Investigating Time Estimation from a Self-Regulated Learning Perspective

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Abstract

The present study investigates university students' time estimation accuracy from a Self-Regulated Learning perspective. Specifically, the study examines students' goal quality, competence for goal completion, and perceptions of goal difficulty as predictors of time estimation accuracy for single study session at three points over a semester. An additional goal of this study was to investigate the relationship between time estimation accuracy and students' reported goal completion. Results show that more than 50% of students underestimated or overestimated their time to complete goals at every time point over the semester. Results of multinomial logistic regression analyses demonstrated that perceived goal difficulty was a predictor of underestimation at the middle and at the end of the semester, competence for goal completion predicted time estimation accuracy at the beginning of the semester, and goal quality was not a significant predictor of time estimation accuracy at any point in the semester. Lastly, students who overestimated the time spent in their study sessions were less likely to attain their goals. These results provide empirical evidence of the prevalence of misestimation during individual study sessions guided by goals created by students for course-relevant tasks and partial support to theoretical principles of SRL which consider task perceptions and goal setting as determinants of the learning process.

Table of Contents

Supervisory Committee ii

Abstract iii

Table of Contents iv

List of Tables vi

List of Appendices vii

Acknowledgements viii

Dedication ix

Introduction 1

Literature Review 3

Factors influencing time estimation accuracy 3

Self-Regulated Learning and Time Estimation 6

Goal quality, perceived goal difficulty, and competence for goal completion 9

Present study 12

Method 14

Participants 14

Research context 14

Procedure 15

Statistical analysis 18

Results 20

How accurate are students' time estimations for self-set goals on individual study sessions throughout a semester? 20

To what extent do goal quality, perceived goal difficulty, and competence for goal completion predict students' time estimation accuracy throughout a semester? 21

Does time estimation accuracy predict goal completion above and beyond goal quality, estimated difficulty, and competence for goal completion? 24

Discussion 28

Time estimation accuracy over a semester 28

Predictors of time estimation accuracy 31

Time estimation accuracy and goal completion 34

Limitations 35

Future avenues for research 36

Conclusion 37

References **38**

Appendices **49**

Appendix 1 ..... *49*

Appendix 2 ..... *51*

List of Tables

TABLE 1 21
TABLE 2 23
TABLE 3 25
TABLE 4 26

List of Appendices

APPENDIX 1 49
APPENDIX 2 51

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Dedication

To my mother and grandmother. I carry you within my heart.

Introduction

University students are expected to self-regulate and manage how, when, and for how long they will engage in academic tasks. Effective task and time management are critical for academic success given the increased independence and responsibility in post-secondary contexts (Theobald, 2021). Nonetheless, some students struggle to organize their independent study time, keep up with course load, and manage simultaneous deadlines (Ainscough et al., 2018; Cameron & Rideout, 2020; Thibodeaux et al., 2017). Literature on time management indicates that engaging in planning practices such as estimating time, setting goals, or identifying priorities are effective ways to overcome these difficulties (Aeon & Aguinis, 2017, Claessens, 2007; Kelly 2002). Specifically, accurate time estimation is necessary to ensure appropriate time allocation to multiple goals and plans (Kelly, 2002).

Research on time estimation has demonstrated that most people are inaccurate at estimating the time needed to complete a task (Buehler et al., 1994; Kahneman & Tversky, 1977). In post-secondary contexts, general consequences of underestimation are the late start of assignments, failure to meet deadlines, poor quality of work, and underachievement (Baumeister et al., 1993). To date, theoretical approaches and empirical studies have shown how some individual differences and specific task conditions influence time estimation accuracy (Halkjelsvik & Jørgensen, 2012). However, the relative simplicity of the tasks and the reliance on experimental designs offer a limited insight of time estimation accuracy in post-secondary contexts. For instance, the complexity of tasks encountered in university are typically divided over multiple study sessions where students need to self-regulate personal and contextual aspects of their learning to complete their task. The directiveness of experimental designs using non-academic tasks make it difficult to investigate time estimation accuracy in demanding or

independent contexts such as university. Empirical research guided by a comprehensive framework considering students' agency to manage complex university tasks and their motivation is needed to have a better understanding of time estimation accuracy in academic contexts (Wolters & Brady, 2020).

Investigating time estimation from an SRL perspective provides a more nuanced understanding of time estimation accuracy in relation to students' active management of their time and tasks during independent studying. Theorists define SRL as an effortful process whereby students regulate different aspects of their own behavior, motivation, and cognition to achieve academic goals (Pintrich & Zusho, 2007; Winne & Hadwin 1998; Zimmerman, 1986). From an SRL perspective, biased estimations are part of a recursive process including students' perceptions of a task, their strategic plans, and adaptations made over multiple study sessions to engage in academic work (Wolters & Brady, 2020). The present study aims to investigate the quality of students' self-set goals for course-relevant tasks, their perceived goal difficulty, and their motivational beliefs as predictors of time estimation accuracy. Further, this study also seeks to explore the relationship between students time estimation accuracy and goal completion during their study sessions at the beginning, middle, and end of the semester. Understanding how students organize and manage their individual study sessions can provide insight of their estimation accuracy over time and its relationship to task completion.

Literature Review

Time estimation refers to a prediction about the amount of time required to complete an activity, task, or goal (Burt & Kemp, 1994). Time estimation accuracy is particularly relevant in post-secondary contexts since students need to organize, plan, and distribute their time around multiple academic tasks to meet deadlines and take care of other extra-curricular commitments like paid work, social activities, and leisure (Brint & Cantwell, 2010). Findings from prior research suggest that students typically underestimate the time it will take them to complete a task or overestimate the time they will spend on academic activities (Baumeister et al., 1993; Thibodeaux et al., 2017). Cramming, unnecessary stress, and low academic performance are some of the consequences of large discrepancies in time estimation accuracy or continuous misestimation of tasks (Aeon et al., 2021; Adams & Blair, 2019; Thibodeaux et al., 2017). For instance, students who continuously underestimate their time usually start their assignments late, fail to meet deadlines, and present poor work quality (Baumeister et al., 1993). Prior literature also suggests that students who overestimate the time they need to dedicate for academic work (i.e., spend less time than intended) perform worse than students who make accurate estimations (Thibodeaux et al., 2017). The high prevalence of misestimation and its costs has led researchers to explain why it takes place, identify the factors that influence estimation accuracy, and describing ways to improve estimation accuracy.

Factors influencing time estimation accuracy

Planning fallacy (Kahneman & Tversky, 1979) and *memory bias* (Roy et al., 2005) are two theoretical explanations about the occurrence of underestimation and overestimation. The planning fallacy assumes that misestimation takes place when individuals attend to intrinsic aspects of the task and overlook external sources of information like past experiences or future

complications (Kahneman & Tversky, 1979). In other words, an estimation based on the components of a task will be inaccurate if prior misestimations, potential obstacles, delays, or conflicting events are ignored. An alternative approach to explain the prevalence of time misestimation is the memory bias account (Roy et al., 2005). This approach suggests that, rather than overlooking previous experiences, underestimation occurs because people make estimations based in faulty memories (Roy et al., 2005; Roy & Christenfeld, 2007). Faulty memories can result from failing to monitor the duration of tasks (Halkjelsvik & Jørgensen, 2012), or are simply due to inaccurate recall (König et al., 2015; Roy et al., 2008, experiment 2). In combination, empirical studies from the planning fallacy account and the memory bias account have identified individual differences and task-related factors that influence the degree and direction of the estimation bias.

Extant research has shown that task length (Roy & Christenfeld, 2008; Thomas et al., 2003) and difficulty level (Min & Arkes, 2012; Thomas et al., 2003) influence time estimation accuracy. Short and simple tasks are commonly overestimated and lengthy and complex tasks are underestimated. For example, Roy and Christenfeld (2007) used a paper counting task with length variations and found that students overestimated the shorter version of the task and underestimated the version with longer durations. Research focused on decreasing underestimation by breaking a task down into its components has also found that the effectiveness of this technique depends on the length and difficulty of the task at hand (Forsyth & Burt, 2008; Kruger & Evans, 2004; Roy et al., 2008). Indeed, underestimation decreases when individuals break down lengthy tasks into specific steps (Forsyth & Burt, 2008) and participants tend to make overestimations when the same technique is applied to short and simple tasks (Roy et al., 2008; Roy et al., 2019).

Individual differences including expertise and motivation appear to influence time estimation accuracy (Halkjelsvik & Jørgensen, 2012). Generally, experienced individuals are more accurate in their estimations than novices. Some studies suggest that time estimation accuracy improves when participants have prior experience with similar tasks (Thomas et al., 2004; Thomas et al., 2007; Thomas & König., 2018). However, other studies suggest that monitoring the passage of time while performing an activity explains why experience is typically associated with accurate estimations (König et al., 2015; Roy & Christenfeld, 2007; Tobin & Grondin, 2015). In other words, monitoring time while performing an activity or being aware of past inaccuracies after performance are critical to learn from experience and reduce bias.

An additional individual characteristic that is posited to influence time estimation is the willingness to complete the task in a specific timeframe (Halkjelsvik & Jørgensen, 2012). Motivational factors influencing time estimation accuracy have been mostly explored in work settings and limited to monetary incentives. Prior findings suggest people are more likely to underestimate their time when offered incentives (Buehler et al., 2010a; Buehler et al., 1977; Byram, 1977). For instance, results from two experiments by Buehler and collaborators (1977) showed that underestimation was greater when monetary incentives were offered to individuals completing an origami task. However, participants with incentives took the same amount of time to complete the task than participants with no incentives. In other words, incentives may prompt people to be more optimistic about their completion speed, but their actions are misaligned with their time estimation expectations.

Time estimation in post-secondary contexts

Extant research investigating time estimation offers an understanding of the factors influencing time estimation accuracy that are not comparable to university demands in two main

ways. First, university tasks are self-directed, and students are expected to figure out how to divide their work over multiple study sessions to complete task requirements. Studies in time estimation have been guided by experimental designs posing a limitation to consider students' perceptions and self-determination to engage in academic work. Moreover, the tasks used in prior studies (e.g., paper counting, ordering documents) are disparate with university assignments that require awareness and integration of task parameters, purpose, and structure (Butler & Cartier, 2004; Hadwin & Winne, 2012). The relative simplicity of the tasks and directiveness of the experimental conditions used in prior research point to a need for research investigating time estimation accuracy in academic contexts using course relevant tasks.

Second, completing academic work is an effortful process influenced by students' motivation to initiate and maintain goal-oriented behaviors (Bembenutty, 2009b; Eccles & Wigfield, 2002). Prior literature in time estimation is limited to the relationship between time estimation and external sources of motivation (e.g., economic incentives), while overlooking internal thoughts and perceptions that are relevant in academic contexts. Over the past three decades, motivational beliefs (e.g., competence beliefs and mindsets) and appraisals (e.g., task value and importance) have been thoroughly studied and associated with academic outcomes in post-secondary contexts (Bakhitar & Hadwin, 2022). Empirical research guided by a comprehensive framework considering the complexity of university tasks and students' motivation to complete them is needed to have a better understanding of time estimation accuracy.

Self-Regulated Learning and Time Estimation

In contrast to prior theoretical approaches investigating time estimation (Kahneman & Tversky, 1979; Roy et al., 2005), SRL considers individuals' agency and motivation to manage

time and tasks in academic contexts. Students engaging in SRL take control of their learning process by directing an effortful process to regulate aspects of their own behavior, motivation, and cognition to achieve academic goals (Pintrich & Zusho, 2007; Winne, 2018). A main assumption of SRL is that the learning is comprised of cyclical phases driven by metacognitive monitoring and adaptation (Panadero, 2017). In the forethought phase, students would analyze the components of a task (e.g., difficulty, structure, learning outcomes), create goals, and identify potential strategies to fulfill task requirements (Efklides, 2011; Hadwin & Winne, 2012). During the performance phase, students enact their goals and monitor their progress towards a desired outcome (Boekaerts & Corno 2005; Winne & Hadwin, 1998). Lastly, students engage in self-reflection when they interpret their experience in terms of their performance, and their reactions at the same time as they make conclusions that will inform future study attempts (Zimmerman, 2000).

Estimating the time needed for a task is closely related to the processes taking place in the forethought phase of SRL (Wolters & Brady, 2020). Task understanding, or the perception students have about academic tasks, is a critical component of forethought that influences the strategic decisions students make to complete academic tasks (Winne & Hadwin, 1998). To form an accurate and complete understanding of a task, students need to analyze its requirements, structure, and purpose (Hadwin & Winne, 2012). In consequence, time estimation should be informed by the perception students have about task components, its difficulty, and their prior experience with similar tasks. An additional process informing time estimation is goal setting. Setting goals is considered a self-regulatory practice that guides independent studying and helps students to keep track of their progress or to recognize discrepancies with actual performance (Hadwin & Winne, 2012; Zimmerman, 2008). Therefore, an articulated goal should give students

some references to inform their estimations like the type of strategy (i.e., if it is time-consuming), or the content (i.e., level of cognitive demand) that are identified for each goal directing their study sessions.

Motivational beliefs are also activated during forethought and can inform students' time estimation on tasks (Wolters & Brady, 2020; Zimmerman 2000). Motivational beliefs are individuals' judgements about their capabilities, interest, and value associated with the task that shape the decisions to engage in academic work (Bandura, 1986; Eccles & Wigfield, 2002; Hidi & Renninger, 2006). For instance, the time allocated to academic tasks can depend on students' perceived value for the task and the estimated time for completion could also be based on how competent they believe they are at performing it. In other words, the perceptions that students hold about themselves in relation to the task can inform the time they will dedicate and that they will require to perform it.

The events occurring during the performance and self-reflection phase can influence, to some extent, students' time estimation accuracy and future time estimations (Wolters & Brady, 2020). The initial perceptions students have about the task can be updated as students obtain feedback from their engagement during their study session (Zimmerman, 2000). For instance, competence beliefs could decrease after noticing that a task is more challenging than expected. The decision to continue or quit their engagement with the goal or study session would impact students' time estimation accuracy by spending more time than expected (i.e., underestimation) or less time than expected (i.e., overestimation). Further, the reflections students make about their engagement and time-related experiences have the potential to influence future SRL cycles (Wolters & Brady 2020). In the event of inaccurate time estimation, students' reflection about

the study session could prompt them to adapt their approach and motivational beliefs for future attempts.

Overall, SRL theory positions biased estimations as part of a recursive process including students' perceptions of a task, their strategic plans, and adaptations made over multiple study sessions to engage in academic work. Only a few empirical studies have explored time estimation accuracy across multiple study sessions or between semesters (Buehler et al., 2010a; Buehler et al., 2010b; Thibodeaux et al., 2017). This research suggest that students underestimate major school assignments and that interruptions between study sessions contribute to their underestimation. However, students' strategic plans for individual study sessions and their task perceptions have been overlooked. Understanding how students organize and manage their individual study sessions can provide insight of their time estimation accuracy across a semester and its relationship to task completion. The present study seeks to address this gap by investigating predictors of time estimation accuracy for individual study sessions that could be monitored and adjusted by students before engaging with the task. The predictors of time estimation accuracy identified in this study are based on the SRL premise that students manage their tasks by creating goals of different quality, difficulty, and that competence beliefs are part of their drive to attain goals within a single study session (Hadwin & Winne 2012; Zimmerman, 2000).

Goal quality, perceived goal difficulty, and competence for goal completion

High-quality goals are assumed to guide engagement in learning (Hadwin & Winne, 2012), and facilitate accurate estimation by prompting relevant information to be considered (Kahneman & Lovallo, 1993). Prior research describes different components of high-quality goals with underlying commonalities. Goal specificity is a characteristic recommended by SRL

interventions to promote task-relevant behaviours such as sustained attention and persistence (Zimmerman, 2008). In relation to time estimation, setting a specific goal could increase the possibilities of accurate time estimation by preventing off-task behaviors. Specific goals have also been used as a debiasing technique in non-academic tasks by prompting participants to identify specific steps for task completion (Forsyth & Burt, 2008). This finding suggests that identifying the steps required to complete a course-relevant task can help students to make an accurate estimation by gauging the time needed for each stage. For single study sessions, McCardle et al., (2017) posit that high quality goals including specific learning actions (i.e., relate, compare), concepts (i.e., terms, topics), standards (i.e., objective evaluation of progress), and timeframe (i.e., duration or time commitment) can help students to regulate their learning. On the same study, McCardle and collaborators showed that some students improved their goal quality halfway through the semester while others improved their goal quality towards the end. Therefore, assessing goal quality at multiple time-points could provide a more nuanced insight of its relationship with time estimation.

In SRL, the role of perceived goal difficulty and competence beliefs for goal completion point to their possible influence on students' time estimation accuracy. According to Schunk (2003), a difficult but attainable goal coupled with students' perceived competence to complete the goal can raise students' motivation and engagement with the task. Whereas a highly demanding task and perceived incompetence can influence students decision to disengage with the task (Beattie et al., 2014; Diseth, 2011). Similarly, prior studies in time estimation suggest that difficult tasks are more likely to be underestimated and simple task are more likely to be overestimated (Forsyth & Burt, 2008; Roy et al., 2008). An important limitation of these studies is that students' perceptions of task difficulty or competence beliefs are overlooked. Researchers

define task difficulty based on a comparison between task characteristics and, typically, students are not aware of these differences or difficulty levels. Students' perceived goal difficulty and competence beliefs is relevant when studying time estimation accuracy because the decision to continue with the task during independent study sessions is partially informed by their judgment.

Present study

The purpose of this study is to examine undergraduate students' time estimation during a study session from a self-regulated learning perspective. Specifically, the study will examine: (a) goal quality, perceptions of goal difficulty and perceived competence for goal completion as predictors of time estimation accuracy, and (b) the relationship between time estimation accuracy and weekly goal completion over a semester in a learning-to-learn course.

1. How accurate are students time estimations for self-set goals on individual study sessions throughout a semester?

   H1a. A combination of underestimation, overestimation, and accuracy of time estimation for self-set goals are expected to be reported by undergraduate students.

   H1b. Estimation accuracy is expected to increase at the same time as underestimation is expected to decrease.

2. To what extent do goal quality, estimated difficulty, and competence for goal completion predict students' time estimation accuracy throughout a semester?

   H2a. Accurate time estimation is expected to be predicted by higher goal quality, moderate perceived difficulty, and when students feel competent to complete their goal within a single study session.

   H2b. Underestimation is expected to be predicted by a lower goal quality, high perceived difficulty, and when students feel confident to complete their goal within a single study session.

   H2c. Overestimation is expected to be predicted by a lower goal quality, high perceived difficulty, and when student do not feel confident to complete their goal within a single study session.

3. Does time estimation accuracy predict goal completion above and beyond goal quality, estimated difficulty, and perceived competence for goal completion in single study sessions?

   H3. Time estimation accuracy will predict goal completion above and beyond goal quality, estimated difficulty, and perceived competence for goal completion.

Method

Participants

Data were collected in spring 2021 as part of a larger grant study titled Promoting Adaptive Regulation sing Innovative Technologies: Par-IT (Hadwin, 2018). Participants were 106 undergraduate students (Female = 36 %) enrolled in an elective learning-to-learn course at a Western Canadian university. The primary goal of the learning-to-learn course was to facilitate the development of study skills for university success. This elective course required students to be enrolled in at least one other university course. Students came from 8 faculties including Education (0.9%), Engineering (17.9%), Fine Arts (2.8%), Human & Social Development (0.9%), Humanities (14.2%), Science (4.7%), Social Sciences (35.8%), Business (22.6%). Students mean study year was 1.7 (*SD* = .94) indicating most were in their first or second year of university, and their mean age was 19.5 years (*SD* = 1.9). Student's age, gender, and major were obtained from institutional data.

Research context

The learning-to-learn course is a semester-long, credited course offered to undergraduate students at a Western Canadian university. The course uses SRL as a framework to guide students to develop knowledge and skills to regulate multiple areas of their learning. Students attended a lecture and applied lab each week. Course topics included: (1) Introduction to SRL; (2) Task understanding and SRL; (3) Goal setting for SRL; (4) Cognition: memory and attention; (5) Cognition: connecting, extending, rehearsing; (6) Learning for meaning; (7) Motivational factors: beliefs and mindsets; (8) Behavioral factors: managing time and procrastination; (9) Social and emotional factors: mental health and well-being; and (9) Exam preparation. In addition to the instruction of content related to SRL, the learning-to-learn course is designed to

promote metacognitive awareness and engagement in SRL cycles by completing weekly or daily study diary activities (McCardle & Hadwin, 2015). Importantly, all assignments/activities required students to apply topics and concepts to another academic course. For example, all goal setting and monitoring activities focused on coursework for at least one other academic course taken concurrently.

Procedure

Participants were asked to complete eight weekly diaries over a semester as a completion-based graded activity for their learning-to-learn course. The diaries were delivered online at the beginning of every week except for weeks 4 and 9, since other activities of the learning-to-learn course replaced the weekly diaries. The diary scripts guided students' planning, engagement, and reflection of single study sessions for another academic course through a series of questions containing drop-down menus and open-text fields. The planning script prompted students to identify an activity from a course on their core academic program and to create a goal for a 1-2-hour study session taking place over the week. Students were expected to execute their goal at the scheduled time and report their experience by completing the post-performance evaluation in the diary before the next iteration. The structure of the weekly diaries was an adaptation from the Personal Planning Tool by Hadwin et al., (2018) and the complete set of questions in the weekly diaries can be viewed in Appendix 1.

The main purpose of the weekly study diaries used in the present study was instructional. However, weekly diaries can also be considered as an experience sampling methodology since they prompt participants to record thoughts, behaviors, or feelings during specific moments in their daily life (Christensen et al., 2003; Karabenick & Zusho, 2015; Schneider, 2006). Particularly, this methodology has been successfully used to explore students' behavior and

performance (Boevé, et al., 2017), self-efficacy (Hu & Yeo., 2020) and overall SRL processes (Fung et al., 2019; McCardle & Hadwin, 2015).

To acknowledge expected development in SRL practices such as goal setting over the semester, data was sampled from the beginning (week 2), the middle (week 6), and end of the semester (week 10). The relationship between course content delivery and data collection is relevant to acknowledge as part of research context. Students were introduced to SRL and academic success by week 2. Concepts on task understanding, planning, and effective goal setting were covered before week 6. Strategies and concepts related to self-regulation of behavior, motivation, and cognition were covered before week 10. A selection of items from the weekly diary were used to measure (a) perception of goal difficulty, (b) judgment of competence for goal completion, (c) time estimation accuracy, and (d) goal completion (Appendix 1). Students' self-set goals for independent studying in another academic course were coded by two independent researchers. This approach has been previously used to assess goal quality (Acee et al., 2012; McCardle et al., 2017).

Measures

The following measures were self-reported by students over the semester using the Weekly Study Diary (Appendix 1).

Perceived difficulty. Students recorded perception of goal difficulty by selecting one of four choices to complete a self-narrative statement (i.e., 'I think this goal will be *[Very easy—Easy—Difficult—Very difficult]* for me to attain'). Difficulty choice was converted to a 4-point numerical scale ranging from (1) *Very easy* to (4) *Very difficult.*

Competence for goal completion. Students completed the following self-statement about their expectation of success (i.e., 'I am *[Not at all certain—Slightly certain— Moderately*

certain— Very certain—Extremely certain] I can achieve the goal in a 1–2-hour study session). Competence selections were converted to a 5-point numerical scale ranging from (1) *Not at all certain* to (5) *Extremely certain*.

Time estimation accuracy. After their study session, students completed a self-statement about the accuracy of their estimation (i.e., I worked towards my goal for [*Zero hours— Less than 1 hour—1-2 hours—2-3 hours—3-4 hours—more than 4 hours)*. Estimation accuracy was categorized in (a) Accurate – students spending from 1-2 hours in their goal; (b) Overestimation – students spending less than 1 hr. in their goal; (c) Underestimation – students reporting spending from 2-3, 3-4, and more than 4 hours in their goal; and (d) No goal attempt – students reporting spending 0 hours in their goal.

Goal completion. After their study session, students completed a self-statement about their goal completion (i.e., 'I [*Fully met—did not met*'] my goal this week). Goal completion was converted to a binary response scale (1) *Fully met* and (0) *Did not met*.

Goal quality and coding process for goal quality

Goal quality was coded on three dimensions consistent with theory (Locke & Latham, 2002; Winne & Hadwin, 1998; Zimmerman, 2008) and empirical findings (Acee et al., 2012; McCardle et al., 2017). The dimensions included (a) specificity, (b) identification of steps to complete the goal, and (c) inclusion of an objective standard to assess goal progress. *Specificity* was coded as: broad goal with general actions (0 points); a goal identifying a specific assignment, course topic or activity (1 point); or a goal identifying a specific learning action or learning strategy (1 point). The remaining two categories were binary, giving a point if the goal included the specified dimension. The average score of each dimension was computed to obtain

a total measure of goal quality. Examples of goals and the quality ratings can be viewed in Appendix 2.

The coding process involved the creation and refinement of a codebook, and the calculation of an inter-rater reliability score to test the agreement between raters due to the categorical nature of goal coding (Gisev et al., 2013). The initial coding schema was created by the author and a member of the supervisory committee of the present study. Two training sessions of approximately 3 hours each took place between the author and an external rater where a codebook was refined for further coding. Between the two training sessions, an experienced researcher (i.e., member of the supervisory committee) was consulted regarding theoretical differences between levels of specificity and the codebook was adjusted accordingly. To calculate the inter-rater reliability score, both raters coded a random subset of goals independently obtaining strong agreement ($\kappa = .85$; Landis & Koch, 1977). The same process was repeated with a second subset of goals obtaining similar results ($\kappa = .92$). The rest of the goals were distributed between both raters and coded until completion.

Statistical analysis

This study aims to describe the prevalence of estimation accuracy in individual study sessions, identify predictors of estimation accuracy, and to explore the relationship between estimation accuracy and goal completion throughout a semester. The prevalence of estimation accuracy was obtained with the frequencies of students' time estimation accuracy at the beginning (week 2), at the middle (week 6), and at the end of the semester (week 10). Multinomial logistic regressions were used at every time point to identify if goal quality, perceived goal difficulty, and competence for goal completion predicted membership to three groups of time estimation accuracy (i.e., overestimation, underestimation, or accurate).

Multinomial regressions were selected because the structure of the weekly diaries provided categorical data. In addition to the predictor variables, year of study and prior accuracy were included as covariates since prior research suggests that experience is a factor influencing time estimation accuracy (König et al., 2015; Thomas & König., 2018). Reported accuracy on week 2 was used as prior accuracy at week 6 and reported accuracy on week 6 was used as prior accuracy at week 10. Lastly, binomial logistic regressions were used to explore estimation accuracy as a predictor of goal completion after controlling for the rest of the predictors and covariates.

Results

How accurate are students' time estimations for self-set goals on individual study sessions throughout a semester?

Each time point depicted on Table 1 shows that less than half of the participants reported an accurate estimation of the time needed for their study session whereas the rest spent less time than planned (overestimation), more time than planned (underestimation), or reported not attempting their goal at all. Specifically, there was an increasing pattern of students' underestimation over the course of the semester (week 2 = 28.7%; week 6 = 35.9%; week 10 = 46.8%), whereas the contrary occurred for those who overestimated their goal (week 2 = 20%; week 6 = 9%; week 10 = 5.1%). Lastly, the small proportion of students who reported not attempting their goal at all fluctuated through the semester (week 2 = 7.5%; week 6 = 10.2%; week 10 = 1.3%).

These results are in line with hypothesis H1a for the first research question, suggesting that some students overestimate, underestimate, and make accurate estimations of the time they will spend on a study session while working on their self-set goals for course-relevant tasks in their discipline. In addition to the occurrence of misestimation at the three time points of assessment, it is important to note the increasing pattern of underestimation across time points. As the semester progressed, more students reported spending more time than planned in their study session (i.e., underestimation). Lastly, the proportion of students who reported not attempting the goal was an unexpected result. Data from these students were removed from further analysis since we considered this group as non-engaging and distinct from the estimation accuracy groups of interest. Considering students' choice to engage with this activity, Table 1 also records the number of participants who decided not to complete the diary at a given week.

An important note is that every student engaged with this activity at least at one assessment point reported in this study.

Table 1
Frequency of students' time estimation accuracy in three time points over the semester.

Groups	Week 2 *n* (%)	Week 6 *n* (%)	Week 10 *n* (%)
Accurate	35 (43.8)	35 (44.9)	37 (46.8)
Underestimation	23 (28.7)	28 (35.9)	37 (46.8)
Overestimation	16 (20)	7 (9.0)	4 (5.1)
Not attempting the goal	6 (7.5)	8 (10.2)	1 (1.3)
Not completing the diary	26	28	27

Note: Total students at each time point was 106. No attempt = students reporting spending 0 hours in their goal. Accurate = students spending from 1-2 hours in their goal; overestimation = students spending less than 1 hr. in their goal; underestimation = students spending from 2-3, 3-4 and more than 4 hours in their goal.

To what extent do goal quality, perceived goal difficulty, and competence for goal completion predict students' time estimation accuracy throughout a semester?

To address the second research question, multinomial logistic regressions were performed at each time point including predictor variables (goal quality, perceived goal difficulty, competence for goal completion) and covariates (year of study and prior accuracy) for each model. Table 2 presents odds ratios and confidence intervals of each variable predicting students' membership to the overestimation, underestimation, and accurate group with the specified reference group. Odds ratios greater than one reflect the odds of students being classified in one group over the reference group. In line with hypothesis H2b of the study, estimated difficulty was a consistent predictor of underestimation versus accurate estimation on

weeks 6 (*OR* = 3.71, *p* = .01) and 10 (*OR* = 3.35*, p* = .01). These results indicate that for every unit increase in students' perception of goal difficulty, the odds of belonging to the group of students who spent more time than planned in their study session (i.e., underestimation) compared to accurate students increased by factors of 3.71 on week 6, and by factors of 3.35 on week 10. Higher goal difficulty in week 10 was also a predictor of spending more time rather than spending less time in a study session (*OR* = 0.04*, p* = .05*).* This finding suggests that for every unit increase in perceived difficulty, the odds of underestimation increase by a factor of 0.04. However, these results should be taken with caution considering the low representation of students on each group.

As depicted on Table 3, additional predictors of estimation accuracy for weeks 2 and 6 were competence for goal completion (*OR* = 0.42*, p* = .06) and prior accuracy (*OR* = 7.58*, p* = .05) respectively. These results indicate that for every unit increase in students' reported competence for goal completion, there was in increased tendency in the odds of being accurate rather than spending less time in their study session (i.e., overestimate) increased by a factor of .42 on week 2. Moreover, making accurate estimations on week 2 increased the odds on overestimating their study session on week 6 by a factor or 7.58. Overall, these results offer partial support to the hypothesis H2a of the study given that competence beliefs influence students' estimation accuracy at different time points in the semester. However, this result should be taken with caution given the low sample size of the over-estimation group. Contrary to expectations (H2a), no significant effects were detected in students' goal quality as predictors of estimation accuracy at any point in the semester.

Table 2
Multinomial logistic regressions predicting time estimation accuracy over a semester.

	Week 2 (*n* = 74)		
	Overestimation vs Accurate	**Underestimation vs Accurate**	**Overestimation vs Underestimation**
	***OR* (95% *CI*)**	***OR* (95% *CI*)**	***OR* (95% *CI*)**
Covariates			
Prior accuracy	--	--	--
Study year	1.16 (0.53, 2.53)	1.64 (0.89, 3.05)	0.71 (0.33, 1.51)
Predictors			
Goal quality	1.17 (0.62, 2.19)	1.26 (0.73, 2.18)	0.93 (0.48, 1.80)
Goal difficulty	0.52 (0.16, 1.73)	0.79 (0.28, 2.25)	0.66 (0.19, 2.34)
Competence for goal completion	0.42 (0.16, 1.09) †	0.73 (0.32, 1.66)	0.58 (0.21, 1.60)
	Week 6 (*n* = 70)		
	Overestimation vs Accurate	**Underestimation vs Accurate**	**Overestimation vs Underestimation**
	OR (95% *CI*)	*OR* (95% *CI*)	*OR* (95% *CI*)
Covariates			
Prior accuracy	3.08 (0.48, 19.81)	0.41 (0.11, 1.56)	7.58 (1.03, 55.89) *
Study year	1.32 (0.51, 3.42)	0.94 (0.53, 1.68)	1.40 (0.54, 3.64)
Predictors			
Goal quality	0.94 (0.45, 1.97)	0.80 (0.49, 1.29)	1.18 (0.56, 2.50)
Goal difficulty	1.43 (0.34, 5.99)	3.71 (1.37, 10.05) *	0.39 (0.08, 1.76)

Competence for goal completion	0.75 (0.26, 2.14)	1.34 (0.65, 2.77)	0.56 (0.19, 1.67)

	Week 10 (n = 78)		
	Overestimation vs Accurate	**Underestimation vs Accurate**	**Overestimation vs Underestimation**
	***OR* (95% *CI*)**	***OR* (95% *CI*)**	***OR* (95% *CI*)**
Covariates			
Prior accuracy	0.39 (0.03, 5.36)	0.62 (0.19, 1.97)	0.62 (0.04, 9.54)
Study year	1.14 (0.33, 3.97)	1.62 (0.90, 2.90)	0.70 (0.20, 2.53)
Predictors			
Goal quality	1.33 (0.48, 3.69)	0.82 (0.52, 1.30)	1.62 (0.57, 4.63)
Goal difficulty	0.14 (0.01, 3.42)	3.35 (1.30, 8.64) *	0.04 (0.02, 1.06) *
Competence for goal completion	0.50 (0.09, 2.83)	0.97 (0.47, 2.02)	0.52 (0.09, 3.07)

Note. *OR*= odds ratio; 95% *CI* = 95% confidence intervals for the odds ratios.

$^{\dagger}p < .07$; $^{*}p < .05$.

Does time estimation accuracy predict goal completion above and beyond goal quality, estimated difficulty, and competence for goal completion?

Binomial logistic regressions were conducted to address the last research question and Hypothesis 3. As shown in Table 3, the same variables included in the model addressing RQ2 were added in the binomial logistic regression analyses with time estimation accuracy as additional predictor for goal completion. Students were classified as accurate students (coded as 1) and inaccurate students (coded as 0). Accuracy was used to predict goal completion (Attained goal = 1, Not attained goal = 0). In line with the hypothesis of this study (H3), estimation accuracy on week 2 (OR = 4.12; p = 0.01) and week 6 (OR = 4.66; p = 0.01) predicted goal

attainment above and beyond other predictors with exception of goal difficulty on week 2 (*OR* = 0.34; *p* = 0.05) and competence for goal completion on week 6 (*OR* = 1.92; *p* = 0.05). This suggest that students who made accurate estimation on weeks 2 and 4 were four times more likely to complete their goal than inaccurate students.

Table 3
Binomial logistic regressions predicting goal completion for week 2, 6, and 10 between accurate and non-accurate students.

	Week 2 (*n* = 74)	**Week 6 (*n* = 70)**	**Week 10 (*n* = 78)**
Variable	***OR* (95% *C.I.*)**	***OR* (95% *C.I.*)**	***OR* (95% *C.I.*)**
Covariates			
Prior accuracy	--	0.79 (0.23, 2.65)	0.75 (0.18, 3.13)
Study year	1.41 (0.87, 2.61)	0.89 (0.51, 1.57)	0.72 (0.40, 1.29)
Predictors			
Goal quality	1.51 (0.87, 2.61)	0.92 (0.57, 1.46)	1.29 (0.74, 2.26)
Goal difficulty	0.34 (0.11, 1.02)*	0.97 (0.41, 2.31)	0.88 (0.30, 2.60)
Competence for goal completion	1.10 (0.49, 2.44)	1.92 (0.41, 2.31)*	1.23 (0.50, 3.02)
Accurate	4.12 (1.20, 14.10)*	4.66 (1.34, 16.12)*	2.90 (0.65, 12.88)

Note. *OR*= odds ratio; 95% *CI* = 95% confidence intervals for the odds ratios.

*$p < .05$.

A second binomial logistic regression was conducted to gain a more nuanced understanding of the inaccurate group as predictor of goal attainment. It was of interest to evaluate whether overestimating or underestimating the time for a single study session could predict goal attainment or non-attainment. Consistent with earlier analysis, the predictor variable

was estimation accuracy. Therefore, students were classified as over estimators (coded as 1) if they spent less time in their study session than planned, or under estimators (coded as 2) if they spent more time than expected in their study session. Overestimation (1 or 0) or underestimation (1 or 0) was used to predict goal completion (Attained goal = 1, Not attained goal = 0). As shown in Table 4, overestimation predicted goal attainment at week 2 (*OR* = 0.14*, p* = .03), week 6 (*OR* = 0.08*, p* = .01), and week 10 (*OR* = 0.06*, p* = .02). This finding suggests that students who reported spending less time than expected in their study session had lower odds of attaining their goal by factors of 0.14, 0.08, and 0.06 at each time point respectively. Lastly, goal difficulty was an additional predictor of goal attainment only on week 2 (*OR* = 0.17*, p* = .02). For every unit increase in perceived goal difficulty, the odds of not attaining the goal increased by a factor of 0.17.

Table 4
Binomial logistic regressions predicting goal completion for week 2, 6, and 10 between overestimation and underestimation.

	Week 2 (*n* = 74)	Week 6 (*n* = 70)	Week 10 (*n* = 78)
Variable	*OR* (95% *C.I.*)	*OR* (95% *C.I.*)	*OR* (95% *C.I.*)
Covariates			
Prior accuracy	--	1.25 (0.26, 6.03)	0.56 (0.13, 2.52)
Study year	1.30 (0.58, 2.88)	0.90 (0.47, 1.71)	0.70 (0.37, 1.32)
Predictors			
Goal quality	1.81 (0.85, 3.85)	1.05 (0.62, 1.77)	1.29 (0.70, 2.39)
Goal difficulty	0.17 (0.04, 0.71)*	0.65 (0.23, 1.85)	0.51 (0.14, 1.81)

Competence for goal completion	1.07 (0.40, 2.89)	1.70 (0.82, 3.52)	1.13 (0.45, 2.80)
Overestimation	0.14 (0.02, 0.80)*	0.08 (0.01, 0.59)**	0.06 (0.01, 0.70)*
Underestimation	0.86 (0.16, 4.57)	0.83 (0.18, 3.77)	0.61 (0.12, 3.17)

Note. Goal completion was coded 0= not attained, 1= attained.

Prior accuracy for week 6 was dummy coded using week 2 accuracy = 1; rest = 0.

Prior accuracy for week 10 was dummy coded using week 6 accuracy = 1; rest = 0.

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

Discussion

Time estimation is a component of planning that informs how much time is needed to complete a task, and its accuracy appears to contribute to effective coursework management in post-secondary contexts (Buehler et al., 2010b; Wolters & Brady, 2020). The prevalence of misestimation of large projects has led prior research to identify individual- and task- related factors influencing time estimation accuracy such as prior experience and task difficulty. However, students' decisions to direct their independent study sessions and their perception of course-relevant tasks have yet to be considered (Buehler, 2010). This study contributes to the literature by investigating the time estimation accuracy of students' self-constructed goals relevant to their respective disciplines during independent study sessions. Our findings suggest that (a) most participants of the study are inaccurate at estimating the time needed to complete self-set goals; (b) students' perceived difficulty and competence beliefs can predict estimation accuracy at different time-points over the semester; and (c) accurate students are more likely to attain their goals than students who made inaccurate estimations of their study session. The implications of time estimation accuracy for goal completion and future avenues for research considering these findings are further discussed.

Time estimation accuracy over a semester

Findings from the present study indicate that students have difficulties making accurate estimations of the time they need to complete self-set goals. Less than half of the participants were accurate in their time estimations, while the rest reported overestimating or underestimating the time dedicated to a single study session over a semester. These results are in line with our hypothesis and with prior studies documenting underestimation and overestimation of single sessions (Buehler et al., 2010b). However, researchers in past studies pre-selected the activities

students addressed on each study session which is contrary to the expectations post-secondary contexts place on students. In addition to the academic work and learning involved in university tasks, students need to figure out how to distribute their workload over multiple study sessions. Our results contribute to the literature by documenting misestimation of single study sessions where students had the autonomy to choose the content and duration of their study sessions. These results are relevant since the compound effect of misestimation over multiple study sessions could further result in time management challenges like cramming, failing to meet deadlines, or delivering poor work quality (Baumeister et al., 1993).

The higher frequency of underestimation at the end of the semester was an unexpected result given the context of SRL instruction that participants attended. This result is contrary to H1b and findings on the effectiveness of SRL training to improve planning, goal setting, time management, and effort management (Jansen et al., 2019; Theobald, 2021). Three possible explanations could account for the increased tendency to underestimate time despite the instructional context of SRL. First, the overlap with external deadlines at the end of the semester can influence students' estimation accuracy and engagement (Buhler et al., 2010b; Heckhausen et al., 2010). Namely, Heckhausen (1999) describes that, as a deadline approaches, there are decreases in opportunities to complete work and increases in perceived constraints. An approaching deadline might leave students with limited options like increasing their effort and engagement at the expense of going beyond their estimated time to meet a closer deadline. In contrast, a further deadline gives students more freedom to abandon the study session since more opportunities to return to the task are available. The difference between perceived high opportunities and low constraints might explain the higher prevalence of overestimation (i.e.,

spend less time than planned) at the beginning of the semester (20%) relative to the end (5%) where students had less opportunities to delay engaging with their task.

A second explanation for a higher frequency of underestimation is students' inaccurate or incomplete task understanding. Task understanding, or students' interpretation of a task's components, is foundational for strategic decisions about goals, plans, and approaches to academic assignments (Hadwin & Winne, 2012). Although empirical evidence of the role of task understanding in students' approach to academic tasks is scarce, recent studies suggest that students with weak task understanding are more likely to set broad goals and to be disorganized with their academic work (Beckman et al., 2021; Cosenfroy et al., 2018). Having an incomplete or inaccurate understanding of a task makes it difficult to assess the content and duration of a study session to progress academic work. Future research should explore the relationship between students' time estimation accuracy and the degree to which students engage in practices to refine their task understanding.

Lastly, a purposeful regulation of effort and motivation prompted by SRL instruction could also explain the higher frequency of underestimation over a semester. The instructional content following week 6 was dedicated to review concepts and practical strategies to regulate motivation, behavior, and cognition. The application of these techniques could have prompted students to sustain engagement. Indeed, prior research suggests that purposeful regulation of effort has been related with time on task and homework timeliness (Bembenutty, 2010; Yang &Tu, 2020). Increasing effort despite going beyond the time estimation may be a byproduct of self-regulation. Further research is warranted to assess whether regulation of effort, or other aspects of students' learning, contributes to time estimation accuracy.

Predictors of time estimation accuracy

Setting goals of greater perceived difficulty predicted students' underestimation of time needed, but their goal quality was not a significant predictor of time estimation accuracy. These results suggest that students were more likely to go above their allotted time for study sessions when they rated a self-set goal of any quality as high in difficulty. The relationship between high task difficulty and underestimation has been previously described by studies where researchers provide students with tasks of varying difficulty levels (Min & Arkes, 2012; Roy & Christenfeld, 2008; Thomas et al., 2003). This study extends prior research by allowing participants to select their weekly tasks and to create goals of any difficulty for each study session. While students have no choices to select the tasks assigned to them in a course, the assumption of agency in SRL implies that students can choose how to approach effortful assignments by creating goals of manageable difficulty (Pintrich, 2007; Zimmerman, 2000). A practical recommendation to students setting difficult goals for themselves who want to avoid underestimation is to revise their goal setting process to create a goal of manageable difficulty (i.e., create goals that can be addressed in a single study session).

Competence for goal completion and prior accuracy were two additional predictors of estimation accuracy at different points in the semester. Specifically, confident students were more likely to report accurate time estimations on week 2 and, in turn, accurate time estimation on week 2 was predictive of future overestimation (i.e., spending less time than planned). Both findings are consistent with prior literature suggesting that students' motivational beliefs and experience influence their estimation accuracy (Halkjelsvik & Jørgensen, 2012; Schunk, 2003). However, each predictor was only significant at one point over the semester. Competence beliefs predicting estimation accuracy only at the beginning can be explained by the performance

outcomes informing students' competence beliefs. Mastery experiences or previous performance are considered as one of the most meaningful sources of self-efficacy (Bandura, 1977). Experiencing underestimation in the study sessions taking place between time points of assessment could have reduced students' general competence beliefs to make accurate estimations and reduce its significance as a predictor. However, this assumption is beyond the scope of the present study since the goals between assessment points were not related to each other.

The time between assessment points and the independence of the aim between students' self-set goals could also explain why prior experience predicted time estimation only at one point in the semester. Students had the choice to select a different course and task as their goal focus at each point of assessment and several study sessions could have taken place between one point of assessment and the next. The aim of the goal and the distance between point of assessment added unaccounted variability to students' time estimations. These conditions make it difficult to assess the cyclical nature of learning assumed in SRL. Wolters & Brady (2020) suggest that self-regulated learners reflect on time-related experiences to inform future SRL cycles. Empirical evidence supporting this assumption shows that self-reflection of previous experiences informs the forethought phase of following SRL iterations (Callan & Cleary, 2019). However, Callan and Cleary used the same task to examine the relationship between SRL phases. Our results contribute to the literature by providing preliminary evidence that internal sources of motivation and prior experience estimating time in academic tasks influence time estimation accuracy. Future research could investigate the relationship between students' experience between study sessions following the same task.

While perceived goal difficulty, competence beliefs, and prior experience were expected findings, goal quality failing as a predictor of estimation accuracy was contrary to our hypothesis. Two possible explanations can account for this finding. First, the components selected to rate goal quality in this study may not be suited to predict estimation accuracy. Prior literature describes different properties of high-quality goals without a clear consensus on the number and the nature of each component. For instance, McCardle et al. (2017) described four key components of learning goals guiding short study sessions (i.e., concepts, action, standards, and timeframe). Whereas Zimmerman (2008) outlined eight properties of high-quality goals driving students' motivation to attain short- and long-term outcomes related to learning and performance. This study limited goal quality to a subset of properties described in the literature and further research could explore the relationship between other goal quality components and time estimation accuracy.

A second explanation for goal quality failing to predict estimation accuracy is overlooking the process students followed to set the goals guiding their individual study sessions. Specifically, SRL posits that task understanding is an antecedent of students' engagement in academic work (Hadwin & Winne, 2012; Zimmerman, 2000). Hadwin and Winne explain that a comprehensive understanding of task components allows students to make a strategic plan to approach a task and distribute their efforts effectively between study sessions. An incomplete task understanding could have influenced students time estimation by missing important task components when creating their goals. Regarding students' goal setting process, Zimmerman (2008) suggests that its effectiveness relies on the inclusion of distal and proximal goals. Distal goals assist students to self-regulate their efforts towards completion (e.g., submitting an essay), while proximal goals serve as standards of their learning process (e.g., summarize one reference

for the essay). Failing to identify a sequence of proximal goals to attain a distal goal could also influence students' approach in their study session. The weekly diary tool used in this study prompted students to identify a course and focus for their study session before creating a goal. Students' task understanding and goal setting process were not contemplated as potential influences in students' goal quality or time estimation.

Time estimation accuracy and goal completion

Students who reported spending less time than planned in their study session (i.e., overestimating) were less likely to complete their goal. This finding suggests that students might have encountered discrepancies between their plan and their actual performance, leading to disengage with their study session without completing their goal. Prior literature refers to 'metacognitive experience' when students realize a discrepancy between planned and actual performance, requiring acting in response to said awareness (Efklides, 2006; Winne & Hadwin, 1998). For instance, during performance, a student might (a) realize that the cognitive resources needed for goal-attainment are different from their initial task perception, (b) re-assess their expectancy-value beliefs of engaging with the task at hand, or (c) notice pleasant or unpleasant affective reactions during the study session (Efklides, 2011). Students may decide to regulate the salient metacognitive experience and engage in meaningful self-regulatory processes (e.g., effort-regulation); or fail to self-regulate by disengaging earlier than expected leaving the goal incomplete (Bembenutty, 2011). In consequence, the self-regulatory decisions students make have the potential to impact their time estimation accuracy. In fact, prior research has shown that homework timeliness is associated with self-regulatory strategies like environmental management, willingness to delay gratification, self-efficacy, and effort regulation (Bembenutty, 2009a; Muljana et al., 2021; Ramdas & Zimmerman, 2011; Yang & Tu, 2020). The present study

provides initial evidence that misestimating the time for individual study sessions influence goal completion. In addition, this study suggests that misestimation can result from a nuanced relationship between student's metacognitive experiences and their attempts to self-regulate.

Limitations

This study contributes to the literature by considering students' agency when estimating time for individual study sessions guided by goals constructed by them for tasks relevant to their respective disciplines. However, the results should be interpreted considering at least three important limitations. The first is the reliance on self-reported data collected through the weekly diary tool. This tool guided students through specific aspects of their planning and self-reflection shaping their approach to a single study session. The results of the predictors identified in this study may be different in study sessions that were not guided by the weekly diary tool. Further, relying on self-reported data requires students to recall their study session and prior research has shown that individuals tend to have faulty memories of past durations (König et al., 2015; Roy et al., 2008). Studies using trace data (Bernacki, 2018) or multimodal data (Järvelä & Bannert, 2021) can address this limitation in further research.

The instructional purpose of the weekly diary tool limited this study to focus on goals that were unrelated to each other. The study diary tool aimed to engage students in SRL iterations rather than following the completion of a single assignment. As a result, students had the freedom to choose from a wide variety of tasks to focus on for their independent studying. The adaptations students made between study sessions and the implications for overall estimation accuracy and task completion were not possible to be assessed under this structure. Lastly, the instructional context provided participants access to information and resources that were designed to improve a range of study habits. The learning-to-learn course covered a variety

of topics related to students' success including time management and goal setting. Students with explicit instruction of SRL and experience engaging in weekly practices to scaffold self-regulatory practices can have an advantage over other students without this knowledge (Jansen et al., 2019).

Future avenues for research

This study highlights the value of studying time estimation from an SRL perspective and our findings point to the need for future research to better understand the processes influencing time estimation accuracy and its implications in post-secondary contexts. We suggest following students' time estimation of a course-relevant task over multiple study sessions until its completion. This approach offers at least three main research pathways contributing to the understanding of undergraduates' time estimation. First, focusing on one task allows to examine students' task understanding and goal setting process in relation to their time estimation accuracy. Task understanding is theorized as a first and critical step in self-regulation that shapes students approach to academic tasks (Hadwin & Winne, 2012; Zimmerman, 2000), and has recently been associated with student's goal setting process and organization of academic work (Beckman et al., 2021; Cosenfroy et al., 2018). The degree of students' engagement in these forethought processes can further explain the frequency of students misestimation and its potential consequences for task completion, learning, and performance. Second, following the completion process of a single task over multiple study sessions provides the opportunity to investigate the cyclical iterations of the SRL process in relationship to students' time estimation accuracy over time. Research focusing on engagement over multiple SRL iterations can inform about the role students' metacognitive experiences and self-regulation attempts have on their time estimation accuracy. Lastly, following students' engagement over time can facilitate

investigating individual differences contributing to time estimation accuracy between students and the factors contributing to estimation accuracy within students over time. Experience, motivational beliefs, and other individual factors can be modelled in relationship to specific outcomes associated with time estimation accuracy (e.g., timely completion of tasks and performance) or other time management practices (e.g., scheduling or prioritizing) to have a better understanding of the role of time estimation in academic contexts.

Conclusion

The present study offers an initial approach to study time estimation accuracy from an SRL perspective by emphasizing the use of course-relevant tasks on individual study sessions guided by students' self-set goals. The prevalence of overestimation and underestimation suggest that students have difficulties to gauge how much progress can be attained within a single study session and make an accurate estimation of the duration of a study session throughout a semester. This is particularly relevant for undergraduate students since most of their academic work and regulation efforts occur during independent study sessions. While the present study focused on a few predictors of time estimation accuracy, the findings suggest that time estimation accuracy is closely related to students' perception and management of a task. This conclusion is in line with theoretical assumptions suggesting that time estimation is a critical component of time management with the potential to influence academic outcomes among undergraduate students (Aeon & Aguinis, 2017; Claessens et al., 2007; Kelly, 2002; Wolters & Brady, 2020).

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Appendices

Appendix 1

Personal Planning Tool (Hadwin et al., 2018)

Purpose of item	Item	Answer schema
	Part 1. Planning	
	This week, I really need to focus on [*Blank*]	Open ended
	During my 1–2-hour study session, on this date and time [*Blank*],	Open ended
	the studying/learning activity I will be working on is [*Blank*]	Open ended
Item coded for goal quality	Therefore, my goal for this 1-to-2-hour study session is [*Blank*]	Open ended
		Open ended
Perceived goal difficulty	I think this goal will be [*Blank*] for me to meet or attain.	Very easy, somewhat easy, somewhat difficult, very difficult.
Competence for goal completion	I am [*Blank*], I can achieve the goal in a 1-2 hr study session	Not at all certain, slightly certain, moderately certain, very certain, extremely certain.
	With [*Blank*] cognitive effort.	No, low, moderate, high, extremely high
	Part 2. Execute the goal	
	Part 3. Post-Performance Evaluation	
Goal completion	I [*Blank*] my goal this week.	Fully met, did not met.
Time estimation accuracy	I worked toward my goal for [*Blank*]	Zero hours, less than 1 hour, 1-2 hours, 2-3 hours, 3-4 hours, more than 4 hours.
	That was [*Blank*] the time I budgeted.	Less than, exactly, more than.
	I am [*Blank*] satisfied with my progress on this goal.	Not at all, slightly, moderately, very, extremely
	Overall, I found my goal to be [*Blank*] I expected,	Significantly easier than, somewhat easier than, the same as, somewhat more difficult than, significantly more difficult than.
	And it required [*Blank*] cognitive effort than I expected.	Significantly less, less, the same, more, significantly more
	This goal turned out to be [*Blank*]	Not at all useful, somewhat useful, extremely useful.
	For attending to my [*Blank*]	Behaviour, learning and attention, motivation, socio-emotional/ well-being, metacognition, something else altogether
	How much of a challenge were each of these during the study session? Motivational Factors I struggled with things related to will or desire to do my work and/or my confidence for academic goals and tasks. In this category, the most challenging thing I faced was [*Blank*]	

This was a big problem for the during my study session [*Blank*]	Strongly disagree, disagree, agree, strongly agree
Behavioural Factors	
I struggled with things related to time management and/or my commitment to engaging in tasks and deadlines	
This was a big problem for the during my study session [*Blank*]	Strongly disagree, disagree, agree, strongly agree
Cognitive Factors	
I struggled with things related to my focus/attention, learning remembering, communicating, or understanding	
This was a big problem for the during my study session [*Blank*]	Strongly disagree, disagree, agree, strongly agree
Socio-emotional Factors	
I struggled with things related to my overall well-being such as mental health, physical health, feeling like I fit here or belong, or managing my emotions	
This was a big problem for the during my study session [*Blank*]	Strongly disagree, disagree, agree, strongly agree
Metacognitive Factors	
I struggled with things related to my self-monitoring and self-awareness, planning (such as understanding academic tasks or breaking things down into learning goals) or strategy choice and implementation	
This was a big problem for the during my study session [*Blank*]	Strongly disagree, disagree, agree, strongly agree
During this study session, the main thing that got in my way was the [*Blank*] challenge I listed above.	Motivational, Behavioural, Cognitive, Socio-emotional, Metacognitive
To address this challenge, I [*Blank*]	List of (22) possible strategies [a]
And it was [*Blank*] successful.	Not at all, slightly, moderately, very, extremely
Next time, I plan to [*Blank*]	List of (22) possible strategies [a]
How engaged was I in the last 7 days?	
1. I attended all classes in my courses	Yes/No
2. I met all my deadlines in my courses	Yes/No
3. I did all my assignments in my courses	Yes/No
4. I completed all the required readings in my courses	Yes/No
5. I asked for help when I didn't understand something in my courses	Yes/No
6. I tried to summarize what I learned in my courses.	Yes/No
What is the most important thing I have learned about myself, my learning, or my motivation this week?	Open ended

Note. Only the items with described purpose were used in the present study.

[a] Possible strategies included: adjusted my goal, adjusted my strategy, adjusted my task understanding, asked for help, collaborated with peers, reprioritized my goals, changed effort, changed thoughts and feelings, evaluated my goal progress, implemented a new strategy, set a new goal, persisted, avoided the task, did nothing, considered the outcomes, changed my beliefs, focused on getting the task done, took a break, changed my learning environment, promised myself a reward, relaxed, did something else.

Appendix 2

Goal coding examples

Goal	Coding scheme				Goal quality
	Specificity		Steps	Standard	
	Assignment/ course / activity	Action / Strategy			
My goal is to review all the materials provided and review my old lab.	0	0	0	0	0
Completing a draft for the ECON assignment.	1	0	0	0	1
Write my discussion post to the best of my ability, connecting course content and personal experiences to the forum question.	1	1	0	0	2
My goal is to take notes from my sources and translate them into a paragraph/forum around emotions and stress that summarizes the article of my choosing while expressing my personal view on the topic. I will complete this in my 1–2-hour study session with a high level of focus and concentration.	1	1	1	0	3
On Tuesday afternoon from 3-5 pm, I am going to compare and contrast different ideas for a speech that I need to create. Once I have finalized an idea then I will write my speech and to make sure I understand what I am talking about I will explain to one of my friends briefly what I am going to be talking about and what direction I will be taking on it. That will show me that I could have it memorized as I don't need to just read off a sheet of paper.	1	1	1	1	4