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Turtle, Task Ninja, or Time Waster? Who Cares? Traditional Task-Completion Strategies Are Overrated

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Abstract
Standard approaches for identifying task-completion strategies, such as precrastination and procrastination, reduce behavior to single markers that oversimplify the process of task completion. To illustrate this point, we consider three task-completion strategies and introduce a new method to identify their use. This approach was tested using an archival data set (N = 8,655) of the available electronic records of research participation at Kansas State University. The approach outperformed standard diagnostic approaches and yielded an interesting finding: Several strategies were associated with negative outcomes. Specifically, both procrastinators and precrastinators struggled to finish tasks on time. Together, these findings underscore the importance of using holistic approaches to determine the relationship among task characteristics, individual differences, and task completion.

Keywords
procrastination, precrastination, task completion, latent profile analysis, discounting, task valuation, open data, open materials

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Each day, we make decisions about how to allocate our effort toward different tasks. Our success depends not only on the amount of effort that we expend but also on when we choose to spend it. If a task is completed immediately, we are less likely to forget about it; however, this requires an early investment of effort. In contrast, delaying a task will reduce our up-front effort but may increase the likelihood that the task will not be completed. Individual differences (Gröpel & Steel, 2008) and task characteristics (e.g., difficulty, incentives; Wickens, Gutzwiller, & Santamaria, 2015) affect our willingness to start, discontinue, return to, or finish tasks. In this way, completion strategies are an important determinant of our success or failure.

Research on task completion has focused on identifying procrastination and its negative consequences (for a review, see Steel, 2007) using single behavioral metrics such as task initiation and completion (Silver & Sabini, 1981) or time on task (e.g., Ferrari & Tice, 2000).[1] Yet readers who reflect on their own experiences will recognize that procrastination is but one of several task completion strategies, procrastination does not always produce negative outcomes, and task-completion strategies cannot always be identified by a single marker.

Recently, researchers have begun to study alternative task-completion strategies, such as steady working (Gevers, Mohammed, & Baytalskaya, 2015) and precrastination (initiating a task as soon as possible; Rosenbaum, Gong, & Potts, 2014); however, procrastination is often disparaged as a maladaptive strategy, in part because it is narrowly defined by single, contextual markers that oversimplify the dynamic process of task completion. In this article, we address these limitations by advancing an identification method that treats task completion as part of an ongoing, fluid process that is defined by

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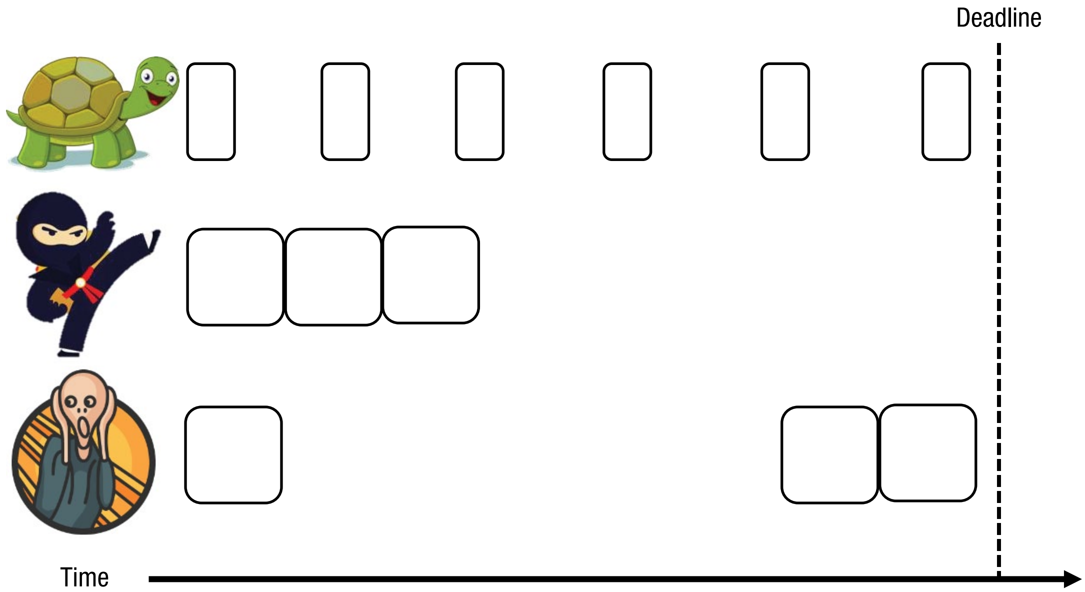

Fig. 1. Schematic illustrating how "turtles" (steady workers), "task ninjas" (precrastinators), and "time wasters" (procrastinators) engage in different patterns of task completion when working toward a deadline. Each rectangle indicates a discrete work period. These strategies are not easily identified by a single behavioral marker.

the individual. We tested and validated this method using educational data.

Patterns of Task Completion

Readers are likely familiar with task-completion strategies. You might be a turtlelike, steady worker who tends to work slowly but surely, spreading a task out over time (Gevers et al., 2015). Perhaps you are a task-ninja precrastinator who bounces e-mails and projects off your plate as quickly as you can (Rosenbaum et al., 2014). Or you might be a time-wasting procrastinator, who puts off tasks and completes most of your work leading up to a deadline (Silver & Sabini, 1981). Researchers (e.g., Steel, 2010) as well as the general public (e.g., Jaffe, 2013) treat these categories as a set of domain-general behaviors or as a lifestyle choice (i.e., "I am a procrastinator"). But what if we could belong to all three categories at once?

Consider the student who suddenly finds him- or herself washing dishes to avoid studying for an exam. Although housework provides an opportunity to procrastinate on academics, it also drives precrastination on a domestic task. If this same student decides to take a 10-min break each hour to level up his or her gaming skills, that student is steadily working toward becoming a pinball wizard. Task-completion strategies depend on how the focal task is defined.

This issue is further complicated in that these categories are not easily identified by a single marker. Consider three students who begin studying for an exam a week in advance. The first takes a turtlelike approach and spends a few minutes studying every day. The second approaches the task with ninjalike focus, studying intensely before moving on to other tasks. The third cracks the book, finds the content difficult, and decides to put off studying until the last minute. Researchers relying on task initiation or time on task would conclude that the three students chose the same task-completion strategy. Those who relied on completion alone would be unable to distinguish the steady worker from the procrastinator. When these behaviors are considered holistically, the differences in strategy become obvious (see Fig. 1); considered separately, they emphasize different aspects of task engagement: initiation, completion, and pursuit. It is a combination of these behaviors that can lead to suboptimal outcomes.

Suboptimality and Task Completion

It is well known that some task-completion strategies can lead to negative outcomes. People who engage in procrastination tend to perform poorly on focal tasks because they do not spend as much time on them as do precrastinators or steady workers (Klingsieck, 2013; Steel, 2007). Similarly, precrastinators sometimes expend more effort than is necessary to complete a task (e.g., Rosenbaum et al., 2014). These observations have given rise to two distinct interpretations of task completion.

The prescriptivist approach asserts that people recognize when their behaviors lead to negative outcomes, yet they persist in these strategies anyway. Researchers who adhere to this approach consider self-reports a required research element (e.g., Krause & Freund, 2014) and may use them as the sole hypothesis test for behavioral models (e.g., Gröpel & Steel, 2008; Steel & Klingsieck, 2016). In contrast, proponents of naturalistic decision-making suggest that irrationality arises from environmental and cognitive constraints that limit peoples' awareness of the factors that lead to decisions (Fournier, Stubblefield, Dyre, & Rosenbaum, 2019; Grund & Fries, 2018; Klein & Klinger, 1991). Under these conditions, people may unknowingly act outside of their best interests and generate post hoc explanations for their behavior that align with social expectations but do not reflect its underlying cause (Nisbett & Wilson, 1977).

Regardless of approach, it is important to note that most discussions of optimality assume that decision makers prioritize tasks that align with scientists' research interests. However, this is not always the case. For example, a student with several midterms may prioritize studying for the one that is most likely to impact his or her grade. When researchers measure study habits, the student is classified as a precrastinator or steady worker for the high-priority exam, but for the lower-priority exam, the student is a procrastinator. Researchers who instead consider the trade-offs that students face and the processes that inform their decisions will produce a richer understanding of task completion.

Discussions of these trade-offs are prevalent in the research literature. The more important, urgent, or easy a task seems, the more likely people are to begin working on it (Kurzban, Duckworth, Kable, & Myers, 2013; Steel, Svartdal, Thundiyil, & Brothen, 2018). In contrast, perfectionistic concerns and fear of failure can lead people to put off finishing tasks (Xie, Yang, & Chen, 2018). Even individuals who start and finish on time can struggle with time management because of misestimations of task difficulty or personal ability (van Eerde, 2015). It is likely that all of these processes contribute to task-completion strategies; more must be done to identify the circumstances under which they do.

An Alternative Perspective

Rather than focusing on single behavioral markers or self-reports, assessments can include multiple measures of task completion. One way to accomplish this is to collect several measures and conduct separate analyses (e.g., Hensley, 2014). This approach determines whether traits and task characteristics are predictive of single markers but cannot assess how these characteristics broadly relate to task completion.

A technique that does leverage multiple performance markers for classification is latent profile analysis (LPA), which simultaneously considers multiple measures before grouping similar individuals into a profile. LPA is comparable with correlational or cluster analytic approaches in that it evaluates subject similarity by comparing their scores on these measures. However, LPA assumes that a latent construct is responsible for these similarities: The more alike two subjects' scores, the more likely they are to share an underlying tendency that produces their behavior. LPA fits multivariate normal distributions to the data set, producing probabilistic profile/group estimates. In this case, the profiles can be used to quantify the degree to which a person's behavior resembles each form of task completion (for a more thorough discussion, see Oberski, 2016). If task completion is best defined by a constellation of behaviors that are indicative of underlying constructs, this approach should outperform other measures of task completion.

Method

Archival data set

We tested whether task-completion strategies could be better defined by multiple markers of task completion, using data from a real-world task: undergraduate students' completion of their mandatory research credits. The data were obtained from the available electronic records of research participation, which spanned from fall 2010 to spring 2018. Because of administrative error, data from the fall 2012, spring 2012, fall 2013, and fall 2014 semesters were not available; the database contained complete records from 8,655 students. Although the archival nature of these data restrict what demographic information is available, these records are reflective of most institutions' research participants (e.g., Arnett, 2008).

Behavioral measures of task completion. The database tracked research-credit completion by noting the dates on which students received credit for their research participation. We converted these dates into the number of days that had elapsed since the start of the semester, as determined by the registrar's calendar, and used these to describe the distributional characteristics of students' task completion with three measures: the first, average, and spread (*SD*) of the days on which students were awarded a research credit. These measures were used to conduct an LPA that determined the degree to which students engaged in procrastination, precrastination, and steady working.

Measures of performance. The data set contained three measures of performance: the number of appointments each student missed during the semester, a yes/no measure of whether students successfully completed their

Table 1. Demographic Information From General-Psychology Students in the Survey Subsample During Spring 2018

Characteristic	*n*	Percentage
Sex		
Male	133	41.8
Female	186	58.2
No response	0	0.0
Ethnicity		
Caucasian/White	247	77.6
Hispanic/Latino/Latina	26	8.2
African American/Black	24	7.5
Asian/Pacific Islander	10	3.1
Other	5	1.6
Native American	3	0.9
No answer	2	0.6

credit requirement through research alone (i.e., before the last week of classes), and a yes/no measure of whether students completed last-minute research-summary papers to avoid receiving a course "incomplete."

Survey subsample

Additional self-report measures were collected from a subset of students ($n = 330$) during spring 2018. Only 318 students (186 females) completed all of the measures required by the survey. These students ranged in age from 17 to 48 years and were predominantly White (see Table 1).

Self-report measures. The online survey contained six scale-based assessments that were presented in a fixed order: the Barratt Impulsivity Scale (BIS-11; Patton, Stanford, & Barratt, 1995), the Big Five Inventory-2 (BFI-2; John & Srivastava, 1999), Tuckman's procrastination scale (Tuckman, 1991), the Bidimensional Impression Management Index (Blasberg, Rogers, & Paulhus, 2014), the Positive and Negative Affect Schedule (Watson, Clark, & Tellegen, 1988), and the survey interest and diligence scale (Meade & Craig, 2012). These scales were administered as part of a separate project on careless responding; to minimize false discoveries, we restricted our analyses to three variables known to correlate with procrastination. We provide a detailed description of relevant measures here; descriptive statistics are reported in Table 2.

Conscientiousness. Conscientiousness was assessed using the Conscientiousness domain scale, a 12-item subscale that is part of the larger BFI-2. This assessment requires people to rate the degree to which they agree or disagree with items that describe behaviors that are conscientious or lack direction (e.g., "I am someone who . . . is persistent, works until the task is finished").

Table 2. Descriptive Statistics for the Self-Report Measures Completed by Students in the Survey Subsample

Scale	*M*	*SD*	95% CI	Range	α
Conscientiousness	4.7	0.9	[4.6, 4.8]	2.3–7.0	.86
Impulsivity	3.6	0.6	[3.5, 3.6]	2.0–5.3	.82
Procrastination tendencies	3.9	1.1	[3.7, 4.0]	1.1–6.4	.92

Note: CI = confidence interval.

Impulsivity. Impulsivity was assessed with the BIS-11, a widely used assessment that is well correlated with other measures of impulsivity and exhibits discriminant validity with unrelated constructs such as thrill seeking (Stanford et al., 2009). It contains 30 self-report items (e.g., "I plan trips well ahead of time").

Procrastination. Self-reported procrastination tendencies were assessed with Tuckman's procrastination scale, a 16-item measure that is well correlated with and exhibits higher internal consistency than other self-report measures of procrastination (Steel, 2010; Svartdal & Steel, 2017). This assessment requires people to reflect on and rate their tendency to engage in behaviors that are indicative of procrastination (e.g., "I am an incurable time waster") and agency (e.g., "Whenever I make a plan of action, I follow it").

Response scales and composite scores. A rating scale from 1 (*strongly disagree*) to 7 (*strongly agree*) was adopted for all measures to improve the ease with which participants could respond to a large number of items. Composite scores were calculated by averaging participants' responses after reverse-coding appropriate items. Higher scores indicated greater levels of conscientiousness, impulsivity, and self-rated procrastination tendencies, respectively.

Results

LPA: identifying task-completion strategies with behavioral measures

An LPA was conducted using the first and average days on which students were awarded research credits, as well as the spread (*SD*) of their credit distribution. Students who received credit for only one research study (archival $n = 300$; subsample $n = 6$) were excluded because their cases had a missing value (spread). Visual inspection revealed that the first-day and spread distributions were positively skewed; log and square-root transformations were applied, respectively.

We used the *mclust* package (Version 5.4.3; Fraley, Raftery, Scrucca, Murphy, & Fop, 2019) in the R programming

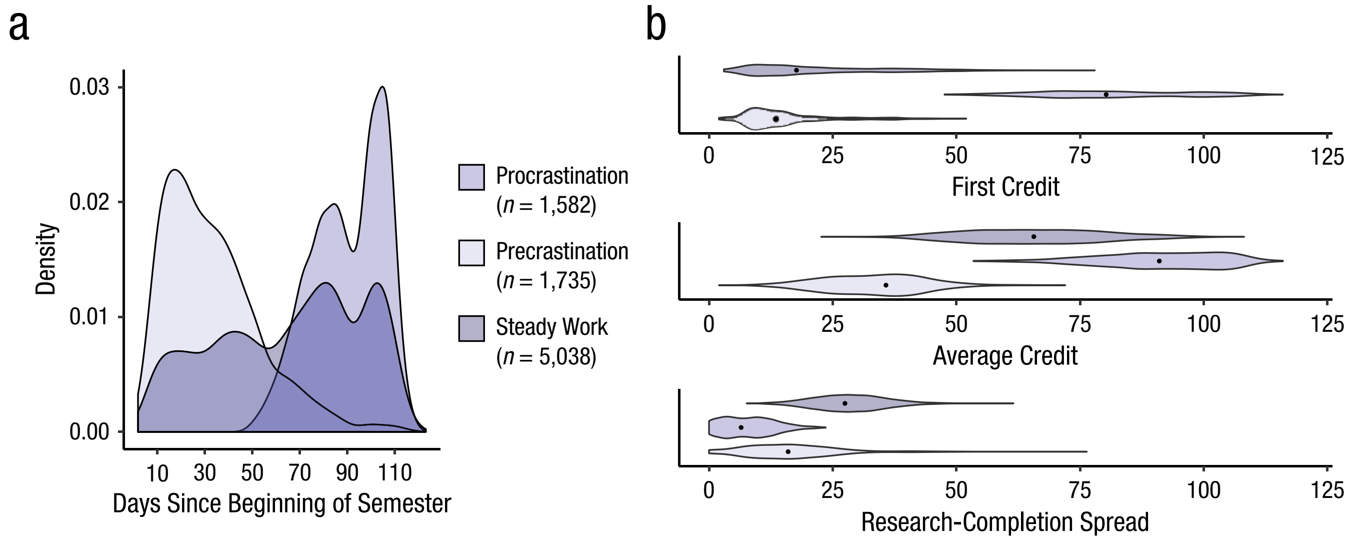

Fig. 2. Distribution of research-credit completion time (a) and violin plots of first credit day, average credit day, and research-completion spread (b) for general-psychology students in each of the three profiles. In (b), dots indicate means and the varying width of each plot shows the relative density of the data. Day of first credit and spread are back-transformed to their original scales; points represent estimated profile means. The bimodality present in the procrastination profile is caused by greater fall enrollment and the timing of the Thanksgiving break.

environment to fit one, two, three, and four varying means, variances, and covariances (VVV) profile models to the archival data set. We selected a three-profile model for its overlap with existing classes of task-completion behavior (i.e., precrastination, procrastination, and steady working). Our full analytic strategy and out-of-sample validation are disclosed on our Open Science Framework project (see https://osf.io/gmaz5/) and in the Analyses file in the Supplemental Material available online to enhance reproducibility and encourage broader adoption of this strategy.

The three-profile model cleanly overlapped with existing task-completion strategies (see Fig. 2). Members of the procrastination profile put off starting their research participation until late in the semester and had a later average credit day and smaller spread. In contrast, members of the precrastination profile started their participation early in the semester. These students tended to complete their credits in quick succession, which gave their distribution a small spread and earlier average credit day. Finally, members in the steady-work profile started their research participation early in the semester and spread their appointments out over time, as evidenced by their later average credit day and larger spread.

Predictive analyses: validating the multiple-measures approach

Because procrastination has been associated with poor task performance, this relationship can be used to validate our approach. That is, the task-completion strategies identified by LPA should hold the same associations with negative outcomes that are observed in correlational and single-measure studies. We hypothesized that members of the procrastination profile would be more likely to miss research appointments and write last-minute papers (because they were less likely to complete their research credits by the deadline). In addition, these predictive models provided an exploratory insight to the consequences of engaging in alternative task-completion strategies. The sole predictor variable in each model, profile membership, was effect coded prior to analysis so that model intercepts could be interpreted as the sample average.

Predicting missed appointments. A Poisson regression indicated that profile membership was predictive of the number of research appointments students missed. Students who were classified as precrastinators missed fewer appointments than those classified as steady workers or procrastinators (see Fig. 3). Still, this difference is quite small given that students missed fewer than one appointment on average (see Table 3).

Predicting completion prior to the research deadline. A logistic regression indicated that profile membership was predictive of whether a student would meet the course requirements through research without resorting to last-minute alternative assignments. Students who were classified as procrastinators were the least likely to complete their credits before the research system closed. By comparison, students who were classified as precrastinators or steady workers had a higher probability of finishing by this time (see Table 3 and Fig. 4).

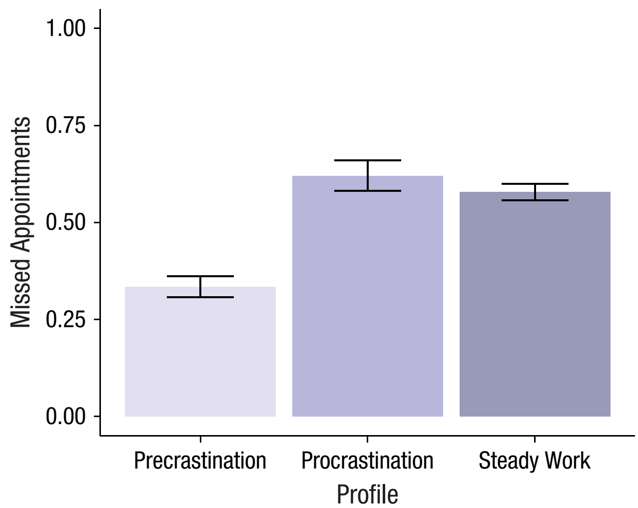

Fig. 3. Predicted number of research appointments that students in each profile missed during the semester. Error bars represent 95% confidence intervals.

Predicting last-minute papers. A second logistic regression indicated that students who were classified as procrastinators were also more likely to compensate for their delay by completing last-minute papers. Unexpectedly, precrastinators were also more likely to succumb to this negative outcome (see Table 3 and Fig. 5).

Personality measures as predictors of task-completion profile

Although our analyses indicated that task-completion strategies were predictive of performance, it is possible that this relationship was driven by underlying constructs that correlate highly with procrastination. To rule out this possibility, we used data from the survey subsample to conduct an exploratory regression of self-reported conscientiousness, impulsivity, and procrastination against profile membership in a single, multinomial regression. Conscientiousness weakly predicted profile membership, $\chi^2(2, N = 312) = 6.23$, $p = .04$; specifically, conscientiousness predicted membership in the precrastination profile compared with the procrastination profile, $b = 0.62$, $SE = 0.28$, $\chi^2(2, N = 312) = 4.76$, $p = .03$. For each 1-point increase in conscientiousness, a student was 1.87 times more likely to be in the precrastination profile (log-odds = 0.63, 95% confidence interval = [0.05, 1.21]) than in the procrastination profile. Conscientiousness did not predict membership in the steady-worker profile, $b = 0.15$, $SE = 0.25$, $\chi^2(2, N = 312) = 0.39$, $p = .53$, nor were self-reported procrastination or impulsivity predictive of profile membership, $\chi^2(2, N = 312) = 0.06$, $p = .97$, and $\chi^2(2, N = 312) = 0.08$, $p = .96$, respectively.

Model comparisons: self-report and single behavioral markers of procrastination

We also used the survey subsample to conduct planned model comparisons to determine whether self-report or single behavioral measures were better predictors of specific performance outcomes than our LPA. Akaike information criterions (Akaike, 1973) suggested that single behavioral measures may be predictive of specific outcomes: The day on which students completed their average research credit (which covaried with task completion) seemed to be a strong predictor of how many appointments students missed, whereas models

Table 3. Parameter Estimates From Regression Models in Which Profile Membership Predicted Performance Metrics

Predictor and profile	*b*	*SE*	*z*	*p*
Missed appointments				
Intercept	−0.71	0.01	−38.21	< .001
Steady workers	0.16	0.02	7.48	< .001
Precrastination	−0.39	0.03	−12.84	< .001
Completion by research deadline				
Intercept	1.64	0.03	49.35	< .001
Steady workers	0.69	0.04	15.70	< .001
Precrastination	0.08	0.05	1.53	.13
Completed last-minute papers				
Intercept	−1.74	0.03	−50.48	< .001
Steady workers	−0.60	0.04	−13.33	< .001
Precrastination	−0.13	0.05	−2.37	.02

Note: Profile membership was effect coded, with procrastination (−1, −1) serving as the baseline.

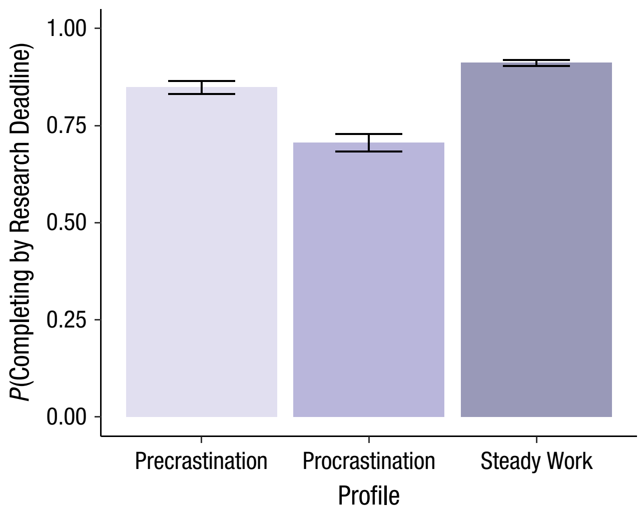

Fig. 4. Probability that students in each profile would complete their credits by the research deadline. Error bars represent 95% confidence intervals.

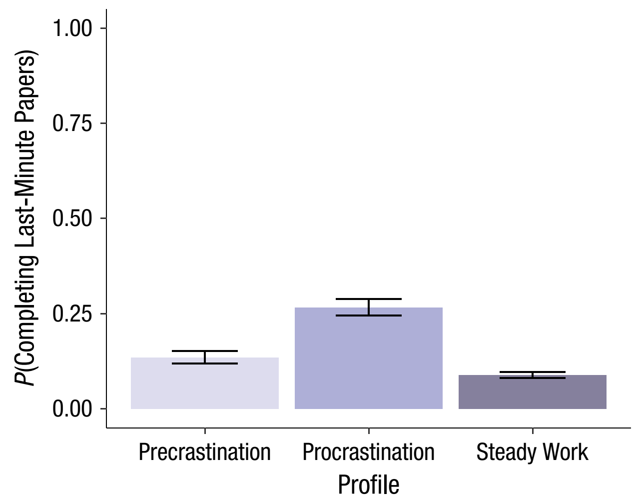

Fig. 5. Probability that students in each profile would complete last-minute papers to meet their research-credit requirement. Error bars represent 95% confidence intervals.

that included the day on which students completed their first research credit (task initiation) or the spread of students' research credits (time management) were no more likely to have produced the data than the LPA model alone (see Table 4). We unpacked the preferred models in exploratory analyses.

The first of these models indicated that task completion was a strong predictor of the number of appointments students missed: Students who on average completed their credits late in the semester missed more appointments than did those whose completed them earlier, $b = 0.04$, $SE = 0.01$, $z = 5.67$, $p < .001$ (see Fig. 6). The second model indicated that students' task initiation was predictive of the likelihood that they would complete their research credits: Students who started earlier in the semester were more likely to finish on time than those who started nearer the end, $b = -0.03$, $SE = 0.01$, $z = -4.33$, $p < .001$ (see Fig. 7). The third model indicated that students who employed poor time-management strategies (i.e., completed their research credits in quick succession) were less likely to finish their research-credit requirement on time, $b = 0.11$, $SE = 0.03$, $z = 4.16$, $p < .001$ (see Fig. 8). Together, these models illustrate the complexity of task completion and underscore the importance of considering multiple measures alongside context when identifying behaviors such as precrastination and procrastination.

Discussion

Our results demonstrate that task-completion strategies cannot always be distinguished using single measures. An LPA, which identified patterns among students' behavioral markers, successfully identified task-completion strategies that aligned with previous research. Students who engaged in procrastination were less likely to complete their credits through research and more likely to compensate with alternative assignments after the deadline had passed. Surprisingly, students who engaged in precrastination were also more likely to submit alternative assignments. A closer examination suggested why: Specific behaviors drove negative outcomes.

We found that students who engaged in procrastination experienced negative outcomes because they

Table 4. Akaike Information Criterions (AICs) for Models Including Self-Report and Single Behavioral Measures of Procrastination

Outcome and predictor	AIC
Missed appointments	
LPA profile	649.48
TPS	653.87
Task initiation	654.52
Task completion	611.29
Time management	656.29
Completion by research deadline	
LPA profile	127.74
TPS	132.18
Task initiation	128.66
Task completion	147.04
Time management	125.78

Note: Selection of an alternative model is justified by a ΔAIC of more than 3. Tuckman's procrastination scale (TPS; Tuckman, 1991) was used as the self-report measure of procrastination. LPA = latent profile analysis.

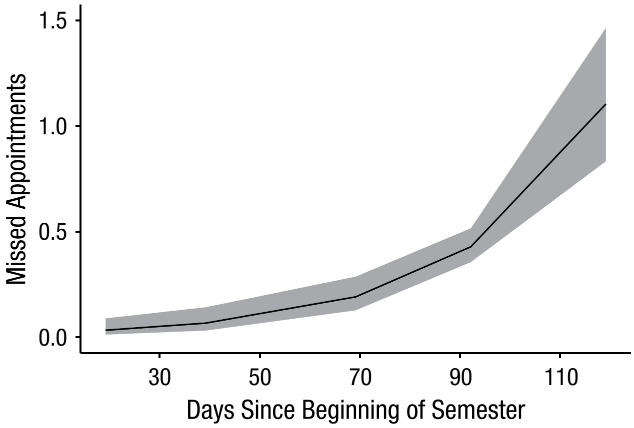

Fig. 6. Average number of research appointments that students missed as a function of the number of days since the beginning of the semester. The error ribbon represents 95% confidence intervals.

completed the majority of their research credits late in the semester and employed poor time-management strategies. When other students engaged in these behaviors, they, too, experienced negative outcomes: Precrastinators' poor time-management strategies made them less likely to finish by the research deadline. These results illustrate the complexity of task completion and underscore the importance of identifying the triggers (e.g., judgments of difficulty) and cognitive mechanisms (e.g., effort discounting) that lead to specific task-completion strategies.

Given that many universities require undergraduate students to complete research credits, we expect that our results will generalize to institutions with similar policies. Although all tasks require initiation, pursuit, and completion, we cannot be certain that our findings will generalize to other samples or tasks (e.g., employees filing client reports). To encourage work in these domains, we have provided the statistical methodology in the on our Open Science Framework project (see https://osf.io/gmaz5/) and offered several recommendations for future research.

Task completion is complex

Because people have the freedom to prioritize their work in a way that maximizes utility, they often make compromises (Simon, 1955) between the continued investment of effort and the consequences of completion (Fournier et al., 2019; Kurzban et al., 2013). Although people generally allocate resources toward tasks that provide greater reward (for a review, see Mitchell, 2017), the perceived utility of task completion can change over time as deadlines near and the consequences of failure or success become more apparent (Ainslie, 1975). Although our historical data set did not include these variables, this is a fruitful direction for future research.

Future directions in task-completion research

To apply strong theoretical approaches to the study of task completion, we recommend the following three strategies.

The first strategy is to include multiple markers. Our rationale is twofold: Multiple markers are necessary to discriminate strategies from one another and to identify the underlying causes of negative outcomes. For example, chronic procrastination is a well-defined problem; however, our results suggest that it is not procrastination itself but specific behaviors and contexts that lead

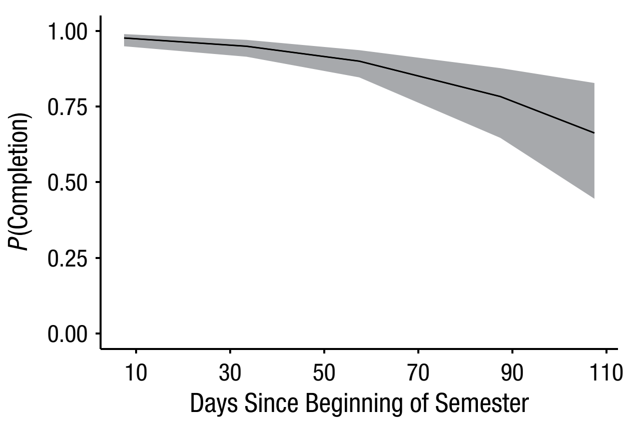

Fig. 7. Probability that students would complete their research-credit requirement as a function of the number of days since the beginning of the semester. The error ribbon represents 95% confidence intervals.

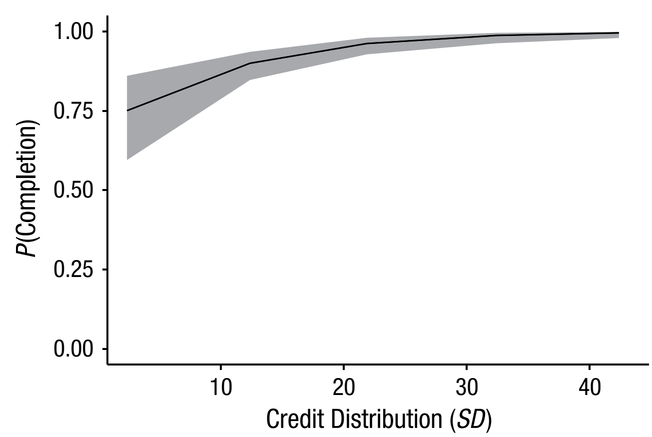

Fig. 8. Probability that students would complete their research-credit requirement by the end of the semester as a function of the spread of days on which students were awarded a research credit (i.e., credit distribution). The error ribbon represents 95% confidence intervals.

to negative outcomes. Multiple measures can be pulled from any task with a clearly defined engagement period, and practitioners with access to samples of 250 or more can employ the LPA approach with ease (Tein, Coxe, & Cham, 2013); those with smaller samples are advised to include multiple measures as predictors in their regression analyses.

The second strategy is to understand self-reports. Students may not be conscious of their task-completion strategies. Whereas it is possible that our self-report measure did not assess procrastination, it is equally likely to have captured students' self-awareness of strategy engagement. Perhaps accuracy depends on context (e.g., weekly quizzes), and procrastination is difficult to recognize when it occurs over longer periods of time. Future studies should disambiguate these hypotheses and, perhaps, discover the circumstances under which students are aware of their behaviors.

The third strategy is to identify latent constructs. We applaud early efforts to identify the factors that influence peoples' task engagement, such as discounting (e.g., Steel et al., 2018). Independently, we stress the importance of confirming such hypotheses through computer simulations and naturalistic, behavioral approaches (e.g., Klein & Klinger, 1991). Such approaches will improve the quality of the science and our understanding of individual differences.

Given that scientists are often encouraged to seek simple explanations for complex processes, it is unsurprising that their studies have gravitated toward the use of single behavioral markers. However, point estimates cannot capture the many facets of dynamic strategies. We encourage readers to use these approaches to better understand how people spend their time while engaged in task completion and to identify the positive and negative consequences of these strategies. By shifting our measures and focus, we can broaden our understanding of task completion.

Transparency

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Author Contributions
L. Vangsness developed the study concept and collected the data. The analysis plan was conceived and designed by L. Vangsness and M. E. Young, and the analyses were conducted by L. Vangsness. Both authors drafted the manuscript and approved the final version for submission.
Declaration of Conflicting Interests
The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.
Open Practices
All data for this study have been made publicly available on the Open Science Framework and can be accessed at https://osf.io/t3ek6/. The analytical approach, code, and out-of-sample validations are detailed in the R markdown document at https://osf.io/t3ek6/. The design and analysis plans for the study were not preregistered. The complete Open Practices Disclosure for this article can be found at http://journals.sagepub.com/doi/suppl/10.1177/0956797619901267. This article has received the badges for Open Data and Open Materials. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

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Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/0956797619901267

Note

1. Although these are by no means the only behavioral measures of procrastination, other metrics (e.g., area under the curve, quarter-life record, and Herfindahl-Hirschman Index) are less common. A more complete listing can be found in the Review file in the Supplemental Material available online.

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