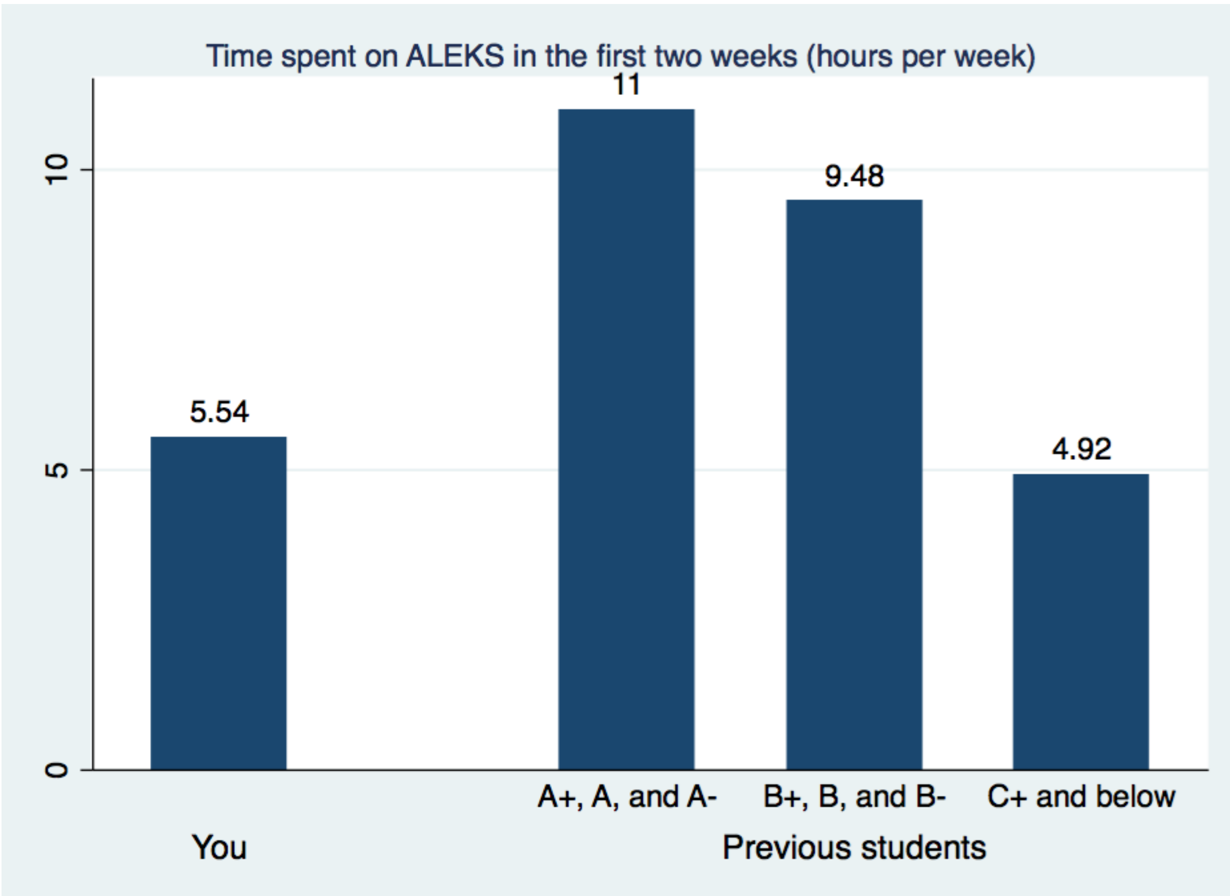

Figure 3.1 An example of the informational feedback students received

Data

Demographic data. The institution provided administrative data on demographics for students who were also enrolled as degree-seeking students at the institution. Among the 286 students in the analytical sample, 13 students were enrolled in another university and therefore did not have any data on demographics. Among the 273 students who were degree-seeking students at the university, there were small percentages of students who had missing data on first-generation status (4.4%) and SAT scores (2.2%).

The first column in Table 3.1 presents descriptive statistics on student characteristics for the analytic sample. The majority of the students were female (77%).

Around half of the analytic sample were first generation students (defined as neither parent having a college degree). About 40% of the analytic sample were low-income students. The analytic sample consisted of 45% Asian American, 34% Hispanic, 8% White, and 13% others. Students in the analytic sample were, on average, 19.44 years old and scored, on average, 1699.85 points on their SAT exam.

Table 3.1
Descriptive Statistics of Students' Pre-Treatment Characteristics of The Main Analytic Sample

	Mean	SD	N
Female	0.77	/	273
First generation college student	0.59	/	261
Low income	0.38	/	273
Race			
Asian	0.45	/	273
White	0.08	/	273
Hispanic	0.34	/	273
Other	0.13	/	273
Age	19.44	0.88	273
SAT score	1699.85	190.07	267
Time (hours) on task in weeks 1 & 2	5.95	3.42	286
Number of topics attempted in weeks 1 & 2	17.76	8.32	286
Midterm score	34.71	12.22	286

Note. The analytic sample included 286 students.

Self-evaluation of course performance. In both rounds of interventions, students in the two treatment conditions were asked to evaluate their current performance in the course by responding to the question "based on the coursework you have done so far, please rate how well you think you are doing in achieving your expected grade". Students were asked to indicate their response on a 5-point Likert scale, where 1 = very poorly, 2 = poorly, 3 = fairly, 4 = well, and 5 = very well.

Attribution. In both rounds of interventions, students in the two treatment conditions were asked how important each of the three causal factors (i.e., effort, ability, and task difficulty) were in determining their current course performance on a 5-point Likert scale (1 = very unimportant; 5 = very important). Three statements were used to measure effort attribution (α = 0.82). Following prior research about attribution (e.g., Lefcourt et al., 1979; Lloyd et al., 2005), these statements were worded differently depending on students' answers to the self-evaluation question. For students who self-reported performing very poorly or poorly, the attribution statements were worded in a negative way (e.g., "You didn't study hard enough for this course"). For students who self-reported performing fairly, the attribution statements were worded in a neutral way (e.g., "How hard you studied for this course"). For students who self-reported performing well or very well, the attribution statements were worded in a positive way (e.g., "You studied hard enough for this course"). Similarly, three statements were used to measure ability attribution (α = 0.80), and the statements were worded in negative, neutral, or positive ways based on students' self-evaluation (e.g., "You are not talented at Chemistry", "The amount of talent you have in Chemistry", or "You are talented at Chemistry"). Finally, three statements were used to measure difficulty attribution (α = 0.75) and were worded differently based on students' self-evaluation (e.g., "Quizzes and exams in this course were difficult", "The ease or the difficulty of the quizzes and exams in this course", "Quizzes and exams in this course were easy"). Data on students' attribution were only available for students who were assigned to the attribution only and attribution with informational feedback groups and participated in the treatment surveys. In particular, I used student attribution measures in the first round of intervention as outcome variables (N = 186). On average, students in the restricted survey sample reported fairly high effort attribution (M = 3.76, SD = 0.88), followed by course difficulty attribution (M = 3.36, SD = 0.91), and ability attribution (M = 2.86, SD = 0.98).

Expected grade. In both rounds of interventions, students in the two treatment conditions were asked what grade they expected to get in the course on a 13-point scale, where 1 = F and 13 = A+. Again, data regarding expected grade were only available for students who participated in the two rounds of intervention surveys, and I used students' expected grade in the first round as an outcome variable (N = 186). On average, students reported an expected grade of 8.29, corresponding to a letter grade of B-.

ALEKS data. ALEKS provided timely data on two measures of students' effort regarding ALEKS assignments: time on task and the number of topics attempted. These data were used to conduct randomization checks, generate individualized informational feedback, and evaluate the effect of the treatments. First, students' average time on task and average number of topics attempted in weeks 1 and 2 were used in the randomization check as the first round of intervention was conducted in week 3. One would expect to see no systematic relationship between student pre-treatment behavioral measures on ALEKS and the treatment assignment. Students' average time on task in weeks 1 and 2 and in week 3 were used to generate the informational feedback graphs presented in the first and second rounds of intervention, respectively. Finally, students' average time on task and average number of topics attempted in weeks 4 and 5 were used as outcome variables to examine whether the treatments had any effect on students' behavior on ALEKS. Table 3.2 presents descriptive statistics for these outcome variables. On average, students in the analytic sample spent 5.23 hours and attempted 11.22 topics per week in weeks 4 and 5 on ALEKS.

Course performance. Three performance outcomes were used, including students' scores on video assignments, final exam scores, and final GPA.[6] Final GPA, measured on a 4-point scale, was determined by a weighted average of the midterm score (40%), final exam score (40%), and score on video assignments (20%). Table 3.2 provides descriptive statistics for course performance outcomes. On average, students in the analytic sample scored 91 out of 100 on the video assignments, 41.19 out of 81 on the final exam, and 2.03 out of 4 as final GPA.

Table 3.2
Descriptive Statistics of Students' Behavioral and Performance Outcomes of the Main Analytic Sample

	Mean	SD	N
Time (hours) on task in weeks 4 & 5	5.23	3.82	286
Number of topics attempted in weeks 4 & 5	11.22	6.46	286
Course grade	2.03	0.92	286
Final exam	41.19	12.87	286
Video assignments	91.07	15.06	286

Note. The analytic sample included 286 students.

Analysis

Randomization Check. Two different samples were used for the first and second research questions. The first research question concerns the effect of inducing attribution with/without informational feedback and requires comparison of the three groups. Therefore, randomization checks were conducted on the full analytic sample (N = 286) to examine whether there were systematic differences in students' pretreatment characteristics among the three groups. The second research question is about the effect of informational feedback and requires comparison of the attribution only and attribution with informational feedback groups. To assess if students in these two groups differed in their pretreatment characteristics, randomization checks were conducted on a restricted

[6] Student scores on ALEKS assignments were only available for 264 students due to some students misspelling their student ID on ALEKS. Therefore, I did not include student ALEKS score as a performance outcome variable.

survey sample of students who were assigned to attribution only and attribution with informational feedback groups and who participated in the first round of intervention by completing the week 3 survey (N = 186).

This restricted survey sample was chosen for three reasons. First, the restriction to students who completed the week 3 survey allowed me to examine the treatment effect on attribution, which was measured by the survey. Second, the restriction allowed me to focus on students who received the informational feedback and estimate the treatment effect on the treated. Finally, one potential threat to the use of the restricted survey sample was that students who chose to take the week 3 survey differed between the attribution only and the attribution with informational feedback groups. This is a lesser concern in the first round of intervention since students had no knowledge about what questions would be presented and their decisions to complete the week 3 survey would therefore not be influenced by the treatment assignment. Indeed, the results from the randomization check for the restricted survey sample suggest that the two groups were fairly equal in expectation.

Similar analyses were conducted for randomization checks for the two samples. Data regarding students' demographic characteristics, behaviors on ALEKS in the first two weeks, and midterm scores were used to assess the experimental balance of the randomization. ANOVA was conducted for each categorical variable (e.g., gender and race) to check if there were large and significant differences among the experimental conditions for both samples. For each continuous variable (e.g., midterm score), regression analyses with F-tests of the overall significance of the experimental conditions/individual t-tests were conducted for the full analytic sample/the restricted survey sample. The results for both samples are presented in Table 3.3.

Another approach for assessing whether the randomization is successful is to directly test whether the treatment assignment is orthogonal to potential outcomes predicted by pretreatment variables available. Therefore, I regressed outcome variables on all pretreatment variables and then used the estimated regression model to predict students' potential outcomes based on pretreatment variables. To maintain the sample size, I kept students who had missing data on demographics and included indicators for missing data on these variables in the regression analysis. Then, I regressed the predicted outcome against the treatment assignment. For the full analytic sample, follow-up F-tests of the overall significance of the treatment assignment were conducted to see whether the treatment assignment would predict students' potential outcomes. The results are presented in Table 3.4.

Overall, the results suggest that the randomization procedure was valid. Results in Table 3.3 indicate that for both samples, none of these pretreatment variables exhibited any significant difference among the groups except for one variable. For the full analytic sample, results in Table 3.4 show that the F-test statistics for the joint significance of treatment assignment predicting potential outcomes were insignificant for all potential outcomes predicted by pretreatment variables. Results in Table 3.4 also indicate that for the restricted survey sample, the treatment assignment had no systematic relationship with students' potential outcomes predicted by pretreatment variables.

Table 3.3

Randomization Test: Students' Pre-Treatment Characteristics by Experimental Conditions for the Full Analytic Sample

	Full Analytic Sample					Restricted Survey Sample			
	Control group	Attribution only group	Attribution + Informational feedback group	N	p	Attribution only group	Attribution + Informational feedback group	N	p
Female	0.816	0.723	0.793	273	0.741	0.693	0.784	176	0.204
First generation student	0.622	0.578	0.562	261	0.43	0.576	0.553	170	0.83
Low income	0.356	0.383	0.402	273	0.53	0.375	0.409	176	0.79
Race									
Asian	0.494	0.457	0.402	273	0.216	0.466	0.409	176	0.449
White	0.0805	0.0426	0.12	273	0.325	0.0455	0.114	176	0.054
Hispanic	0.276	0.383	0.359	273	0.251	0.364	0.352	176	0.734
Other	0.149	0.117	0.12	273	0.557	0.125	0.125	176	0.958
Age	19.66 (1.24)	19.39 (0.66)	19.29 (0.60)	273	0.016	19.39 (0.67)	19.29 (0.60)	176	0.304
SAT score	1707.1 (190.70)	1692.5 (188.50)	1700.8 (192.90)	267	0.878	1692.8 (190.90)	1704.5 (195.20)	176	0.768
Time on task in weeks 1 & 2	5.928 (3.40)	5.694 (3.58)	6.246 (3.27)	286	0.528	5.717 (3.59)	6.394 (3.28)	184	0.262
Topics attempted in weeks 1 & 2	17.31 (7.80)	16.98 (8.74)	18.98 (8.29)	286	0.2	17.09 (8.76)	19.33 (8.33)	184	0.101
Midterm score	35.12 (12.07)	35.16 (12.37)	33.86 (12.30)	286	0.708	35.22 (12.51)	34.44 (12.19)	184	0.463

Table 3.4

Randomization Test: Regression of Experimental Conditions on Possible Outcomes Predicted by Pretreatment Characteristics

	Time on task in weeks 4 & 5	Number of topics attempted in weeks 4 & 5	Course grade	Final exam	Video assignments
Full Analytic Sample					
Attribution only group	-0.074	0.011	0.003	-0.229	-0.002
	(0.393)	(0.612)	(0.122)	(1.455)	(1.379)
Attribution + Informational feedback group	0.401	0.804	-0.07	-1.031	1.232
	(0.397)	(0.618)	(0.124)	(1.470)	(1.393)
F-statistics	0.86	1.14	0.23	0.28	0.54
N	286	286	286	286	286
R-square	0.006	0.008	0.002	0.002	0.004
Restricted Survey Sample					
Attribution + Informational feedback group	0.671	1.055	-0.047	-0.606	1.254
	(0.452)	(0.708)	(0.130)	(1.590)	(1.480)
N	184	184	184	184	184
R-square	0.012	0.012	0.001	0.001	0.004

Note. All coefficients are standardized.

Main effect of the treatments. Linear regressions were employed to estimate the main effect of treatment assignment on student outcomes using the following equations. Equation (1) was used to estimate the effect of inducing students to make attributions with and without informational feedback and Equation (2) was used to estimate the effect of providing informational feedback:

$$Y_i = \alpha + \beta_1 Attribution\ Only_i + \gamma_1 Attribution\ with\ Informational\ Feedback_i + \theta_i + \varepsilon_i \quad (1)$$

$$Y_i = \alpha + \eta_1 Attribution\ with\ Informational\ Feedback_i + \theta_i + \varepsilon_i \quad (2)$$

Where Y_i represents the outcome of student *i*. For the first research question, students' behavior on ALEKS in weeks 4 and 5 and their course performance were used as the outcome variables. Students' attribution and expected course grade measured in week 3 were added as additional outcome variables for the second research question. θ_i is a vector of student-level covariates, including the demographic variables listed in Table 3.1, students' time spent on and number of topics attempted in ALEKS in weeks 1 and 2, and their midterm scores. $Attribution\ Only_i$ indicates whether the student was assigned to the attribution only group and $Attribution\ with\ Informational\ Feedback_i$ indicates whether the student was assigned to the attribution with informational feedback group. Therefore, β_1 and γ_1 in Equation 1 measure the main effect of inducing students to make attributions without and with informational feedback respectively. η_1 in Equation 2 measures the main effect of providing informational feedback.

Heterogeneity check. For the first research question, I hypothesized that the attribution questions worded in the positive/negative directions may have positive/negative effects on students' behavior and performance. Since the type of attribution questions students would receive depends on their responses to the self-evaluation question, to directly test this hypothesis requires examining the effects of attribution questions on students who self-reported performing poorly or very poorly and the effects on students who self-reported performing well or very well. However, since control students did not receive the question about self-evaluation, students' midterm scores were used as approximate measures of their self-evaluation. Indeed, there was a strong correlation between students' midterm scores and their self-evaluation in week 3 among students in the two treatment groups, $r(184) = .643$, $p < .001$. Therefore, students in the full analytic sample were divided into two subgroups using median split on their midterm scores, and the effects of attribution questions with/without informational feedback on these two student subgroups were examined using the following equation:

$$Y_i = \alpha + \beta_2 Attribution\ Only_i + \beta_3 Attribution\ Only_i * Midterm_{High_i} + \gamma_2 Attribution\ with\ Informational\ Feedback + \gamma_3 Attribution\ with\ Feedback * Midterm_{High_i} + \theta_i + \varepsilon_i \tag{3}$$

Where $Midterm_{High_i}$ indicates whether the student's midterm score was equal to or above the median. Therefore, β_2 and γ_2 represent the treatment effects for students whose midterm score was below the median. $\beta_2 + \beta_3$ and γ_2+γ_3 represent the treatment effects for students whose midterm score was equal to or above the median.

For the second research question, I hypothesized that the effect of the informational feedback would be concentrated on students who self-reported performing very poorly or poorly. Therefore, students were divided into three groups based on their self-evaluation of their performance, including students who self-reported performing poorly or very poorly (N = 52), students who self-reported performing fairly (N = 67), and students who self-reported performing well or very well (N = 65). The effects of informational feedback on these three subgroups of students were examined using the following equation:

$$Y_i = \alpha + \eta_2 Attribution\ with\ Informational\ Feedback_i + \eta_3 Attribution\ with\ Informational\ Feedback_i * Fairly_i + \eta_3 Attribution\ with\ Informational\ Feedback_i * Well_i + \theta_i + \varepsilon_i \quad (4)$$

Where $Fairly_i$ indicates whether the student self-reported performing fairly and $Well_i$ indicates whether the student self-reported performing well or very well in the first round of intervention. Therefore, $\eta_2, \eta_2 + \eta_3, \eta_2 + \eta_4$ represent the effects of informational feedback on students who self-reported performing poorly or very poorly, fairly, and well or very well, respectively.

Results

The effects of attribution questions with and without informational feedback

Main effects. The first two columns in Table 3.5, corresponding to coefficients β_1 and γ_1 in Equation 1, show the effects of inducing attribution without and with informational feedback in comparison to the control condition. Since the two treatment conditions were tested simultaneously, F-tests were also conducted for the overall significance of the coefficients on the two treatment conditions to examine if either treatment had any significant effect on the outcomes. The results of F-tests are presented in the third column of Table 3.5.

Results from the joint F-tests indicate neither of the treatments had any significant effect on students' behavioral or performance outcomes. In terms of behavioral outcomes, students in the attribution only group, on average, spent less time (β = -.076, p = .479) and attempted fewer topics (β = -.013, p = .907) on ALEKS in weeks 4 and 5 than students in the control group did. On the contrary, students in the attribution with informational feedback group, on average, spent more time (β = .042, p = .700) and attempted more topics (β = .002, p =.989) on ALEKS than students in the control group did. However, in alignment with the results from the F-tests, these differences were not statistically significant. In terms of performance outcomes, students in both the attribution only and attribution with informational feedback groups had higher course grades and final exam scores but lower video assignment scores than students in the control group. Again, none of these differences were statistically significant.

Heterogeneity effects. The lack of significant effects of attribution questions with/without informational feedback may be because the attribution questions were worded differently for different students, which may cause different effects on students. In particular, students received positively, neutrally, or negatively worded attribution questions depending on their self-evaluation of their current performance in the course. To examine how these questions may affect students differently, heterogeneity analysis was conducted based on students' midterm scores, which were released three days before the intervention, since these scores may serve as an important reference for students to evaluate their course performance.

Columns four to nine in Table 3.5 present the results from the heterogeneity analysis. Columns four and five, corresponding to coefficients β_2 and γ_2 in Equation 3, show the effects of the two treatments on students whose midterm score was below the median. Joint F-tests for the overall significance of the two coefficients were conducted to examine if either of the treatments had any significant effects on students whose midterm score was below the median. Columns seven and eight, corresponding to the sums of the coefficients

β_2 and β_3 (β_2+β_3) and γ_2 and γ_3 ($\gamma_2 + \gamma_3$) in Equation 3, present the impacts of the two treatments on students whose midterm score was equal to or above the median. Again, joint F-tests for the overall significance of the two sums were conducted.

For students whose midterm score was below the median, results from the F-tests indicate that neither of the treatments had any significant effect on time on task, number of topics attempted, course grade, or final exam score, suggesting the negatively worded attribution questions had no effect on these outcomes. However, the lack of significant findings may also be due to potential misidentification of students who received the negatively worded attribution questions. Students in both treatment groups consistently scored more than 0.2 standard deviations lower in video assignments than students in the control group, suggesting the attribution questions might have negative effects on students' video assignment performance. However, perhaps due to the small sample size, the result from the F-test indicates that neither of the differences between the two treatment groups and the control group was statistically significant at the 10% level, $F(2, 267) = 1.96$, $p = .1428$.

For students whose midterm score was equal to or above the median, while no significant effects were found for other outcomes, the F-test indicates there were significant differences in final exam scores between at least one of the treatment groups and the control group at the 10% level, $F(2, 267) = 2.70$, $p < .1$. Results from the regression analysis show that students in the attribution with informational feedback group had significantly higher final exam scores than students in the control group ($\beta = .316$, $p < .05$). Students in the attribution only group also scored around 0.1 standard deviations higher on the final exam than students in the control group, although the difference was not significant. These results suggest that the attribution with informational feedback intervention had positive effects on students' exam performance, which may be partially due to the positively worded attribution questions.

Table 3.5

The Effects of Attribution Question with and Without Informational Feedback Using the Full Analytic Sample

	Main effect			Heterogeneity effect					
	All students			Midterm score below median			Midterm score above median		
	Attribution only	Attribution + Informational feedback	F-statistics	Attribution only	Attribution + Informational feedback	F-statistics	Attribution only	Attribution + Informational feedback	F-statistics
Behaviors									
Time on task in weeks 4 and 5	-0.076 (0.108)	0.042 (0.110)	0.65	-0.119 (0.154)	0.053 (0.153)	0.71	-0.028 (0.151)	0.043 (0.155)	0.11
Number of topics attempted in weeks 4 and 5	-0.013 (0.116)	0.002 (0.118)	0.01	0.013 (0.165)	-0.118 (0.164)	0.41	-0.032 (0.161)	0.147 (0.166)	0.68
Performance									
Course grade	0.024 (0.062)	0.013 (0.063)	0.08	-0.024 (0.088)	-0.082 (0.087)	0.48	0.076 (0.086)	0.123 (0.088)	1.00
Final exam	0.098 (0.096)	0.145 (0.098)	1.14	0.078 (0.137)	-0.016 (0.136)	0.29	0.117 (0.134)	0.316* (0.137)	2.70+
Video assignments	-0.139 (0.118)	-0.16 (0.120)	1.04	-0.232 (0.169)	-0.328+ (0.169)	1.96	-0.052 (0.166)	0.010 (0.170)	0.08
N	286			286					

Note. All coefficients are standardized. +*p*<0.1 * *p*<0.05 ** *p*<0.010 *** *p*<0.001

Table 3.6

The Effects of Informational Feedback Using the Restricted Survey Sample

	Main effect	Heterogeneity effect		
	All students	Performing poorly	Performing fairly	Performing well
Attribution and Expectancy				
Attributing to effort	0.094	0.518+	-0.101	-0.018
	(0.149)	(0.275)	(0.247)	(0.256)
Attributing to ability	-0.141	-0.653*	0.183	0.117
	(0.151)	(0.267)	(0.240)	(0.249)
Attributing to course difficulty	-0.025	0.029	0.009	0.086
	(0.152)	(0.247)	(0.222)	(0.231)
Expected course grade	0.019	0.139	0.060	-0.074
	(0.110)	(0.178)	(0.161)	(0.167)
Behaviors				
Time on task in weeks 4 and 5	0.117	0.390*	0.132	-0.117
	(0.106)	(0.197)	(0.177)	(0.183)
Number of topics attempted in weeks 4 and 5	0.008	0.074	-0.062	0.046
	(0.115)	(0.212)	(0.191)	(0.198)
Performance				
Course grade	-0.008	0.018	-0.057	0.038
	(0.065)	(0.121)	(0.109)	(0.113)
Final exam	0.066	0.155	-0.110	0.240
	(0.100)	(0.184)	(0.165)	(0.171)
Video assignments	-0.006	-0.293	0.184	0.082
	(0.130)	(0.240)	(0.216)	(0.224)
N	184		184	

Note. All coefficients are standardized. +*p*<0.1 * *p*<0.05 ** *p*<0.010 *** *p*<0.001

The effect of informational feedback

Main effects. The first column in Table 3.6, corresponding to the coefficient η_1 in Equation 2, represents the differences in outcomes between students in the attribution with informational feedback group and students in the attribution only group and therefore measures the effect of informational feedback.

The results indicate while students in the attribution with informational feedback group, on average, scored higher on effort attribution, lower on ability attribution and course difficulty attribution, and higher on expected course grade relative to students in the attribution only group, these differences were not statistically significant. Similarly, the differences in behavioral and performance outcomes between the two treatment conditions were generally small and were not statistically significant. These results suggest that the informational feedback had no significant main effects on students' attribution, expectancy, behavior, or performance.

Heterogeneity effects. The second, third, and fourth columns in Table 3.6, corresponding to η_1, the sum of η_1 and η_2, the sum of η_1 and η_3 in Equation 4, represent the effects of informational feedback on students who self-reported performing poorly, fairly, and well. Differential effects were observed when examining treatment heterogeneity across the three subgroups.

I first report the treatment effects for students who self-reported performing poorly. For this subgroup, those who received the informational feedback tended to report significantly higher values for effort attribution by more than half of a standard deviation relative to their counterparts who did not receive the feedback. This is consistent with my hypothesis that the informational feedback could help students objectively estimate their effort levels and the relationships between effort and performance, both of which could correct their attribution bias. In addition, for this subgroup, those who received the informational feedback reported significantly lower ability attribution by more than 0.6 of a standard deviation as compared to their counterparts who did not receive the feedback, though no significant differences were found for the tendency to attribute poor performance to course difficulty, β =.029, p = .908. These results together suggest that informational feedback could correct students' attribution bias and encourage them to attribute failures to insufficient effort rather than low ability. Finally, among students who self-reported performing poorly, the difference in expected course grade between those who received and did not receive the informational feedback was, though not significant, positive and relatively large, β = .139, p = .438.

In terms of the behavioral outcomes of this subgroup, students who received the informational feedback spent significantly more time on ALEKS in weeks 4 and 5 (β = .390, $p < .05$) than those who did not receive the feedback, though no significant difference was found for number of topics attempted. Large, though not significant, differences were found for course performance outcomes. For students who self-reported performing poorly, those who received the informational feedback scored 0.155 of a standard deviation higher on the final exam and 0.293 of a standard deviation lower on the video assignments than those who did not receive the feedback. However, these differences were not significant, which may be due to the small sample size.

In contrast, there was no significant effect on any of the outcomes for students who self-reported performing fairly or well. First, while the informational feedback had a positive effect on effort attribution for the subgroup of students who self-reported performing poorly, it had no effect on effort attribution for the subgroups of students who self-reported performing fairly (β = -.101, p = .683) or well (β = -.018, p =.943). Moreover, the effect on effort attribution differed significantly between the subgroup of students who self-reported performing poorly and the subgroup of students who self-reported performing fairly (β = -.620, p < .1). In addition, while the informational feedback had a negative effect on ability attribution for the subgroup of students who self-reported performing poorly, it had no effect on ability attribution for students who self-reported performing fairly (β = .183, p = .446) or well (β =.117 p = .640). Moreover, the effect on ability attribution differed significantly between the subgroup of students who self-reported performing poorly and the subgroups of students who self-reported performing fairly (β = .837, p < .05) and well (β = .770, p < .05). Finally, while the informational feedback had a positive effect on time on task in weeks 4 and 5 for the subgroup of students who self-reported performing poorly, it had no effect on the subgroups of students who self-reported performing fairly (β = .132, p = .455) or well (β = -.117, p = .526). The effect on time on task differed significantly between the subgroup of students who self-reported performing poorly and the subgroup of students who self-reported performing fairly (β = .507, p < .1).

Discussion

Key findings

In this study, a randomized control trial was conducted to explore the effects of providing students with informational feedback about their effort level. Unlike previous studies that mainly focus on behavioral and performance outcomes, this study included students' attribution as an outcome of informational feedback, which sheds light on the psychological mechanisms through which informational feedback may change students' behavior and performance. Due to concerns about the attribution questions affecting students' motivation and behavior, the effect of inducing students to make attributions for their course performance was also examined.

Overall, inducing students to make attributions with and without providing informational feedback had no significant effect on any of the behavioral or performance outcomes. However, the treatments seem to influence high-performing and low-performing students differently. In particular, there was suggestive evidence that inducing students to make attributions with informational feedback had negative effects on low-performing students' video assignment performance and positive effects on high-performing students' final exam scores. Although the effects of only asking attribution questions were not significant for either of the two outcomes, the effects were similar in size and direction as compared to the effects of asking attribution questions with informational feedback. These results suggest that the attribution questions may partially contribute to the negative effect found for low-performing students and the positive effects found for high-performing students. One potential explanation for these findings is that low-performing students tended to report performing poorly and therefore received negative statements of attribution (e.g., "You didn't study hard enough for this course") while high-performing students tended to report performing well and therefore received positive statements of attribution (e.g., "You studied hard enough for this course"). Students presented with negative or positive statements of attribution may be prompted to internalize the negative or positive images of themselves and consequently had lower or higher motivation, engagement, and performance.

Moreover, no overall significant effects were found for informational feedback on attribution, behaviors, or performance. However, results from heterogeneity analysis indicate that the informational feedback differentially affected students who varied in their self-evaluations of their course performance. For students who self-reported performing poorly, the informational feedback had a significantly positive effect on effort attribution and a significantly negative effect on ability attribution. In agreement with my hypothesis, these results suggest that informational feedback could correct students' attribution bias by helping them develop a more accurate perception on the relationship between effort and performance and more objectively estimate their effort levels. Moreover, the significant effect of informational feedback on effort attribution was only found for students who self-reported performing poorly and not for students who self-reported performing fairly or well. These results may suggest that students who were not satisfied with their performance may be more likely to suffer from attribution bias, which is supported by previous studies that found people are less likely to make effort attributions when experiencing failures as compared to successes (e.g., Davis & Davis, 1972; Federoff & Harvey, 1976; Fontaine, 1975). Another potential explanation could be that students who are not satisfied with their performance are more likely to actively seek for and attach high values to external information that may help explain their poor performance and therefore are more likely to be influenced by the informational feedback.

Finally, in alignment with my hypothesis, informational feedback had a positive effect on students' subsequent effort, though not performance, for students who self-reported performing poorly. While the lack of significant effect on performance may be due to a small sample size, it may also indicate that an increase in effort may not necessarily improve course performance. Previous studies have shown that how students spend their time and what learning strategies they use also play an important role in determining course performance (e.g., Greene, Miller, Crowson, Duke, & Akey, 2004; Pintrich & De Groot, 1990; Puzziferro, 2008). If the informational feedback mainly induced students to spend more time on ineffective activities, such as reciting and memorizing the answers of the questions on ALEKS, it may have no effect on course performance. Therefore, more research is needed to explore using informational feedback to not only increase student effort but also to guide students in using their time more effectively.

There are several implications that can be inferred from these results. First, this study suggests attribution measures may make the self-reflection process more conscious; induce students to internalize either negative or positive images of themselves, the tasks, and the learning environments; and substantially change students' perceptions, behaviors, and performance. Therefore, studies that use attribution measures need to take into account potential effects from these instruments and interpret data collected using these instruments with caution. In addition, this study applies attribution theory and self-regulation theory to explain how students interact with external informational feedback about their behavior in online learning. The results from this study show that external informational feedback could influence students' attribution process and intervene in the cyclical process of self-regulated learning. Finally, informational feedback can induce positive attributions in online learning. The same intervention can be scaled up by building into learning systems programs that automatically generate and push reports about individuals' learning processes to students.

Limitations

There are several limitations involved in this study. First, this study had a relatively small sample size given that the effects of the attribution questions and the informational feedback were concentrated only on subgroups of students in the sample. The small sample size may not allow for detection of small or medium size effects. Indeed, while for students who self-reported performing poorly or very poorly, those who received the informational feedback had higher final exam scores than those who did not by 0.1 of a standard deviation, the difference was not significant. Further research using a larger sample size is needed to detect small but practically relevant effects on performance.

In addition, this study was not able to examine the effect of only providing informational feedback without attribution questions on students' effort and performance. Although there was limited evidence that the attribution question had any effects on students' subsequent effort and performance outcomes except for video assignments, the attribution question may moderate the effect of the informational feedback. For instance, the attribution question asked right after the informational feedback may guide students to interact with the information in a more systematic and effective way, which may amplify the effect of the informational feedback. Indeed, some researchers argue that well-designed pedagogical activities are necessary to guide students in interpreting and making productive use of informational feedback (Wise, 2014). However, the examination of the moderating effect of the attribution question on the effect of informational feedback requires a four-arm randomized controlled trial, which was not feasible in this study due to the small sample size. Thus, future researchers are encouraged to extend this work by examining how the effect of informational feedback may be amplified by attribution activities or other well-designed activities that can guide students' interaction with the information.

Conclusions

This study took advantage of the rich and detailed clickstream data available in technology-enhanced learning environments to provide students with timely and individualized feedback on their learning processes. By conducting a randomized control trial, I found that the informational feedback had positive effects on students' adaptive attribution and subsequent effort. Overall, this study provides evidence that informational feedback can support self-regulated learning by helping students make more informed attribution and productive changes in their learning processes. It also provides practitioners with an effective attribution intervention that can be easily scaled up for large numbers of students by building into the online learning environment programs that automatically generate and deliver timely and individualized informational feedback.

CHAPTER 4: Summary, Implications, and Conclusion

Summary

The primary goal of my dissertation was to use clickstream data collected from online learning platforms to explore the behavioral consequences of attribution and design individualized attribution interventions to support online students. In Chapter 2, I used the clickstream data collected from a learning management system to develop behavioral measures of time management and effort regulation and then verified these measures by examining their relationships with students' self-report data and course performance. I found that the clickstream measures were significantly associated with students' self-reported time management and effort regulation after the course. In addition, these clickstream measures could significantly improve the prediction of students' performance in the current and subsequent courses over self-report measures. These results provide evidence for the validity of the clickstream measures, which can be adapted and used in future education research to explore how personal and environmental factors may relate to behaviors.

In Chapter 3, I examined the relationships between attributing failures to effort rather than ability, expected change in outcomes for a subsequent exam, changes in subsequent behavior (i.e., changes in time on task, completing quizzes on time, and watching lectures on time), and actual changes in performance on the subsequent exam in an online class. In addition, I investigated how these relationships may be moderated by students' prior behavior and desired scores. I found that the tendency to attribute failures to effort rather than ability was associated with higher expected change in exam outcomes only for students who had low levels of prior behavior. In addition, I found that expected change in exam outcomes was associated with increases in subsequent behavior only for students who had low levels of prior behavior and high levels of desired scores. These results partially confirmed the positive role of attributing failures to effort rather than ability in the context of online learning. Moreover, the results revealed that there may be certain boundaries to the benefits of attributing failures to effort rather than ability, and interventions targeting effort attribution may need to be tailored to students' unique goals, academic history, and background characteristics.

In Chapter 4, having found that attributing failures to effort may buffer students against the negative effect of failures, I used the timely and rich clickstream data collected from an online homework system to generate an individualized attribution intervention for students in an online class. To correct potential informational biases in students' attribution process, I presented students with information on how much time they spent on the homework system as compared to relevant peers. I found that the intervention induced students to attribute poor academic outcomes to lack of effort rather than lack of ability. Moreover, the intervention had positive effects on students' subsequent time on task, though not course performance.

Implications for practice and research

Implications for research. My dissertation provides an example of how to use clickstream data from technology-enhanced learning environments to measure important academic-related behaviors and demonstrate the process and benefits of using these behavioral measures to provide novel insights into how motivational processes may shape students' behaviors. Previous studies mainly rely on observations or self-reports to measure students' behaviors, which can be noisy and may not be feasible for large numbers of students. The automatically collected clickstream data, however, provides objective measures of students' behaviors that can be used to examine the relationships between behaviors and underlying motivational processes for a large number of students. Moreover, the longitudinal nature of the clickstream data can be utilized to investigate not only how motivational processes may influence students' behavior but also how students' previous experiences may impact their motivational beliefs. Finally, my dissertation provides future research with valid clickstream measures that can be adapted and used to explore how other motivational processes, such as interest and goal setting, may shape students' behavior.

In addition, using the clickstream data available from online learning environments, my dissertation confirms the link between attribution and behavior and provides correlational and experimental evidence for the positive effects of attributing failures to lack of effort. However, the results also suggest that there are many factors that interact with the attribution process and attribution interventions may not be useful for every student. Researchers are encouraged to explore how other personal and environmental factors may influence the role of attribution and what the boundary conditions for the positive effects of attributing failures to lack of effort are.

Implications for practice. My dissertation confirms the important role of attribution in online courses. Instructors are encouraged to pay close attention to low-performing students during the course and provide timely supports to encourage them to make informed and adaptive attributions. Providing students with timely and individualized informational feedback on their and peers' learning processes is found to be effective for promoting adaptive attribution and improving students' subsequent effort. To scale up this type of timely and individualized intervention, practitioners could build into online learning platforms automatically generated and delivered reports about individuals' learning processes.

Conclusion

This dissertation contributes to understanding the process and consequences of academic attribution and ways to support it in the context of online learning by taking advantage of the clickstream data uniquely available in technology-enhanced learning environments. By conducting three studies, I first developed and verified clickstream measures of students' self-regulation behaviors and then used these clickstream measures to explore the relationships between attribution and changes in students' behavior. Having confirmed the link between attribution and students' behavior, I then conducted a randomized controlled trial to test the effect of informational feedback on students' attribution, behavior, and performance. I believe the dissertation provides researchers with guidelines on how to use clickstream data from technology-enhanced learning environments to extend our understanding of existing theories about students' learning processes. In addition, it sheds light on the complexity of attribution processes and suggests that multiple factors may interact with attribution processes in determining students' academic-related behaviors. Finally, it confirms the positive effects of attributing failures to lack of effort and provides practitioners with an example of effective attribution interventions that can be used to promote effort attribution.

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Appendix A: Robustness Analysis for the Relationship between Clickstream Measures and Performance

Table A1.

Clickstream Measures Predicting Student Performance in the Current Course

	Course Grade		Final Exam Score	
	M1	M2	M1	M2
Studying on time_CL	0.284***	0.216**	0.225**	0.170*
	(0.07)	(0.07)	(0.07)	(0.07)
Studying in advance_CL	0.220***	0.138*	0.224***	0.149*
	(0.06)	(0.06)	(0.06)	(0.06)
Studying in advance_CL^2	-0.008	-0.000	-0.015	-0.007
	(0.03)	(0.03)	(0.03)	(0.03)
Spacing_CL	-0.053	-0.046	-0.026	-0.030
	(0.06)	(0.05)	(0.06)	(0.06)
Spacing_CL^2	-0.032	-0.018	-0.045	-0.026
	(0.04)	(0.04)	(0.04)	(0.04)
Change in time on task_CL	0.203**	0.224***	0.221***	0.239***
	(0.06)	(0.06)	(0.06)	(0.06)
Change in time on task_CL^2	-0.127***	-0.112***	-0.119***	-0.103***
	(0.03)	(0.03)	(0.03)	(0.03)
Student controls		X		X
N	319	307	319	307
R square	0.369	0.500	0.344	0.460

Note. All coefficients are standardized. +p<0.1 * p<0.05 ** p<0.010 *** p<0.001

Table A2.

The Moderation Effect of the Levels of Time on Task in Module 1 on the Relationships Between the Change in Time on Task and Course Performance

	Course Grade					Final Exam Score				
	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
Change in time on task_CL	0.347**	0.038	0.267*	0.315*	0.247+	0.337*	0.001	0.264+	0.263	0.217
	(0.13)	(0.16)	(0.13)	(0.16)	(0.13)	(0.14)	(0.16)	(0.14)	(0.16)	(0.14)
Change in time on task_CL*Time on task	0.039	0.239	0.117	-0.011	0.108	0.054	0.277	0.122	0.042	0.127
M1_Median	(0.17)	(0.21)	(0.17)	(0.19)	(0.16)	(0.17)	(0.22)	(0.17)	(0.20)	(0.17)
Change in time on task_CL*Time on task	0.057	0.233	0.284+	0.031	0.096	0.065	0.263	0.259	0.077	0.128
M1_High	(0.16)	(0.20)	(0.16)	(0.19)	(0.15)	(0.16)	(0.21)	(0.17)	(0.20)	(0.16)
Change in time on task_CL^2		-0.019	-0.129	-0.020	-0.107	-0.041	0.062	-0.051	-0.008	-0.047
	(0.14)	(0.15)	(0.14)	(0.15)	(0.14)	(0.15)	(0.15)	(0.14)	(0.16)	(0.14)
Change in time on task_CL^2*Time on task	-0.311+	-0.351*	-0.279+	-0.413*	-0.251	-0.310+	-0.350*	-0.285+	-0.356*	-0.257
M1_Median	(0.16)	(0.17)	(0.16)	(0.17)	(0.16)	(0.17)	(0.18)	(0.17)	(0.18)	(0.17)
Change in time on task_CL^2*Time on task	-0.029	-0.081	-0.031	-0.068	0.003	-0.076	-0.142	-0.090	-0.058	-0.040
M1_High	(0.15)	(0.15)	(0.15)	(0.16)	(0.14)	(0.15)	(0.16)	(0.15)	(0.17)	(0.15)

Table A2.
Continued

Dummy variables for Time on task in M 1	X	X				X	X			
Clickstream measures of time management		X					X			
Clickstream measures of time management*Time on task M1_Median		X					X			
Clickstream measures of time management*Time on task M1_High		X					X			
Self-report measures_PRE			X					X		
Self-report measures_PRE *Time on task M1_Median			X					X		
Self-report measures_PRE *Time on task M1_High			X					X		
Self-report measures_POST				X					X	
Self-report measures_POST *Time on task M1_Median				X					X	
Self-report measures_POST *Time on task M1_High				X					X	
Student Controls					X					X
Student Controls*Time on task M1_Median					X					X
Student Controls*Time on task M1_High					X					X
N	238	238	238	238	230	238	238	238	238	230
R-square	0.302	0.404	0.395	0.379	0.520	0.254	0.362	0.341	0.319	0.472

Note. In the first regression model, we divided students into three groups based on their time on task levels in the first module (i.e., low, medium, and high groups with the low-level group being the reference group) and regressed these group membership variables, the change in time on task, and the interaction terms between them on students' grades and final exam scores in the current course. Results from Model 1 showed that the clickstream measure of the change in time on task predicted course performance for all of the three groups and there were no significant differences in the relationships between the clickstream measure and course performance. These results suggest that there is no ceiling or floor effects of the clickstream measure of change in time on task. However, we did find evidence that the positive relationship between the measure of change in time on task becomes smaller or even insignificant after adding other control variables and the interaction terms between the group membership variables and the control variables. In particular, results in Model 2 showed that, after adding the clickstream measures of time management and the corresponding interaction terms, the change in time on task was not predictive of course performance for any groups. In addition, results in Model 4 showed that after adding post-course survey measures and the corresponding interaction terms, the change in time on task was predictive of course performance only for the medium- and high-level groups and not for the low-level group. It is not surprising to find that other measures, such as the clickstream measures of time management had better predictive power over course performance than the clickstream measure of change in time on task when there is small variation in the latter. However, these results suggested that other clickstream measures that have better predictive power are needed to identify at-risk students among students who started with similar effort levels. All coefficients are standardized. * p<0.05 ** p<0.010 *** p<0.001

Appendix B: Robustness Analysis for the Outcome of Actual Change in Exam Scores

Table B1

Regression-Adjusted Differences in Actual Changes in Exam Performance Between Students with High and Low Levels of Expected Change in Exam Scores After Excluding Outliers

		Change on exam performance							
		M1	M2	M3	M4	M5	M6	M7	M8
Subgroups									
Time on task_T2_Low + Desired score_High	Expected change_Low			-0.224	-0.258	-0.269	-0.088	-0.371	-0.074
				(0.33)	(0.36)	(0.30)	(0.34)	(0.30)	(0.32)
	Expected change_High	0.376	0.108	0.152	-0.149	0.107	0.020	0.005	0.035
		(0.29)	(0.34)	(0.32)	(0.40)	(0.30)	(0.31)	(0.29)	(0.32)
Time on task_T2_Low + Desired score_Low	Expected change_Low	0.224	0.258			-0.045	0.170	-0.147	0.184
		(0.33)	(0.36)			(0.33)	(0.41)	(0.33)	(0.39)
	Expected change_High	0.760**	0.719*	0.536+	0.461	0.491+	0.631*	0.390	0.645+
		(0.28)	(0.34)	(0.32)	(0.38)	(0.29)	(0.31)	(0.28)	(0.33)
Time on task_T2_High + Desired score_High	Expected change_Low	0.269	0.088	0.045	-0.170			-0.101	0.014
		(0.30)	(0.34)	(0.33)	(0.41)			(0.30)	(0.33)
	Expected change_High	0.627*	0.314	0.403	0.056	0.358	0.226	0.257	0.240
		(0.30)	(0.39)	(0.33)	(0.44)	(0.30)	(0.33)	(0.30)	(0.35)
Time on task_T2_High + Desired score_Low	Expected change_Low	0.371	0.074	0.147	-0.184	0.101	-0.014		
		(0.30)	(0.32)	(0.33)	(0.39)	(0.30)	(0.33)		
	Expected change_High	0.537+	0.185	0.313	-0.072	0.268	0.097	0.167	0.112
		(0.28)	(0.39)	(0.31)	(0.44)	(0.29)	(0.32)	(0.28)	(0.35)
Control		No	Yes	No	Yes	No	Yes	No	Yes
N		82	82	82	82	82	82	82	82

Table B1
Continued

		Change on exam performance							
		M1	M2	M3	M4	M5	M6	M7	M8
Subgroups									
Completing quizzes on time_T2_Low + Desired score_High	Expected change_Low			-0.028	0.044	-0.141	0.061	-0.384	-0.013
				(0.32)	(0.33)	(0.30)	(0.34)	(0.32)	(0.39)
	Expected change_High	0.414	0.095	0.387	0.139	0.273	0.156	0.030	0.082
		(0.29)	(0.33)	(0.30)	(0.35)	(0.27)	(0.28)	(0.30)	(0.33)
Completing quizzes on time__T2_Low + Desired score_Low	Expected change_Low	0.028	-0.044			-0.113	0.017	-0.356	-0.056
		(0.32)	(0.33)			(0.31)	(0.35)	(0.33)	(0.38)
	Expected change_High	0.605+	0.544	0.577+	0.587	0.464	0.605+	0.221	0.531
		(0.31)	(0.36)	(0.32)	(0.37)	(0.29)	(0.31)	(0.32)	(0.37)
Completing quizzes on time__T2_High + Desired score_High	Expected change_Low	0.141	-0.061	0.113	-0.017			-0.243	-0.074
		(0.30)	(0.34)	(0.31)	(0.35)			(0.31)	(0.35)
	Expected change_High	0.577+	0.245	0.549+	0.289	0.436	0.306	0.192	0.233
		(0.31)	(0.38)	(0.32)	(0.40)	(0.29)	(0.32)	(0.32)	(0.36)
Completing quizzes on time__T2_High + Desired score_Low	Expected change_Low	0.384	0.013	0.356	0.056	0.243	0.074		
		(0.32)	(0.39)	(0.33)	(0.38)	(0.31)	(0.35)		
	Expected change_High	0.436	-0.053	0.409	-0.009	0.295	0.008	0.052	-0.065
		(0.29)	(0.42)	(0.30)	(0.43)	(0.27)	(0.32)	(0.30)	(0.39)
Control		No	Yes	No	Yes	No	Yes	No	Yes
N		82	82	82	82	82	82	82	82

Table B1

Continued

		Change on exam performance							
		M1	M2	M3	M4	M5	M6	M7	M8
Subgroups									
Watching lectures on time_T2_Low	Expected change_Low			-0.107	-0.504	-0.314	-0.251	-0.250	-0.312
+ Desired score_High				(0.32)	(0.36)	(0.31)	(0.34)	(0.33)	(0.37)
	Expected change_High	0.370	0.323	0.263	-0.181	0.056	0.072	0.121	0.011
		(0.30)	(0.34)	(0.29)	(0.35)	(0.27)	(0.30)	(0.30)	(0.30)
Watching lectures on time__T2_Low	Expected change_Low	0.107	0.504			-0.207	0.253	-0.143	0.192
+ Desired score_Low		(0.32)	(0.36)			(0.30)	(0.34)	(0.32)	(0.37)
	Expected change_High	0.763*	0.918*	0.656*	0.414	0.448	0.667*	0.513	0.606+
		(0.32)	(0.36)	(0.31)	(0.37)	(0.29)	(0.32)	(0.32)	(0.33)
Watching lectures on time__T2_High	Expected change_Low	0.314	0.251	0.207	-0.253			0.065	-0.061
+ Desired score_High		(0.31)	(0.34)	(0.30)	(0.34)			(0.31)	(0.32)
	Expected change_High	0.502+	0.359	0.395	-0.145	0.187	0.108	0.252	0.047
		(0.30)	(0.39)	(0.29)	(0.41)	(0.27)	(0.34)	(0.30)	(0.31)
Watching lectures on time__T2_High	Expected change_Low	0.250	0.312	0.143	-0.192	-0.065	0.061		
+ Desired score_Low		(0.33)	(0.37)	(0.32)	(0.37)	(0.31)	(0.32)		
	Expected change_High	0.592+	0.398	0.485	-0.106	0.277	0.147	0.342	0.086
		(0.32)	(0.41)	(0.31)	(0.44)	(0.29)	(0.36)	(0.32)	(0.34)
Control		No	Yes	No	Yes	No	Yes	No	Yes
N		82	82	82	82	82	82	82	82

Note. All coefficients are standardized. * p<0.05 ** p<0.010 *** p<0.001