A low-intensity, high-frequency intervention to reduce procrastination

Jason Wessel*, Graham L. Bradley* and Michelle Hood*

*School of Applied Psychology
Griffith University
176 Messines Ridge Rd, Mount Gravatt
Queensland
Australia

Jason Wessel (corresponding author), jason.wessel@griffithuni.edu.au,
ph: +61 412 811 626

Graham L. Bradley, g.bradley@griffith.edu.au

Michelle Hood, michelle.hood@griffith.edu.au

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Abstract

Studies assessing the efficacy of interventions aimed at reducing procrastination have generally lacked robust longitudinal measurement tools. Recent developments in communication technology and applications of the Experience Sampling Method (ESM) have made observations of such dynamic phenomena possible. We leveraged recent advancements in smartphone technology and ESM to measure delay associated with procrastination, while testing a low-intensity, high-frequency intervention to reducing that delay. First-year university students ($N = 107$) reported their progress on an assignment twice daily over 14 days prior to the required submission date. Half ($n = 51$) were randomly allocated to an intervention condition in which they were also asked open-ended questions designed to prompt reflection on 4 domains proposed to reduce procrastination, namely *expectancy*, *value*, *delay sensitivity*, and *metacognition*. Multilevel mixed effect models revealed lower behavioral delay in the intervention condition compared to the control condition. This effect was strongest in those who at baseline scored below the median on trait procrastination. Behavioral delay over the 14-day period was not associated with later assignment submission or lower assignment marks. These findings support a novel method for reducing delay and suggest procrastination can be alleviated in a wide range of contexts using relatively inexpensive and non-intrusive strategies.
1.0 Introduction

To procrastinate is to delay performing an intended task, despite believing delay will be harmful (Corkin et al., 2011; Howell & Watson, 2007; Nguyen et al., 2013; Steel, 2007). The range of tasks, goals, and behaviors that are prone to delay are many, and the personal and organizational impacts of procrastination can be profound. Many strategies have been proposed to reduce the prevalence and impact of procrastination (Kachgal et al., 2001; Steel, 2007). However, a limited number of studies have investigated the efficacy of these strategies (van Eerde & Klingsieck, 2018).

Research into the efficacy of procrastination interventions has been limited for many reasons, including difficulties associated with embedding interventions in ecologically valid contexts, assessing behavioral delay, and gaining the high level of commitment required of participants in intensive interventions (van Eerde & Klingsieck, 2018). We report the findings of a study that used experience sampling and a randomized control design to evaluate a low-intensity, high-frequency, and relatively brief intervention aimed at reducing student procrastination on a written assignment.

1.1 Prevalence and Consequences of Procrastination

As many as 20% of US adults identify as having problems with procrastination (Harriott & Ferrari, 1996), and 25% of US adults consider procrastination to be one of their defining traits (Nguyen et al., 2013). These percentages are particularly high in students, with a meta-analysis by Steel (2007) finding 80 to 90% of college students procrastinate, 75% self-identify as procrastinators, and 50% procrastinate consistently and problematically. Indeed, Pychyl et al. (2000) surveyed students 40 times over five days, finding that, on average, they procrastinated over a third of that time.

The impact of procrastination is considerable. Student procrastinators, for example, have been found to experience greater anxiety and receive significantly lower grades on both written assignments and exams compared to non-procrastinators (Tice & Baumeister, 1997). Among workers, procrastination is associated with lower income, shorter employment duration, and a higher likelihood of underemployment (Nguyen et al., 2013), with white-collar workers reporting higher levels of chronic procrastination than blue-collar workers (Gupta et al., 2012; Hammer & Ferrari, 2002). Several studies have also observed group-level procrastination, with the initially slow rate of productivity among business teams increasing as the remaining available work time decreases (Waller et al., 2002). Office workers may spend up to 1.5 hours per work day procrastinating, costing employers an estimated average of USD$8,875 per employee per year (D'Abate & Eddy, 2007). The economic impact of such
dilatory behaviors extends beyond the office to a range of personal finance issues as well, with procrastinators less likely to redeem gift certificates (Ferrari, 1993) and as many as 80% of Americans delaying saving so long that an adequate retirement income is unlikely (Byrne et al., 2006). Consequently, the likely economic and social benefits associated with reducing maladaptive dilatory behavior are considerable.

1.2 Measuring Procrastination

When people work on a task, rather than distributing their effort equally across the time available, they often begin slowly, and gradually increase their effort as a deadline approaches. Thus, theory (Steel & König, 2006) suggests, and research (Wessel et al., 2019) shows, that progress over time tends to follow an accelerating, or hyperbolic, curve. Notwithstanding this, research has documented individual differences in pacing style, delay behavior, and in the shape of the curve in task performance (Gevers et al., 2015; Wessel et al., 2019). Indeed, the task-focused behavior of individuals who are high in trait procrastination has been shown to display a particularly steep curve over time, indicative of either a considerably delayed start and/or a prolonged initial period of limited activity before effort and output increase (Wessel et al., 2019; see also Svartdal et al., 2020).

Until recently, there was no clearly established method for reliably observing behavioral delay associated with procrastination. To address this deficit, Wessel et al. (2019) introduced the use of Experience Sampling Method (ESM) via brief but frequent (twice daily) mobile phone surveys to measure task progress and map behavioral delay in university students. Results showed that individuals who were high in trait procrastination displayed particularly marked hyperbolic progress curves, whereas the progress of individuals low in trait procrastination tended to be distributed over time in a more linear manner. Consistent with this, the current research tested the proposition that, while progress generally follows a hyperbolic curve, departures from linearity increase with trait procrastination.

1.3 Procrastination Interventions

Few studies report attempts to reduce procrastination (Steel & Klingsieck, 2016). Extant research either assesses the effects of a single, targeted personal change intervention such as time-management training or therapeutic treatments such as CBT, or evaluates interventions embedded into naturalistic task environments. The efficacy of personal change interventions has typically been assessed not by way of reductions in actual delay behavior, but by changes in trait procrastination (van Eerde, 2003; van Eerde & Klingsieck, 2018; Rozenthal et al., 2018). The practicality and cost-effectiveness of these interventions are limited by multiple factors, such as the availability and skill of practitioners, barriers to
participant access, and time investment required of participants (Rozental et al., 2015; van Eerde & Klingsieck, 2018). Naturalistic task interventions, such as scheduled daily writing tasks and random compliance checking (Boice, 1989), are more scalable, do not need highly trained therapists, and are often able to use more objective measures of task delay to quantify efficacy. However, studies evaluating these interventions are scarce and findings have been inconsistent, with recent examples producing mixed success in reducing procrastination (Ariely & Wertenbroch, 2002; Delaval et al., 2015).

1.4 Strategies to reduce procrastination

While empirical evidence of effective procrastination interventions, particularly those measured against behavioral delay, is limited, the literature is rife with suggested strategies that could be incorporated into a comprehensive procrastination intervention. Other than interventions that seek to reduce procrastination through an externally-imposed deadline, most strategies can be categorized as targeting one of four elements linked to procrastination. The first three are summarized by Steel and König (2006) in their Temporal Motivation Theory (TMT), namely, expectancy of task success, perceived value of the task or behavior, and sensitivity to delay (see also Steel, 2007). A fourth category, comprising general metacognitive strategies, could be added as research has linked these to lower trait procrastination (Corkin et al., 2011; Howell & Watson, 2007; Steel & Klingsieck, 2016).

Expectancy-value theories of motivation are well known and widely applied in work and other contexts (e.g., Porter & Lawler, 1968; van Eerde & Thierry, 1996; Vroom, 1964). However, we know of no applied approaches targeting expectancy or value in the context of reducing procrastination. Nonetheless, Steel (2007) suggested that procrastination can be tackled by increasing expectations of the likelihood that positive outcomes will result from initiating and/or completing targeted behaviors. One way to do this is to present evidence or examples of other like-individuals who have started the behavior early and successfully completed it on time. This kind of descriptive norm or ‘social proof’ information has been shown to influence behavior in other contexts (Goldstein et al., 2008). While effects on procrastination have not previously been demonstrated, informing people of the behaviors displayed by similar and successful others may help to build expectancy and, thereby, reduce procrastination.

To increase perceived value of task progress and completion, scholars have recommended visualization techniques like mental contrasting or mental time travel (e.g., Blouin-Hudon & Pychyl, 2017, Steel & Klingsieck, 2016; Taylor & Wilson, 2016). These techniques involve the vivid imagining of future goal attainment and the associated rewards.
Participants may be encouraged to savor the feelings associated with task completion, both independently and compared to their current state or to non-attainment (Kappes et al., 2012). Procrastination has been shown to be inversely related to the ability to visualize future scenarios and the implications of current behavior (Rebetez et al., 2016). Thus, providing opportunities for visualization might make outcomes appear more proximate and desirable, and, thereby, reduce procrastination.

Delay sensitivity refers to a higher likelihood of impulse-driven behavior when a deadline is temporally distant (Steel, 2007). To decrease delay sensitivity and promote purposive use of time, a parsimonious approach involves encouraging individuals to break large complex tasks into smaller achievable steps, and, thus, build momentum through earlier achievement of milestones. This has been shown to produce quick gains (Abbasi & Alghamdi, 2015) and has been variously referred to as chunking (Ferrari, 2010), success spiraling, or island hopping (Steel, 2007). We posit that the focus on more immediate ‘quick wins’ can exploit an innate bias towards acting in one’s present interests (O’Donoghue & Rabin, 1999) and reduce fixation on the larger complex task that may otherwise be perceived as overwhelming.

In addition to these three kinds of strategies anticipated by TMT, a fourth broad category, general metacognitive strategies, has been linked to lower trait procrastination (Corkin et al., 2011; Howell & Watson, 2007; Steel & Klingsieck, 2016). Metacognitive strategies involve reflection on the thinking (e.g., planning, decision-making) behind one’s task approach or time use. One possible way to enhance this is to prompt thoughts as to specific actions that could be, but are not currently, done to facilitate on-time task completion. Promoting this type of thinking might enhance awareness not only of task progress, but also of the most efficacious way forward. If procrastinating, metacognitive reflection may lead to self-correcting behaviors (Rozental et al., 2018; van Eerde, 2000).

These strategies are often proposed to reduce procrastination; however, none is likely to be effective in all circumstances. Rather, their efficacy may vary with both task and individual factors (Claessens et al., 2010). For example, individuals who expect success relating to one task may not expect success in another, and those who place little value on the pursuit of one task may highly value another. Similarly, individual and task-related differences will exist for delay sensitivity and the depth of metacognitive reflection on delay. Leveraging a spectrum of strategies has two main advantages. First, it increases the likelihood that one of the strategies will be efficacious for the particular task and with each of the individuals requiring a reduction in procrastination. Second, it has the benefit of reducing
monotony during an intervention, particularly one that is delivered over a prolonged period of time. For these reasons, naturalistic task interventions are likely to benefit from an approach incorporating all the above strategies.

1.5 The current study

To our knowledge, no prior attempt has been made to combine these four types of strategies into a single procrastination reduction intervention. Moreover, no known study has used an in situ measure of behavioral delay to evaluate the procrastination intervention against delay curves. Following Wessel et al. (2019), we used ESM delivered by smartphone twice daily to repeatedly measure students’ progress toward goal attainment, namely, on-time submission of a course assignment. In addition to requesting goal progress reports, we delivered intervention strategy messages to reduce procrastination based on the four approaches described above. We used an equal mix of the four strategies, presented in a random order, to both maintain participant engagement and hedge against individual sensitivity to the four strategies. Given evidence as to the potential benefits of the strategies when used independently, we expected that using all four in combination would be effective in reducing procrastination. In addition, we examined whether reducing behavioral delay leading up to assignment submission was associated with earlier submission of, and/or higher grades for, the assignment.

Participants recorded their progress on an assignment twice daily over a 2-week period leading up to the submission deadline. Half were randomly assigned to receive the intervention messages; the other half functioned as a control group who did not receive these messages. We anticipated that, compared to the control group, the intervention group would display less behavioral delay.

Three hypotheses were tested:

**Hypothesis 1.** Participants’ task progress over time as the submission date approaches is best modeled by a hyperbolic function.

**Hypothesis 2.** Trait procrastination will predict behavioral delay.

**Hypothesis 3.** An intervention comprising a series of brief, twice daily prompts targeting task expectancy, value, delay sensitivity, and general metacognitive strategies will reduce behavioral delay.

2.0 Method

2.1 Participants and Procedure

First-year psychology students at a public Australian university participated in exchange for course credit. They first completed a baseline questionnaire and provided their

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(cell) mobile phone number to receive links to brief but frequent Short Message Service (SMS) texts. SMSs were sent twice daily (morning and evening) for the two weeks leading up to the submission deadline of a written assignment, which was worth 30% of the students’ final grade (total = 28 messages). Each message contained a brief questionnaire that required a SMS reply to indicate the extent of progress on the assignment. Of the initial 148 respondents (from 463 eligible students), 8 were granted extensions, 3 never submitted their assignment, and 30 responded to fewer than 30% of surveys, so were excluded. A Mann-Whitney test indicated that trait procrastination was higher for participants in receipt of an extension ($Mdn = 33$) than for the retained sample ($Mdn = 24$), $U = 248$, $p = .047$. No other differences between groups (e.g., in Grade Point Average, GPA) were identified. Of the remaining 107 participants (aged between 17.7 and 55.9 years; $M = 23.54$, $SD = 8.42$), 69% were female. They responded to an average of 81.24% ($SD = 19.4\%$) of ESM surveys.

Participants were randomly assigned to the intervention ($n = 52$) or control ($n = 55$) condition.

### 2.2 Materials

**Baseline survey.** Trait procrastination was measured through the 6-item Passive Procrastination Scale (PPS; Chu & Choi, 2005), which measures maladaptive procrastination on a response scale from $1 = \text{not at all true}$ to $7 = \text{very true}$. Chu and Choi (2005) reported coefficient alpha internal reliability as .82 and alpha from the current sample was .88. Items include “I tend to leave things until the last minute.” Following reversal of the single negatively-keyed item, responses were summed, with higher scores indicating higher trait procrastination. In support of scale validity, past research (e.g., Wessel et al., 2019) has shown that scores on the PPS predicted behavioral delay as expected. Participants provided demographic details including gender, age, GPA, hours of paid work, number of courses taken, and carer responsibilities.

**ESM.** Twice daily for 14 days, all participants received via their smartphone a question “As of right now, what proportion of your assignment have you completed (0% - 100%)?” Data were collected as to the number of these ESM messages answered by each participant.

**Intervention condition.** Intervention participants received one of four open-ended prompts or questions at the end of each ESM survey. Each prompt was designed to elicit reflection on one of the four strategies to reduce procrastination. The prompt participants received varied randomly between consecutive ESM surveys to minimize participant boredom and consequent inattentiveness. The four prompts were:

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1. Expectancy: “Our analyses suggest that students who do best in this course start early and submit their Lab Report the day before it’s due. To demonstrate you have read the above statement, in the following box please repeat what students who perform the best do:”;
2. Value: “I want you to imagine yourself the day before this assignment is due, and you haven’t started working on it. How do you feel?”;
3. Delay sensitivity: “Research has found breaking larger tasks (like completing an assignment) into smaller tasks (like brainstorming 3 dot-points) can help with motivation. What is your next small step?”, and
4. General metacognition: “If you could do one thing to ensure you finish the Lab Report on time, what would it be?”

All intervention condition participants received each prompt on approximately seven occasions (28 SMS messages / 4 different prompts = 7 times per prompt).

**Assignment performance.** At the end of the semester, assignment submission date (including time of day) and assignment mark were collected from university records for the 107 participants as well as for other students who were enrolled in the course but did not participate in this study (non-participants; n = 315). Collecting these details from non-participants enabled identification of any effect on assignment completion associated with participation in the study. There were no statistically significant differences in submission date or assignment mark between study participants and the remainder of the course cohort.

**3.0 Results**

The major dependent variable, average modeled delay, was formed by averaging the reported percentage assignment completed values for each participant’s responses over the 28 ESM observations and subtracting the value from 100. Higher numbers indicate later assignment progress and higher behavioral delay. Missing data were handled in an unconditional multilevel mixed model (described below) by Restricted Maximum Likelihood (REML; Heck et al., 2010). As behavioral trajectory data were used to derive a within-person average for correlational purposes, average modeled delay contained no missing data.

Table 1 reports descriptive statistics and correlations. Trait procrastination was positively correlated with average modeled delay. Both trait procrastination and average modeled delay were correlated with assignment submission date but not assignment mark. Proportion of ESM non-responses was correlated with study load, but correlations with key variables were non-significant or trivial. There was no association between intervention condition and trait procrastination, indicating that random assignment was effective.

|TABLE 1 ABOUT HERE|

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Testing of H1 required assessment of linear and quadratic progress towards assignment completion over the 14 days of observation. To achieve this, completion trajectories were identified through single-level unconditional and multi-level covariate linear and growth curve mixed models. The unconditional model (model 1) tested the rate of progress on the assignment (as indicated by reports of the percentage completed at each of the 28 time points). The model included two time variables: Time (the linear effect) and $Time^2$ (the quadratic or hyperbolic effect). Put simply, we expected a significant quadratic effect, or departure from linearity. Coefficients represented units of percentage increase in assignment completion either at the start of the two weeks (intercept), additional change over 1 day (slope), or additional change over 1 day$^2$ (quadratic; see online supplemental materials for more details). Model results for Hypotheses 1 to 3 are displayed in Table 2.

The unconditional model trajectory supported clear linear growth ($t_{10} = 4.00, p < .001$) from a starting value of 27.74% assignment completed ($\beta_0$; at Time 1, 14 days prior to the assignment due date), and, in support of H1, significant positive quadratic growth ($t_{20} = 3.50, p < .01$). Participant mean completion percentage and modelled completion trajectory are depicted in Figure 1.

Wald Z tests were used to identify significant between-person differences in linear (Wald $Z = 6.49, p < .001$) and quadratic growth (Wald $Z = 6.50, p < .001$). Results indicate variance in growth trajectories was not satisfactorily explained by the unconditional model.

To assess the degree to which trait procrastination (H2) and the intervention (H3) explained between-person variance in assignment completion trajectory over the two-week period, separate growth curve mixed models were run including either trait procrastination (model 2) or intervention condition (model 3) as covariates at Level 2 (Heck, Thomas, & Tabata, 2010). Model fit and parsimony were assessed by the Akaike Information Criteria (AIC), where smaller values indicate a closer and/or more parsimonious fit between the model and data. Results are summarized in Table 2.

Model 2 tests revealed a significant interaction between trait procrastination and both linear ($t_{11}^{PPS} = -3.37, p < .01$) and quadratic ($t_{21}^{PPS} = 3.03, p < .01$) growth curves, supporting H2 and the veracity of the PPS as a strong predictor of behavioral delay, and, conversely, behavioral delay providing a robust indication of trait procrastination. Furthermore, inclusion of trait procrastination as a covariate improved model fit ($\Delta$AIC = -30.10). The interaction between time and trait procrastination is illustrated in Figure 2, where participant modeled
and actual completion trajectories by PPS quartiles show clear increases in delay with higher trait procrastination.

[FIGURE 2 ABOUT HERE]

Inclusion of intervention condition as a covariate in model 3 resulted in significant linear ($t_{11}^{\text{Intervention}} = 3.05, p < .01$) and quadratic ($t_{21}^{\text{Intervention}} = -2.51, p = .01$) trajectories. However, in contrast to trait procrastination with negative linear and positive quadratic growth, students allocated to the intervention condition displayed positive linear and negative quadratic trajectories. In support of H3, this indicates a trajectory of significantly less behavioral delay (i.e., earlier assignment progress) among participants in the intervention condition compared to the control condition. Alternatively stated, the average modelled delay reported by those in the intervention condition ($M = 41.4, SD = 26.6$) was lower than that in the control condition ($M = 49.1, SD = 26.8$; Cohen’s $d = .29$). The significant intervention effect is depicted in Figure 3.

[FIGURE 3 ABOUT HERE]

Given this evidence as to the effectiveness of the intervention, on a post hoc basis participants were split into either high or low trait procrastination groups based on the median score, and multilevel mixed models were run on each group with participation in the intervention as a covariate. Results showed that, consistent with the trends evident in the whole sample, participants with below median procrastination scores displayed significant positive linear ($t_{11} = 2.70, p < .05$) and negative quadratic ($t_{21} = -2.75, p < .01$) growth (see Figure 4a). That is, those lowest in trait procrastination reported significantly less delay if in the intervention condition ($M = 26.9, SD = 16.2$), compared to those in the control condition ($M = 37.8, SD = 25.3$; Cohen’s $d = .51$). However, there were no significant differences between experimental and control conditions in linear ($t_{11} = 1.15, p > .05$) or quadratic ($t_{11} = -0.41, p > .05$) assignment completion trajectories among participants scoring in the higher 50% of trait procrastination (see Figure 4b; Intervention $M = 52.9, SD = 27.6$; Control $M = 59.1, SD = 24.1$; Cohen’s $d = .24$).

[FIGURE 4A ABOUT HERE]  
[FIGURE 4B ABOUT HERE]

The intervention model (model 3) was replicated in Mplus (Muthén & Muthén, 1998-2011) for post hoc power analyses using Monte Carlo simulation (Bolger & Laurenceau, 2013). Factoring in 18.76% missing data, our study was slightly under-powered to identify significant changes to the linear and quadratic trajectories in the intervention condition (power = .75 and .72, respectively, where .80 is the ideal). A further simulation using a

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sample of 130 identified sufficient power of .83 for the intervention effect on increased slope, and .81 for the intervention effect on reduced quadratic trajectory.

Introducing age, gender, GPA, hours of paid work per week, study load, and carer responsibilities as demographic control variables did not substantively change $t$ coefficients or their statistical significance in any model.

Finally, there were no significant differences in submission date ($t_{90.71} = -1.28, p = 0.21$, Control $M = -0.97, SD = 1.68$, Intervention $M = -0.63, SD = 1.04$) or assignment mark ($t_{105} = 0.46, p = .65$, Control $M = 22.22, SD = 3.61$, Intervention $M = 21.85, SD = 4.70$) between students in the control and intervention conditions. Similarly, there were no significant differences in assignment submission date or mark between the two groups when analyses were restricted to just the high, or just the low, procrastination participants.

4.0 Discussion

Despite problematic procrastination affecting as much as 20% of the general population (Harriott & Ferrari, 1996) and 50% of students (Steel, 2007), there are relatively few robust and empirically supported intervention strategies to reduce it (Steel, 2007). This study introduces a novel approach to reducing procrastination that involved leveraging the accessibility of smartphones to deliver brief but frequent prompts. The intervention used a combination of regular progress reporting and targeted open-ended questions designed to prompt reflection on task expectancy and value, to mitigate sensitivity to delay, and to promote relevant metacognition. Results indicate that the operationalization of these constructs was successful in reducing behavioral delay in an undergraduate university sample with respect to progress in completing an assignment.

Our findings supported the first two hypotheses. As expected, student progress on the assignment followed a hyperbolic delay curve (H1), and students who scored higher in trait procrastination demonstrated a more pronounced delay curve than those who scored lower (H2). These findings add credence to the method employed to measure delay associated with procrastination, replicate findings from Wessel et al. (2019) regarding delay trajectories over time, and support the Passive Procrastination Scale as a valid measure of trait procrastination in this sample.

Our major hypothesis (H3) was also supported. In both conditions, progress was made salient by the requirement for regular progress reporting, yet reduced delay was evident in participants randomly allocated to the intervention condition. Thus, the intervention effect can be confidently attributed to receipt of the prompts to reflect in the four targeted domains, rather than to general reflection on or awareness of task progress.
Unexpectedly, we found that this intervention effect was qualified by level of trait procrastination. The intervention significantly reduced delay in participants scoring in the lower 50% on trait procrastination, but not the higher 50%. It is possible that change in those with higher levels of trait-based procrastination requires a stronger or longer-term intervention across a range of contexts (Roberts et al., 2017). Reduced behavioral delay from the intervention among those scoring lower on procrastination may indicate change in what is to them an occasional and discretionary behavior, while behavioral delay may reflect a more deeply entrenched, and, thus, less malleable, habit in individuals higher in trait procrastination. It is also possible that, for high procrastinators in the control condition, the requirement to frequently report progress had a motivating effect large enough to crowd out any intervention effect.

Though the introduction of regular reflection prompts generally reduced behavioral delay, and behavioral delay was correlated with submission date, there was no observed effect of intervention condition on either submission date or assignment mark. These findings do not invalidate the effectiveness of the intervention, but they do warrant explanation. Regarding submission date, this may not be identical to completion date: given the high-weighting of the assignment (worth 30% of participant grades), students who completed the assignment early may have intentionally delayed submission to allow final revision ‘just in case’ (Gregory & Morón-García, 2009). Although we have no data directly pertaining to this point, the observed task progress curves suggest there may have been more early completion-delayed submission students in the intervention than in the control condition. In addition, many students who submitted on time may not have felt they had completed the assignment to the best of their ability and would have ideally taken more time to feel the piece of work was fully complete. Moreover, we removed a large portion of variability around submission date by excluding participants who were granted extensions. Though removal of these cases was necessary to maintain a standardized timeline for statistical modeling, higher trait procrastination among those receiving an extension (see section 2.1) suggests behavioral delay may have been an underlying factor.

The absence of an intervention effect on assignment mark invites questioning of the value of reducing behavioral delay. Nevertheless, performance as measured by grades is only one known consequence of problematic procrastination. Reductions in behavioral delay may free up time for incidental learning and performance of other tasks, may reduce other adverse consequences such as experiences of negative affect, and may limit spill-over to other life domains while procrastinating (Pychyl et al., 2000).
4.1 Strengths and limitations

This study is particularly robust in its measurement of procrastination as both a trait and behavior by longitudinally quantifying delay. Moreover, the significant effect of the intervention and use of a randomized control design was robust to controlling for a variety of variables such as engagement (i.e., ESM reply rate) and demographic variables (including competing demands on students’ time from work, other courses, and caring responsibilities). A major strength of this intervention pertains to the reflection prompts that were used: they were brief, frequent, but not onerous. This low-intensity approach may have led to a high participant retention rate relative to past ESM interventions (Modecki & Mazza, 2017). The prompts were also quite generic, and can, thus, be adapted to a wide range of tasks and applied contexts inside and outside of education. Finally, the intervention is highly scalable, and, compared to more intensive and personalized treatments, has the potential to be delivered in cost-effective ways that meet the demands of a problem as prevalent as procrastination.

We relied on subjective reports of progress, which introduces the potential for social desirability confounds and measurement error. This may be overcome by studying progress on objectively quantifiable assignments such as with students working on an online project where the amount of work can be accurately tracked over time. In many programming projects, for example, the number functioning features or completed events can be automatically recognized (Kazerouni et al., 2017). Modern learning management systems and educational technology tools with the capacity for tracking not just task completion, but incremental progress, may also enable a more objective measurement of progress.

As control participants reported their assignment progress as frequently as those in the intervention condition, it is possible that progress reporting alone increased all participants’ motivation, and, therefore, would not have accurately reflected their completion trajectory had they not participated in the study. This is both a research limitation and a strength: by ensuring that progress reporting was both frequent and consistent across conditions, we potentially under-estimated the true effect size of the intervention, but were able to attribute the intervention effect unambiguously to the reflection prompts.

Finally, expectancy, value, and delay sensitivity as articulated by Steel and König (2006) have received limited research attention or support in the procrastination literature beyond this targeted intervention. We acknowledge that our use of reflection prompts that targeted only these domains, plus metacognition, overlooked other possible barriers to timely task completion.

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4.2 Recommendations for future research

The prompts and questions in the present study were designed to promote reflection on behaviors associated with academic assignment writing. Future research may explore whether this low-intensity, high-frequency, reflective approach can be effectively applied to a range of different activities on which people are prone to procrastinate. For example, progress toward professional development goals may be more consistent if workers are regularly prompted to visualize future benefits of achieving those goals, health-related behavior change such as smoking cessation, weight loss, or other advice following a medical appointment may be more consistent if patients are regularly prompted to define their next small and achievable actions, and regular contributions to their retirement account may be more likely if workers are regularly exposed to and compelled to describe the early behaviors of those who are financially comfortable upon retirement. Research seeking to clarify the effect that regular progress reporting has on behavioral delay may seek to experimentally manipulate ESM survey frequency without the use of reflection prompts to further understand the “dose effect” required to change delay. Future research may use the different prompts separately to isolate their independent/unique effects and may conduct post-intervention trait measurements of procrastination to detect possible trait-level change.

Future research should seek to enhance the effectiveness of the current intervention, particularly when applied to individuals who are high in trait procrastination. This could involve use of reflection prompts targeting other known covariates of procrastination such as perfectionism. Other strategies could be borrowed from therapies such as CBT, where participants may be asked to challenge common dysfunctional thoughts around procrastination, identify environmental cues to action, or nominate their problem behaviors and propose solutions. As procrastination is a cross-cultural phenomenon (Ferrari et al., 2007), we invite researchers from non-English speaking countries to replicate these findings, and, when doing so, recommend a minimum sample of 130 participants to insure a sufficiently powered study.

4.3 Conclusion

Studies demonstrating effective reduction in procrastination are scarce. By combining regular progress reporting with open questions to prompt reflection, this study provides evidence for a novel method of reducing behavioral delay. Put simply, compared to those in the control condition, intervention condition participants displayed less delay (i.e., earlier assignment progress). The approach is likely to suit replication in a variety of non-academic
domains where individuals frequently delay taking action (e.g., saving for retirement, or engaging in healthier behaviors).
References


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Table 1

Descriptive Statistics and Correlations (N = 107)

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<th>11.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Gender</td>
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<tr>
<td>2. Age (years)</td>
<td>23.54</td>
<td>8.42</td>
<td>-.07</td>
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<tr>
<td>3. Grade Point Average</td>
<td>4.91</td>
<td>1.71</td>
<td>-.13</td>
<td>-.27</td>
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<tr>
<td>4. Study Load (no. courses)</td>
<td>3.66</td>
<td>0.60</td>
<td>.03</td>
<td>-.45</td>
<td>.12</td>
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<tr>
<td>5. Paid Work (hours per week)</td>
<td>2.50</td>
<td>0.81</td>
<td>-.09</td>
<td>.23</td>
<td>-.03</td>
<td>.08</td>
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<td>6. Dependents</td>
<td>.18</td>
<td>0.38</td>
<td>.15</td>
<td>.28</td>
<td>-.20</td>
<td>-.23</td>
<td>.05</td>
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<td>7. Trait procrastination</td>
<td>23.18</td>
<td>6.70</td>
<td>-.23</td>
<td>-.21</td>
<td>.03</td>
<td>.17</td>
<td>-.08</td>
<td>-.12</td>
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<td>8. Intervention condition</td>
<td>0.49</td>
<td>0.50</td>
<td>-.12</td>
<td>.06</td>
<td>-.11</td>
<td>.12</td>
<td>-.01</td>
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<td>9. Average modeled delay</td>
<td>45.52</td>
<td>27.63</td>
<td>-.06</td>
<td>-.14</td>
<td>.13</td>
<td>.14</td>
<td>-.04</td>
<td>-.10</td>
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<td>-.14</td>
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<td>10. ESM response rate</td>
<td>22.75</td>
<td>5.42</td>
<td>.03</td>
<td>.20</td>
<td>-.21</td>
<td>.21</td>
<td>.10</td>
<td>-.12</td>
<td>.08</td>
<td>-.02</td>
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<td>11. Submission date</td>
<td>-0.80</td>
<td>1.40</td>
<td>-.09</td>
<td>-.19</td>
<td>-.03</td>
<td>.08</td>
<td>-.06</td>
<td>-.10</td>
<td>.43</td>
<td>.12</td>
<td>.39</td>
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<td>12. Assignment mark (%)</td>
<td>73.46</td>
<td>13.87</td>
<td>-.25</td>
<td>-.10</td>
<td>.27</td>
<td>.09</td>
<td>-.05</td>
<td>-.17</td>
<td>-.03</td>
<td>-.05</td>
<td>.02</td>
<td>.11</td>
<td>.05</td>
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</tbody>
</table>

Note. Gender is coded as 0 = Male, 1 = Female. Dependents is coded as 0 = no dependents, 1 = > 0 dependents. Submission date was coded as the proportion of a day around the due time that the assignment was submitted, with 0 as the due time, and 1 equating to one day post deadline (lower numbers indicate an earlier submission time). Intervention condition is coded as 0 = Control, 1 = Intervention.
Correlations > .189 significant at \( p < .05 \) (two-tailed); correlations between .25 and .28 significant at \( p < .01 \); correlations > .28 significant at \( p < .001 \). Significant correlations are highlighted in bold. (Correlations entered as .19, but not highlighted in bold, were rounded up from a value between .185 and .188).
Table 2
Multilevel Mixture Model Fit (AIC) and Growth Curve Standardized Estimates (N = 107)

<table>
<thead>
<tr>
<th>Covariate model</th>
<th>AIC</th>
<th>Δ</th>
<th>$t_{00}$</th>
<th>$t_{10}$</th>
<th>$t_{20}$</th>
<th>$t_{11}$</th>
<th>$t_{21}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Unconditional</td>
<td>19,173.19</td>
<td>-</td>
<td>9.18***</td>
<td>4.00***</td>
<td>3.50**</td>
<td>-</td>
<td>-</td>
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<tr>
<td>2. Procrastination (PPS)</td>
<td>19,143.09</td>
<td>-30.10</td>
<td>9.64***</td>
<td>4.07***</td>
<td>3.75***</td>
<td>-3.37**</td>
<td>3.03**</td>
</tr>
<tr>
<td>3. Intervention</td>
<td>19,159.06</td>
<td>-14.13</td>
<td>8.93***</td>
<td>4.35***</td>
<td>3.47**</td>
<td>3.05**</td>
<td>-2.51*</td>
</tr>
</tbody>
</table>

* $p < .05$. ** $p < .01$. *** $p < .001$. All statistical tests were two-tailed.

Note. I = Intervention; Δ denotes AIC change from the baseline unconditional model; $t_{00}$ = standardized intercept estimate; $t_{10}$ = standardized slope estimate; $t_{20}$ = standardized quadratic estimate; $t_{11}$ = standardized covariate by slope interaction estimate; $t_{21}$ = standardized covariate by quadratic interaction estimate. Unstandardized coefficients are provided in Supplemental material.
Procrastination quartiles

Days of observation

Assignment completed (%)
Intervention and Control group trajectories

Days of observation

Assignment completed (%)
Intervention and Control group trajectories

- Intervention modeled
- Intervention means
- Control modeled
- Control means

Assignment completed (%) vs Days of observation

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