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Enhancing behavioural engagement and academic performance in a web-based platform through personalised feedback and planning prompts

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Effective behavioural engagement (BE), such as putting effort and time into using learning materials, is critical to academic success. However, students often struggle to maintain their BE over time. As web-based learning becomes increasingly integral to STEM education, offering students the flexibility to consolidate complex materials at their own pace, supporting BE is essential. This longitudinal study examines the effect of an intervention—using biweekly planning prompts and personalised feedback during a 9-week course—on BE and course performance. In addition, the moderating role of motivation on this effect was examined. BE was operationalised using theory-driven log-type indicators capturing several aspects of online effort and time. Students (N=173) were randomly assigned to one of three conditions: (1) control group received general reminders, (2) planning-only group received planning prompts, and (3) planning-feedback group received planning prompts and personalised emails comprising process-based feedback based on their BE with the web-based platform. Results showed that planning prompts could enhance student effort in completing the tasks. Personalised feedback combined with planning prompts could promote consistent BE among students with strong value beliefs, suggesting the need for better integration of motivational support. The study provides insights into the development of adaptive systems to support complex engagement processes.

Keywords: feedback, mathematics education, motivation, personalisation, student engagement, web-based learning

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Introduction

Student engagement is key to student success in STEM courses (Wang et al., 2016). Web-based learning, increasingly used in STEM education to complement instruction and enhance the consolidation of complex concepts (Khalid et al., 2025), relies on effective engagement to achieve positive learning outcomes (Papageorgiou et al., 2025a). Engagement is a multidimensional construct, encompassing affective, behavioural, and cognitive components (Fredricks et al., 2004). This study focuses on behavioural engagement (BE), which is particularly relevant in web-based environments where engagement processes can be measured through log data (Wiedbusch et al., 2023). In self-paced learning, such as traditional homework and web-based practice, BE is defined as time and effort investment (Flunger et al., 2015; Papageorgiou et al., 2025b). Effort has been further described as compliance, persistence, and regularity. Time and effort invested in studying have been positively associated with academic performance (Flunger et al., 2015).

The process through which students engage in self-paced environments, such as web-based practice, has been studied through self-regulated learning (SRL) theory (Cleary & Zimmerman, 2012; Trautwein & Köller, 2003). Zimmerman's (2002) three-phase cyclical SRL model describes how processes in the forethought phase, such as planning and underlying motivations, influence SRL processes in the performance and reflection phases, such as study strategies. In turn, these SRL processes shape BE in a task. Given the challenges of sustaining engagement in web-based environments (Papageorgiou et al., 2025b), supporting students in study planning can be promising for enhancing BE.

Prompting is an indirect instructional method that supports SRL and, hence, can activate engagement (Wong et al., 2019). Prompting students to plan their studying has shown positive effects on compliance with assigned tasks (e.g., on-time completion), regularity, time spent, and performance (Davis et al., 2016; Felker & Chen, 2022, 2023; Wong et al., 2021; Yeomans & Reich, 2017). However, students might not always perceive the need to plan their study (Kizilcec et al., 2016) and often struggle to create effective and realistic plans, which highlights the value of feedback (Wong et al., 2019). Feedback, i.e., information that students receive about their learning, can increase students' awareness and influence their strategies (Lim et al., 2019). Personalised feedback via email has been used to guide students toward actions critical for success (Lim et al., 2019; Pardo et al., 2019). These studies report positive effects on compliance and course performance. However, few studies have combined feedback and planning to enhance BE (Dever et al., 2024).

Motivation is central to SRL and drives engagement (Trautwein & Köller, 2003). In self-paced settings, expectancy-value theory posits that expectancy (one's perceived abilities to succeed) and value beliefs (the significance assigned to this task) influence engagement and performance (Eccles & Wigfield, 2020; Trautwein & Köller, 2003). For example, students with higher expectancy are more likely to invest in planning. Although prior work has shown that expectancy and value beliefs predict BE and subsequent academic performance (Sutter et al., 2022; Vo & Ho, 2024), the role of motivation in shaping the effect of prompting and feedback on BE and performance is less studied.

Current study

The current study was conducted in a nine-week probability theory and statistics course for engineering undergraduates, with two weekly lectures and assessments via a midterm (Week 5) and final exam (Week 9). After each lecture, students completed homework in a web-based platform, Grasple (https://www.grasple.com). The exercises were offered at three levels: basic, practice, and challenging. The system provided automated feedback through hints and, after three unsuccessful attempts, full explanations.

Despite the importance of practice for learning mathematics (Akın, 2022), low levels of engagement with online materials remain a challenge (Denbel, 2023; Jaggars, 2014). Longitudinal research shows that BE declines over time, with diverse trajectories across students. Starting a course with low BE often represents a persistent state (Papageorgiou et al., 2025b). Therefore, longitudinal and personalised support may be necessary to sustain BE. This study examines the impact of biweekly personalised feedback and planning prompts on students' online BE and academic performance. Furthermore, the study investigates how student motivation influences the effectiveness of the intervention.

The following research questions were formulated:

RQ1: What is the effect of planning prompts and personalised feedback on online BE?

RQ2: What is the effect of planning prompts and personalised feedback on course performance?

RQ3: To what extent do students' expectancy and value beliefs moderate the effects of planning prompts and personalised feedback on online BE and course performance?

Methods

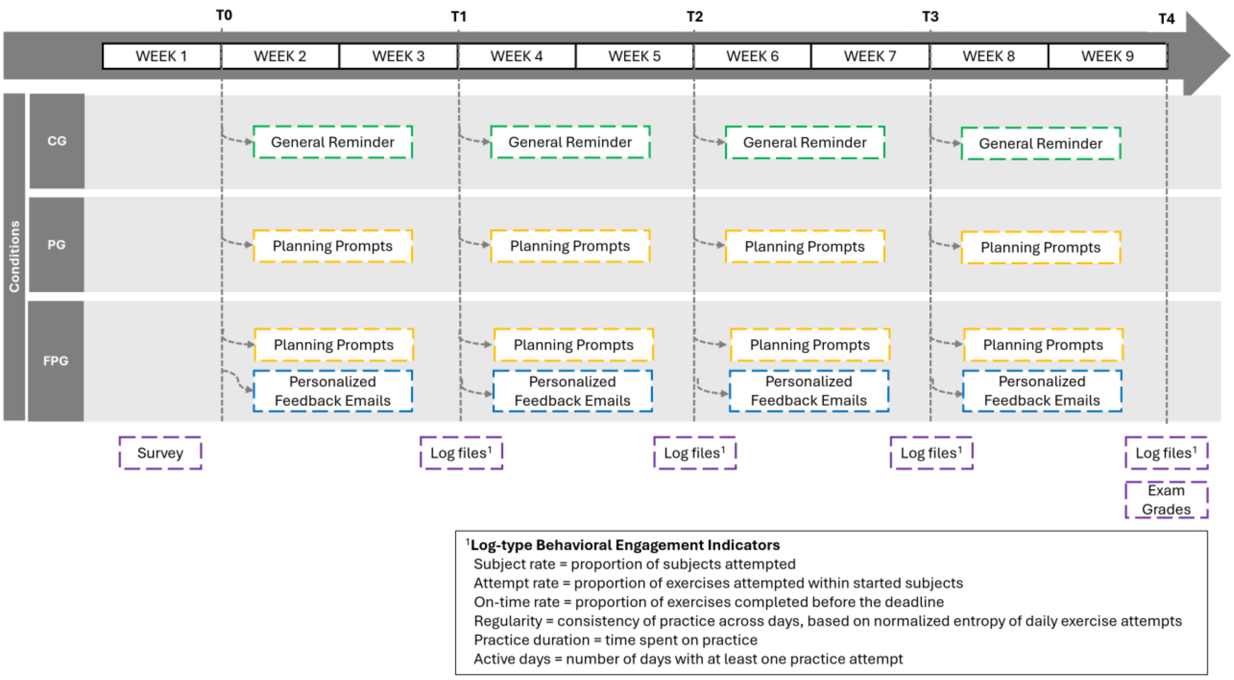
Participants

The participants were 173 undergraduate engineering students who were randomly assigned to one of three conditions: Feedback and Prompt Group (FPG) (n = 57), Prompt Group (PG) (n = 57), or Control Group (CG) (n = 59). Most participants were younger than 20 years old (53%) or between 20 and 25 years old (45%), while 2% were between 25 and 30 years old. Out of the 173 students, 17% identified as females, 81% as males, 1% as other, and 2% did not specify. Participants were recruited through the authors via in-class and online announcements, and they gave consent to participate in the study voluntarily. The study was pre-registered and received ethics approval from the University Ethics Committee (Reference No: 4526).

Measurements

BE was measured via six indicators using log data on students' interactions with Grasple and was operationalised as effort and time investment. Effort was measured with four log-type indicators: subject rate, attempt rate, on-time rate, and regularity. Time investment was measured with two log-type indicators: practice duration and active days. The six indicators were measured once a fortnight at four time points (T1-T4) (see Figure 1).

Figure 1: Overview of the study procedure and measurement



Course performance was measured using the grade obtained in the final exams. The exams consisted of multiple-choice and open-answer questions. To pass the exams, students need to achieve a minimum score of 6 out of 10.

Expectancy and value beliefs were measured using an adapted version of the Homework Motivation Scale (Yang & Xu, 2018). The expectancy scale consisted of nine items that measured students' beliefs concerning their ability to successfully complete their web-based practice (α = .78). The value scale consisted of six items that measured the utility of web-based mathematics practice (α = .80).

Procedure

Figure 1 provides an overview of the procedure. Besides using Grasple as usual, participants were asked to complete surveys on expectancy and value beliefs at the beginning of the course. The respective interventions were delivered once a fortnight, starting in Week 2.

CG participants received a general message as a reminder to work on their practice before the assigned deadline. Both PG and FPG participants received a planning prompt at the start of each fortnight (Figure 2). The *planning prompts* asked participants to respond to three questions to create a study plan. In addition to the *planning prompts*, FPG participants received *personalised feedback* comprising four types of information: a) performance metrics, such as number of attempted exercises, remaining exercises, and scores per lecture, b) behaviour-based guidance tailored to students' engagement patterns (e.g., reattempt rates), aimed at directing students to seek help, encouraging persistence, or affirming effective strategies, c) reminders and study tips, including upcoming deadlines, relevance of the material, and evidence-based strategies (e.g., spaced practice), and d) an interactive poll, offering the choice to immediately plan homework or postpone. For a detailed presentation of the procedure and measurement, we refer the reader to the supplementary material.[1]

Statistical analysis

Data were prepared for two types of analyses: intent-to-treat (ITT) and treatment-on-treated (TOT) (Lamb et al., 2015). For the ITT analysis, we retained the initial groups to compare students across the three conditions regardless of whether or not they interacted with the intervention materials. For the TOT analysis, we identified which students interacted with the platform and materials as intended.[2] For the TOT analysis, the group distribution was as follows: CG= 53, PG= 55, FPG= 25. In the current paper, we report the TOT analysis as we aim to examine the effects of the intervention. Results for the ITT analysis can be found in the supplementary material.

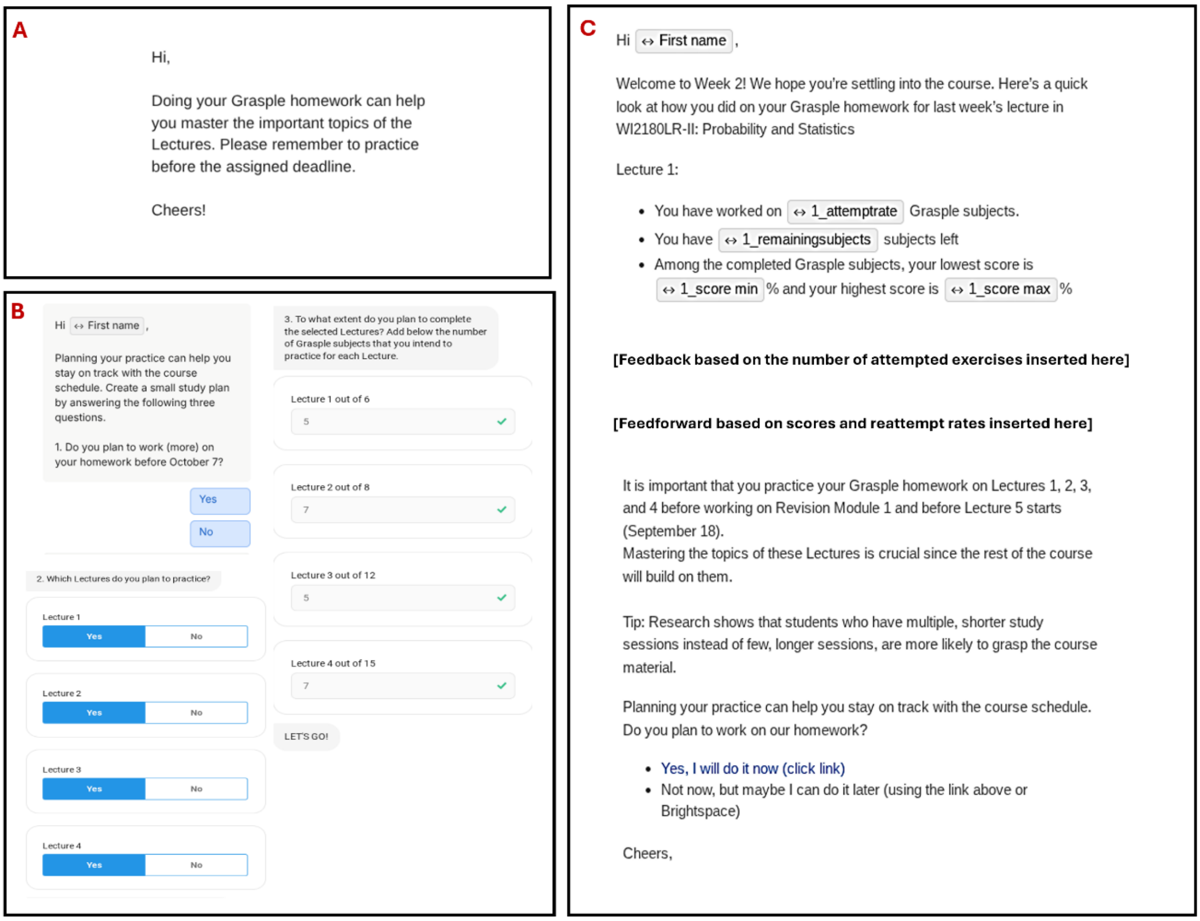
All analyses were performed using R Studio software (R Core Team, 2025). To examine the effect of the intervention on BE indicators (RQ1), we conducted mixed-design analysis of variance (ANOVA) for each of the six BE indicators with condition as a between-subject factor and the four time-points in which each BE was measured as the within-subject factor. Due to violations of assumptions (i.e., normality, outliers, and unbalanced groups), we performed both classical and robust ANOVA using 20% trimmed means (Mair & Wilcox, 2020). In this paper,

[1] https://osf.io/gdbs3/?view_only=bb3ae2f7e62e47b18780e0fab3b7fcb0

[2] First, we excluded students who were inactive on the platform throughout the course (n_{CG}= 6, n_{PG}= 4, n_{FPG}= 6). Second, we excluded students of the PG who only viewed and did not interact with the planning prompts (n_{PG}= 15). Third, we excluded students of the FPG who did not view at least one email and interact with at least one prompt (n_{FPG}= 9). Fourth, students of the FPG who only interacted with prompts were perceived to have received the intervention intended for the prompt condition and were moved to the PG (n_{FPG}= 17).

we report the results of the robust ANOVA.[3]

Figure 2: Screenshots from A) the CG reminder, B) the PG and FPG planning prompt, and C) the FPG personalised email



To examine the effect of the intervention on course performance (RQ2), we had planned to conduct a one-way ANOVA. However, due to violation of the normality assumption, a non-parametric Kruskal–Wallis test was conducted.

Given that expectancy-value theory suggests motivational beliefs shape how students respond to self-regulatory support (Eccles & Wigfield, 2020), we tested whether expectancy and value beliefs moderated intervention effects. To examine this moderating role (RQ3), we conducted multiple linear regression using robust standard errors. BE indicators were averaged across the four time-points to create composite scores.[4]

[3] For classical ANOVA, Greenhouse–Geisser corrections were applied when the assumption of sphericity was violated. Classical ANOVA results can be found in supplementary materials. Robust ANOVA uses trimmed means to reduce the influence of outliers and violations of normality or variance assumptions. For repeated-measures or mixed designs, robust ANOVA can handle both within- and between-subject factors under assumption violations. A 20% trimming level is widely recommended in robust ANOVA because it provides an optimal balance between reducing the influence of outliers and retaining statistical power (Mair & Wilcox, 2020).

[4] Assumptions of independence of errors and multi-collinearity were met across all the models. The assumption of linearity was met for all the models, except for the active days model. After conducting a square root transformation on the variable 'active days', the assumption of linearity was met. The assumptions of normality and homoscedasticity were violated in most of the models, therefore, we used heteroskedasticity-consistent (HC3) robust standard errors, which adjust the coefficient standard errors to remain valid even when error variances are unequal.

Results

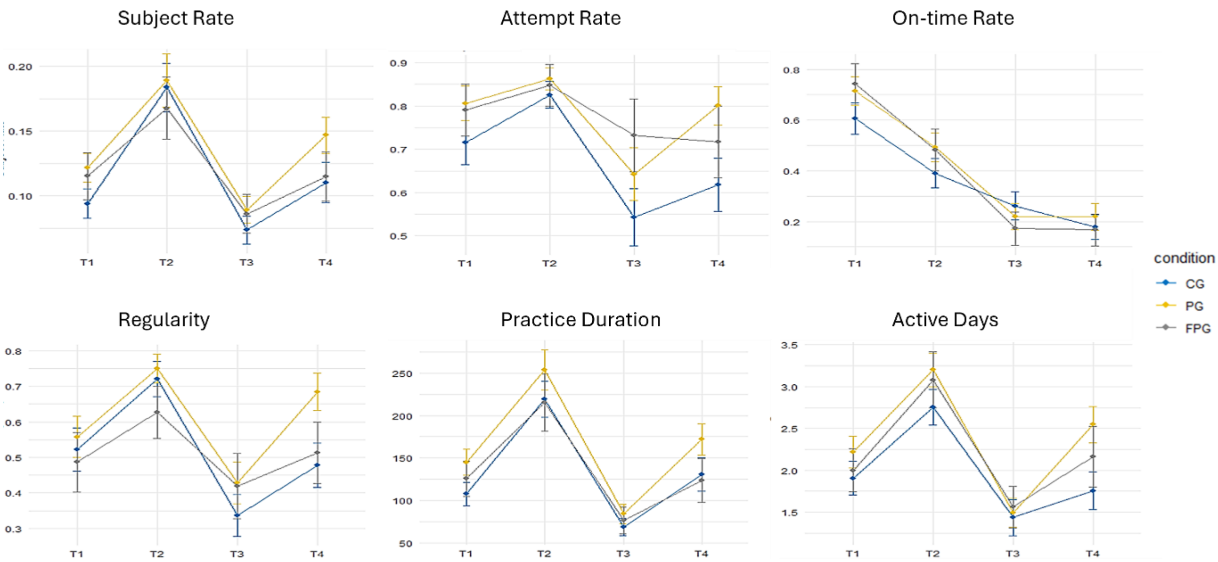
Descriptive statistics and correlational analyses were performed for the BE indicators, course performance, expectancy beliefs, and value beliefs. The Shapiro-Wilk test was significant (p<.05) for all the variables except for the expectancy beliefs (p=.31), suggesting violations of the normality assumption. Therefore, Spearman's rank-order correlations were conducted to examine the association between the variables and to provide an understanding of their relationships, which also informed the moderator analysis in RQ3. Spearman's test revealed that course performance was significantly associated with subject rate (ρ=.19, p=.019), on-time rate (ρ = .28, p < .001), practice duration (ρ = .24, p =.003), and expectancy beliefs (ρ = .36, p < .001). Moreover, value beliefs were significantly associated with subject rate (ρ = .167, p = .04), active days (ρ = .17, p = .037), practice duration (ρ = .19, p = .017), and expectancy beliefs (ρ = .29, p < .001).

Effects on BE indicators

Robust mixed-design ANOVA revealed significant main effects of time on all six BE indicators, with effect sizes ranging from moderate (ξ = .02) to large (ξ = .17). Pairwise comparisons revealed a significant increase in BE scores from T1 to T2, followed by a significant decline from T2 to T3, and a subsequent modest increase at T4, suggesting that students increased their BE during the midterm period and before the final exams. Only the on-time rate indicator was highest at T1 and declined over subsequent time points.

Analyses also showed that the main effect of condition approached significance for attempt rate based on the permutation test, $Q(2, 58.97) = 2.98$, p = .058 (permutation p = .05), with a small effect size (ξ = .017), suggesting that the results should be interpreted with caution. Pairwise comparisons revealed that PG and FPG had significantly higher attempt rates than CG. No significant effects of condition or of the interaction between condition and time were found for the remaining indicators (Figure 3).

Figure 3: Comparison of BE indicators across the three conditions and the four time points



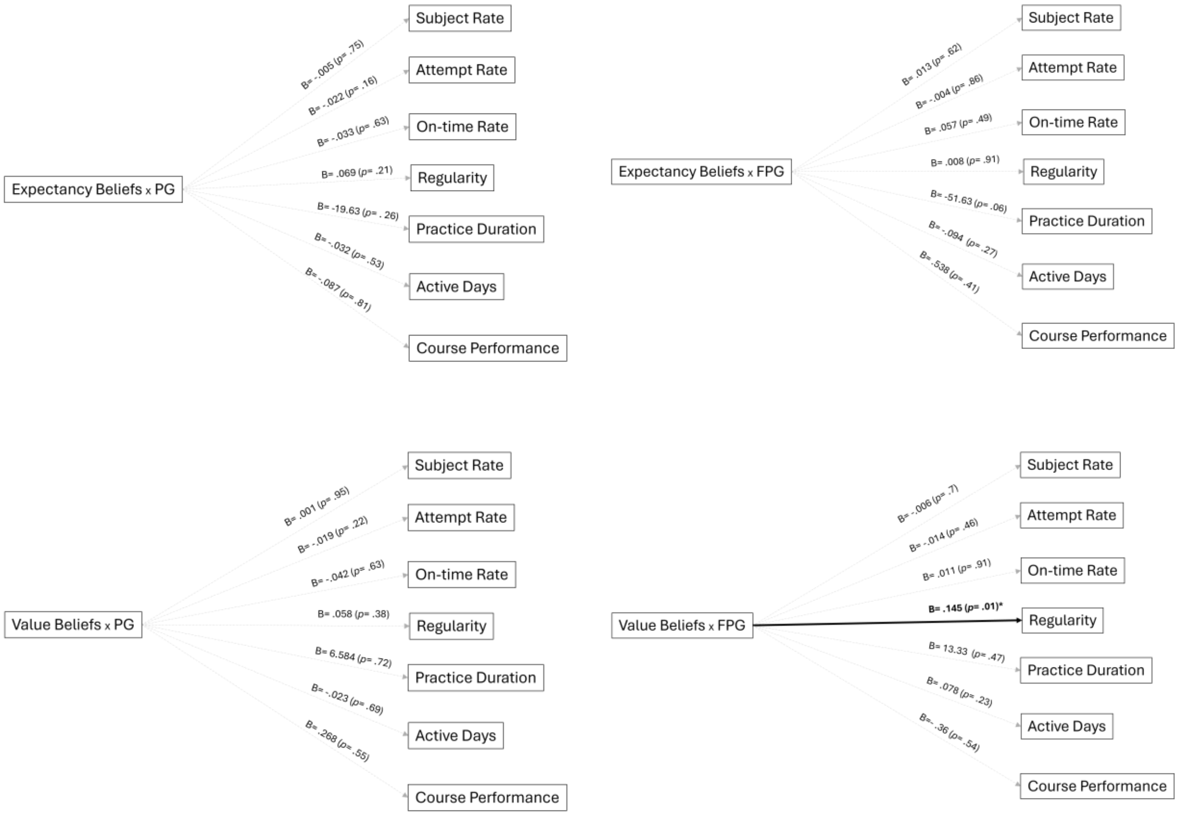
Effects on course performance

The non-parametric Kruskal-Wallis test revealed no significant effects of condition on course performance, $H(2) = 0.69$, p = .710, suggesting that the CG (M = 6.98, SD = 1.79), PG (M = 6.50, SD = 2.57), and FPG (M = 6.56, SD = 1.99) performed similarly on the final exams.

Moderating effects of expectancy and value beliefs

Multiple linear regression revealed a significant positive interaction between FPG group membership and value beliefs on regularity, indicating that higher value beliefs strengthened the positive effect of personalised feedback and planning prompts on regularity. For the remaining BE indicators and course performance, interaction terms were non-significant (Figure 4).

Figure 4: Multiple linear regression results (coefficient and p-value) on the interaction effects between motivation and intervention. CG was used as the reference category.



Discussion

To address BE in web-based learning for an engineering probability and statistics course, this study compared a general reminder (CG) with planning prompts only (PG) and planning prompts combined with personalised feedback emails (FPG). Expectancy and value beliefs were also examined as potential moderators. Results showed that all groups significantly changed their BE over time by displaying similar temporal patterns. Consistent with prior literature (von Keyserlingk et al., 2025), BE indicators increased during midterm and exam periods, reflecting the strong influence of course milestones.

The three groups did not differ significantly in most BE indicators and course performance, except for the PG group, which tended to show a higher attempt rate, indicating an aspect of effort. Consistent with prior work (Davis et al., 2016; Wong et al., 2021), students who received planning prompts completed more exercises compared to those who did not receive planning prompts. The lack of effect of prompts on the remaining BE aspects may relate to the prompt delivery method. Prompts appeared only within Grasple, which students access primarily for homework, by which point study plans may have been made. Embedding prompts in a more frequently used environment (e.g., the LMS) could increase their salience (Wong et al., 2021). Additionally, in prior studies, prompt completion sometimes carried course credit (e.g., Felker & Chen, 2023), whereas our prompts were non-graded, which may have reduced students' incentives to follow through on planning. Finally, while prior work had no-treatment control groups (Felker & Chen, 2023), our control group received general reminders, which might have supported their BE and thereby reduced the impact of the intervention.

Unlike prior findings (Lim et al., 2019; Pardo et al., 2019), personalised feedback emails did not significantly impact BE or performance. A potential explanation concerns feedback delivery. In earlier work, feedback emails were sent by instructors, often tied to critical course junctures such as exams, and reflected overall course activity (Lim et al., 2019; Pardo et al., 2019), whereas, in this study, feedback was generated by the research team and targeted only homework practice, which may have reduced its perceived relevance. Students might perceive the feedback from a course instructor with whom they have a personal connection to be more important and be more motivated to act on the feedback rather than on that of a researcher. This interpretation aligns with our RQ3 findings. Within the FPG, students with higher value beliefs were more likely to sustain regular practice, suggesting that students with stronger value beliefs may be less reliant on external endorsement and thus more likely to act on researcher-provided feedback. Future work should examine whether instructor-delivered feedback preferentially benefits students with lower initial task value. The lack of significant interactions for other BE indicators and course performance indicates that expectancy-value beliefs might influence these outcomes less directly. Future research could examine other motivational constructs to clarify how different aspects of motivation influence BE.

Limitations and conclusion

This study underscores the need to tailor support for different aspects of BE in online STEM learning. Planning prompts may enhance task effort, while combining feedback and prompts can promote consistent engagement over time among students with strong value beliefs. However, more research is required to understand how planning prompts and personalised feedback can be leveraged to enhance BE and performance in web-based practice. Limitations of the study include the lack of repeated self-reported engagement data to complement the log-type indicators, partial compliance with interventions, and participant attrition, which may have introduced bias and reduced statistical power. Nonetheless, the study provides insights into the effect of planning prompts and personalised feedback on BE and highlights the need to consider motivational support to sustain BE in web-based learning environments.

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Disclosure of the use of AI-assisted technologies during writing

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References

Akın, A. (2022). The effectiveness of web-based mathematics instruction (WBMI) on K-16 students' mathematics learning: A meta-analytic research. *Education and Information Technologies*, *27*(6), 8015–8040. https://doi.org/10.1007/s10639-022-10931-x

Cleary, T. J., & Zimmerman, B. J. (2012). A cyclical self-regulatory account of student engagement: Theoretical foundations and applications. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds), *Handbook of research on student engagement* (pp. 237–257). Springer US. https://doi.org/10.1007/978-1-4614-2018-7_11

Davis, D., Chen, G., van der Zee, T., Hauff, C., & Houben, G.-J. (2016). Retrieval practice and study planning in MOOCs: Exploring classroom-based self-regulated learning strategies at scale. In K. Verbert, M. Sharples, & T. Klobučar (Eds), *Adaptive and adaptable learning* (pp. 57–71). Springer International Publishing. https://doi.org/10.1007/978-3-319-45153-4_5

Denbel, D. G. (2023). Challenges of teaching and learning mathematics courses in online platforms. *International Journal of Online Pedagogy and Course Design (IJOPCD)*, *13*(1), 1–15. https://doi.org/10.4018/IJOPCD.321155

Dever, D. A., Wiedbusch, M. D., Romero, S. M., & Azevedo, R. (2024). Investigating pedagogical agents' scaffolding of self-regulated learning in relation to learners' subgoals. *British Journal of Educational Technology*, *55*(4), 1290–1308. https://doi.org/10.1111/bjet.13432

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

Felker, Z., & Chen, Z. (2022). Using a planning prompt survey to encourage early completion of homework assignments. *Proceedings of the Ninth ACM Conference on Learning @ Scale*, 446–450. https://doi.org/10.1145/3491140.3528297

Felker, Z., & Chen, Z. (2023). Reducing procrastination on introductory physics online homework for college students using a planning prompt intervention. *Physical Review Physics Education Research*, *19*(1), 010123. https://doi.org/10.1103/PhysRevPhysEducRes.19.010123

Flunger, B., Trautwein, U., Nagengast, B., Lüdtke, O., Niggli, A., & Schnyder, I. (2015). The Janus-faced nature of time spent on homework: Using latent profile analyses to predict academic achievement over a school year. *Learning and Instruction*, *39*, 97–106. https://doi.org/10.1016/j.learninstruc.2015.05.008

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, *74*(1), 59–109. https://doi.org/10.3102/00346543074001059

Jaggars, S. (2014). Choosing between online and face-to-face courses: Community college student voices. *American Journal of Distance Education*, *28*, 27–38. https://doi.org/10.1080/08923647.2014.867697

Khalid, I. L., Abdullah, M. N. S., & Mohd Fadzil, H. (2025). A systematic review: Digital learning in STEM education. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, *51*(1), 98–115. https://doi.org/10.37934/araset.51.1.98115

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2016). Recommending self-regulated learning strategies does not improve performance in a MOOC. *Proceedings of the Third ACM Conference on Learning @ Scale*, 101–104. https://doi.org/10.1145/2876034.2893378

Lamb, A., Smilack, J., Ho, A., & Reich, J. (2015). Addressing common analytic challenges to randomized experiments in MOOCs: Attrition and zero-inflation. *Proceedings of the Second ACM Conference on Learning @ Scale*, 21–30. https://doi.org/10.1145/2724660.2724669

Lim, L., Gentili, S., Pardo, A., Kovanovic, V., Whitelock-Wainwright, A., Gasevic, D., & Dawson, S. (2019). What changes, and for whom? A study of the impact of learning analytics-based process feedback in a large course. *Learning and Instruction*, *72*. https://doi.org/10.1016/j.learninstruc.2019.04.003

Mair, P., & Wilcox, R. (2020). Robust statistical methods in R using the WRS2 package. *Behavior Research Methods*, *52*(2), 464–488. https://doi.org/10.3758/s13428-019-01246-w

Papageorgiou, E., Wong, J., Liu, Q., Khalil, M., & Cabo, A. J. (2025a). A systematic review on student engagement in undergraduate mathematics: Conceptualization, measurement, and learning outcomes. *Educational Psychology Review*, *37*(3), 66. https://doi.org/10.1007/s10648-025-10046-y

Papageorgiou, E., Wong, J., Khalil, M., & Cabo, A. J. (2025b). Nonlinear effort-time dynamics of student engagement in a web-based learning platform: A person-oriented transition analysis. *Journal of Learning Analytics*, *12*(2), 237–258. https://doi.org/10.18608/jla.2025.8663

Pardo, A., Jovanovic, J., Dawson, S., Gašević, D., & Mirriahi, N. (2019). Using learning analytics to scale the provision of personalised feedback. *British Journal of Educational Technology*, *50*(1), 128–138. https://doi.org/10.1111/bjet.12592

R Core Team. (2025). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/

Sutter, C. C., Hulleman, C. S., Givvin, K. B., & Tucker, M. (2022). Utility value trajectories and their relationship with behavioral engagement and performance in introductory statistics. *Learning and Individual Differences*, *93*, 102095. https://doi.org/10.1016/j.lindif.2021.102095

Trautwein, U., & Köller, O. (2003). The relationship between homework and achievement—Still much of a mystery. *Educational Psychology Review*, *15*(2), 115–145. https://doi.org/10.1023/A:1023460414243

Vo, H., & Ho, H. (2024). Online learning environment and student engagement: The mediating role of expectancy and task value beliefs. *The Australian Educational Researcher*, *51*(5), 2183–2207. https://doi.org/10.1007/s13384-024-00689-1

von Keyserlingk, L., Lauermann, F., Li, Q., Yu, R., Rubach, C., Arum, R., & Heckhausen, J. (2025). Students' study activities before and after exam deadlines as predictors of performance in STEM courses: A multi-source data analysis. *Learning and Individual Differences*, *117*, 102598. https://doi.org/10.1016/j.lindif.2024.102598

Wang, M.-T., Fredricks, J. A., Ye, F., Hofkens, T. L., & Linn, J. S. (2016). The math and science engagement scales: Scale development, validation, and psychometric properties. *Learning and Instruction*, *43*, 16–26. https://doi.org/10.1016/j.learninstruc.2016.01.008

Wiedbusch, M., Dever, D., Li, S., Amon, M. J., Lajoie, S., & Azevedo, R. (2023). Measuring multidimensional facets of SRL engagement with multimodal data. In V. Kovanovic, R. Azevedo, D. C. Gibson, & D. Ifenthaler (Eds), *Unobtrusive observations of learning in digital environments: Examining behavior, cognition, emotion, metacognition and social processes using learning analytics* (pp. 141–173). Springer International. https://doi.org/10.1007/978-3-031-30992-2_10

Wong, J., Baars, M., Davis, D., Van Der Zee, T., Houben, G.-J., & Paas, F. (2019). Supporting self-regulated learning in online learning environments and MOOCs: A systematic review. *International Journal of Human–Computer Interaction*, *35*(4–5), 356–373. https://doi.org/10.1080/10447318.2018.1543084

Wong, J., Baars, M., De Koning, B. B., & Paas, F. (2021). Examining the use of prompts to facilitate self-regulated learning in Massive Open Online Courses. *Computers in Human Behavior*, *115*, 106596. https://doi.org/10.1016/j.chb.2020.106596

Yang, F., & Xu, J. (2018). Homework expectancy value scale: Measurement invariance and latent mean differences across gender. *Journal of Psychoeducational Assessment*, *36*(8), 863–868. https://doi.org/10.1177/0734282917714905

Yeomans, M., & Reich, J. (2017). Planning prompts increase and forecast course completion in massive open online courses. *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 464–473. https://doi.org/10.1145/3027385.3027416

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice*, *41*(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2