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GenAI as a learning partner: Supporting self-regulated learning over time without replacing effort

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Generative AI (GenAI) offers significant potential to scaffold self-regulated learning (SRL) by acting as an adaptive agent or "co-regulator". However, effectively balancing technological assistance with student effort requires AI systems that recognise SRL not as a static trait, but as a temporal and personalised process. This study investigates these dynamics over a full semester, utilising surveys at the beginning of, during, and at the end of semester to track the SRL, motivation, and emotion of 75 first-year university students. We first examine pre- and post-semester shifts, finding individual consistency alongside systemic declines in metacognitive knowledge and wellbeing. We then analyse week-to-week fluctuations, identifying curriculum demands—such as major assessment deadlines—as primary drivers of shifts in student internal states. Finally, we provide a proof-of-concept demonstration by leveraging this longitudinal and contextual information within a Large Language Model to generate tailored support directions. Our findings demonstrate that, when provided with personal, temporal, and contextual information, GenAI can identify appropriate directions for SRL support that respond to a learner's evolving cognitive and metacognitive needs. This work underscores that, for GenAI to function as an effective learning partner, it must be designed with strong contextual awareness, adapting its scaffolding to support students without replacing their cognitive effort.

Keywords: co-regulation, GenAI, learning partner, self-regulated learning

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Introduction

The transition to higher education demands a significant shift in learner autonomy, requiring students to self-regulate their cognitive effort across competing subjects and responsibilities. While self-regulated learning (SRL) is critical for academic success, the rapid proliferation of generative AI (GenAI) complicates this landscape, introducing risks alongside novel opportunities for support. Among these risks, the "mindless" use of GenAI raises significant concerns regarding cognitive and metacognitive offloading. Treating GenAI as a mere tool risks the "externalisation" of cognition (Cukurova, 2025), where delegating core tasks to machines bypasses the productive struggle necessary for learning, potentially resulting in the long-term atrophy of students' metacognitive abilities. Conversely, researchers are exploring GenAI's potential to actively foster SRL. For example, targeted GenAI prompts can remind students to plan, engage with, and reflect on their learning, an area showing initial success in experimental settings (Li et al., 2025; Pan et al., 2025).

While using GenAI to support SRL is promising, finding the balance between technological assistance and the cognitive effort required by students is complex. Ensuring this approach works in practice requires alignment with the personalised and temporal nature of SRL (Winne & Hadwin, 1998). First, SRL is highly personalised; each individual applies a unique baseline tendency toward self-regulation across diverse settings (Song et al., 2025). Second, SRL is a temporally evolving process (Broadbent & de Barba, 2023). Rather than a static trait, SRL fluctuates dynamically to changing external conditions. As academic schedules progress and demand shift, a student's capacity and strategy for self-regulation continually adapt. If an AI system ignores these dimensions, it fails to calibrate its support, risking over-assistance (leading to cognitive offloading) or under-assistance during critical periods of academic stress.

These characteristics of SRL present challenges for current GenAI solutions, which typically rely on rule-based models that extract SRL processes without genuine personalisation (Li et al., 2025), overlooking how the exact same learning behaviour has vastly different implications depending on a student's individual habits and baseline wellbeing. Furthermore, because research typically occurs within short-term laboratory settings, there is a lack of consideration regarding the longitudinal dynamics of SRL—such as how a learner's internal state fluctuates continuously in response to shifting external demands and assessment schedules (Higgins et al., 2023).

To act as an effective learning partner that supports SRL without replacing student effort, GenAI must dynamically adapt to these evolving individual and contextual dimensions (Xia et al., 2026). As academic semesters typically have a weekly schedule, it was found that students' online learning behaviours demonstrate week-by-week fluctuations (Pardo et al., 2019), but there is a lack of investigation of students' evolving SRL states behind such fluctuations and how GenAI might adapt to such changes. In this work, we first examine students' SRL changes from a longitudinal, week-by-week perspective and propose two research questions:

RQ1: To what extent do pre- and post-study surveys reveal individual consistency and systemic shifts in students' metacognition and wellbeing?

RQ2: How do daily surveys reveal the week-by-week fluctuations in tasks, self-efficacy beliefs, interest, and emotion, and to what extent are these dynamics influenced by the subject schedule?

Then, we utilise these results to provide a proof-of-concept demonstration of personalised, context-aware GenAI support.

Methods

This research utilises survey data from first-year Bachelor of Science students at a large Australian university, collected over a 12-week academic semester. Seventy-five participants consented to the survey and signed the ethics form (#22276) to participate.

To address RQ1, pre- and post-semester surveys evaluated longitudinal shifts in students' SRL through the dimensions of metacognition and wellbeing. While metacognitive factors are positioned as the primary drivers of the regulatory process, wellbeing also has a reciprocal relationship with SRL, where positive functioning serves as both a driver of persistent effort and a direct outcome of self-regulatory success (Boekaerts & Cascallar, 2006; Davis & Hadwin, 2021). We utilised the Metacognitive Awareness Inventory (MAI) (Harrison & Vallin, 2018) to assess students' metacognitive knowledge (MAI_K; i.e., what they know about their thinking) and regulation (MAI_R; i.e., how they control it). To assess wellbeing, we utilised the Warwick-Edinburgh Mental Well-being Scale (WEMWBS) (Tennant et al., 2007). Fifty-four participants completed both the pre- and post-semester surveys.

To analyse these surveys for RQ1, linear regression was performed to examine the R-squared values, with higher values demonstrating greater individual consistency between pre- and post-semester results. After checking normality assumptions, we also conducted paired t-tests to investigate systemic changes in students' MAI_K, MAI_R, and wellbeing.

Building on RQ1, RQ2 investigated the fluctuations of SRL within the semester at a higher level of granularity (i.e., weekly) using daily survey data. For this analysis, we selected from the broader sample a cohort of 38 participants who were enrolled in the same computing subject (COMP), allowing us to map SRL dynamics against a specific academic context. These daily surveys were distributed via SMS at the conclusion of each day in weeks 4, 6, 8, and 9, with 246 total responses.

To measure students' SRL in the daily survey (RQ2; see Appendix for the survey), we utilised a concise 6-item short questionnaire measuring metacognitive regulation (MAI_R) (Harrison & Vallin, 2018). In this survey, students reported whether they had undertaken any study of that subject on the learning management system on the day, and—if so—which of the 6-item options of metacognitive regulation they had used during those study sessions. For simplicity, we refer to this survey instrument as *SRL tasks*. Furthermore, because SRL theory posits that learning extends beyond the mere execution of cognitive tasks, we recognise that motivational and affective factors both influence, and are influenced by, the SRL process (Winne & Hadwin, 1998). Accordingly, we assessed students' interest and self-efficacy beliefs via single-item measures rated on a 5-point Likert scale, and their emotions through multiple-choice questions (Pekrun et al., 2002), which were subsequently categorised as positive or negative for analysis.

Given the weekly university schedule, cohort-level longitudinal SRL fluctuations are likely more pronounced at a weekly rather than daily level. While daily fluctuations are subject to factors such as the day of the week and specific learning activities (e.g., tutorial) which vary by individual, aggregating to the weekly level smooths out this individual variance and provides a more consistent basis for cohort-wide analysis. Therefore, daily survey responses were aggregated by week to examine how students' SRL changed across the semester timeline. Visualisation was employed to demonstrate these longitudinal changes at the population level.

Building on the findings from these research questions, we then investigated how GenAI can act as an adaptive co-regulator. To demonstrate this approach, we integrated the personalised baseline data (RQ1) and the temporal, context-specific survey data (RQ2) into a Large Language Model (LLM) to generate tailored SRL support directions. A detailed analysis of two representative student cases is provided in the forthcoming sections.

Results

RQ1: The individual consistency and systemic change of metacognition and wellbeing

The analytical results of the pre- and post-semester surveys are presented in Table 1. The R-squared values from the linear regression indicate a moderate to high level of relative stability across the cohort, meaning students generally maintained their rank or position relative to their peers. However, the results of the paired t-tests revealed that the cohort's overall MAI_K and wellbeing decreased significantly over the term. This suggests that while a student's baseline aptitude relative to their peers is a stable trait, the entire group experienced a systemic decline in wellbeing and confidence regarding their cognitive processes and self-regulation. Such overall declines likely stem from the compounding challenges or academic demands that students experience during the term (Higgins et al., 2023), requiring the more granular, continuous, context-specific investigation undertaken in RQ2.

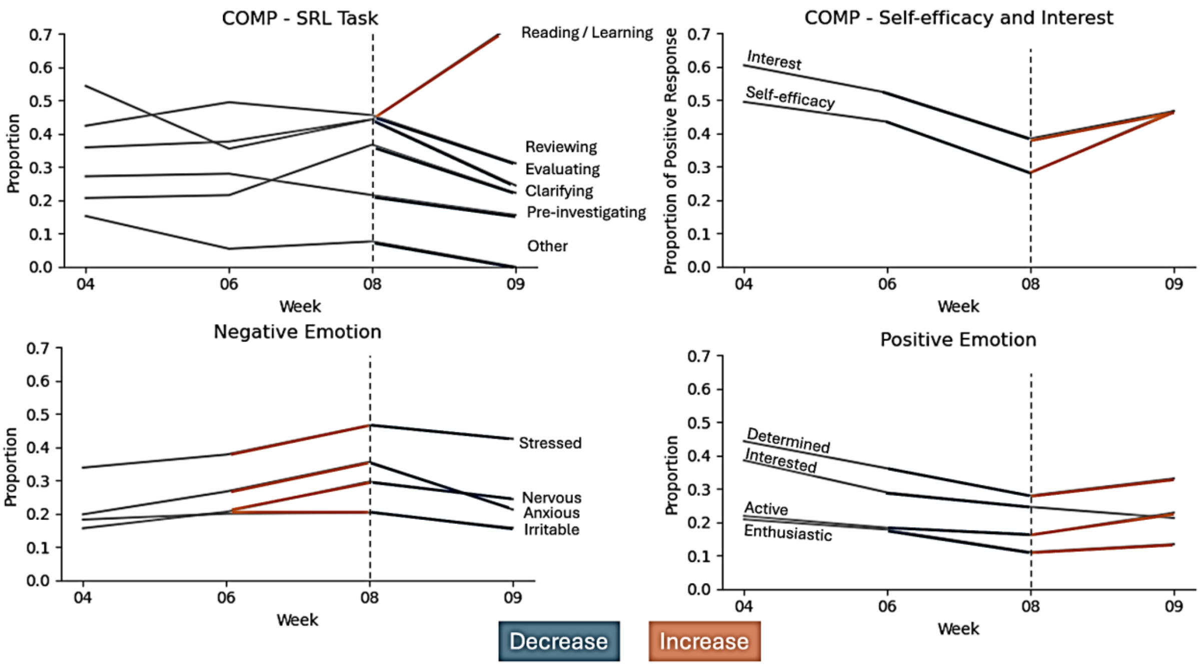
Table 1: The pre- and post-semester survey results on metacognitive knowledge (MAI_K), metacognitive regulation (MAI_R) and wellbeing, showing consistency at the individual level and systemic change at the population level.

Metric	Pre-semester median	Post-semester median	R-Squared (individual consistency)	Paired t-test result (population-level change)
MAI_K	3.50	3.12	0.73 (High)	t(51) = 3.71, p = 0.0005 (significant decrease)
MAI_R	3.27	3.27	0.49 (Moderate)	t(51) = 0.43, p = 0.67 (no significant change)
Wellbeing	20.70	19.30	0.59 (Moderate)	t(51) = 2.76, p = 0.0081 (significant decrease)

RQ2: Week-by-week fluctuations of SRL

To answer RQ2, we illustrate in Figure 1 the week-by-week fluctuations of students' SRL tasks, self-efficacy, and interest in COMP, along with their overall emotional states. Notably, the COMP subject had a major project deadline in Week 8, which is clearly reflected in the survey responses for Weeks 8 and 9.

Figure 1: Week-by-week aggregated daily survey results for student SRL tasks, self-efficacy, and interest in the computing subject, alongside longitudinal emotional fluctuations. The vertical marker indicates the major project deadline in Week 8.



Regarding the SRL tasks performed, students showed a marked increase in reading and acquiring new information in Week 9, accompanied by a decline in tasks involving planning or reviewing. This shift likely occurs because the Week 8 project required a holistic approach—incorporating reviewing, evaluating, and clarifying—to apply existing knowledge. Once the deadline passed, the students' cognitive focus shifted towards processing new material.

Beyond the SRL tasks themselves, students reported decreased interest, self-efficacy, and emotional wellbeing (i.e., positive and negative emotions) immediately prior to the deadline. Notably, most of these affective metrics naturally recovered following the assessment.

These findings suggest that the impact of the academic schedule and subject workload is holistic, extending beyond specific SRL processes to influence the learner's internal motivational states and affective responses. While this temporal impact is evident across the overall cohort, it is important to acknowledge that each student possesses a unique SRL aptitude and wellbeing baseline (as established in RQ1). Consequently, individuals might respond to academic stress in highly diverse ways. This intersection of personal baselines and temporal academic demands highlights the need for personalised, context-aware GenAI support.

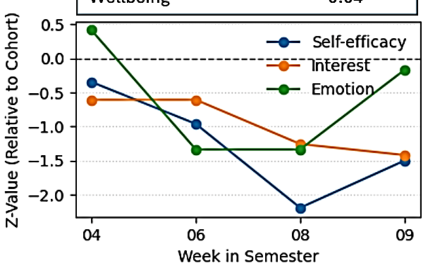
Proof-of-concept demonstration: Identifying directions for SRL support using GenAI

Given that SRL is both temporal and personalised, we adopted a hybrid approach: separating the formal measurement of SRL from the GenAI's interpretation. We provided an LLM (*Gemini 3*) with each student's specific, psychometrically-validated baseline results, their week-by-week fluctuations, and the academic context of the Week 8 assessment. We then prompted the model not to diagnose the student from scratch, but to translate these formal metrics into three adaptive scaffolding directions designed to support students' SRL in Week 9. Two researchers involved in this research subsequently evaluated the quality of the LLM's output. For demonstration purposes, we selected two students; their survey results are shown in the left panel of Figure 2, with the corresponding summarised LLM output in the right panel.

Figure 2: Individual survey results and corresponding GenAI-generated support directions for two example students: Student 1 and Student 2.

Student 1 - Survey Result

Pre-semester survey	Z-score
MAI_K	-1.25
MAI_R	0.23
Wellbeing	-0.04

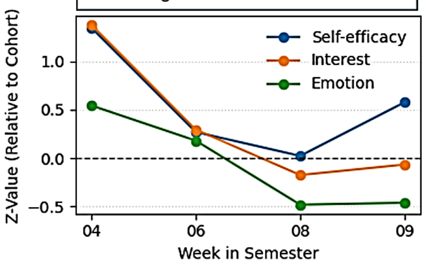


GenAI Directions for Week 9 Support

1. *Strategy selection*: help students to distinguish different strategies to address the deficit in metacognitive knowledge
2. *Interest intervention*: re-establish the utility of the content to stop the continuous decline in interest.
3. *Self-efficacy calibration*: focus on small, attainable mastery experiences in Week 9 to support the slow recovery of their confidence.

Student 2 - Survey Result

Pre-semester survey	Z-score
MAI_K	1.14
MAI_R	1.58
Wellbeing	0.95



1. *Interest intervention*: reconnect the academic content with personal values
2. *Strategic management*: leverage high regulation skills to pace effort
3. *Value-focused reflection*: shift the metacognitive focus from task completion to personal utility to combat emotional fatigue

Student 1 demonstrated a metacognitive knowledge score more than one standard deviation below the mean in the pre-semester survey. The LLM identified this as a primary issue and proposed targeted interventions to assist the student in identifying and adopting efficient learning strategies. Additionally, the LLM highlighted the need to foster student interest and to use small, attainable milestones to progressively rebuild the student’s self-efficacy. These directions emphasise foundational SRL skill building.

In contrast, Student 2 reported significantly higher metacognitive knowledge and regulation compared to the cohort average in the pre-semester survey. However, they showed a substantial decline in self-efficacy, interest, and emotion prior to the assessment deadline. Recognising this temporal shift, the LLM proposed leveraging the student's existing metacognitive skills to aid their post-assessment recovery. Rather than providing fundamental guidance on learning strategies as seen for Student 1, the AI focused on supporting Student 2’s post-assessment recovery through pacing effort and re-boosting interest and emotion.

Upon reviewing the LLM output for all eligible participants, the researchers considered the suggested directions to be appropriate, pedagogically sound, and successfully calibrated to the learners' specific contexts.

Discussion

By capturing the dynamic properties of students’ SRL across a 12-week study period, this research highlights that GenAI SRL support systems need to be deeply anchored in students’ personal and temporal realities.

Our findings confirm that while students’ self-regulation baselines exhibit a high degree of relative stability—aligning with aptitude-based conceptualisations of SRL as a stable trait (Broadbent & de Barba, 2023)—students’ actual reported metacognitive and emotional states undergo a systemic decline over the semester. This holistic, temporal fluctuation in response to assessment schedules corroborates existing longitudinal research (Higgins et al., 2023).

Together, the dual properties of SRL—both as a stable aptitude and as a dynamic state—present critical implications for how educators and institutions deploy GenAI. Educational AI systems claiming personalisation based solely on baseline aptitude remain blind to shifting academic calendars and fluctuating internal states. This rigid “one-time-fits-all" approach risks miscalibration, over-assisting during productive struggle or under-assisting during deadline-induced downturns. Instead, pedagogical integrations of GenAI must be temporally mapped to the curriculum to ensure support is responsive to the student's evolving journey.

Although this study adopted a weekly granularity because cohort-level SRL fluctuations were more pronounced week-by-week across the semester than day-to-day, the selection of a temporal unit should ultimately depend on the specific research context. For example, daily or more granular analysis may be more appropriate for intensive, short-term learning environments where rapid systemic shifts in SRL are expected. By aligning GenAI prompts with the academic calendar, educators can design scaffolds that shift their pedagogical focus; for example, prioritising foundational planning and goal-setting during early-semester phases, before pivoting to emotional regulation and reflection immediately following high-stress assessments (such as a Week 8 project). Such a context-aware approach ensures that AI-driven support is tuned to both the learner’s baseline and the shifting temporal demands of the unit.

Our proof-of-concept demonstrates the value of a hybrid intelligence approach (Cukurova, 2025). Deliberately separating the formal measurement of SRL from the LLM’s pedagogical interpretation ensures that measurement remains theory-based and reliable. By passing students’ calculated internal states and academic schedules to the GenAI, the model interprets these dynamics to make students' evolving needs visible, scaffolding their cognitive and metacognitive processes. This addresses emerging tensions between technological assistance and the cognitive effort necessary for meaningful learning. Ultimately, this approach leverages the AI not to diagnose, but to translate our validated metrics into actionable communication, tailoring support for either long-term strategy development or immediate motivational regulation. This points to a broader research agenda examining how GenAI operationalises learner profiles into pedagogical support, and the extent to which such outputs are evidence-based, interpretable, and ethically accountable, as opposed to opaque black-box interventions.

Conclusion

To find the balance between technological assistance and student effort, the pedagogical integration of GenAI must move beyond static applications to become personalised, temporal, and context-aware. Our longitudinal tracking demonstrates that while students' baseline SRL traits remain stable, their metacognitive and emotional states fluctuate continuously with academic demands. To prevent GenAI from acting as an autopilot that induces cognitive offloading, we present a proof-of-concept grounded in hybrid intelligence. By measuring students' internal states in a research-informed, temporal manner, and utilising GenAI for interpretation and support, educators can deploy GenAI as an adaptive learning partner. This approach provides calibrated scaffolding that supports the learner's dynamic journey while preserving the effort required for independent learning.

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References

Boekaerts, M., & Cascallar, E. (2006). How far have we moved toward the integration of theory and practice in self-regulation? *Educational Psychology Review*, *18*(3), 199–210. https://doi.org/10.1007/s10648-006-9013-4

Broadbent, J., & de Barba, P. (2023). Self-regulated learning and the student experience in online higher education. In C. Baik & E. R. Kahu (Eds.), *Research handbook on the student experience in higher education* (pp. 179–190). Edward Elgar Publishing. https://doi.org/10.4337/9781802204193.00021

Cukurova, M. (2025). The interplay of learning, analytics and artificial intelligence in education: A vision for hybrid intelligence. *British Journal of Educational Technology*, *56*(2), 469–488. https://doi.org/10.1111/bjet.13514

Davis, S. K., & Hadwin, A. F. (2021). Exploring differences in psychological well-being and self-regulated learning in university student success. *Frontline Learning Research*, *9*(1), 30–43. https://doi.org/10.14786/flr.v9i1.581

Harrison, G. M., & Vallin, L. M. (2018). Evaluating the metacognitive awareness inventory using empirical factor-structure evidence. *Metacognition and Learning*, *13*(1), 15–38. https://doi.org/10.1007/s11409-017-9176-z

Higgins, N. L., Rathner, J. A., & Frankland, S. (2023). Development of self-regulated learning: A longitudinal study on academic performance in undergraduate science. *Research in Science & Technological Education*, *41*(4), 1242–1266. https://doi.org/10.1080/02635143.2021.1997978

Li, T., Nath, D., Cheng, Y., Fan, Y., Li, X., Raković, M., Khosravi, H., Swiecki, Z., Tsai, Y.-S., & Gašević, D. (2025). Turning real-time analytics into adaptive scaffolds for self-regulated learning using generative artificial intelligence. *Proceedings of the 15th International Learning Analytics and Knowledge Conference*, 667–679. https://doi.org/10.1145/3706468.3706559

Pan, M., Lai, C., & Guo, K. (2025). Effects of GenAI-empowered interactive support on university EFL students' self-regulated strategy use and engagement in reading. *The Internet and Higher Education*, *65*, 100991. https://doi.org/10.1016/j.iheduc.2024.100991

Pardo, A., Gasevic, D., Jovanovic, J., Dawson, S., & Mirriahi, N. (2019). Exploring student interactions with preparation activities in a flipped classroom experience. *IEEE Transactions on Learning Technologies*, *12*(3), 333–346. https://doi.org/10.1109/TLT.2018.2858790

Pekrun, R., Goetz, T., Titz, W., & Perry, R. P. (2002). Academic emotions in students' self-regulated learning and achievement: A program of qualitative and quantitative research. *Educational Psychologist*, *37*(2), 91–105. https://doi.org/10.1207/S15326985EP3702_4

Song, Y., Oliveira, E., de Barba, P., Kirley, M., & Thompson, P. (2025). Investigating validity and generalisability in trace-based measurement of self-regulated learning: A multidisciplinary study. *Proceedings of the 15th Learning Analytics and Knowledge Conference*. https://doi.org/10.1145/3706468.3706511

Tennant, R., Hiller, L., Fishwick, R., Platt, S., Joseph, S., Weich, S., Parkinson, J., Secker, J., & Stewart-Brown, S. (2007). The Warwick-Edinburgh Mental Well-being Scale (WEMWBS): Development and UK validation. *Health and Quality of Life Outcomes*, *5*(1), 63. https://doi.org/10.1186/1477-7525-5-63

Winne, P., & Hadwin, A. (1998). Studying as self-regulated learning. In D. Hacker, J. Dunlosky, & A. Graesser (Eds.), *Metacognition in educational theory and practice.* (pp. 277–304). Taylor & Francis.

Xia, Q., Liu, Q., Tlili, A., & Chiu, T. K. F. (2026). A systematic literature review on designing self-regulated learning using generative artificial intelligence and its future research directions. *Computers & Education*, *240*, 105465. https://doi.org/10.1016/j.compedu.2025.105465

Appendix: Daily survey used in the study

Daily experience survey

LMS Access

Have you had study sessions in the LMS over the past 24 hours? (excluding access for scheduled classes)

Yes / No (Note: Selecting 'No' terminates the survey)

Affective Emotion

How have you been feeling over the past 24 hours? (Select all that apply)

Interested / Enthusiastic / Determined / Active / Anxious / Nervous / Irritable / Stressed

Subject Selection

What subject(s) have you worked on in the Canvas LMS over the past 24 hours? (Select all that apply)

[Dynamic checklist populated by the student's subject enrolment]

Subject-specific survey

[The following items are repeated dynamically for each subject selected in the preceding question. In this paper, we use students' answers for the subject COMP.]

SRL Task

What activities did you do for the subject [Subject Name] in the Canvas LMS over the past 24 hours? (Select all that apply)

Investigating what I need to do/learn before beginning a task/subject

Reviewing contents/topics to understand the relationship between them

Evaluating what I have done/learnt so far

Clarifying a misunderstanding

Reading/making sense of new material

Other (Open-ended text entry)

Interest and Self-Efficacy

Please rate your level of agreement with the following statements regarding your activities for [Subject Name] over the past 24 hours:

I was very interested in this activity / these activities.

Not at all / A little / Moderately / Quite a bit / Extremely

I was confident in my ability to successfully complete this activity / these activities.

Not at all / A little / Moderately / Quite a bit / Extremely