Received: 8 December 2023 | Accepted: 28 July 2024
DOI: 10.1111/bjep.12712

ARTICLE

Only a matter of time? Using logfile data to evaluate temporal motivation theory in university students' examination preparation

Marc Philipp Janson[1] | Theresa Wenker[1] | Lisa Bäulke[2]

[1]University of Mannheim, Mannheim, Germany
[2]University of Tübingen, Tübingen, Germany

Correspondence
Marc Philipp Janson, School of Social Sciences, University of Mannheim. A5 6, Mannheim 68161, Germany.
Email: janson@uni-mannheim.de

Abstract

Background: While previous research has emphasized the importance of personal beliefs (expectancy-value theories) for achievement-motivated behaviour, it lacks the integration of temporal factors that are also discussed as important drivers of achievement-motivated behaviour. Temporal Motivation Theory (TMT) combines both approaches in a formalized manner.

Aims: Although TMT is supported by empirical studies with self-reported academic procrastination, it has not been tested on actual achievement-motivated behaviour.

Materials & Methods: We evaluated the predictive power of the TMT on $N = 2351$ learning days of 127 psychology students' self-regulated examination preparation for statistics over the course of one semester using logfile data of an e-learning system.

Results: The proposed TMT score, incorporating expectancy and value beliefs, sensivitiy to delay, and actual time till examination predicted students' achievement-motivated behaviour significantly.

Discussion: Further analyses revealed that not the trait compositions of the TMT, but the temporal proximity of the statistics examination was the main driver of this association.

Conclusion: The results have important implications for understanding the factors that shape students' motivation to learn and subsequent academic success in actual learning situations. Thus, research should continue to take situational aspects, especially the temporal proximity of goals more into account.

KEYWORDS
academic success, achievement motivation, e-learning, intelligent tutoring system, logfile data, temporal motivation theory

BACKGROUND

Achievement motivation is one of the most important determinants of academic success (Lavrijsen et al., 2022; Schneider & Preckel, 2017). A vast majority of studies investigate links between achievement motivation and achievement-motivated behaviour, such as effective and persistent studying (Koenka, 2020). However, one criticism of well-established motivation theories such as expectancy-value theories is that they do not consider time as a factor that impacts learning behaviour (Steel & König, 2006). Yet, time is discussed as an important factor shaping achievement-motivated behaviour (mostly considered as temporal proximity to a deadline; Peetz & Wilson, 2013). Particularly in the context of university students' examination preparation, an upcoming examination is a critical factor that is hypothesized to shape trajectories of learning motivation (Capelle et al., 2022).

Temporal Motivation Theory (TMT, Steel & König, 2006) combines key components of expectancy-value theories (Eccles et al., 1983) with a temporal perspective in a formalized manner. TMT poses that achievement-motivated behaviour, i.e. the motivation to engage in a task, is mainly driven by personal factors (such as expectancy and value beliefs), the temporal proximity of deadlines ("delay") as well as individuals' sensitivity to this delay. Despite the fact that TMT served as a fruitful theoretical framework for many studies in the past years, three main research gaps do exist: (1) So far, the theory has mainly been tested with self-report data, and studies using objective data use high levels of data aggregation (e.g., Steel et al., 2018). Current studies, however, emphasize the merit of the integration of fine-grained observational data and self-report data (Ellis et al., 2017). (2). To date, the TMT theory has been predominantly used to explain why students do *not* engage, but postpone their learning activities (academic procrastination, Steel, 2007; Steel et al., 2018; Steel & Klingsieck, 2016) instead of modelling achievement-motivated behaviour as it is stated in the theory. (3) To the best of our knowledge, no existing literature evaluates the predictive power of the TMT and its subcomponents' validity in a comparative way. Hence, with our present research, we aim to address these open research gaps by applying the TMT formula to self-regulated learning examination preparation. By strictly following the formalized propositions of the TMT, we examine its validity under real-world conditions using the power of logfile data to observe self-regulated activities (Baker et al., 2020). Until now, only some aspects of basic assumptions of the TMT have been tested empirically, focusing on procrastination research (Netzer Turgeman & Pollak, 2023; Siaputra, 2010; Steel et al., 2018). However, a comprehensive test of the TMT is still missing, which is fundamental to provide a solid foundation for further theory development. Further, we will discuss how the TMT can be embedded in the current developments of the situated expectancy-value framework (SEVT, Eccles & Wigfield, 2020, 2023), as motivation research proceeds to more situational differences in achievement motivation (Dietrich et al., 2022; Moeller et al., 2022; Murayama et al., 2017), which is only reflected partly in the TMT yet. Finally, as e-learning systems are particularly suitable for gaining objective data on learning persistence and performance (Janson et al., 2022, 2023), this approach helps us to better understand the self-regulatory processes of motivated behaviour.

Achievement motivation in terms of expectancies and values as a key to academic success

Internationally, fostering academic success in higher education is a central educational goal (Sneyers & De Witte, 2018). Comprising multiple dimensions, current studies consider academic achievement as a core aspect, (i.e., grades obtained in examinations, van der Zanden et al., 2019; York et al., 2015). Thus, intensive research efforts examine factors that promote academic achievement in higher education. Of these, self-regulated learning activities during the semester and examination preparation proved to be essential for academic success (Capelle et al., 2022; Rodriguez et al., 2022). Particularly high-stakes examinations—such as statistics in the study program of psychology (Förster et al., 2018; Schwerter et al., 2022)—are important gatekeepers to continued academic success for many university majors (Garfield & Ben-Zvi, 2007).

According to models of self-regulated learning (Zimmerman & Schunk, 2011), achievement motivation is among the key determinants of successful self-regulated learning. Achievement motivation is most proximally linked to academic achievement beyond measures of intelligence and personality (Lavrijsen et al., 2022). A well-established theoretical framework that allows a differentiated perspective on achievement motivation is the expectancy-value theory (Eccles et al., 1983). To explain differences in students' motivation to pursue and persist in achievement-motivated behaviour, expectancy-value theory (EVT, Eccles et al., 1983) postulates that achievement motivation comprises two major components: expectancies for success and subjective task value. Whereas expectancies for success indicate whether students feel capable of succeeding in the task ("Can I do it?", cf. personal efficacy, Bandura, 1977), subjective task value states how valuable the task is to them considering both benefits and costs due to task engagement ("Why would I do it?").

Time matters – A temporal perspective on achievement motivation

Per Eccles and Wigfield (2020), research on achievement motivation should be complemented by considering situative factors. These can be further systemized in contextual characteristics and time (Pekrun & Marsh, 2022). Recent research findings particularly pointed to the importance of temporal variation of motivation (Dietrich et al., 2019; Moeller et al., 2022; Pekrun & Marsh, 2022). However, time as such is not a psychological variable and psychological processes are needed to link the effects of time to achievement motivation. In terms of achievement motivation, time has been mostly considered as temporal proximity to a deadline (Peetz & Wilson, 2013), also addressed as a temporal landmark (Dai & Li, 2019). Insights from pico-economics and social psychology (Steel & König, 2006) offer theoretical perspectives to explain the effects of such temporal landmarks on achievement motivation.

Major theories including such a perspective are for example temporal discounting (Ainslie, 2010; Rubinstein, 2003) and construal level theory (Liberman & Trope, 1998; Trope et al., 2007), both stating that judgement and decision making is dependent on the temporal perspective. Temporal discounting refers to the individual's tendency to value outcomes higher if they are more proximal in time (Ainslie, 2010). Construal level theory states that considerations about future events are more abstract compared to those closer in time (Liberman & Trope, 1998; Trope et al., 2007). From both theoretical approaches, one can conclude that achievement motivation should increase as deadlines approach. In terms of temporal discounting, one may assume higher associated value to learning activities with closer time (see Capelle et al., 2023) as well as more concrete (planning of) learning activities closer to examinations due to the less abstract mental representation of the needed examination preparation. To our best knowledge, current studies in educational psychology address the issue of incorporating time as a variable (Capelle et al., 2022, 2023), but still lack a thorough integration of the temporal perspective – in terms of strictly formalized propositions – into existing frameworks (Dietrich et al., 2022; Eccles & Wigfield, 2020; Moeller et al., 2022; Murayama et al., 2017), which can make a unique contribution to explaining motivated behaviour (Steel & König, 2006).

Temporal motivation theory and achievement motivation

Combining key components of the classic expectancy-value approach with a temporal perspective, the Temporal Motivation Theory (TMT; Steel & König, 2006) aims to explain the emergence and development of achievement motivation in an integrative theory on achievement motivation predicting achievement-motivated behaviour. The theory combines a trait perspective on achievement motivation and time to a formalized and testable proposition. According to the TMT, motivation at any given time is the product of expectancy and value, divided by individuals' sensitivity to delay (in terms of lack of self-control and impulsiveness) and the amount of time until the deadline (delay). As illustrated in the following equation, the approach is formularized to explain achievement motivation (sometimes referred to as utility; Steel & König, 2006) based on the described parameters:

$$\text{Achievement Motivation}_t = \frac{\text{Expectancy} \times \text{Value}}{\text{Sensitivity to delay} \times \text{Delay}_t}$$

Hence, according to this formula, achievement motivation at any time point t is determined by stable interindividual differences and the progression of time expressed by the delay at time point t. Following Steels' (2007) reasoning, all four components of the TMT are highly associated with students' achievement-motivated behaviour as a behavioural expression of achievement motivation. Following the formula, achievement motivation is higher, when learners have higher expectancies about success and derive more value. Additionally, achievement motivation will be lower when the sensitivity to delay and the time till the deadline is high. It is important to note that above and below the fraction line, multiplicative terms are stated. Hence, achievement motivation will remain low, even when values are high if the expectancy for success is nonexistent (see also, Nagengast et al., 2011). Also, even if the sensitivity to delay is high, achievement motivation will not be significantly lowered when the delay is small, i.e. the deadline is imminent. A graphical representation of achievement motivation development in dependency of time until a deadline is displayed in Figure 1.

Despite the formula provides a longitudinal perspective on achievement motivation, only the delay component varies across time, while the interindividual differences are treated as stable. Due to the reciprocal entering of the delay component, achievement motivation of time follows a curve with stronger increasing achievement motivation closer to the deadline. The interindividual differences describe the position and shape of the curve. Hence, achievement motivation is higher for individuals with higher (stable) expectancies and values. As deadlines approach (meaning delay decreases), achievement motivation increases for individuals, with those having lower sensitivity to delay experiencing a steadier rise

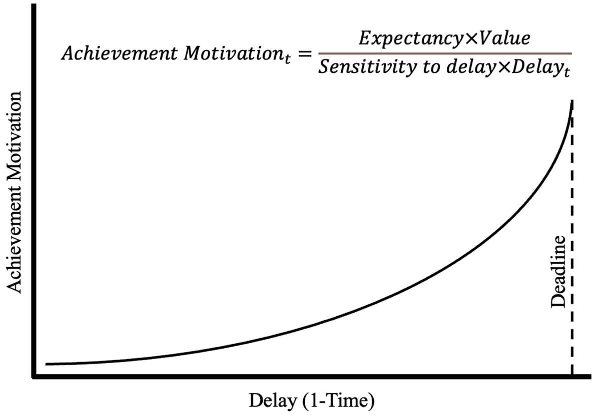

FIGURE 1 Illustration of the development of achievement motivation over time according to temporal motivation theory (Steel, 2007). Development of achievement motivation based on Steel's (Steel, 2007) Temporal Motivation Theory. Achievement motivation is dependent on time until a deadline (delay represents the inverted measurement) and expectancy, value and sensitivity to delay are stable dispositions that alter the steepness of the curve.

in motivation compared to those with higher sensitivity, who might exhibit a steeper increase close to the deadline.

Although TMT is an effort to provide a general theory of achievement motivation, its empirical application focuses primarily on academic procrastination. To date, research in the higher education context predominantly used the theory to investigate university students' procrastination tendencies (Steel, 2007; Steel et al., 2018; Steel & Klingsieck, 2016).

However, it is still unclear to which extent the formula predicts actual achievement-motivated behaviour, beyond the mere focus on its inverted outcome procrastination. Previous approaches for determining achievement-motivated behaviour using the TMT approach focused for example on the number of completed assignments (Steel et al., 2018). In this study, participants completed learning assignments over the course of the semester with recommended timeslots for completion. They were incentivized with additional points for the final examination when they completed the assignments on time. However, this somewhat restricts the degree of autonomous self-regulated learning activities, so objective data on actual self-regulated achievement-motivated behaviour is still missing. Moreover, the previous research also suffered from methodological setbacks as studies often lacked an intensive longitudinal design and data gathered in the actual context of studying (Roe, 2014; Steel et al., 2018). Hence, in the present work, we aim to investigate whether the TMT holds true in a real-world setting of high-stakes statistics examination preparation and the usage of objective observational data for measuring achievement-motivated behaviour, thereby extending previous research that mainly used self-reports.

THE PRESENT STUDY

In recent years, e-learning opportunities have emerged that depend on learners' self-regulatory capacities in their effectiveness (Azevedo et al., 2011; Cheng & Xie, 2021; Winters et al., 2008). One kind of e-learning systems that support students' self-regulated learning are intelligent tutoring systems. These provide individually adapted guidance to the learner during learning activities (Mousavinasab et al., 2021) which are shown to be as effective as human tutoring (VanLehn, 2011). Besides the effectiveness for learners, such tutoring systems can be used for objectively measuring learning processes (Janson et al., 2022, 2023).

According to Eccles and Wigfield (2020) achievement motivation leads to achievement-related choices and higher persistence to maintain achievement-motivated behaviour. Applying this theoretical assumption, learners' total usage of an intelligent tutoring system (e.g., their total learning time) should also depend on achievement motivation. In the present study, we thus aim to use logfile data of an intelligent tutoring system to extend previous research on TMT in two ways: First, by testing the formula with motivational variables that were examined via a self-report questionnaire in regard to the preparation of an important statistics examination. Second, by using actual behavioural logfile-data for self-regulated examination preparation from an intelligent tutoring system (Baker et al., 2020). The basic research aim of the current study is depicted in Figure 2. Based on theoretical assumptions of TMT (Steel, 2007; Steel & König, 2006), we hypothesized that a higher level of achievement-motivated behaviour (higher total learning time per day) is positively predicted by higher achievement motivation represented by a compound score using the TMT formula (Hypothesis 1). Second, we also assumed that subcomponents of the TMT formula predict achievement-motivated behaviour (total learning time per day). In particular, we aim to examine the hypothesis that higher learning time is associated with higher expectancies, values, sensitivity to delay, and delay in terms of less time until the examination (Hypothesis 2). It is important to note that, despite the current developments regarding situational changes in achievement motivation (Dietrich et al., 2022; Eccles & Wigfield, 2020; Moeller et al., 2022; Murayama et al., 2017), we strictly follow the TMT approach of only varying the delay component. This way, we aim to evaluate which components of the TMT are driving the effect by inspecting the components separately.

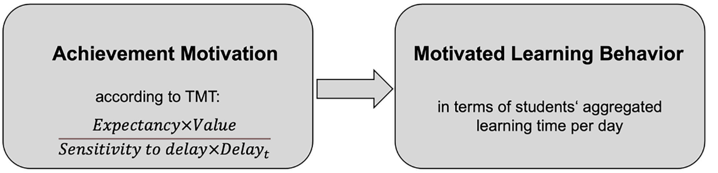

FIGURE 2 Basic research aim of the current study. Expectancy, value and sensitivity to delay are measured with self-report data; delay and motivated learning behaviour with objective data from an intelligent tutoring system. Motivated learning behaviour is measured every day and together with the delay variable represents intraindividual differences while the self-report variables are (in accordance with the TMT) treated as traits and assessed at first login.

METHOD

Design and sample

We assessed data during the fall semester of 2022 at a German university. Psychology students who were using the intelligent tutoring system CoTutor (Siebert & Janson, 2018) for self-regulated examination preparation for a first-semester statistics course were invited to participate in the study at the first login to the software. The web-based software is offered on a commercial base and is used by a vast majority of the students. After giving consent to participate in the study, the users answered the provided questionnaires on achievement motivation. Afterward, students were able to use the software at their own pace and no further interventions or measurements in the software took place, but the learning data were protocolized in an automated manner keeping track of every single action (i.e. exercise answer) within the software. Students received course credits in exchange for participation.

To evaluate the predictive power of the TMT on motivated behaviour during self-regulated examination preparation, we assessed data from $N = 127$ first-semester psychology students (79.5% female, 19.7% male; .8% diverse) with a mean age of 20.25 years ($SD = 1.99$). We measured learners' expectancies and values as well as their self-control capacities at their individual learning onset. We continuously collected the logfile data of the learning activities until examination day.

Materials

To test the research questions, we measured every component of the TMT with either objective data, self-reports, or a combination of objective data and self-reports. The objective data was retrieved from the intelligent tutoring system CoTutor (Siebert & Janson, 2018). The software provides practice exercises tailored to the respective statistics course including multiple choice exercises to consolidate understanding and arithmetic problems for practice testing (Roediger & Karpicke, 2006a, 2006b). We analysed the logfiles of the software revealing that learners spent 27.94 h of total learning time on average (SD = 14.42). It is important to note that the software automatically logs out after longer periods of inactivity and learning time is defined as the time difference between learning onset and last activity before logout. Hence, the total learning time measurement does not incorporate large periods of absence.

Achievement-motivated learning behaviour: Objective data

We measured achievement-motivated behaviour by using objective logfile data of the intelligent tutoring system CoTutor (Siebert & Janson, 2018). More precisely, we individually aggregated students' learning time per day (in minutes) as an objective indicator to measure achievement-motivated learning behaviour.

Delay: Objective data

Delay was assessed in terms of days until the examination. We also used logfile data from CoTutor (Siebert & Janson, 2018) to calculate the days until the examination objectively.

Achievement motivation in terms of expectancy and value beliefs: Self-reports

We assessed the expectancy-value components as well as the sensitivity to delay once using self-reports when learners first logged into the intelligent tutoring system. To measure university students' expectancy and value beliefs, we used the MoVE Scale (Motivation: Value and Expectancy Scale; Schnettler et al., 2020). The scale comprises one subscale for learners' expectancies for success of three items which are based on three items from Kosovich et al.'s study (2015) that Fleischer et al. (2019) translated into German. Congruent with the TMT, our measure did not include negative value components (effort, emotional, and opportunity costs; Eccles et al., 1983; Flake et al., 2015), but only items on the positive value components. The MoVE scale comprises 15 items for assessing intrinsic value, attainment value and utility value (by further differentiating attainment and utility value in two subscales each) which we combined into an average score. We asked the participants to answer the three items measuring expectancies for success and the 15 items measuring the positive value components with respect to the statistics course participants were attending. Participants answered all items on a Likert-scale with answer options ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). The items of the scale are printed in the Data S1.

Sensitivity to delay: Self-reports

We collected participants' self-control capacities as measurement of sensitivity to delay with a German translation of the short version of the Self-Control-Scale (SCS-KD; Bertrams & Dickhäuser, 2009; Tangney et al., 2004). Steel (2007) suggested self-control as a central variable that corresponds to the sensitivity to delay factor within his formula. The scale includes 13 items measuring this sensitivity to delay with statements like “I am good at resisting temptation” or “Pleasure and fun sometimes keep me from getting work done” and participants were asked to answer them on a Likert-scale with the endpoints ranging from 1 (*not at all*) to 5 (*very much*).

Achievement motivation: Combining self-reports and objective data

The final measure of students' achievement motivation according to TMT was calculated via the aforementioned formula. We standardized expectancy for success, positive value components, and self-control as well as days until examination. We used Z-standardization ($M = 100$, $SD = 10$) to prevent negative terms and divided the multiplicated expectancy-value term by the self-control and days until examination product.

Data analyses

We conducted multilevel regression analyses to evaluate the predictive power of the TMT on participants' learning activities with the lme4 package (Bates et al., 2014) in R using ML estimation. Achievement-motivated learning behaviour in terms of learning time per day (in Minutes) served as the dependent variable (level 1, L1). Of note is that we coded no learning activities as 0 in our dataset on days after initial learning onset. No learning activities before an individual's learning onset were treated as missing data. This way we consider presence and absence of learning behaviour after initial learning onset. Taken together, we predicted learning time per day (L1) using the TMT score of individuals at this day (L1), which reflects changes in time till examination (L1) as well as interindividual differences in expectancies, values, and self-control (L2). Hence, in subsequent analyses of the effects of the single components we compare effects of L1 and L2 predictors as well as cross-level-interactions. We did not impute any missing data. We standardized all variables before entering the models. We reran the analyses with unstandardized variables (cf. Moeller, 2015) as well as using robust regression models to test the robustness of our results. Those additional models were presented in the Data S1 as results did not differ substantially.

RESULTS

In Table 1, we present descriptive statistics, internal consistencies and bivariate correlations of all variables. Furthermore, we depict aggregated learning time per day in Figure 3. A visual inspection reveals a cramming curve with intensified learning activities close to the examination date. However, other significant events during the semester are observable on a descriptive level as can be seen in slightly higher learning activities close to the mock examination or much lower total learning time on the day of the departments' pre-Christmas party. Overall, we captured 2351 observed learning days of our 127 participants in total, of which 1753 took place after the pre-Christmas party[1]. As the study onset varied between participants, we checked whether a later assessment date of the initial questionnaire (expectancies for success, positive value components, and self-control) was systematically associated with the self-report measures, but only found non-significant tendencies for expectancy ($r = .14$, $p = .11$), a composite value score ($r = -.15$, $p = .10$), and self-control ($r = -.17$, $p = .06$).

Main analyses

All regression estimates and model criteria can be seen in Table 2. In light of the skewed distribution of the dependent variable, we also included additional robustness checks with a transformed dependent variable and robust models, which also provided convergent support of our finding (see Data S1). To test our first hypothesis regarding the predictive validity of the TMT score (comprising expectancy, value, sensitivity to delay, and delay) for achievement-motivated behaviour, we investigated whether higher total learning time per day (indicative of motivated learning behaviour) is predicted by higher compound scores. Therefore, we entered a compound score indicative of achievement motivation built upon the formula stated by the TMT as the level 1 predictor. To achieve the score, we scaled all contributing variables, resulting in a score that had a constant interpersonal (L2) component and the situative time component (L1). In support of our hypothesis, the result indicates that the TMT

TABLE 1 Descriptive statistics, internal consistencies and bivariate correlations between components of the TMT.

Variable	*M*	SD	Skewness	1	2	3
1. Expectancy beliefs	4.70	.87	−.41	(.85)		
2. Value beliefs	4.32	1.00	−.34	.40***	(.95)	
3. Self-control	3.14	.61	−.23	.12	.07	(.84)
4. Total learning time (in minutes)	1676.22	865.11	.78	.00	.04	.23***

Note: Internal consistencies (McDonald's omega) in brackets.
***$p < .01$.

[1]In the electronic supplement, we provide an analysis only including learning activities after the pre-Christmas party which provided convergent findings.

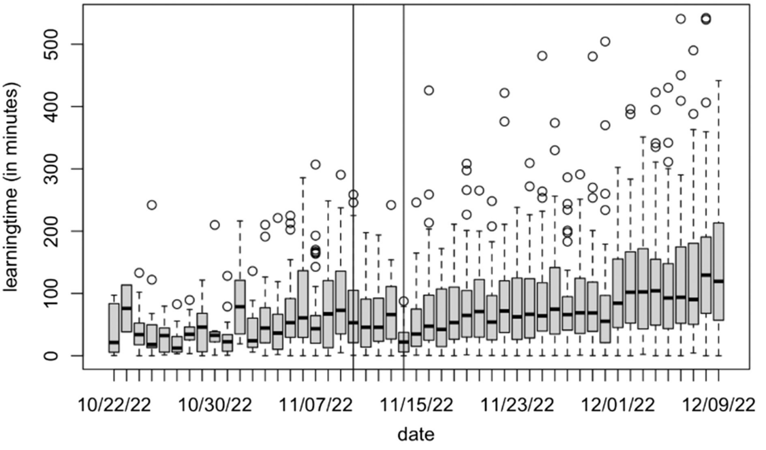

FIGURE 3 Aggregated learning time over the course of one semester. Vertical lines highlight events during the semester: Mock examination on 11/10/22; pre-Christmas party on 11/14/22.

TABLE 2 Multilevel linear regression of learning time per day on achievement-motivation in an intelligent tutoring system.

	TMT	Main-effects	Interactions	Delay linear	Delay curvilinear
	Est. (SE)	Est. (SE)	Est. (SE)	Est. (SE)	Est. (SE)
Level 1 (day level)					
TMT composite score	.336*** (.033)				
Days till examination		−.278*** (.020)	−.278*** (.020)	−.277*** (.020)	−.596*** (.068)
Days till examination (2nd polynom)					.333*** (.068)
Level 2 (person level)					
Expectancy beliefs		−.002 (.037)	−.001 (.037)		
Value beliefs		−.013 (.036)	−.014 (.036)		
Self-control		.033 (.034)	.032 (.033)		
Cross-level-interactions					
Expectancy beliefs: Days till examination			.007 (.021)		
Value beliefs: Days till examination			−.006 (.022)		
Self-control: Days till examination			−.021 (.020)		
Constant	.005 (.046)	.009 (.033)	.011 (.033)	.008 (.033)	.006 (.033)
Observations	2351	2351	2351	2351	2351
Akaike Inf. Crit.	6490.39	6379.87	6384.638	6374.966	6352.954
Bayesian Inf. Crit.	6513.44	6420.21	6442.264	6398.016	6381.767

Note. Learning time per day served as dependent variable. All variables were standardized before entering the analyses. The TMT composite score is a compound score using the formula proposed by the temporal motivation theory: TMT = Expectancy × Value/(Self-control × days till examination).

*$p < .1$; **$p < .05$; ***$p < .01$.

score was predictive of students' achievement-motivated learning behaviour in terms of learning time per day.

To test our second hypothesis regarding the prediction of subcomponents of the TMT formula for total learning time per day, we included the components of the TMT separately resulting in three L2 variables, (expectancy, composite value, and self-control) and the L1 indicator of days until examination as predictors of total learning time per day. Out of the four variables, only days until examination was a significant predictor of learning time, indicating on average 22 minutes higher learning time for every next day. In a third model, we entered interaction terms of the L2 components with the temporal factor, also not revealing any significant effects beyond the temporal effect. Finally, we solely entered the expectancy-value perspective, revealing a slight, albeit non-significant, tendency of an interaction between expectancy and value on learning time using one-tailed testing. Taken together, our second hypothesis was only partly supported as days until examination (indicative of delay) was the only significant predictor of achievement-motivated behaviour.

Post hoc analyses

To analyse the nature of the cramming curve, we compared regression models using polynomial trends for the temporal indicators for both datasets. While days until examination as a linear predictor was a significant sole predictor for both datasets ($\beta = -.28$, $p < .001$), the predictive power after adding a 2nd polynomial parameter was slightly higher ($\beta_{\text{linear trend}} = -.59$, $p < .001$, $\beta_{\text{2nd polynom}} = .33$, $p < .001$). This indicated that delay is not only a linear predictor of achievement-motivated behaviour, but also that learning activities intensify as the examination deadline approaches. Complete regression models are included in the Data S1.

DISCUSSION

Although achievement motivation plays a central role in predicting academic achievement over the course of studies, contemporary motivation theories mostly lack the integration of a temporal perspective. This is addressed by Temporal Motivation Theory which combines central components of expectancy-value theory (Eccles et al., 1983) with a temporal perspective (Steel & König, 2006) in a formalized manner. With the present study, we aimed to evaluate the predictive power of the propositions stated by the Temporal Motivation Theory (TMT; Steel, 2007; Steel & König, 2006) on motivated learning behaviour in self-regulated achievement settings.

An important strength of the current study is that we used a combination of objective and subjective data to test the TMT formula in a concrete learning situation compared to solely relying on self-reports or distal outcomes of achievement-motivated behaviours like handing in assignments (Steel et al., 2018). While one has to keep in mind, that behaviour is not only dependent on motivation but also volition (Heckhausen & Gollwitzer, 1987), this approach enabled us to test the significance of every single component of the formula as well as their combined influence on achievement-motivated learning behaviour as a proximal outcome. Using the logfile data of an intelligent tutoring system additionally provides insights into actual learning behaviour. In this way, all assumptions made by TMT could be tested in a systematic manner.

Our hypotheses could partly be confirmed. The compound score indicative of achievement motivation was predictive of achievement-motivated learning behaviour (hypothesis 1). Out of the single components of the TMT, only the temporal indicator was a significant predictor for learning time in most models. But does that mean that only time matters for achievement-motivated learning behaviour—and nothing else? Several considerations must be made for answering this question:

The TMT makes strictly formalized propositions regarding achievement motivation, with four key factors influencing achievement motivation: Expectancy, value, sensitivity to delay and delay. However, our results might indicate that not all components of the formula are at the same time and situation as important for achievement-motivated learning behaviour. This contrasts with earlier findings that indicated empirical support for the propositions of TMT. However, these are based on research that mostly focused on academic procrastination which was treated as an inversed outcome of achievement-motivated behaviour (Steel, 2007; Steel et al., 2018; Steel & Klingsieck, 2016). Thus, our study considered students' actual learning activities as behavioural expressions of achievement motivation to investigate the other endpoint of this behavioural continuum.

Another challenge in evaluating the TMT is the not clearly defined operationalization of the components. As already mentioned, Steel (2007) states that sensitivity to delay is linked to *self-control*, but also to constructs like *distractibility* and *impulsiveness* (Ainslie, 1975; Madden et al., 1997; Ostaszewski, 1996, 1997; Petry, 2001; Richards et al., 1999). For the value component, Steel (2007) claimed *task aversiveness* as the most proximal construct, which reflects the opposite of intrinsic value conceptualization by expectancy-value theory (Eccles et al., 1983; Eccles & Wigfield, 2020), but also *need for achievement* and *boredom proneness*. This way of conceptualizing the components of the TMT makes it difficult to empirically test the core of the theory as well as compare empirical findings of different studies evaluating TMT. Moreover, the TMT does not incorporate negative value components like effort, emotional, and opportunity costs (Eccles et al., 1983; Flake et al., 2015). In our present work, we strictly followed the TMT propositions. However, as negative value components are also important drivers of learners' achievement motivation (Jiang et al., 2018), future research should take these components into account.

From our point of view, the most crucial aspect is that the statistical power of the level 1 variable measuring delay (intraindividual level) was much stronger than the interpersonal assessments of the other components (expectancy, value, sensitivity for delay) on level 2. Hence, it might not surprise that we were able to identify a prediction of learning activities following the cramming curve (Capelle et al., 2022). However, the TMT does not propose any state assessment of expectancy, value and sensitivity to delay and explicitly states the delay as the situational account in the formula. Nevertheless, it seems not justified to conclude from our findings that interindividual differences are not meaningful to explain differences in actual learning behaviour. Our analyses revealed some tendencies replicating the multiplicative expectancy-value propositions (Eccles et al., 1983; Nagengast et al., 2011; Perez et al., 2019). The present research treated the assessed constructs, in line with the TMT, as stable constructs. However, recent research on achievement motivation has switched the focus towards taking different motivational states into account (Dietrich et al., 2022; Moeller et al., 2022), also leading to new perspectives in the development of the expectancy-value theory (Wigfield & Eccles, 2000) towards the situated expectancy-value theory (Eccles & Wigfield, 2020, 2023), which clearly distinguishes trait and state components of achievement motivation. We also suggest distinguishing trait and state components of expectancies, values, and sensitivity to delay. As ongoing developments of the TMT are taking place to make the theory more dynamic (Dishop, 2020), we would recommend differentiating state and trait assumptions of the TMT further by integrating the theory into the SEVT framework (Eccles & Wigfield, 2020, 2023).

An integration of temporal motivation theory into the situated expectancy-value framework

To best of our knowledge, achievement motivation research on the one hand makes no clear predictions regarding temporal effects in the SEVT (Eccles & Wigfield, 2020, 2023), like the effects of strict deadlines like upcoming examinations which are a major driver in learners' self-regulated learning activities (Capelle et al., 2022). On the other hand, the current state of research also lacks empirical work on the predictive validity of the TMT on actual self-regulated learning behaviour, e.g., in terms of the observed time spent studying. From our perspective, SEVT and TMT are not mutually exclusive, as they share a common theoretical framework based on interindividual differences of expectancies and values as well as intraindividual factors shaping achievement motivation. In contrast, we suggest integrating the strong formalized approach towards time into the TMT into the SEVT framework. Hence, future studies should validate the TMT (Steel, 2007; Steel & König, 2006) in the context of achievement-related behaviour to expand our knowledge of temporal factors driving achievement motivation, which leads to a better understanding and stronger formalization of the situational components stated in the SEVT (Eccles & Wigfield, 2020, 2023).

Hence, we suggest that a more dynamic approach to the TMT is necessary (cf. Dishop, 2020), not only taking temporal distance as intrapersonal variable component. Integrating the TMT into the situated expectancy-value theory (Eccles & Wigfield, 2023), the TMT should be extended as follows by adding an index t for the current point in time to every single component:

$$\text{Achievement Motivation}_t = \frac{\text{Expectancy}_t \times \text{Value}_t}{\text{Sensitivity to delay}_t \times \text{Delay}_t}$$

This *Situated Temporal Motivation Theory (STMT)* might improve researchers' efforts in explaining learners' achievement motivation and provide a useful extension to the SEVT framework with a closer look on temporal aspects, i.e. upcoming examinations or deadlines for assignments. We want to highlight that it is crucial to also include negative value components (Jiang et al., 2018) to further integrate our proposed STMT into the SEVT framework.

Moreover, it is important to consider the very formalized character of the (S)TMT. Other approaches towards achievement motivation exist, which have a broader perspective on the interplay of achievement motivation-related constructs (like the SEVT, Eccles & Wigfield, 2020). These require other methodological approaches like profile analyses or machine learning approaches. However, strongly formalized approaches like the presented ones are more parsimonious, easily testable and provide derivable implications for practitioners.

Limitations

The present research comes with limitations inherent to the chosen design. We were solely able to observe learning behaviour within the software in terms of learning persistence (Janson et al., 2022, 2023) and are not able to make holistic considerations about the learners' overall achievement motivation. A student could for example purposefully and rationally postpone learning activities within the software (i.e., strategic delay; Klingsieck et al., 2012) and use traditional learning materials upfront. Therefore, our measured delay in terms of days until the examination could also be inferred with rather elaborative learning strategies, which are not maladaptive. Moreover, learning behaviour depends on motivation and volition. Future research on our proposed STMT might therefore either try to assess achievement motivation directly or also control for volitional differences.

A second limitation comes with the assessment of the expectancy-value components. As described, we investigated first-semester psychology students. Their self-efficacy beliefs as well as the perceived values of preparing for a statistic examination might not be as realistic and mature as supposed. On the other hand, it should be noted that the learning software was presented to the students after some initial weeks of getting familiar with the respective subject. However, using this initial assessment of students' expectancy and value beliefs, we approach the causal chain by assessing the predictors first. Also, we want to highlight that due to the study design, the assessment of the self-reports happened on the first day the students used the software and was thus not taking place at the same time for all students. Although we did not find significant associations of the assessment date and our self-report scales, we observed that the reported self-control of the participants was reduced the later they used the learning software for the first time.

CONCLUSION

Taken together, the present study found empiric support for the predictive validity of the prominent Temporal Motivation Theory (TMT; Steel, 2007; Steel & König, 2006) on achievement-motivated learning behaviour. With the usage of learning data from an e-learning system we extend the literature by providing objective data. Our results highlight the strong importance of situative aspects of achievement motivation, and more specifically the crucial role of temporal landmarks (Capelle et al., 2022). Despite the general effectiveness of intelligent tutoring systems (Mousavinasab et al., 2021), our research once again underlines the dependency of such tools on self-regulatory capacities and the need to develop design features supporting learners' self-regulation.

To better understand differences in achievement motivation and their impact on self-regulation, we strongly recommend considering the current theoretical developments regarding the inclusion of situative measures of achievement motivation to the TMT framework (Dietrich et al., 2022; Moeller et al., 2022), thereby expanding the theory to match the current advances in achievement motivation theory. This way, our proposed situated TMT (STMT) can be embedded in current research on situated expectancy-value theory (Eccles & Wigfield, 2020, 2023).

AUTHOR CONTRIBUTIONS

Marc Philipp Janson: Conceptualization; formal analysis; methodology; writing – original draft; writing – review and editing. **Theresa Schnettler:** Conceptualization; writing – review and editing; writing – original draft. **Lisa Bäulke:** Conceptualization; writing – review and editing.

ACKNOWLEDGEMENTS

The authors thank the editor and the reviewers for their valuable feedback on this research. Moreover, the authors thank their student assistants Emilia Zickermann and Julia Hilpert for their support. Open Access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST STATEMENT

None.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ORCID

Marc Philipp Janson https://orcid.org/0000-0001-5371-1277
Theresa Wenker https://orcid.org/0000-0002-8764-7215
Lisa Bäulke https://orcid.org/0000-0002-7807-139X

REFERENCES

Ainslie, G. (1975). Specious reward: A behavioral theory of impulsiveness and impulse control. *Psychological Bulletin*, *82*(4), 463–496.

Ainslie G. (2010). Procrastination: The basic impulse. In C. Andreou & M. D. White (Eds.), *The thief of time: Philosophical essays on procrastination*. Oxford University Press.

Azevedo, R., Johnson, A., Chauncey, A., & Graesser, A. (2011). Use of hypermedia to assess and convey self-regulated learning. In B. J. Zimmerman & D. H. Schunk (Eds.), *Handbook of self-regulation of learning and performance* (pp. 102–121). Routledge/Taylor & Francis Group.

Baker, R., Xu, D., Park, J., Yu, R., Li, Q., Cung, B., Fischer, C., Rodriguez, F., Warschauer, M., & Smyth, P. (2020). The benefits and caveats of using clickstream data to understand student self-regulatory behaviors: Opening the black box of learning processes. *International Journal of Educational Technology in Higher Education*, *17*(1), 13. https://doi.org/10.1186/s41239-020-00187-1

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191–215. https://doi.org/10.1037/0033-295X.84.2.191

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2014). Fitting linear mixed-effects models using lme4. ArXiv. http://arxiv.org/abs/1406.5823

Bertrams, A., & Dickhäuser, O. (2009). Messung dispositioneller Selbstkontroll-Kapazität: Eine deutsche Adaptation der Kurzform der Self-Control Scale (SCS-K-D). *Diagnostica*, *55*(1), 2–10. https://doi.org/10.1026/0012-1924.55.1.2

Capelle, J. D., Grunschel, C., Bachmann, O., Knappe, M., & Fries, S. (2022). Multiple action options in the context of time: When exams approach, students study more and experience fewer motivational conflicts. *Motivation and Emotion*, *46*(1), 16–37. https://doi.org/10.1007/s11031-021-09912-3

Capelle, J. D., Senker, K., Fries, S., & Grund, A. (2023). Deadlines make you productive, but what do they do to your motivation? Trajectories in quantity and quality of motivation and study activities among university students as exams approach. *Frontiers in Psychology*, *14*, 1224533. https://doi.org/10.3389/fpsyg.2023.1224533

Cheng, S.-L., & Xie, K. (2021). Why college students procrastinate in online courses: A self-regulated learning perspective. *The Internet and Higher Education*, *50*, 100807. https://doi.org/10.1016/j.iheduc.2021.100807

Dai, H., & Li, C. (2019). How experiencing and anticipating temporal landmarks influence motivation. *Current Opinion in Psychology*, *26*, 44–48. https://doi.org/10.1016/j.copsyc.2018.04.012

Dietrich, J., Moeller, J., Guo, J., Viljaranta, J., & Kracke, B. (2019). In-the-moment profiles of expectancies, task values, and costs. *Frontiers in Psychology*, *10*, 1662. https://doi.org/10.3389/fpsyg.2019.01662

Dietrich, J., Schmiedek, F., & Moeller, J. (2022). Academic motivation and emotions are experienced in learning situations, so let's study them. Introduction to the special issue. *Learning and Instruction*, *81*, 101623. https://doi.org/10.1016/j.learninstruc.2022.101623

Dishop, C. R. (2020). A simple, dynamic extension of temporal motivation theory. *The Journal of Mathematical Sociology*, *44*(3), 147–162. https://doi.org/10.1080/0022250X.2019.1666268

Eccles, J. S., Adler, T. F., Futterman, R., Goff, S. B., Kaczala, C. M., Meece, J. L., & Midgley, C. (1983). Expectancies, values and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motivation* (pp. 75–146). W. H. Freeman.

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

Eccles, J. S., & Wigfield, A. (2023). Expectancy-value theory to situated expectancy-value theory: Reflections on the legacy of 40+ years of working together. *Motivation Science*, *9*(1), 1–12. https://doi.org/10.1037/mot0000275

Ellis, R. A., Han, F., & Pardo, A. (2017). Improving learning analytics – Combining observational and self-report data on student learning. *Journal of Educational Technology & Society*, *20*(3), 158–169.

Flake, J. K., Barron, K. E., Hulleman, C., McCoach, B. D., & Welsh, M. E. (2015). Measuring cost: The forgotten component of expectancy-value theory. *Contemporary Educational Psychology*, *41*, 232–244. https://doi.org/10.1016/j.cedpsych.2015.03.002

Fleischer, J., Leutner, D., Brand, M., Fischer, H., Lang, M., Schmiemann, P., & Sumfleth, E. (2019). Vorhersage des Studienabbruchs in naturwissenschaftlich-technischen Studiengängen. *Zeitschrift für Erziehungswissenschaft*, *22*(5), 1077–1097. https://doi.org/10.1007/s11618-019-00909-w

Förster, M., Weiser, C., & Maur, A. (2018). How feedback provided by voluntary electronic quizzes affects learning outcomes of university students in large classes. *Computers & Education*, *121*, 100–114. https://doi.org/10.1016/j.compedu.2018.02.012

Garfield, J., & Ben-Zvi, D. (2007). How students learn statistics revisited: A current review of research on teaching and learning statistics. *International Statistical Review*, *75*(3), 372–396. https://doi.org/10.1111/j.1751-5823.2007.00029.x

Heckhausen, H., & Gollwitzer, P. M. (1987). Thought contents and cognitive functioning in motivational versus volitional states of mind. *Motivation and Emotion*, *11*(2), 101–120. https://doi.org/10.1007/BF00992338

Janson, M. P., Siebert, J., & Dickhäuser, O. (2022). Compared to what? Effects of social and temporal comparison standards of feedback in an e-learning context. International journal of educational technology. *Higher Education*, *19*(1), 54. https://doi.org/10.1186/s41239-022-00358-2

Janson, M. P., Siebert, J., & Dickhäuser, O. (2023). Everything right or nothing wrong? Regulatory fit effects in an e-learning context. *Social Psychology of Education*, *26*, 107–139. https://doi.org/10.1007/s11218-022-09733-3

Jiang, Y., Rosenzweig, E. Q., & Gaspard, H. (2018). An expectancy-value-cost approach in predicting adolescent students' academic motivation and achievement. *Contemporary Educational Psychology*, *54*, 139–152. https://doi.org/10.1016/j.cedpsych.2018.06.005

Klingsieck, K. B., Fries, S., Horz, C., & Hofer, M. (2012). Procrastination in a distance university setting. *Distance Education*, *33*(3), 295–310. https://doi.org/10.1080/01587919.2012.723165

Koenka, A. C. (2020). Academic motivation theories revisited: An interactive dialog between motivation scholars on recent contributions, underexplored issues, and future directions. *Contemporary Educational Psychology*, *61*, 101831.

Kosovich, J. J., Hulleman, C. S., Barron, K. E., & Getty, S. (2015). A practical measure of student motivation: Establishing validity evidence for the expectancy-value-cost scale in middle school. *The Journal of Early Adolescence*, *35*(5–6), 790–816. https://doi.org/10.1177/0272431614556890

Lavrijsen, J., Vansteenkiste, M., Boncquet, M., & Verschueren, K. (2022). Does motivation predict changes in academic achievement beyond intelligence and personality? A multitheoretical perspective. *Journal of Educational Psychology*, *114*(4), 772–790. https://doi.org/10.1037/edu0000666

Liberman, N., & Trope, Y. (1998). The role of feasibility and desirability considerations in near and distant future decisions: A test of temporal construal theory. *Journal of Personality and Social Psychology*, *75*(1), 5–18. https://doi.org/10.1037/0022-3514.75.1.5

Madden, G. J., Petry, N. M., Badger, G. J., & Bickel, W. K. (1997). Impulsive and self-control choices in opioid-dependent patients and non-drug-using control patients: Drug and monetary rewards. *Experimental and Clinical Psychopharmacology*, *5*(3), 256–262. https://doi.org/10.1037/1064-1297.5.3.256

Moeller, J. (2015). A word on standardization in longitudinal studies: Don't. *Frontiers in Psychology*, *6*, 1389. https://doi.org/10.3389/fpsyg.2015.01389

Moeller, J., Viljaranta, J., Tolvanen, A., Kracke, B., & Dietrich, J. (2022). Introducing the DYNAMICS framework of moment-to-moment development in achievement motivation. *Learning and Instruction*, *81*, 101653. https://doi.org/10.1016/j.learninstruc.2022.101653

Mousavinasab, E., Zarifsanaiey, N., Niakan Kalhori, R., Rakhshan, M., Keikha, L., & Ghazi Saeedi, M. (2021). Intelligent tutoring systems: A systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments*, *29*(1), 142–163. https://doi.org/10.1080/10494820.2018.1558257

Murayama, K., Goetz, T., Malmberg, L.-E., Pekrun, R., Tanaka, A., & Martin, A. J. (2017). Within-person analysis in educational psychology: Importance and illustrations. In D. W. Putwain & K. Smart (Eds.), *BJEP monograph series II: Part 12 the role of competence and beliefs in teaching and learning*. British Psychological Society. https://doi.org/10.53841/bpsmono.2017.cat2023.6

Nagengast, B., Marsh, H. W., Scalas, L. F., Xu, M. K., Hau, K.-T., & Trautwein, U. (2011). Who took the "×" out of expectancy-value theory?: A psychological mystery, a substantive-methodological synergy, and a cross-national generalization. *Psychological Science*, *22*(8), 1058–1066. https://doi.org/10.1177/0956797611415540

Netzer Turgeman, R., & Pollak, Y. (2023). Using the temporal motivation theory to explain the relation between ADHD and procrastination. *Australian Psychologist*, *58*(6), 448–456. https://doi.org/10.1080/00050067.2023.2218540

Ostaszewski, P. (1996). The relation between temperament and rate of temporal discounting. *European Journal of Personality*, *10*(3), 161–172. https://doi.org/10.1002/(SICI)1099-0984(199609)10:3%3C161::AID-PER259%3E3.0.CO;2-R

Ostaszewski, P. (1997). Temperament and the discounting of delayed and probabilistic rewards: Conjoining European and American psychological traditions. *European Psychologist*, *2*(1), 35–43. https://doi.org/10.1027/1016-9040.2.1.35

Peetz, J., & Wilson, A. E. (2013). The post-birthday world: Consequences of temporal landmarks for temporal self-appraisal and motivation. *Journal of Personality and Social Psychology*, *104*(2), 249–266. https://doi.org/10.1037/a0030477

Pekrun, R., & Marsh, H. W. (2022). Research on situated motivation and emotion: Progress and open problems. *Learning and Instruction*, *81*, 101664. https://doi.org/10.1016/j.learninstruc.2022.101664

Perez, T., Dai, T., Kaplan, A., Cromley, J. G., Brooks, W. D., White, A. C., Mara, K. R., & Balsai, M. J. (2019). Interrelations among expectancies, task values, and perceived costs in undergraduate biology achievement. *Learning and Individual Differences*, *72*, 26–38. https://doi.org/10.1016/j.lindif.2019.04.001

Petry, N. M. (2001). Delay discounting of money and alcohol in actively using alcoholics, currently abstinent alcoholics, and controls. *Psychopharmacology*, *154*(3), 243–250. https://doi.org/10.1007/s002130000638

Richards, J. B., Zhang, L., Mitchell, S. H., & de Wit, H. (1999). Delay or probability discounting in a model of impulsive behavior: Effect of Alkohol. *Journal of the Experimental Analysis of Behavior*, *71*(2), 121–143. https://doi.org/10.1901/jeab.1999.71-121

Rodriguez, D., Carrasquillo, A., Garcia, E., & Howitt, D. (2022). Factors that challenge English learners and increase their dropout rates: Recommendations from the field. *International Journal of Bilingual Education and Bilingualism*, *25*(3), 878–894. https://doi.org/10.1080/13670050.2020.1722059

Roe, R. A. (2014). Time, performance and motivation. In *Time and work, Vol. 1: How time impacts individuals* (pp. 63–110). Psychology Press.

Roediger, H. L., & Karpicke, J. D. (2006a). Test-enhanced learning: Taking memory tests improves long-term retention. *Psychological Science*, *17*(3), 249–255. https://doi.org/10.1111/j.1467-9280.2006.01693.x

Roediger, H. L., & Karpicke, J. D. (2006b). The power of testing memory: Basic research and implications for educational practice. *Perspectives on Psychological Science*, *1*(3), 181–210. https://doi.org/10.1111/j.1745-6916.2006.00012.x

Rubinstein, A. (2003). "Economics and psychology"? The case of hyperbolic discounting. *International Economic Review*, *44*(4), 1207–1216. https://doi.org/10.1111/1468-2354.t01-1-00106

Schneider, M., & Preckel, F. (2017). Variables associated with achievement in higher education: A systematic review of meta-analyses. *Psychological Bulletin*, *143*(6), 565–600. https://doi.org/10.1037/bul0000098

Schnettler, T., Bobe, J., Scheunemann, A., Fries, S., & Grunschel, C. (2020). Is it still worth it? Applying expectancy-value theory to investigate the intraindividual motivational process of forming intentions to drop out from university. *Motivation and Emotion*, *44*(4), 491–507. https://doi.org/10.1007/s11031-020-09822-w

Schwerter, J., Dimpfl, T., Bleher, J., & Murayama, K. (2022). Benefits of additional online practice opportunities in higher education. *The Internet and Higher Education*, *53*, 100834. https://doi.org/10.1016/j.iheduc.2021.100834

Siaputra, I. B. (2010). Temporal motivation theory: Best theory (yet) to explain procrastination. *Anima Indonesian Psychological Journal*, *25*(3), 206–214.

Siebert, J., & Janson, M. P. (2018). CoTutor [computer software].

Sneyers, E., & De Witte, K. (2018). Interventions in higher education and their effect on student success: A meta-analysis. *Educational Review*, *70*(2), 208–228. https://doi.org/10.1080/00131911.2017.1300874

Steel, P. (2007). The nature of procrastination: A meta-analytic and theoretical review of quintessential self-regulatory failure. *Psychological Bulletin*, *133*(1), 65–94. https://doi.org/10.1037/0033-2909.133.1.65

Steel, P., & Klingsieck, K. B. (2016). Academic procrastination: Psychological antecedents revisited. *Australian Psychologist*, *51*(1), 36–46. https://doi.org/10.1111/ap.12173

Steel, P., & König, C. J. (2006). Integrating theories of motivation. *Academy of Management Review*, *31*(4), 889–913. https://doi.org/10.5465/amr.2006.22527462

Steel, P., Svartdal, F., Thundiyil, T., & Brothen, T. (2018). Examining procrastination across multiple goal stages: A longitudinal study of temporal motivation theory. *Frontiers in Psychology*, *9*, 327. https://doi.org/10.3389/fpsyg.2018.00327

Tangney, J. P., Baumeister, R. F., & Boone, A. L. (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *Journal of Personality*, *72*(2), 271–324. https://doi.org/10.1111/j.0022-3506.2004.00263.x

Trope, Y., Liberman, N., & Wakslak, C. (2007). Construal levels and psychological distance: Effects on representation, prediction, evaluation, and behavior. *Journal of Consumer Psychology*, *17*(2), 83–95. https://doi.org/10.1016/S1057-7408(07)70013-X

van der Zanden, P. J. A. C., Denessen, E., Cillessen, A. H. N., & Meijer, P. C. (2019). Patterns of success: First-year student success in multiple domains. *Studies in Higher Education*, *44*(11), 2081–2095. https://doi.org/10.1080/03075079.2018.1493097

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist*, *46*(4), 197–221. https://doi.org/10.1080/00461520.2011.611369

Wigfield, A., & Eccles, J. S. (2000). Expectancy–value theory of achievement motivation. *Contemporary Educational Psychology*, *25*(1), 68–81. https://doi.org/10.1006/ceps.1999.1015

Winters, F. I., Greene, J. A., & Costich, C. M. (2008). Self-regulation of learning within computer-based learning environments: A critical analysis. *Educational Psychology Review*, *20*(4), 429–444. https://doi.org/10.1007/s10648-008-9080-9

York, T. T., Gibson, C., & Rankin, S. (2015). Defining and measuring academic success. *Practical Assessment, Research and Evaluation*, *20*(1), 5. https://doi.org/10.7275/HZ5X-TX03

Zimmerman, B. J., & Schunk, D. H. (2011). Self-regulated learning and performance: An introduction and an overview. In D. H. Schunk & B. J. Zimmerman (Eds.), *Handbook of self-regulation of learning and performance* (pp. 1–12). Routledge.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Janson, M. P., Wenker, T., & Bäulke, L. (2024). Only a matter of time? Using logfile data to evaluate temporal motivation theory in university students' examination preparation. *British Journal of Educational Psychology*, *94*, 1192–1207. https://doi.org/10.1111/bjep.12712