Will they or won't they make it in time? The role of contextual and behavioral predictors in reaching deadlines of mandatory assignments

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Abstract

Procrastination and other forms of irrational delay are widespread among university students, leading to an array of potential negative consequences. While the reasons for this type of behavior are manifold and many facilitating factors have been identified, which of these factors are able to predict dilatory behavior in online/distance education has received comparatively little attention in the literature so far. In this study, we intended to compare the performance of two sets of objective predictors of delay, namely contextual variables based on characteristics of the assignment, and behavioral variables based on log data. Using historical data drawn from our university's learning management system, we calculated Bayesian multilevel models. The strongest and most consistent predictors of dilatory behavior turned out to be interval between the first click on the assignment and its deadline, the interval between the start of a block and the first click on the assignment, the number of clicks on the assignment, and the deadline type. The combination of both sets of predictors slightly improved the model's performance.

CCS Concepts

• **Performance**; • **Modeling methodologies**; • **E-learning**;

Keywords

procrastination, dilatory behavior, deadlines, predictive models, log data

ACM Reference Format:
Christof Imhof, Martin Hlosta, and Per Bergamin. 2025. Will they or won't they make it in time? The role of contextual and behavioral predictors in reaching deadlines of mandatory assignments. In *LAK25: The 15th International Learning Analytics and Knowledge Conference (LAK 2025), March 03–07, 2025, Dublin, Ireland*. ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3706468.3706514

LAK 2025, March 03–07, 2025, Dublin, Ireland

ACM ISBN 979-8-4007-0701-8/25/03
https://doi.org/10.1145/3706468.3706514

1 Introduction

Procrastination, defined as the irrational delay of important tasks and conceptualized as a failure of self-regulation [45], is a common occurrence, especially among students in higher education. The prevalence of procrastination among university students is reportedly as high as 70% [39], with some studies even suggesting prevalences higher than 80% [see 46], with roughly 50% of students showing this type of behavior in a way considered problematic. Academic procrastination often manifests itself in the form of delayed exam preparations, submission of term papers, administrative tasks, attending classes, or submission of assignments [34]. Not every act of delay is considered to be procrastination since the dilatory behavior needs to be voluntary and against the person's better judgment. While positive forms of delay such as purposeful delay do exist [4, 11], procrastination is mal-adaptive by definition and as such is linked to negative consequences, both for students' academic performance [20] and retention (i.e., increased likelihood of drop-outs, [7]), as well as their physical and mental well-being (i.e., increased stress, bad mood, and lower self-worth, see [10]; [37]; [42]; [49]).

1.1 Reasons for academic procrastination and facilitating factors

Research has shown that the reasons why students procrastinate on their academic work are varied, which can be linked to the complex nature of procrastination. While this behavior is stable over time, implying a trait-like nature, situational factors also play a major role, revealing a state component [see e.g. 52], with some authors suggesting that the subjective experience and actual delay could be separate constructs altogether [30]. Moreover, procrastination involves cognitive and affective dimensions as well as self-evaluations of one's competence [51]. Some studies link procrastination to personality traits such as impulsivity [45, 47], the Dark Triad (i.e., non-pathological psychopathy, narcissism, and Machiavellianism) [29], or perfectionism [40], and other personal factors such as insufficient time and effort management skills [35], low self-regulation and/or self-efficacy [52], or preferring short-term gratification over more distal rewards [31], while others identify task aversiveness as the driver of that behavior [1]. According to the latter, students avoid tasks that are perceived as boring, confusing, too difficult, stressful, or even anxiety-inducing, prompting them to either work on other tasks (which can themselves be unpleasant, such as cleaning) or seek out other distractions. In that sense, procrastinators prioritize improving their negative task-induced mood over long-term academic goals [43]. Task aversiveness is linked to fear of failure, which is a particularly commonly cited reason, meaning students procrastinate to avoid negative feelings towards a task, e.g., fearing poor objective performances or not meeting personal standards [39].

While a lot of research has investigated motivational, affective and personality factors that facilitate (or even lead to) procrastination, only few studies have focused on environmental, social, contextual, and organizational factors contributing to that behavior. [48] identify 9 such factors that are tied to academic procrastination, which they categorize into three groups: social factors, contextual factors related to skills and motivation, and contextual factors related to self-regulation.

The social factors include inefficient group work and peer influence. Group work is often ineffective due to a lack of collaborative skills, increasing the likelihood of social loafing among the group, which may cause students to prefer to work alone instead, in turn amplifying the risk of procrastination [21]. Peer influence may affect procrastination through norms (be they social or organizational) or observational learning, i.e., peers acting as role models [21, 33]. The contextual factors related to skills and motivation include task aversiveness, low focus on study skills training, and lack of efficacy-building opportunities. As [12] found in their qualitative study, students often report a lack of study skills as a reason to procrastinate, which can be traced back to them not being taught such skills [see 8]. This may render tasks more frustrating, in turn increasing task aversiveness. Similarly, learning environments and task designs that don't foster self-efficacy (e.g., by tasks being too long and unwieldy) may increase task aversiveness, which in turn amplifies the risk of procrastination [48]. This idea aligns with research that indicates that self-efficacy may indirectly be related to academic procrastination through task aversiveness, rather than directly [25].

The third set of factors relate to self-regulation, namely limited information to allow proper self-monitoring, temptations and distractions, a large degree of freedom, and long deadlines. Many study environments fail to provide students with sufficient information to allow for proper self-monitoring and the indicators that are available are of little use to them [48]. Moreover, given how vulnerable procrastinators tend to be towards distractions, environments that offer such opportunities (e.g., unrestricted Internet access) increase the students' motivation to direct their attention towards more pleasurable activities, especially when the tasks at hand are aversive. Online learning environments (e.g., in distance education) are particularly affected, since they grant students a large degree of freedom. These environments expect students to be autonomous, self-regulated, and self-directed learners able to implement effective learning strategies [5, 56]. However, this amount of freedom may overwhelm students with deficits in self-management skills [23] or metacognitive learning strategies [15]. The course structure also plays a role, with less structured courses being associated with more procrastination [33]. Lastly, procrastination is more likely to occur when rewards are only offered in the future, which is commonly the case with academic tasks. Thus, deadlines play a role, especially if they appear to be distant, reducing the sense of urgency [15]. Long deadlines may also imply that a task is particularly important or difficult, causing students to allocate more effort towards it, which can ironically increase the intention-action gap so that it takes students longer to finally start working on the task [57]. The strictness of deadlines also factors in, as strict deadlines can reduce procrastination [12] whereas lenient ones may promote it [41].

1.2 Prediction models

Trait procrastination is traditionally measured subjectively via self-assessed questionnaires. With the advent of e-learning and learning management systems (LMS), an efficient way to assess state procrastination has emerged, namely through the delayed submission of mandatory assignments (e.g. [18]; [32]). In this context, the more general term "dilatory behavior" is often used, since the act of delay can be indicative of procrastination, but it may also reflect purposeful delay or an act of delay for valid reasons (see e.g., [26]). This development allows dilatory behavior to serve both as predictor in models (e.g., to predict study success or well-being, e.g., [3]; [24]; [6]; [56]) as well as the outcome variable itself. Examples for the latter include the following: [13], who predicted whether students were going to meet the deadline of the first submission via a classification approach, [59], who predicted state procrastination via trait procrastination, and [9], who used a clustering approach to discern between types of procrastinators. Thus, while studies investigating dilatory behavior as the outcome do exist, they are still scarce. This is a research gap, since predicting if and how long students delay their assignments can be vital information. Teachers and/or adaptive learning systems could use this information to identify students at risk and provide interventions in time, e.g., through notifications, guidance, or counselling. This gap prompted us to conduct our own study [17] as well as a follow-up [16]. In both studies, we aimed to determine whether subjective measures (i.e., trait procrastination, trait purposeful delay, academic self-efficacy, and self-directed learning) or objective, log-data based variables were better able to predict dilatory behavior, measured as the temporal difference between the deadline of mandatory assignments and the submission thereof.

In the first study [17], we used Bayesian multilevel models to predict dilatory behavior with the abovementioned four subjective measures and the following three log-data based variables: the interval between the start of a learning unit (block) and the first click on the assignment, the sum of clicks on relevant learning activities in the course, and the sum of clicks on the assignment itself. The models with objective predictors had a better fit than the ones with subjective ones and explained more variance, while the models that combined all seven predictors barely improved the performance. To our surprise, we found a very small but consistent effect of the type of deadline, which was included as a covariate in addition to the department and participants' age, gender and study experience. The type of deadline was a binary predictor with deadlines either being absolute (i.e., a date and time) or relative (e.g., two weeks before the next face-to-face lesson). The absolute deadlines were associated with less delay, aligning with the findings of [12] and [41]. In the follow-up study [16], we used the exact same data set to compare the performance of multiple machine learning approaches for our predictions with the Bayesian multilevel models from the previous study serving as the baseline. For the models relying purely on objective predictors, the Bayesian multilevel models emerged as the best-performing approach.

1.3 Present study

As our previous studies have shown, subjective and objective factors are helpful for the prediction of dilatory behavior, with the latter outperforming the former. However, the role of contextual factors should not be underestimated because they can help explain that behavior, as demonstrated by the research outlined above. Our previous study [17] featured a handful of contextual factors as covariates, some of which had effects (albeit very small), such as the type of deadline. For this reason, we set out to replicate our findings and expand the models by including more contextual predictors, which in combination with a much larger sample, should result in better-performing models. Since we worked with a data set of historical data extracted from our university's LMS, there are no subjective predictors included this time. Following a data-driven approach, the goal of the present study is twofold: First off, we aim to replicate the effects of the log-data based (which we now call behavioral) predictors found in the previous study with a much larger sample and one additional behavioral predictor, namely the interval between the first click on the assignment and the deadline. Secondly, we set out to investigate the effect of contextual predictors, particularly ones related to deadlines or task aversiveness. The contextual predictors, which we derived from the literature (e.g., [3] and [6]), were the following: the type of deadline, the presence or absence of a cut-off date, the expected effort based on the workload estimated by the course designers (in hours), and the length of the assignment description. We distinguish between deadlines, due dates and cut-offs as follows: deadlines are the time a submission is supposed to be handed in, the term 'due date' is used to describe a subtype of deadlines with explicit dates, and cut-off dates refer to strictly enforced deadlines (meaning no submission afterwards are possible anymore, which would still be the case with due dates and other deadlines). The block number (indicating how late in the semester the assignments were due) and whether the courses were conducted during or before/after the COVID-19 pandemic were added as covariates.

The principal research question is thus as follows: What role do contextual factors play in comparison to behavioral variables when predicting the extent of dilatory behavior?

Based on our previous findings and the literature, we formulated the following hypotheses: We expected that a higher number of clicks on relevant activities (H1), clearer deadlines (H2), and the presence of cut-off dates (H3) are associated with less delay of assignment submissions, and that a higher number of clicks on the assignment (H4), a longer interval between the start of a block and the first click on the assignment (H5), higher expected effort (H6), and longer assignment descriptions (H7) are associated with more delay. For the interval between the first click on the assignment and the deadline, we expected an effect (H8), but since the variable could theoretically serve as both an indicator for task initiation (as does the other interval) and as a proxy for how far away the deadline appeared when the assignment description was first clicked on, we did not hypothesize a specific direction of the effect. The former interpretation would have a negative effect on delay (meaning earlier submissions) and the latter a positive effect (meaning more delay). We also hypothesized that models that include both sets of predictors outperform the models with only behavioral or contextual predictors (H9).

2 Methods

2.1 Sample

Our sample consisted of 50,090 individual assignments across 1,784 courses and 3,605 students, which is much larger than the sample from our previous studies (1,107 individual assignments across 126 courses and 134 students). There were 7,815 unique assignments. Due to the anonymized nature of the historical data, we had no demographic information regarding the students whose data was analyzed for this study. The courses were randomly selected from the university's online archive with a few limitations. In order to be eligible, courses needed to have been conducted within the last five years and had to feature at least one mandatory assignment with a deadline and at least one face-to-face lesson. The courses at our university follow a blended learning approach with course content being hosted on Moodle and several face-to-face lessons per semester (usually either five or ten) being conducted either in person or online. Courses are organized in thematic blocks, with each block generally involving one face-to-face lesson and at least one assignment. The presence of face-to-face lessons was required to calculate the beginning of each block, which do not have official dates, but generally start two weeks ahead of the respective face-to-face lesson and end two weeks thereafter.

2.2 Procedure

After gathering the sample, we calculated the predictor variables, which were split into two groups, namely behavioral (i.e., log-data-based) and contextual (i.e., task design) predictors. Three of the behavioral predictors were the same as in [17]. The *sum of clicks on relevant course activities* was calculated as the sum of all clicks on learning activities within each course that indicated engagement with the learning material (i.e., forums, assignments, resources, quizzes, glossaries, etc.), grouped by both student and course. The *number of clicks on the assignment* was calculated for each student, while we determined the *interval between the start of a block and the first click on the assignment* by subtracting the start of the block each assignment belonged to from the time the first click on the assignment was made (in days). The start of each block was defined as two weeks ahead of the respective face-to-face lesson when there were either five lessons overall (or ten, but with two occurring on the same day, as some courses have lessons in the morning and in the afternoon, counting as separate lessons in the system). In cases with fewer or more than five lessons, we instead calculated the average distance between them and used that difference as a proxy to determine the start of each block. The new behavioral predictor was the *interval between the first click on the assignment and its deadline*, indicating how long before the deadline the task was initiated (and perhaps instant indicating how distant the deadline was or at least appeared when the students first engaged with the description of the assignment), which was calculated as the difference in days between the deadline and the point in time the first click was made.

The contextual factors were derived from the literature, as outlined above. The type of deadline was determined by categorizing the various ways deadlines were defined by the course designers into several groups. Some assignments had due dates on Moodle, which lecturers can set up in the task settings. This option is used rather rarely, since in our university, course designers create a reference course with all the content, which is then copied every year and for every class and, if necessary, edited by the respective lecturer. Often, the lecturers do not change the placeholder deadlines from the reference course (which would have to be done manually), resulting in the due date option not being available for most of the assignments in our data set. For the remaining assignments, we instead used regular expressions to extract the deadlines from the task descriptions, which were then sorted into the following six categories: before/after a specific lesson (e.g., before lesson 3), before/after the next lesson (which was determined via the block each assignment belonged to), due dates in the task description (e.g., the 12th of January 2022 at 11:59pm), before/after the end of a specific (or the next) block, and until the end of a specific (or the next) block or lesson. For the analysis, these categories were further consolidated into the six following categories, ordered from the most to the least explicit type of deadline: 1) due date system, 2) due date description, 3) until the next lesson, 4) until a specific lesson, 5) a particular day before/after the next lesson, and 6) a particular day before/after a specific lesson. Categories 5) and 6) required a calculation (e.g., '3 days before the fourth lesson' or 'Monday before the next lesson'), which is why we considered those options to be the least explicit, whereas the system due date was unambiguous with a clear day and time.

Moodle not only allows due dates to be defined, but also to be enforced in the form of a cut-off date (meaning no submissions can be made anymore after the deadline has passed), which we added as a binary predictor (*enforced deadline*). It is important to note that most of the assignments had lenient deadlines and only a small subset had enforced deadlines (see Table 2). The *expected effort* was extracted from the title of the assignments as our courses require the information to be added there, meaning course designers have to estimate the workload for each task in hours. Despite this, many assignments did not feature an estimated workload, which is why we categorized the predictor rather than using the raw numbers as a predictor, which would have resulted in substantial data loss. No workload estimate being available meant 'unclear' expected effort, values above or equal to the median of 4 hours meant 'high' expected effort and value below 4 hours indicated 'low' expected effort. The final predictor was the *length of the assignment description*, simply calculated as the number of characters within the description.

The covariates were defined as follows: the *block number*, indicating how late in the semester the assignment was located, was extracted from Moodle data linking the assignments and the blocks, whether the courses were conducted during the *COVID-19 pandemic* was determined by the semester (i.e., the spring semesters of 2020 and 2021 plus the fall semester of 2020), and the *level* (i.e., whether courses were part of BSc, MSc, or advanced study programs) was extracted from the course names. Finally, the outcome variable *delay* was calculated as the difference between the deadline and the time of submission. For deadlines that did not specify the time, we assumed the assignment was due on 11:59pm the previous day. In some cases, deadlines were defined both in the assignment description and in the system, which did not necessarily align. In these cases (6,684 to be precise), we favored the deadline as indicated in the system because these had to be defined by the teacher manually, whereas the ones in the task descriptions were copied from the reference course, meaning the former was more likely to be up to date and thus reflect the intended deadline. Another choice we had to make was whether to consider the first or final submissions for the delay calculations. We decided on the former since a first submission already signifies an intention to submit, even if the assignment may not be finalized at that point.

The variables and the reasoning behind their inclusion are all summarized in Table 1.

In order to extract and wrangle the data, calculate the Bayesian multilevel models, and analyze the results, we used R [Version 4.4.1; [38]] and the following packages: 'brms' [2], 'ggpubr' [19], 'knitr' [55], 'lubridate' [44], 'moments' [22], 'performance' [28], and 'tidyverse' [53]. The main reason we chose Bayesian models was because we intended to use priors from the previous study [17], which also implemented Bayesian models, to inform our models. Moreover, the Bayesian models produced the best predictions for the objective predictors in the follow-up study [16].

3 Results

3.1 Descriptives

The average delay was 6.51 days and the median delay was -0.26 days. Positive values mean delayed submissions and negative values indicate early submissions (see Fig. 1 for a visualization of the data distribution). The distribution had a low skewness (1.17) but a high kurtosis (11.04), the result of a majority of submissions having made shortly before or after the deadline.

The mean values, standard deviations, minimum, and maximum of the continuous predictors and covariates are displayed in Table 2, along with the frequency of each category for the categorical predictors and covariates. Before being entered into the models, the continuous variables were all standardized (i.e., z-transformed) due to their vastly different scales.

3.2 Bayesian multilevel models

We chose Bayesian multilevel models to account for the hierarchical structure of our data. Each *assignment* (level 1) was nested within two grouping variables (level 2), namely *student* and *course*, as each assignment was completed by different students and there were several assignments in each course. The two level-2 factors were nested inside each other as well, but due to the complexity of our models, we chose not to account for this level of nesting and instead specified them as separate grouping factors for the random parts of our mixed models. All of our predictors were associated with the assignment except for the sum of clicks on relevant course materials and two of the covariates (level and COVID-19), which

Table 1: Variable overview

Variable	Role	Reasoning for inclusion
Sum of clicks on relevant course activities	Behavioral predictor	Replication of previous study
Number of clicks on the assignment	Behavioral predictor	Replication of previous study
Blockstart-click-interval	Behavioral predictor	Replication of previous study
Click-deadline-interval	Behavioral predictor	Indicator of task initiation (or the distance of the deadline)
Type of deadline	Contextual predictor	Indicator of the clarity of the deadline and its urgency
Enforced deadline	Contextual predictor	Indicator of the strictness of the deadline
Expected effort	Contextual predictor	Indicator of task aversiveness
Length of the assignment description	Contextual predictor	Indicator of task aversiveness
Block number	Covariate	Controlling for the influence of the course progress
COVID-19 pandemic	Covariate	Controlling for the influence of the pandemic
Level	Covariate	Controlling for the influence of the course level
Delay	Outcome variable	Variable of interest

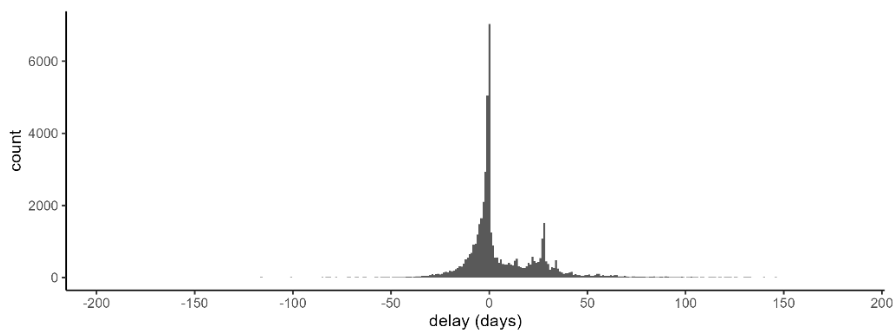

Figure 1: Distribution of delay (in days)

Table 2: Descriptives

Variable	Mean	SD	Min	Max	Variable	Category	N
Sum of clicks on relevant course activities	674.34	556.58	13	5308	Type of deadline	Due date System	1671
Number of clicks on the assignment	15.08	9.23	2	142		Due date description	4026
Blockstart-click-interval (days)	3.10	28.93	-151.24	171.13		Next lesson	12962
Click-deadline-interval (days)	16.39	33.86	-157.49	212.38		Day +- next lesson	15998
Length of the assignment description	1488.23	963.31	0	6941		Specific lesson	6350
Block number	2.86	1.66	1	10		Day +- spec lesson	9353
Delay (days)	6.51	22.93	-196.35	182.10	Enforced deadline	No	47613
						Yes	2477
					Expected effort	High	22726
						Low	15516
						Unclear	11848
					COVID-19	Pre/post	31854
						During	18236
					Level	BSc	37913
						MSc	4043
						Adv	8134

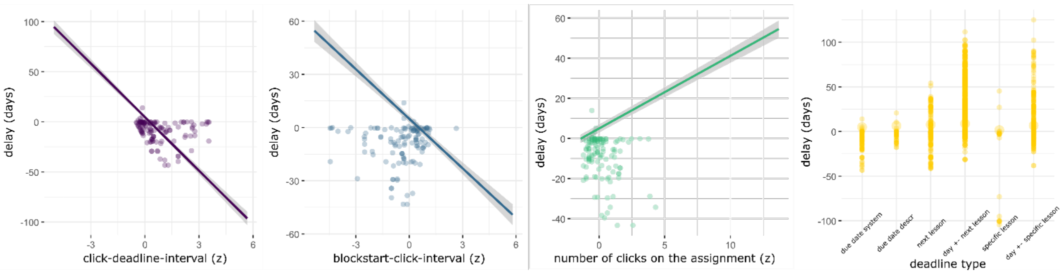

Figure 2: Effects of the four best-performing predictors

were predictors on the course level. Due to a lack of demographic data, we had no predictors on the student level.

In order to address the research questions, we calculated the following Bayesian multilevel models using brms: an intercept-only model ($model_{IO}$), two models with contextual predictors only, i.e., one with random intercepts ($model_{RI\text{-}context}$) and the other with added random slopes ($model_{RS\text{-}context}$), two models with behavioural predictors only, again with random intercepts ($model_{RI\text{-}behavior}$) and added random slopes ($model_{RS\text{-}behavior}$), and finally two models with all predictors combined, again with and random intercepts and added random slopes ($model_{RI\text{-}all}$ and $model_{RS\text{-}all}$). The three covariates were included in all of the RI and RS models. All of the models shared delay as the outcome variable with a Gaussian distribution. Although a Student-T distribution would have provided a better fit due to the high kurtosis of our distribution, we opted for a Gaussian distribution since the more complex models did not converge anymore, with some of the Rhats being above 1.6 even. We used default (i.e., weakly informative) priors for all the models. For the models with behavioral predictors, we tested versions with informative priors derived from the results of [17] since three of the four predictors were identical, however, the resulting models provided no improvement, which is why we ultimately decided against including these models. Below, we provide an R code snippet, showing how we specified the models using $model_{RS\text{-}all}$ as an example.

delay_model_RS_all <- brm(delay ~ deadline_type + expected_effort + enforced_deadline_z + length_descr_z + n_clicks_relevant_z + n_clicks_assign_z + blockstart_click_interv_z + click_deadline_interv_z + block_nr_z + covid_z + level + (1 + deadline_type + expected_effort + enforced_deadline_z + length_descr_z + n_clicks_relevant_z + n_clicks_assign_z + blockstart_click_interv_z + click_deadline_interv_z + block_nr_z|UserID) + (1 + deadline_type + expected_effort + enforced_deadline_z + length_descr_z + n_clicks_assign_z + blockstart_click_interv_z + click_deadline_interv_z + block_nr_z|CourseID), data=delay_df_complete, family='gaussian', chains=4, cores=4, iter=4000)

In the following, we first report the effects, followed by the respective effect sizes. While the effects were calculated for all the models (except for the predictor-free intercept-only model), we only report the effects of the best-fitting model, $model_{RS\text{-}all}$. In total, we found effects for four predictors (see Fig.2).

The largest effect we found was that of the interval between the first click on the assignment and its deadline across all four models that included that predictor (E_{RS-all}=-17.84, [-19.02, -16.63]). We also found three consistent predictors with weaker effects. The first one was the interval between the start of a block and the first click on the assignment (E_{RS-all}=-9.31, [-10.31, -8.30]). The second predictor in this group was the number of clicks on the assignment (E_{RS-all}=3.62, [3.35, 3.89]). The final noteworthy predictor was the type of deadline with multiple comparisons, where the category *due date system* always served as the baseline, being the most explicitly formulated category. The baseline was compared with the other categories, only some of which had effects, meaning 0 was not included in the respective credible interval. The categories with effects were *until the next lesson* (E_{RS-all}=2.85, [1.02, 4.70]), *until a specific lesson*, (E_{RS-all}=-3.36, [-5.19, -1.58]), and *a particular day before/after the next lesson* (E_{RS-all}=3.86, [2.11, 5.66]). The other two comparisons yielded no effects: *due date description* (E_{RS-all}=1.46, [-0.67, 3.60]), and *a particular day before/after a specific lesson* (E_{RS-all}=1.74, [-0.07, 3.54]).

The remaining fixed effects did not pass the threshold for small effect sizes as per Cohen's f^2 at 0.02, but we still report them due to their effect sizes being above 0 and their credible intervals not including 0. These are the sum of clicks on relevant course materials, which only had effects in the two random-intercept models that included that predictor, which is why we report the effect in $model_{RI\text{-}all}$ rather than $model_{RS\text{-}all}$ (E_{RI-all}=-1.71, [-2.09, -1.34]) and low expected effort in comparison with unclear expected effort as the baseline (E_{RS-all}=-4.04, [-5.24, -2.86]). The remaining predictors and all of the covariates had credible intervals that included 0, meaning their influence was negligible. We also found random effects in all of the RS models and for both groups. For spatial concerns, in Table 3 we only report the fixed effects and the three strongest random effects per grouping factor of $model_{RS\text{-}all}$. In that model, there was a total of 84 random effects whose credible intervals did not include 0 out of 225 possible effects (34 out of 105 on the course level and 50 out of 120 on the student level).

The effect sizes are reported for all of the models. Since the standardized regression coefficients can be distorted by a high-kurtosis distribution, we report Cohen's f^2 to represent the effect sizes, as recommended by [27]. The effect sizes were all medium for interval between the first click on the assignment and its deadline ($f^2_{\text{RI-behavior}}$=0.27, $f^2_{\text{RI-all}}$=0.24, $f^2_{\text{RS-behavior}}$=0.27, $f^2_{\text{RI-all}}$=0.24) and small for the other three effects, i.e., the interval between the start of a block and the first click on the assignment ($f^2_{\text{RI-behavior}}$=0.02, $f^2_{\text{RI-all}}$=0.02, $f^2_{\text{RS-behavior}}$=0.02, $f^2_{\text{RS-all}}$=0.02), the number of clicks on the assignment ($f^2_{\text{RI-behavior}}$=0.08,

Table 3: All fixed effects and selected random effects in model$_{\text{RS-all}}$

	Estimate (E)	Est. error	lower 95% CI	Upper 95% CI	Rhat
Fixed effects					
Intercept	4.68	1.04	2.68	6.67	1.01
deadline_type duedate_descr	1.46	1.09	-0.67	3.60	1.02
deadline_type next_lesson	2.85	0.95	1.02	4.70	1.01
deadline_type day+-next_lesson	3.86	0.90	2.11	5.66	1.01
deadline_type specific_lesson	-3.36	0.91	-5.19	-1.58	1.00
deadline_type day+-specific_lesson	1.74	0.91	-0.07	3.54	1.01
expected_effort high	-0.71	0.55	-1.79	0.37	1.01
expected_effort low	-4.04	0.61	-5.24	-2.86	1.01
enforced_deadline	-0.45	0.24	-0.91	0.02	1.01
length_descr_z	0.52	0.25	0.02	1.01	1.00
n_clicks_relevant_z	-1.71	0.19	-2.09	-1.34	1.00
n_clicks_assign_z	3.62	0.14	3.35	3.89	1.00
blockstart_click_interv_z	-9.31	0.51	-10.31	-8.30	1.00
click_deadline_interv_z	-17.84	0.60	-19.02	-16.63	1.00
blockstart_nr_z	-0.27	0.18	-0.62	0.10	1.00
covid_z	0.33	0.25	-0.15	0.83	1.00
level BSc	1.12	0.65	-0.12	2.39	1.00
level MSc	-5.90	1.10	-8.03	-3.72	1.00
Random effects (course)					
sd(click_deadline_interv_z)	12.47	0.52	11.50	13.52	1.00
sd(expected_effort low)	11.31	0.71	9.90	12.71	1.01
sd(blockstart_click_interv_z)	10.55	0.47	9.67	11.51	1.00
Random effects (student)					
sd(click_deadline_interv_z)	4.10	0.16	3.79	4.43	1.00
sd(deadline_type next_lesson)	3.81	0.30	3.24	4.40	1.01
sd(expected_effort low)	3.37	0.28	2.83	3.91	1.02

Note. Due to spatial concerns, only the three strongest random effects for both grouping factors are reported. CI=credible interval.

Table 4: Effect sizes

	$f^2_{\text{RI-context}}$	$f^2_{\text{RI-behavior}}$	$f^2_{\text{RI-all}}$	$f^2_{\text{RS-context}}$	$f^2_{\text{RS-behavior}}$	$f^2_{\text{RS-all}}$
predictors						
deadline_type	0.05	-	0.05	0.05	-	0.05
expected_effort	0.01	-	0.01	0.01	-	0.01
enforced_deadline_z	0.00	-	0.00	0.00	-	0.00
length_descr_z	0.00	-	0.00	0.00	-	0.00
n_clicks_relevant_z	-	0.01	0.00	-	0.01	0.00
n_clicks_assign_z	-	0.08	0.06	-	0.08	0.06
blockstart_click_interv_z	-	0.02	0.02	-	0.02	0.02
click_deadline_interv_z	-	0.27	0.24	-	0.27	0.24
covariates						
block_nr_z	0.00	0.00	0.00	0.00	0.00	0.00
covid_z	0.00	0.00	0.00	0.00	0.00	0.00
level	0.00	0.00	0.00	0.00	0.00	0.00

Note. Effect sizes (Cohen's f^2) of predictors and covariates for all models expect the intercept-only model

$f^2_{\text{RI-all}}$=0.06, $f^2_{\text{RS-behavior}}$=0.08, $f^2_{\text{RS-all}}$=0.06), and the deadline type ($f^2_{\text{RI-context}}$=0.05, $f^2_{\text{RI-all}}$=0.05, $f^2_{\text{RS-context}}$=0.05, $f^2_{\text{RS-all}}$=0.05). The magnitudes of the fixed effects are reported in Table 4.

Table 5: Model fit comparison and explained variance

Model	elpd diff	SE diff	R^2 Bayes	R^2 Bayes marginal	R^2 loo-adjusted
$\text{model}_{\text{RS-all}}$	0	0	0.78	0.29	0.73
$\text{model}_{\text{RS-context}}$	-2908.51	124.4	0.74	0.29	0.69
$\text{model}_{\text{RS-behavior}}$	-7926.01	302.84	0.68	0.08	0.63
$\text{model}_{\text{RI-all}}$	-12258.45	288.75	0.58	0.25	0.55
$\text{model}_{\text{RI-context}}$	-12639.17	293.82	0.57	0.23	0.55
$\text{model}_{\text{RI-behavior}}$	-17830.21	384	0.47	0.05	0.44
model_{IO}	-32321.68	478.58	0	-	0

Note. Comparison of the model fit by leave-one-out cross validation (LOO). Elpd diff indicates the difference between the expected log pointwise predictive density for a new dataset and SE diff is the standard error of elpd diff. Negative elpd diffs favor the first model, in this case $model_{RS\text{-}all}$. The marginal R^2 indicates the percentage of explained variance without random effects.

Afterwards, we conducted a model fit comparison by comparing the effect sizes of the models, represented by R^2, calculated using the *r2_bayes* function from the *performance* package. The best-performing model was $model_{RS\text{-}all}$, with an explained variance of R^2= 0.78 with random effects (conditional) and 0.29 without random effects (marginal). We calculated the loo-adjusted R^2as a proxy for an adjusted R^2 measure, which was 0.73. In order to determine the ranking of the models in terms of model fit, we ordered them by the expected log pointwise predictive density (elpd diff). The values are all reported in Table 5.

4 Discussion

4.1 Main findings

The aim of this study was to examine the influence behavioral and contextual predictors exert on the timely submission of mandatory assignments in an LMS and whether a combination of these two sets of predictors resulted in better-performing models. In order to answer these questions, we calculated several Bayesian multilevel models with the same outcome variable but different sets of predictors. The models mostly converged with satisfying Rhats, indicating a decent fit with our large dataset of over 50k assignments. In the largest model however ($model_{RS\text{-}all}$), a handful of Rhats in the random parts of the model were between 1.05 and 1.09, which indicates convergence issues. The model fit values and explained variance thus need to be interpreted carefully. The most reliable behavioral predictor of delay was the interval between the first click on the assignment and its deadline. In line with our hypothesis H5, this interval had a medium-sized negative effect on delay, meaning that the earlier the first click on the assignment was made, the sooner students handed it in (hence negative delay). This strongly supports the idea that this interval better serves as an indication of task initiation rather than as a proxy of how far the deadline was (or appeared to be), which also aligns with researching showing that early task initiation (even just opening the assignment!) is generally associated with less delay [36]. The interval between the start of a block and the first click on the assignment, as the second-strongest predictor this time and the best predictor in the previous study [17], had a weaker and reversed effect (meaning it was negative, as opposed to positive as in the previous study), contrasting with our hypothesis H8. This can be explained by the high negative correlation between the two intervals of R= -0.80, which indicates multicollinearity. This high correlation makes sense, considering both intervals include the point in the time the first click on the assignment was made. Given how little the blockstart-click-interval adds in presence of the click-deadline-interval, relying on the latter and omitting the former seems advisable for future prediction models. This also indicates that the perceived distance of the deadline as a proxy for urgency needs to be assessed in a different way, as the click-deadline-interval cannot fulfill both roles.

The number of clicks on the assignment, the third-best predictor, had a positive effect on delay, meaning the more students clicked on the assignment, the later they handed it in. While this finding is at odds with the idea that more activity implies less delay [3], this is consistent with the findings from our previous study [17] and our hypothesis H1. As before, we argue that fewer clicks are associated with timely submissions since repeated clicking on the assignment has no clear benefit and may instead indicate uncertainty or students repeatedly rereading the assignment instructions since they get distracted with other tasks and need to remind themselves what the assignment entails. The sum of clicks on relevant course materials still having no substantial effect was surprising, given the much larger sample compared to the previous study. However, this time, the effect was negative, which aligned better with our expectations and hypothesis H4 than the positive effect found in [17]. The results indicate that more activity with course materials is associated with less delay, which is also consistent with the findings of [3].

The deadline type, the fourth-best predictor, also had an effect on delay, although the order is not entirely what we expected in H2. Using the most explicit type of deadline, system due dates, as the baseline, we hypothesized the effects of all categories to be positive (meaning all other types are associated with more delay). This was true for the most part, however, the least delay occurred with assignments whose deadline was formulated in relation to a specific lesson. As Figure 2 shows, there was a cluster of assignments with a submission around 100 days ahead of the deadline, which could partially account for that effect. The effects of the other groups were consistent with our expectations (e.g., due date description being the closest to due date system and the due dates that involve calculations being associated with more delay than their calculation-free counterparts).

The expected effort showed a very small consistent effect across models, albeit below the threshold for Cohen's f^2. Assignments with low effort were linked to less delay compared to unclear effort. The credible intervals of high effort included 0, so no conclusions can be drawn here, but the findings point towards a small benefit of providing students with information concerning how large the expected workload is, which does not confirm our hypothesis H6, but at least aligns with it. The enforced deadline and the length of the assignment description had no effects, negating our hypotheses H3 and H7. In contrast, the three covariates not yielding any effects was expected. The priors from [17] provided no benefits to our models, which could be the result of having different covariates than before with two being replaced (covid and block number rather than age and gender), one being altered (department becoming level), another being turned into an actual predictor (deadline type), and one being omitted altogether (study experience).

Overall, the models produced quite a few consistent fixed effects and had respectable effect sizes, including explained variance (despite the random part of the largest model not fully converging). As before, the models also produced many random effects and the models with random slopes and intercepts outperformed the models with random intercepts by quite a margin, indicating the importance of individual and course-specific differences. While a small benefit of a combination of contextual and behavioral predictors over the separate models can be observed in the model comparison, aligning with H9, as stated before, the order needs to be interpreted carefully. The models with behavioral predictors consistently outperformed their contextual counterparts, as evidenced by the higher number of effects (three behavioral predictors vs one contextual predictor), having a better model fit, and explaining more variance. While not all the predictors had strong effects, our results show that predicting delay with contextual and behavioral variables is viable.

4.2 Theoretical and practical implications

The results have several theoretical and practical implications. The behavioral predictors highlight the importance of the first click as an indication of task initiation, which is linked to the early submission of assignments. Given how accessible log data is in most types of LMS, this information can be of great help to identify potential procrastinators. This is vital for interventions, especially early in the semester, e.g. by sending students reminders to start the initiation of their tasks. However, since our models predict dilatory behavior in general, not necessarily maladaptive forms of it such as procrastination, interventions would need to be applied carefully since purposeful delayers or students who have valid reasons to delay a task may not need interventions (see [26]). Moreover, as [50] point out, relying on single behavior markers may be an oversimplification. In their study, "precrastinators" (i.e., students who initialized the task as quickly as possible) often had time management issues as well, resulting in similarly subpar performances as those of procrastinators. Thus, despite this sizeable effect, other predictors should be factored in as well and tested in other study environments to make sure the results can be generalized. The number of clicks on the assignment again being associated with more delay implies that some students likely make meaningless clicks on the assignment. Thus, it could be helpful to encourage students to read their tasks carefully and to break them into more manageable subtasks (in accordance with the tenets of self-regulated learning, see [58]) to avoid unnecessary clicks. However, since this could also imply issues with the task descriptions, more research is necessary to fully interpret the meaning of this effect. The sum of clicks on relevant course material again not producing a proper effect, despite the importance of activity in the literature and the difference between courses that we found, implies that temporal patterns need to be looked at. Perhaps, the distribution of learning activities across the semester would be more useful in conjunction with our other predictors rather than merely the sum of the clicks.

As the contextual predictors are concerned, the effect of the deadline type implies that educators and course designers should pay more attention to the way deadlines are defined and communicated. Which specific formulation yields the best results needs to be investigated further since the order we found does not necessarily align with explicitness. While we picked the categories to distinguish between levels of explicitness in the formulation of the deadline, the categorization may also reflect other differences, such as a sense of urgency. After all, distant-appearing deadlines decrease the sense of urgency, encouraging procrastination [15, 48]. The deadline being stated as 'the 21st of April 2022' or 'the third lesson' (which is on the same date) may not appear to be equally distant (and thus urgent), despite objectively being equivalent. It is possible that some students' mental calendar is framed around the block structure of the course, rather than actual dates, or that students simply prefer some deadline formulations over others. If dates appear more distant to students than specific lessons do, this could explain the effect. Moreover, a large portion of our model is explained by individual differences, which also affects this predictor, meaning this relation would need to be investigated further to reach a conclusion. While a potential effect of enforced deadlines could be trivial (since assignments with enforced deadlines cannot have positive delay values, rendering them more likely to have lower delay values by default), the fact we did not find any implies that it is not necessarily helpful for educators to define cut-off dates in an LMS, at least as far their effect on timely submissions is concerned. However, since this could be explained by the low number of assignments that had cut-off dates in the first place, more data is necessary to confirm this.

The length of the task description may not be as indicative of task aversiveness as we suspected (at least when it comes to subsequent delay). It is thinkable that some longer descriptions may involve case examples or helpful hints, be less vague than shorter descriptions, engage students by giving them more options to explore, or use motivational formulations which could reduce task aversiveness [41, 45, 54], whereas other long descriptions may be perceived as tedious, complex, and open-ended, increasing task aversiveness. Thus, it's not necessarily the length that may have an effect, but rather the content and didactical approach to the description. A future study could thus analyze the content and complexity of the descriptions rather than just their length. Finally, the expected effort having a tiny effect implies that it could be beneficial for educators to indicate how large the workload of each assignment is. This estimation could help students manage their overall course workload better by having an "objective" indicator of how much time they need to factor in for each task. Given the importance of individual differences in our models, it would also be of interest to compare the performance of our models with that of models that involve personal characteristics. As previous results have shown [17], questionnaire data may be of limited use, however, more measures to assess task aversiveness and other relevant personal characteristics could be beneficial, e.g., perceived difficulty ratings of tasks, which could directly be implemented on an LMS.

5 Limitations

Apart from the abovementioned convergence issues, a limitation of our study is the lack of information about students' performance in their assignments. Even with a much larger sample than before, we still did not have enough information about students' scores, and the scores that we did have access to were again heavily skewed and thus far from normally distributed. Given the close links between dilatory behavior and performance, such data would be crucial to incorporate, as would be the impact on eventual dropouts. Moreover, there are still contextual and individual characteristics that could be integrated into our models (such as motivational factors or additional indicators of self-regulation), as well as socioeconomic data which could also provide more context. However, such sensitive data is not always readily available in the context of analyzing purely historical data. A further limitation is that we analyze dilatory behavior, which is not necessarily the same as procrastination since students could delay their tasks purposefully or may have valid reasons (such as illness) to delay the submission of their task. In order to clearly categorize such behavior, which would be necessary before interventions can be designed, more contextual data would need to be assessed, be it personal or course-related. Another limitation is the focus on mandatory tasks (which was a necessity due to non-mandatory tasks usually not having any deadlines), which may not accurately reflect students' overall behavior during their interactions with the learning content. This could be remedied by taking a closer look at temporal patterns across the semester in a future study. The spacing of assignments could also be addressed in such a study, analyzing the influence of how the assignments are organized (e.g., comparing the distribution of the workload across the semester and if big assignments are treated differently than multiple smaller ones).

6 Conclusion

In conclusion, the timely submission of mandatory assignments (or lack thereof) can be predicted by both behavioral and contextual predictors, with a combination of both sets yielding slightly better results. The strongest predictors turned out to be the interval between the first click on the assignment and its deadline, the interval between the start of a block and the first click on the assignment, the number of clicks on the assignment, and the deadline type. The models with behavioral predictors outperformed the models with contextual predictors. The results show that models relying on log data and assignment characteristics can predict the extent of delay, especially in the context of early predictions, however, more contextual data needs to be integrated to account for the large differences between students and courses and to categorize dilatory behavior.

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