Original Article

Mind the Gap!

Unmet Time Schedules Predict University Students' Negative Affect During the Examination Phase

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Abstract: The goal of this study was to investigate the dynamic interplay of affect and time investment during exam preparation using daily learning diaries. University students (N = 56) reported a simultaneous increase in negative affect as well as intended and actual time investment over the course of the survey period (30 days). Cramming of study time partially accounted for the increase in negative affect. More planning strategies were associated with lower negative and more positive affect. Unmet time schedules predicted higher negative and lower positive affect. Results further revealed compensatory feedback loops: Higher negative affect in the evening predicted higher intended time investment on the next morning, but without improvements in planning strategies. Results suggest that unmet time schedules could contribute to the increase in negative affect during exam preparation. Interventions should promote students' planning to reduce the difference between intended and actual time investment.

Keywords: negative affect, time investment, planning, learning diaries, feedback loops, multilevel analysis

Verfehlte Zeitpläne sagen negativen Affekt Studierender während der Prüfungsphase vorher

Zusammenfassung: In der vorliegenden Studie wurde das dynamische Zusammenspiel zwischen Affekt und Zeitinvestment während der Prüfungsphase untersucht. Studierende (N = 56) füllten täglich Lerntagebücher aus und berichteten eine gleichzeitige Zunahme von negativem Affekt, geplantem Zeitinvestment und tatsächlicher Lernzeit über den Erhebungszeitraum (30 Tage). Der Anstieg des negativen Affekts konnte teilweise durch den Anstieg in der Lernzeit zu Semesterende erklärt werden. Bessere Planungsstrategien waren mit geringerem negativem und höherem positivem Affekt assoziiert. Verfehlte Zeitpläne sagten einen höheren negativen und geringeren positiven Affekt voraus. Die Ergebnisse zeigten zudem kompensatorische Feedbackschleifen: Negativer Affekt am Abend sagte ein höheres geplantes Zeitinvestment am nächsten Morgen vorher, jedoch ohne Verbesserungen der Planungsstrategien. Die Ergebnisse legen nahe, dass verfehlte Zeitpläne zum Anstieg des negativen Affekts während der Prüfungsvorbereitung beitragen könnten. Interventionen sollten Planungsstrategien fördern, um Studierende darin zu unterstützen, die Differenz zwischen geplanter und echter Lernzeit zu reduzieren.

Schlüsselwörter: Negativer Affekt, Zeitinvestment, Planung, Lerntagebücher, Feedbackschleifen, Mehrebenenanalyse

Negative affect among university students is increasingly recognized as a topic of public concern. University students from all over the globe and from various fields of study report high levels of negative affect (e.g., Dyrbye et al., 2006; Shankland et al., 2019; Stallman, 2010). In a recent large-scale survey among German university students, 24% suffered from high psychological distress and 55% reported strikingly low general well-being (Lutz-Kopp et al., 2019). Daily stress events are associated with various types of negative affect, such as anxiety, worry, or inner tension (McIntyre et al., 2019). The individual's negative affective response to stressful events, in turn, contributes to the adverse effects of stress on well-being and health (Böke et al., 2019; Watson & Pennebaker, 1989). However, reasons for the high level of negative affect among university students are not fully understood.

Which factors could trigger negative affect in students? High workload is discussed as one reason for increased negative affect (Lutz-Kopp et al., 2019; Schmidt et al., 2019; Sieverding et al., 2013). However, a recent study revealed that students' actual time investment stays well below the expected workload of 40 hr a week (Liborius et al., 2019). One explanation for this discrepancy is that students cram their study time during the examination phase at the end of the semester (Theobald et al., 2018). Students, then, generalize the increased workload at the end of the semester to their experiences during the entire term (Liborius et al., 2019). Hence, cramming could, in

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part, explain students' negative affect during the examination phase.

Besides cramming, other poor self-regulated learning strategies could lead to negative affect, for example, missing one's time schedule or a lack of planning strategies (Schmitz & Wiese, 2006). In the context of this study, unmet time schedules refer to a mismatch between intended study time and actual study time. Planning strategies refer to students' plans (before learning) about how they can approach their study tasks most efficiently. However, to date, it has not been tested whether unmet time schedules or planning strategies predict students' affect during the examination phase.

The present study aims to shed light on the daily interplay of students' affect, study time, and planning strategies. First, trajectories of daily affect, intended study time, and actual time investment are described. Second, we test whether unmet time schedules or poor planning strategies predict daily affect. Third, we explore compensatory feedback loops between students' affect in the evening, and intended time investment and planning strategies on the subsequent morning. Thereby, this study provides a differentiated picture of the relationship between daily affect, time investment, and planning strategies using fine-grained, longitudinal diary data.

Literature Review

Affect and Self-Regulated Learning

Affective states can be broadly classified as positive activating (PA) and negative activating (NA) states (Tellegen et al., 1999): High PA encompasses positive, activating states (e.g., enthusiastic or active) while low PA entails negative, low activating states (e.g., bored or sleepy). By contrast, high NA is characterized by negative, activating states (e.g., tense or distressed), and low NA is associated with positive, low activating states (e.g., calm or relaxed). In fact, PA (hereafter referred to as "positive affect") and NA (hereafter referred to as "negative affect") have been shown to represent two separable factors rather than two ends of the same scale (Tellegen et al., 1999; Watson et al., 1988).

It has, however, not been tested how NA and PA develop during the examination phase where general workload is typically higher. Stressful events and high workload are mainly accompanied by high negative affect (McIntyre et al., 2019; Schallberger, 2005). Further, negative affect is strongly related to health complaints and general distress while positive affect is not (Schilling & Diehl, 2014; Watson & Pennebaker, 1989). Therefore, it is important to differentiate between positive affect and negative affect when investigating students' response to increased workload.

Self-regulated learning (SRL) is described as a process whereby learners set goals and regulate cognition, affect, and behavior to achieve self-set goals (Zimmerman, 2002). SRL can be divided into three phases (Schmitz & Wiese, 2006): a preaction phase, an action phase, and a postaction phase. In the preaction phase, before learning, learners set goals and make plans on how to approach the task. In this study, we focus on the number of hours a student intends to study on a given day as one aspect of students' goal setting. In the action phase, during learning, learners invest a certain amount of study time (learning quantity). Further, students apply learning strategies that support task execution (learning quality). In the postaction phase, after learning, learners reflect on their learning outcomes in terms of quantity and quality. In the context of this study, for instance, learners compare their intended study time and their actual study time. That is, students evaluate whether they met their time schedule and generate internal feedback. This internal feedback can, in turn, affect the subsequent preaction phase, for example, time schedules and planning on the next day. Hence, SRL can be viewed as a cyclic process.

Affect plays a central role in SRL. For instance, it has been shown that students' affect (before learning) predicted the choice of learning strategies during learning as well as learning outcomes (see Pekrun et al., 2002 for an overview). However, in this study, we focus on students' affect after learning, when students evaluate their learning progress. It has been suggested that affect arises from an internal feedback loop that monitors current progress toward a self-set standard (Carver, 2015). For instance, students compare their intended study time (standard) with their actual study time. This internal feedback process is assumed to evoke positive affect if the standard has been met (or exceeded), and negative affect if the standard has not been met. Hence, affect can be viewed as an integral part in SRL.

Negative Affect as a Result of Poor SRL Strategies

High workload is discussed as one source of study-related negative affect. However, the relationship between actual time investment and affect is usually small or nonexistent (Sieverding et al., 2013). For instance, Sieverding et al. (2013) asked students about their average time investment per week over the whole semester. Actual time investment contributed only marginally to the explanation of study-related negative affect. Similarly, a diary study revealed that students' average time investment stays well below the expected workload of 40 hr a week (Liborius et al., 2019). Therefore, it has been suggested that cramming of study time could contribute to the increase in negative affect during the examination phase at the end of the semester. In this view, cramming of study time is closely related to the concept of procrastination. Procrastination refers to a voluntary delay of intended actions despite being worse off for the delay (Klingsieck, 2013; Steel, 2007), which is associated with goal failure (e.g., Wäschle et al., 2014) and negative affect (e.g., Steel et al., 2001). Indeed, it has been found that time investment typically increased at the end of the semester because students oftentimes failed to distribute their study time (Goda et al., 2015; Theobald et al., 2018). This cramming of study time could lead to a temporary increase in negative affect at the end of the semester.

H1: Cramming, that is, an increase in time investment over the course of the survey period, predicts more negative affect.

Besides actual time investment, intended time investment could play a role in students' affect. Before learning, students typically make a time schedule, for example, they plan how much time they intend to study on a given day. In the evening, students compare intended and actual study time investment and evaluate whether they met their time schedule. A discrepancy between intended and actual study time is assumed to trigger an affective response (Carver, 2015). In other words, if students fell short of their self-set standard (i.e., their intended time investment), negative affect should arise. For instance, students who intend to study for a (unrealistically) high amount of time might be more likely to miss their time schedule. However, to date, it has not been tested whether (not) meeting one's time schedule predicts students' affect. On the basis of the model by Carver (2015), we expect that:

H2: Unmet time schedules (mismatch between intended and actual study time) predict higher negative affect.

Furthermore, poor planning strategies could contribute to negative affect. Planning constitutes a metacognitive strategy that refers to having a specific plan according to which students approach their study-related tasks (Pintrich et al., 1991). Planning strategies are assumed to help learners focus on the study task even in light of distractions (Gollwitzer & Oettingen, 2011). By contrast, students with poor planning strategies might spend their time in front of the desk without attaining their goal, which could trigger negative affect. In support of this claim, diary studies showed that students who indicated more planning strategies in the morning were more satisfied in the evening (Liborius et al., 2019) and reported lower negative affect (Schmitz & Wiese, 2006). Hence, students' planning strategies (in the morning) could contribute to student' affect in the evening:

H3: More planning strategies predict lower negative affect.

Feedback Loops Between Affect and Subsequent Intended Study Time and Planning

Process models claim that study sessions are interrelated through internal feedback loops (Schmitz & Wiese, 2006). That is, students continually generate internal feedback about their current progress (relative to their self-set standard) and use this internal feedback to adapt their studying in the next study session. Affect is assumed to have a signaling function in this process (Carver, 2015). Affect signals a discrepancy between the self-set standard and the current learning progress. Students should then try to reduce this discrepancy in the next study session. That is, students' affect signals the need to adapt study behavior.

How could this feedback loop be applied to the current study? Before learning, students set an internal standard. In this study, this standard refers to the number of hours a student intends to study on a given day. After learning, students compare this standard with their actual time investment and evaluate whether they have met their time schedule. A discrepancy between intended and actual study time is assumed to trigger an affective response (see H2). This affective response should encourage a compensatory mechanism; for instance, negative affect signals, for example, that actual study time was lower than intended study time. To reduce this discrepancy, students should increase their effort in the next study session to compensate for their previous failure. That is, students could increase intended time investment or could make more plans on the next day to catch up with what they had missed today. Put differently, negative affect (or lower positive affect) could encourage students to adapt their intended study time or planning strategies on the next day. Hence, we expect that:

H4: Negative affect (and lower positive affect) predicts higher intended time investment (H4.1) and more planning strategies (H4.2) on the subsequent morning.

Of note, according to the control-value theory of achievement emotions (Pekrun, 2006; Pekrun et al., 2002), negative affect could also impede subsequent self-regulated learning. Negative affect tends to foster superficial, rigid learning strategies and the reliance on external guidance. Hence, although negative affect signals that current learning progress is too low, negative affect does not necessarily lead to better self-regulation strategies. Thus, considering the control-value theory of achievement emotions, negative affect could predict fewer planning strategies on the subsequent day.

The Present Study

The current study investigated the daily, dynamic interplay of time investment, planning strategies, and affect in an ecologically valid setting during the examination phase. We focused on the last weeks of the semester as time investment usually piles up during this period. We first described trajectories of students' affect, intended time investment, and actual time investment during the examination phase. Second, unmet time schedules (discrepancy between intended and actual time investment) as well as planning strategies were considered as predictors of daily affect. Lastly, we tested feedback loops between affect and subsequent intended time investment and planning strategies. Thereby, we aimed to deepen the understanding of potential precursors of students' affect. Results can inform practitioners on the development of interventions that prevent stressful study days.

Method

Participants

A total of 62 university students were recruited at a large university campus in Germany and volunteered to participate in a study on daily learning routines. The final sample comprised 56 subjects after excluding dropouts who had cancelled participation during the first week of the study. Wilcoxon tests revealed that dropouts (n = 6) were comparable to participants who completed the study with regard to gender, age, semester, time management strategies, and overall study load reported before the beginning of the survey period (all p values > .05). Participants were on average 22 years old (M = 21.95, SD = 2.39, [18; 30]), in their fourth semester of studies (M = 3.30, SD = 1.78, [1; 8]), and came from various fields of study, for example, economics and political science (34%), teacher training (22%), natural sciences (21%), humanities and social sciences (15%), and languages (8%). Participants completed about 24 out of 30 diary entries (M = 24.00, SD = 5.89, [7; 30]).

Design and Procedure

Participants registered for the diary study online using a link to the pre-questionnaire implemented in SoSci Survey (Leiner, 2019; https://www.soscisurvey.de/). Before starting the questionnaire, students received information on the study procedure and data privacy and gave their informed consent. The survey period (running 30 days from June 18 to July 17, 2019) fell within the typical examination phase at the end of the lecture period (ending on July 13). Participants could only register for the study if they reported that they prepared for at least one written or oral exam in July or August. This was done to ensure that all participants prepared for an exam during the survey period. The day after the last learning diary had been sent out, students were asked to fill in a post-questionnaire. Students who completed at least 22 learning diaries (75 %) received 50 € for participation.

The electronic learning diary was implemented in SoSci Survey and comprised a morning questionnaire (available from 6 a.m. to 2 p.m.) and an evening questionnaire (available from 5 p.m. to 1 a.m. on the next day). Participants received daily e-mail invitations to fill in the morning and evening questionnaire, which took about 10 min to complete altogether. If students neither planned nor actually performed study-related tasks on a given day, they were asked to fill in an alternative diary in the morning and in the evening. The alternative diary contained an equivalent amount of open and closed questions asking students about their leisure time activities.

Table 1 provides an overview of the diary items that were used to test our research questions. The current project was part of a larger project. A full list of variables assessed in the learning diary can be accessed via the open science framework (https://osf.io/nzt25/). For data analyses, we focused on students' time for self-studying throughout the analyses rather than students' time for attending lectures. Time for attending lectures followed a fixed schedule. That is, as soon as a student had decided to attend a lecture, time spent attending this lecture was not self-regulated by the student. In support of this claim, time spent attending lectures was not significantly correlated with planning strategies (r = –04), nor with negative affect (r = –.01).

Measures

Planning

We used three items to assess daily planning strategies in the morning (see Table 1). The items were developed based on the German Learning Strategies Inventory

Table 1. Overview on the daily diary items in the morning and evening questionnaire

Variable	Item	
Morning questionnaire		
Study goals	Today, I am setting myself the following study goals: [open text field]	
Time schedule (self-study)	Today, I am planning to invest the following time for self-study: [number of hours]	
Time schedule (lecture time)	Today, I am planning to spent the following time attending lectures: [number of hours]	
Planning (3 items, 6-point Likert scale ranging from *disagree* to *fully agree*)	Today, I have a specific plan, according to which I will perform today's study-related tasks. Today, I thought about how I can study most effectively. Today, I know in which order I would like to approach my study-relevant tasks.	
Evening questionnaire		
Goal attainment	Today, I have achieved my goals: [percentage 0 – 100 %]	
Time investment (self-study)	Today, I spent the following amount of time for self-study: [number of hours]	
Time investment (lecture time)	Today, I spent the following time attending lectures: [number of hours]	
Affect (6-point scale)	You have just thought about your study day and what you have achieved today. How do you feel right now?	
	Negative affect (4 items)	Positive affect (4 items)
	worried – carefree calm – tense distressed – relaxed peaceful – angry	tired – awake energetic – weak excited – bored sluggish – motivated

(LIST; Wild & Schiefele, 1994) and were rephrased to refer to daily planning strategies. Multilevel reliability analyses indicated satisfactory internal consistencies within subjects over time (ω = .64) and between subjects (ω = .92).

Time Investment, Unmet Time Schedules, and Goal Attainment

Students reported their intended time investment (hours) for self-studying in the morning (intended time investment) and indicated how much time they had actually spent studying in the evening (actual time investment) (see Table 1). We computed the difference between intended and actual time investment to assess whether students met their time schedule. Positive values on that measure indicate that students' intended time investment exceeded actual time investment. Negative values imply that students' intended time investment was lower than their actual time investment. This measure, thus, assessed the discrepancy between intended and actual time investment. In addition, students rated whether they attained their goals on a scale ranging from 0 % to 100 % (see Table 1).

Affect

We used the PANAVA-KS (Schallberger, 2005) to assess positive affect and negative affect in the evening (see Table 1). High positive affect is characterized by high levels of energy or excitement, whereas low positive affect is characterized by tiredness and lethargy. By contrast, high negative affect subsumes aversive mood states, such as anger or distress, whereas low negative affect encompasses low activating states such as calmness or relaxation. The terms "positive affect" and "negative affect" suggest that the two factors represent two ends of the same scale. However, factor analytic studies repeatedly revealed that positive and negative affect represent distinctive dimensions that are internally consistent (Tellegen et al., 1999; Watson et al., 1988). That is, the affective states that are summarized as positive affect and negative affect build internally consistent higher-order factors (Tellegen et al., 1999; Watson et al., 1988) that is justified as aggregation of those affective states. In line with this, multilevel reliability analyses yielded good internal consistencies within subjects over time (negative affect: ω = .82; positive affect: ω = .72) and between subjects (negative affect: ω = .93; positive affect: ω = .91).

Table 2. Descriptive statistics and within-subject correlation analyses.

Variables	*M* (*SD*)	ICC	1	2	3	4	5	6
Planning$_m$	4.39 (.73)	.43	-					
Intended study time (self-study)$_m$	4.02 (1.55)	.42	.20**					
Actual time investment (self-study)$_e$	3.43 (1.45)	.31	.22**	.71**				
Unmet time schedule (discrepancy intended – actual study time)	.54 (.56)	.09	-.06*	.19**	-.55**			
Self-reported goal attainment$_e$ (%)	.68 (.15)	.24	.17**	.06*	.36**	-.46**		
Negative affect$_e$	3.26 (.80)	.42	-.03	.12**	.05	.07*	-.29**	
Positive affect$_e$	2.99 (0.55)	.26	.03	-.05	.03	-.08*	.21**	-.45**

Note. N = 56. *p < .05; **p < .001 (two-tailed). $_m$ Item assessed in the morning questionnaire. $_e$ Item assessed in the evening questionnaire.

Missing Data and Multilevel Analysis

The maximum number of observations that could be obtained was 56 subjects*30 days = 1,680. Of those, k = 278 (17%) were missing and on k = 268 (16%) occasions, students reported that they did not study on that day, that is, they took a day off and answered the alternative diary. Hence, we used k = 1,133 observations for data analyses.

To test our hypotheses, we conducted multilevel analyses (days on Level 1 clustered within subjects on Level 2) considering that observations that originate from one person cannot be assumed to be independent of each other (Raudenbush & Bryk, 2002). Further, to account for temporal dependency of observations from the same person that are closer in time, we included lagged effects of the respective dependent variable (e. g., negative affect on day *t-1* was included as predictor of negative affect on day *t*). All predictors were centered on their group mean, that is, the subject's mean, over the survey period. This was done to separate within-subject relationships from between-subject differences, for example, regarding average time investment over the survey period. Data analyses were performed using R (R Core Team, 2019) and Mplus (Muthén & Muthén, 2017).

Results

Descriptive Statistics and Correlation Analyses

Table 2 shows the average subject's mean level across the observation period as well as the interclass coefficients (ICC), which represent the percentage of variance that lies between subjects. ICCs ranged between 9% and 41%, meaning that within-subject variability over time was greater than between-subject variance for all diary variables. Within-subject correlation analyses revealed that a higher intended time investment and unmet time schedules were associated with more negative and less positive affect. By contrast, neither actual time investment nor planning strategies were related to students' affect.

Results further showed that actual time investment stayed constantly almost 1 hr below intended time investment over the whole survey period. This result also explains the remarkably high correlation between intended and actual time investment (see Table 2 and Figure 1). Thus, the high correlation does not imply that students perfectly adhered to their time schedule but rather that students consistently missed their time schedule by approximately 1 hr. Indeed, on the majority of days (k = 553, 49% of days), students studied fewer hours than intended. On 22% of days, students spent more time studying than intended (k = 232), and on 27% of days (k = 292) students spent exactly as much time studying as intended (difference between intended and actual study time equaled zero). Further, unmet time schedules were substantially correlated with self-reported goal attainment. Hence, students were less likely to achieve their goals on days where they failed to adhere to their time schedule. This correlation speaks against the alternative interpretation that students managed to achieve their goals in a shorter amount of time. Together, these results suggest that students frequently did not meet their time schedule and that not meeting one's time schedule was associated with lower self-reported goal attainment.

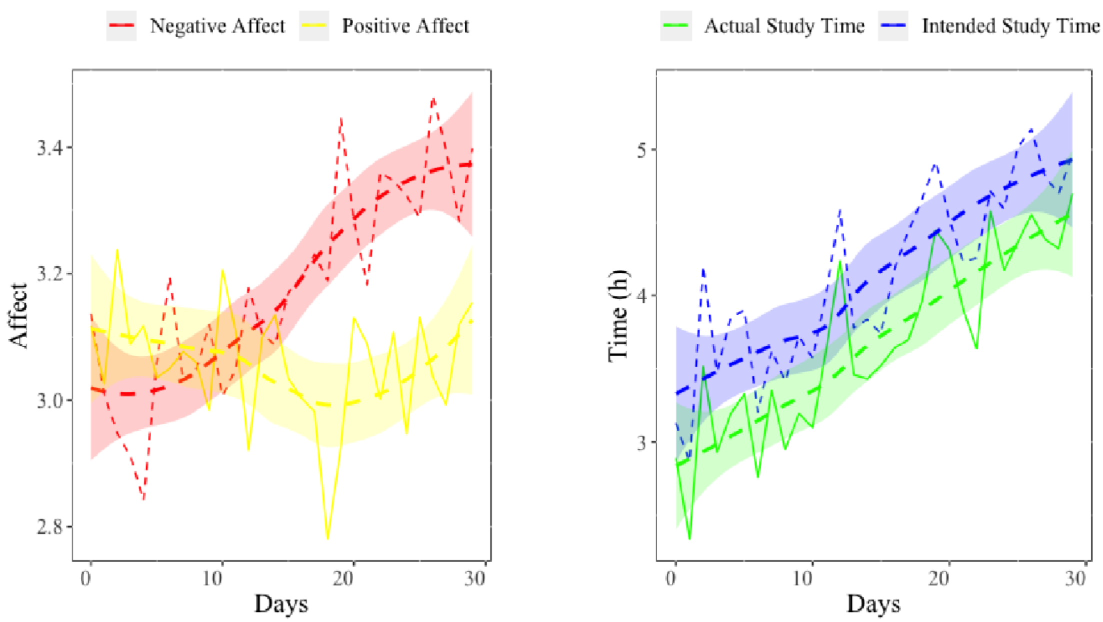

Figure 1. Development of daily positive affect (left side, yellow/light grey), negative affect (left side, red/dark grey), intended study time (right side, blue/dark grey), and actual study time (right side, green/light grey) over survey period.

Development of Daily Time Investment and Affect Over Exam Period

First, we investigated how affect, intended time investment, and actual time investment developed over the course of the survey period (see Figure 1). We found a linear increase in negative affect as the exam phase approaches (β = .12, p < .001). The model with random slope fitted the data significantly better, $\chi^2(6)$ = 10.08, p = .006, indicating that students differed in their development of negative affect over time. There was no linear trend for positive affect (β = –.03, p = .214). As expected, intended time investment (β = .26, p < .001) and actual time investment (β = .22, p < .001) increased over time. A model with random time slope fitted the data significantly better for intended time investment, $\chi^2(6)$ = 31.77, p < .001, and actual time investment, $\chi^2(6)$ = 36.17, p < .001, respectively. Hence, students differed in the trajectories of intended time investment and actual time investment over the course of the study. We further explored quadratic trends to test whether the increase in negative affect and time investment accelerated over time. We did not find quadratic trends for negative affect (β = <.01, p = .996), nor positive affect (β = .15, p = .134), nor intended time investment (β = .12, p = .149), nor actual time investment (β = .15, p = .089).

According to H1, we tested whether the increase in actual time investment over the course of the semester, that is, cramming, predicted students' affect: We tested the interaction between the time variable (days) and actual time investment as predictor of daily affect. Regarding negative affect, we found that actual time investment was associated with lower negative affect (β = –.18, p < .001). However, the interaction between the time variable and actual time investment predicted more negative affect (β = .20, p < .001). Thus, in line with H1, cramming over the course of the semester predicted an increase in negative affect over time. Regarding positive affect, we found that neither actual time investment (β = .04, p = .077) nor the interaction between the time variable and actual time investment (β = –.04, p = .187) predicted positive affect.

Taken together, results revealed a simultaneous increase in negative affect, intended time investment, and actual time investment over the course of the semester. The increase in actual time investment over the semester was associated with more negative affect. These results suggest that cramming of study time contributed to the increase in negative affect throughout the examination phase.

Predicting Daily Affect

Next, we tested unmet time schedules and planning strategies as predictors of students' affect (see Table 3).

Results revealed that more planning strategies (reported in the morning) predicted lower negative affect and more positive affect in the evening. Results further revealed that students reported more negative affect

Table 3. Unmet time schedules and planning strategies as predictors of daily affect

	Dependent variable: Negative affect			Dependent variable: Positive affect		
Predictors	Estimates	CI	p	Estimates	CI	p
(Intercept)	2.96	2.75, 3.17	< .001	3.07	2.91, 3.22	< .001
			Fixed effects			
Level 1 (within)						
Time slope (days)	.14	.08, .19	< .001	-.03	-.08, .03	.343
Autocorrelation (t-1)	.07	.02, .11	.004	-.20	-.28, -.13	< .001
Unmet time schedule	.06	.01, .11	.024	-.07	-.13, -.02	.005
Planning strategies	-.05	-.01, -.09	.041	.05	.00, .11	.042
			Random effects			
Intercept variance	.39			.12		
Time slope variance	< .01			< .01		
Residual variance	.76			.73		
R^2	.45			.23		

Note. N = 56 (k = 1,023 observations). Regression weights are standardized. R^2 describes the proportion of intraindividual residual variance explained by the fixed and random factors.

(and less positive affect) if they deviated from their time schedule. In other words, the more students fell short of their initially intended study time, the higher the negative affect and the lower the positive affect.

To illustrate this association between unmet time schedules and affect, we divided the dataset into two separate sets: occasions where students intended to study less than they actually studied (see Figure 2 A) and occasions where students intended to study more than they actually studied (see Figure 2 B). Failing to meet one's time schedule in either direction predicted more negative and less positive affect. If students studied more hours than they initially intended (Figure 2 column A), students reported more negative affect ($\beta = -.14$ $p = .043$) and less positive affect ($\beta = .16$, $p = .016$). If students studied fewer hours than they initially intended (Figure 2 column B) students reported more negative affect ($\beta = .07$, $p = .010$) and less positive affect ($\beta = -.12$, $p < .001$). Together, these results suggest that a larger gap between intended and actual study time (in either direction) predicted higher negative affect and lower positive affect.

Predicting Intended Study Time and Planning Strategies

Next, we tested whether students' affect predicted the next day's intended study time and planning strategies. We conducted separate analyses for negative and positive affect because of the high intercorrelation among the two variables (see Table 2).

Negative and positive affect predicted the next day's intended study time (see Table 4, left column). In other words, on days when students reported more negative and less positive affect (compared with their own average), they increased the intended study time on the next day. Self-reported goal attainment did not predict changes in intended time investment. Together with the finding that high intended time investment was associated with more negative affect, results point to an adverse feedback loop between intended time investment and negative affect.

Regarding planning strategies, we found that neither positive nor negative affect predicted planning strategies on the subsequent day (see Table 4, right column). However, if students reported lower goal attainment (compared with their own average), they reported using more planning strategies on the subsequent morning. This result suggests that students adapt their planning strategies after they fail to achieve their goal.

Discussion

The present study provided novel insights into the trajectories of negative affect, goal setting, and time investment during the examination phase. University students completed daily learning diaries in the morning and in the evening over the course of 30 days, which allowed us to examine the dynamic interplay of self-regulated learning and affect in an ecologically valid

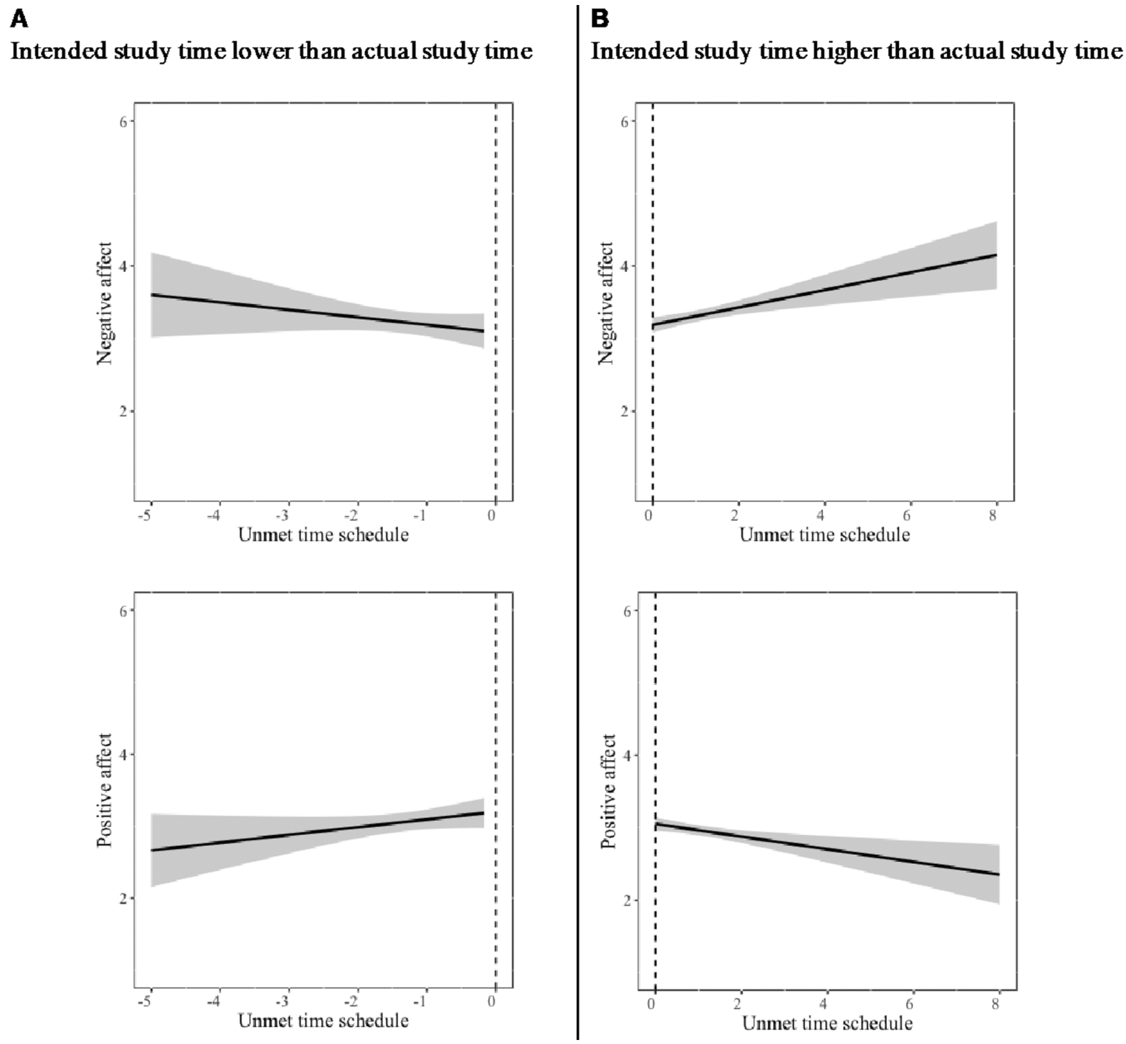

Figure 2. Unmet time schedules predict students' affect. The larger the discrepancy between intended and actual study time the higher students' negative affect and the lower students' positive affect. Students reported higher negative affects and lower positive affect if intended study time e was lower than actual study time (*k* = 232 occasions; A) and if intendes study time e exceeded actual study time (k = 553 occasions; B).

setting. The daily assessment offered the opportunity to explore within-subject processes using a rich, longitudinal dataset. In the following, we discuss our findings in the light of previous research and potential limitations before deriving practical conclusions.

Several researchers have challenged the link between actual time investment and increased negative affect (Liborius et al., 2019; Schmidt et al., 2019; Sieverding et al., 2013). This study adds to the literature by showing that a higher actual time investment even predicted lower negative affect, perhaps because a higher time investment was also related to a higher self-reported goal attainment. However, results further showed that cramming of study time at the end of the semester was associated with higher negative affect. Cramming of study time at the end of the semester might indicate that students procrastinated during the semester. Hence, findings support previous research that linked procrastination to higher negative affect (e.g., Steel et al., 2001). Taken together, the increase in study time at the end of the semester could, in part, account for the increase in negative affect over time.

Notably, positive affect followed a different trajectory over the survey period. Positive affect was not related to intended or actual time investment. Further, we did not find that cramming at the end of the semester predicted (less) positive affect. One explanation is that positive affect is determined by other factors than workload. For instance, it has been shown that motivational beliefs, that is, control and value beliefs, contribute to everyday positive affect (Goetz et al., 2010). It has further been shown that stressful events and high workload are mainly accompanied by high negative affect rather than positive affect (McIntyre et al., 2019; Schallberger, 2005). Together, these results suggest that cramming of study time is

Table 4. Predictors of daily planning strategies and intended time investment

	Dependent variable					
	Intended time investment			Planning strategies		
Predictors	Estimates	CI	*p*	Estimates	CI	*p*
			Model for negative affect			
(Intercept)	3.36	2.91, 3.80	< .001	4.35	4.14 – 4.55	< .001
			Fixed effects			
Level 1 (within)						
Time slope (days)	.23	.17, .28	<.001	.10	.04, .14	.001
Autocorrelation (*t-1*)	.08	.02, .13	<.001	.06	.01, .12	.016
Negative affect (*t-1*)	.07	.01, .12	.020	.04	-.02, .09	.194
Goal attainment (%) (*t-1*)	<.01	-.05, .06	.825	-.09	-.14, -.03	.001
			Random effects			
Intercept variance	2.10			.43		
Residual variance	2.56			.57		
R^2	.49			.45		
			Model for positive affect			
(Intercept)	3.30	2.87, 3.74	< .001	4.34	4.14, 4.54	< .001
			Fixed effects			
Level 1 (within)						
Time slope (days)	.23	.17, .28	< .001	.10	.04, .15	< .001
Autocorrelation (*t-1*)	.08	.02, .13	< .001	.06	.01, .12	.016
Positive affect (*t-1*)	.12	.04, .20	.003	.04	-.04, .12	.314
Goal attainment (%) (*t-1*)	< .01	-.04, .06	.759	-.09	-.14, -.04	.001
			Random effects			
Intercept variance	1.99			.44		
Residual variance	2.56			.57		
R^2	.49			.45		

Note. N = 56 (k = 829 observations) Regression weights are standardized. R^2 describes the proportion of intraindividual residual variance explained by the fixed and random factors.

associated with more negative affect rather than with less positive affect.

Besides cramming, unmet time schedules predicted more negative and less positive affect. This result suggests that negative affect originates from a gap between intended and actual study time. Notably, actual study time stayed on average almost 1 hr below intended study time in this study. That is, students tended to make ambitious time schedules that they repeatedly failed to meet, which was associated with more negative and less positive affect. At the same time, negative affect predicted even higher intended time investment on the next day. This compensatory loop could contribute to the increase in negative affect over time. Students who repeatedly fall short of their intended study time and try to compensate by making even more ambitious (probably unrealistic) time schedules run the risk of not meeting their time schedule. This can lead to a vicious circle especially in light of the finding that higher negative affect was not accompanied by more planning strategies on the subsequent day. This is in line with previous research showing that negative affect tends to foster superficial, rigid learning strategies thereby impeding self-regulated learning (Pekrun, 2006; Pekrun et al., 2002). This vicious circle between high time investment and negative affect could even be aggravated at the end of the semester because students typically cram their study time right before the examinations take place.

Taken together, results revealed several factors that could contribute to students' affect during the examination phase: cramming of study time, unmet time schedules, and poor planning strategies. Results further suggest that negative affect and less positive affect encourage a (potentially detrimental) compensatory loop: Negative affect signaled a gap between intended and actual study time (Carver, 2015). Students then upregulated their intended study time on the next day to compensate for their previous failure. Conversely, results also revealed a positive compensatory mechanism: If goal attainment was low, students increased their self-reported planning strategies on the next day. That is, students adapted their planning strategies and reported making more concrete plans after they missed their goals. Together with the finding that more planning strategies predicted less negative affect (and more positive affect), results point to a potentially efficient regulatory loop.

Study Limitations and Ideas for Further Research

The results of the present study offer several avenues for further research. First, in this study, time investment and planning strategies were assessed using self-report measures, which might be prone to memory biases (Roth et al., 2016). However, due to the standardized daily questionnaires in the morning and evening, we were able to measure situative changes in planning and time investment and minimized the risk of memory biases. Nonetheless, future studies could collect objective behavioral correlates of time investment, for example, log-file data (Theobald et al., 2018). Relatedly, students were asked to report their current negative affect when thinking about their study day and achievement. Thus, students had to remember several learning situations that happened on that day to rate their average negative affect. For this reason, we placed the negative affect measure at the end of the learning diary to offer students the possibility to refresh their memory. Moreover, it has recently been shown that an end-of-day measure of negative affect shows substantial overlap with an aggregated measure that includes several measurement points per day (Neubauer et al., 2020). Thus, an end-of-day measure seems sufficient to assess students' average negative affect on a given day. However, future studies could ask students to rate their affect several times a day and with regard to a specific learning task. This repeated assessment would allow one to explore fluctuations in negative affect over the day and to test whether students' affect varies depending on a specific learning task.

Another caveat is that learning diaries can evoke reactivity effects. Learning diaries could function as an intervention itself, for example, by increasing students' self-monitoring and self-reflection (Schmitz & Perels, 2011). However, recent studies demonstrated that learning diaries alone do not suffice to foster SRL in university students (e.g., Bellhäuser et al., 2016). Therefore, we believe that training effects are negligible.

Moreover, we cannot rule out that unmeasured third variables changed synchronously with time investment, planning strategies, and affect. Daily motivation, such as control and value appraisals, could predict students' affect (Pekrun, 2006; Pekrun et al., 2002). For instance, a previous diary study found more positive affect among students who reported that they have the learning situation under their control and who perceive a given learning activity as personally relevant (Goetz et al., 2010). Future research could, thus, examine control and value appraisals as antecedents of daily negative affect as well.

Future studies could further target discrete achievement emotions. In this study, positive and negative affect subsumed several affective states to assess students' general affect during the examination phase. However, it has been suggested that specific achievement emotions can differentially predict subsequent behavior (Carver, 2004). For instance, it has been suggested that anger constitutes an approach-related emotion while anxiety constitutes an avoidance-related emotion (Carver & Harmon-Jones, 2009). That is, students who feel angry if they failed to meet their time schedule might increase their effort to meet their schedule on the next day. By contrast, students who feel anxious after they failed to meet their time schedule may be more likely to give up. Therefore, it is important to test how achievement emotions might differentially guide subsequent learning decisions.

Further, to infer causality, well-controlled experimental studies are needed. However, laboratory studies oftentimes suffer from the artificial setting in which they are conducted. As our main goal was to investigate daily dynamics in time investment and affect, we decided to use ecologically valid measures of students' study behavior in their natural learning environment. Nonetheless, future studies should aim to infer causality by conducting experimental studies in the field.

Finally, the number of data points on Level 2 (the student level) was rather small. However, the number of data points on Level 1 (the daily level) was much higher because students answered the learning diaries multiple times over the course of 30 days. Since we analyzed within-subject effects on Level 1, post hoc power analysis revealed that, given our sample size, we were able to detect small effect sizes with 80 % power (Arend & Schäfer, 2019). However, as we focused solely on intra-individual processes, most effect sizes in this study were rather small. Thus, future studies could raise the number of participants to investigate interindividual differences or to examine potential cross-level interactions.

Practical Implication and Conclusion

The current study revealed that university students report an increase in negative affect throughout the examination phase. Considering that negative affect is related to health complaints and general distress (Schilling & Diehl, 2014; Watson & Pennebaker, 1989), results highlight the importance of developing effective interventions to reduce students' negative affect.

Results suggest that careful planning and realistic time schedules could help reduce negative affect. In line with this, intervention studies demonstrated positive effects of training programs that foster planning strategies on perceived stress (Häfner, Stock, & Oberst, 2015). Attending such a training program even prevented an increase in perceived stress towards the end of the semester in the training group compared to a control group (Häfner et al., 2014). Hence, more planning strategies can be regarded as one possibility to reduce negative affect. Since not every student knows how to self-regulate study time most efficiently, SRL training programs should be offered to students with poor time management strategies (Bellhäuser et al., 2016; Häfner et al., 2014; Häfner et al., 2015).

Adaptive learning diaries with individual feedback are especially promising since they not only facilitate daily monitoring of goal progress but also provide situative suggestions on how to improve time management. Interventions should encourage students to distribute their study time more equally over the semester. Distributed learning not only prevents heightened levels of stress due to the cramming of study time but also benefits long-term retention and enhances students' academic achievement (Theobald et al., 2018).

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Open Data
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