Examining Student Learning Engagement in Canvas to Support Personalized Learning

Zhaowei Zhang
Department of Educational and Psychological Studies
University of South Florida
Tampa, USA
zhaowei@usf.edu

Bo Pei
Department of Educational and Psychological Studies
University of South Florida
Tampa, USA
bpei@usf.edu

James Hatten
Department of Educational and Psychological Studies
University of South Florida
Tampa, USA
jameshatten@usf.edu

Zhiting Zhou
Department of Computer Science
Vanderbilt University
Nashville, USA
zhiting.zhou@Vanderbilt.Edu

***Abstract*—This research category full paper explores the dynamic associations between learning engagement and learning outcomes in an asynchronous computing course. Learning engagement acts as an essential mediator between learning contexts and learning outcomes, providing significant insights into instructional strategies and student success. In this study, we first conceptualized and quantified student learning engagement with a multifaceted framework from behavioral, academic, cognitive, and affective aspects. Then, we examined the temporal dynamics of students' learning engagement using the state space model, and further evaluated its associations with students' weekly learning outcomes. The analytical results of this research provided significant implications for supporting learning and teaching in a large-scale asynchronous computing course.**

Keywords—Learning Analytics, Learning Engagement, State Space Model, Computing Education

I. Introduction

Learning engagement plays a vital role in academic outcomes [1], [2], [3]. This is particularly true for asynchronous learning settings in the wake of the COVID-19 pandemic when students are expected to engage with academic work at a self-directed pace and the degree of their engagement profoundly influences learning outcomes [4], [5]. A comprehensive understanding of the associations between learning engagement and outcomes in online settings supports instructors in providing targeted interventions and personalized learning experiences, thereby further enhancing students' online learning outcomes [6], [7].

Currently, a number of studies have utilized learning data from Learning Management Systems (LMS) to investigate online learning engagement with the goal of optimizing learning outcomes [7], [8], [9]. For instance, [5] highlighted metrics such as LMS log frequency, assessment data, and student-produced artifacts that can be used to explore the associations between online engagement and learning outcomes. [7] identified the frequency of logins and the times of assignment submissions as key indicators of engagement levels and further employed the k-means clustering algorithm to group students with twelve engagement metrics. [8] detailed several analytical methods commonly used to assess learning engagement levels and highlighted the critical roles of cluster and factor analysis technologies. Furthermore, [9] developed engagement scores for an undergraduate online engineering course by leveraging data mining techniques to analyze students' temporal interaction patterns with course elements within the LMS.

Yet, these studies primarily focused on behavioral and academic engagement with easily accessible LMS log data, while overlooking the cognitive and affective dimensions that are always crucial to a comprehensive understanding of student engagement. Furthermore, there is a paucity of research examining the longitudinal trajectory of online engagement and its impact on learning outcomes from a holistic angle [10]. It is necessary to evaluate online learning engagement from a multifaceted perspective since the cognitive and affective dimensions could influence the manifestation of academic and behavioral engagement, thereby affecting the overall learning performances [11].

To address this gap, the current study employed a holistic framework quantifying students' learning engagement from behavioral, academic, cognitive, and affective dimensions, situated in an asynchronous undergraduate computing course within Canvas. LMS traces were collected and the state space model was employed to model learner engagement. By examining the temporal dynamics of learning engagement and its associations with weekly learning outcomes, the study revealed how certain learning behaviors could affect learning engagement and outcomes over time. The analytical results have the potential to provide insights for timely interventions in a fine-grained manner, supporting teaching and learning in a large-scale asynchronous computing course. Particularly, this study was guided by the following two research questions.

RQ1. How to quantify students' learning engagement in an asynchronous undergraduate computing course deployed within Canvas?

RQ2. How to provide personalized learning experiences based on the identified student learning engagement to enhance learning outcomes?

A. *How does students' learning engagement change throughout the course?*

B. How does students' learning engagement associate with their learning outcomes on a weekly basis*?*

II. Literature Review

A. Conceptualization and operationalization of student engagement

Conceptualizing and understanding student engagement has been a topic of significant interest in the field of education and learning research due to its strong association with academic achievement and student retention [1]. Previous research has explored various aspects of engagement, including behavioral, emotional, cognitive, and social dimensions [3]. Behavioral engagement refers to students' active participation and involvement in academic activities, such as attending classes, completing assignments, and participating in discussions. Emotional engagement encompasses students' affective reactions and feelings toward their learning experiences, including interest, boredom, happiness, or anxiety [4]. Cognitive engagement involves the investment of effort and self-regulation strategies employed by students in their learning process, such as utilizing deep learning strategies, metacognitive monitoring, and critical thinking [12].

In the context of online learning environments, engagement has been conceptualized and studied from various perspectives. Researchers have explored behavioral indicators of engagement, such as login frequencies, time spent on tasks, and participation in online discussions. Additionally, emotional engagement has been examined through measures of student satisfaction, perceived value, and sense of community. For instance, [13] examined predictors of student engagement and perceived learning in emergency online education during the COVID-19 pandemic from a Community of Inquiry (CoI) perspective. Cognitive engagement in online settings has been studied through the analysis of student-generated artifacts, such as written assignments, discussion board posts, and reflective journals [14]. For example, [15] employed the content analysis approach to analyze students' cognitive efforts in discussion posts based on ICAP framework using logistic regression. [16] employed discourse analyses to measure students' cognitive engagement with discussion forum posts through linguistic features such as analyzing narrativity, syntactic simplicity, and word concreteness using an exploratory modeling technique. However, these studies mainly investigated learning engagement from a single angle without exploring the multifaceted aspects encompassing behavioral, academic, cognitive, and emotional engagements.

B. Learning analytics in learning engagement and learning outcomes

Learning analytics (LA) has emerged as a powerful tool for understanding and enhancing student engagement and learning performance in digital learning environments. Various data sources have been explored to capture students' interactions, participation levels, and patterns of behavior. One prominent data source is the LMS, which records extensive logs of student activities.

Several studies have explored students' online engagement and learning performances within LMS with LA. For example, by using k-means algorithm to cluster students based on 12 engagement metrics and categorize them into interaction-related and effort-related groups, [7] pinpointed the number of LMS logins and average duration of assignment submissions as major indicators of student engagement level. [9] implemented a data mining approach using LMS interaction data to develop engagement scores for an online undergraduate engineering course. They scrutinized the engagement indicators of various course components, such as quizzes, assignments, and discussion forums, over a specified "analysis window length" of three days to trace and understand the temporal patterns of student interactions with these course elements. [10] highlighted the potential of analytics in identifying at-risk students early by monitoring their online behavior patterns of LMS logs for predictive assessments. [17] identified key indicators of engagement that correlate with academic success, which include time on task, frequency of LMS logins, and the number of posts in discussion forums.

C. LA in learning engagement and personalized learning in computing education

In addition to exploring the associations between learning engagement and learning outcomes within LMS, prior studies have also evaluated learning engagement within the context of personalized learning, specifically situated in the field of computing education with online programming courses. For instance, [8] quantitatively examined how students engage with online help-seeking activities through computer-mediated conversations such as Q&A forums and online office hours (OHQ) in an introductory programming course, facilitating the design of online resources to support students with the course at scale. [19] examined students' engagement with their LMS weekly usage data including the frequency of viewing course content, times of participating in discussions, and weekly quiz performances to explore the impact of personalized metacognitive feedback support on students' engagement with an online Computing II Course. [20] investigated how AI-enabled personalized recommendations influenced learning engagement among students with varying levels of motivation in a systems programming course. They quantitatively assessed students' learning engagement by tracking frequency-based indicators like the number of times watching videos, the number of videos watched, and the number of weekly posts to generate individual learners' LMS learning profiles.

While the approaches for quantitatively evaluating students' learning engagement within LMS have been extensively investigated in the previous studies, they primarily focused on behavioral and academic metrics from log data without considering the cognitive and affective aspects of learning engagement. Additionally, the temporal dynamics of learning engagement and its association with learning performance are also underexplored. To address this gap, this study undertakes the following analysis (1) quantifies learning engagement in a more comprehensive framework, (2) explores the longitudinal trajectory of student learning engagement over the semester, and (3) examines its association with learning outcomes.

III. Theoretical Framework

This study adopted Joksimović et al.'s (2018) theoretical model of online engagement and tailored it to our context investigating students' learning engagement in a computing course offered via Canvas. This multifaceted model categorized online learning engagement into behavioral, academic, cognitive, and affective dimensions. With the technologies of the learning analytics, the original goal of the model was to explain students' learning process by considering the associations between contextual factors, student engagement, and academic outcomes within MOOCs.

Behavioral engagement refers to participation in academic and extracurricular activities, which is essential for achieving positive academic outcomes. Academic engagement is quantified through time and efforts dedicated to academic activities and tasks such as time spent on instructional materials and assignments. The cognitive and affective engagement draw on the analysis of student-generated artifacts in computer-mediated learning environments, such as contributions to discussion forums [21]. To this end, the quality of discourse manifested by linguistic indicators can be a proxy to examine students' cognitive efforts, while emotions, such as positive and negative expressions, can serve as a proxy to measure affective engagement [22]. Additionally, Hierarchical Modes of Cognitive Engagement (Interactive, Constructive, Active, and Passive, ICAP) are incorporated as a key metric for assessing students' cognitive engagement with discussion forums [23].

To align the framework with our research context, we implemented minor modifications considering the inherent attributes of Canvas system and the characteristics of the learning data. Instead of using linguistic indicators like narrativity and syntactic simplicity for assessing cognitive engagement, we examined the cognitive facets of linguistic features including expressions indicative of cognitive processes and emotional states to quantify students' cognitive and affective engagement through Natural Language Processing (NLP) techniques. This is because our course prioritizes hands-on computing skills over conceptual knowledge. This approach allows us to evaluate cognitive and psychological constructs that delve beyond the mere textual surface. [24], [25].

IV. Method

A. Research Context

The context for this study is an asynchronous computing course offered at a large public university within Canvas, involving 90 undergraduate students' real-time learning data. The students study a diverse range of academic subjects, including science and social science. There are 10 modules in this course, with each module being released weekly. Each module entails learning materials and various types of assignments. The former encompasses readings and videos that elucidate the key concepts of each module's topic; the latter involves quizzes, discussions, essays, and multimedia projects. Quizzes are distributed across each module and are graded automatically by the system. There are three discussions allocated to modules 1, 4, and 5 to foster students' comprehension of core concepts. Three essays are required in modules 3, 7, and 9 to enhance students' analytical and critical thinking abilities. Five multimedia projects are designed for modules 2, 4, 5, 7, and 8 which involve tasks such as creating posters, critically analyzing videos, making presentations, and designing websites. The projects intend to help students internalize and apply their knowledge to practice creatively. These assignments are graded based on their alignment with module content and the fulfillment of assignment criteria.

B. Data Collection

We extracted and analyzed data every week, aligning with the schedule of the instructor's releasing learning materials and students' submitting assignments for each module. The dataset was sourced in two ways. The click-stream data generated by Canvas was utilized to code and analyze the metrics indicative of students' behavioral and academic engagements (TABLE I). Students' weekly learning outcomes are indicated by their grades for each module's assignments. The degree of cognitive engagement and affective engagement of assignments was derived using large language models (LLMs).

Specifically, Linguistic Inquiry and Word Count (LIWC) was employed to evaluate students' cognitive engagement indicated by the score of cognitive processes, analytical skills, and authenticity (TABLE I). It was also used to evaluate affective engagement indicated by the score of positive tone and negative tone of the writing since certain syntactic structures and lexical choices can exemplify writers' cognitive and affective states in discourse [26], [27]. Specifically, analytical thinking is evaluated by the extent to which words reflect formal, logical, and hierarchical thinking. The use of intuitive and personal language is associated with a low score, while writing that employs academic language and logical reasoning scores high in analytical thinking skills. Authenticity relates to the writer's ability to internalize theoretical knowledge and connect concepts to their own experiences. The cognitive process is indicated by the overall coherence of the text and the use of logical connectives, such as "therefore" and "thus," to illustrate cause-and-effect relationships. To apply the tool into our context, we imported students essays into the LIWC tool (https://www.liwc.app/) for automatic scoring and then manually reviewed each score and made adjustments where necessary. For the multimedia assignments, we utilized supervised machine learning techniques to develop an AI model to generate scores for cognitive engagement, with predefined criteria such as the level of reflection of module key points and response to assignment requirements, scored on a scale from 1 (minimal engagement) to 3 (maximum engagement). Supervised ML has been widely applied to classify data into pre-defined categories based on text relevance and similarity [20]. For discussion, the level of cognitive engagement was analyzed based on Chi's (2009) ICAP taxonomy using the pre-trained AI model [28], [29]. The pre-defined criteria were established by the two domain experts based on the overarching course objective and specific goals of each module. Considering the uneven distribution of assignments to each module, students' weekly and final grades were calculated as the weighted sum of the scores: quiz 0.4, multimedia projects: 0.2, discussion 0.2, essays: 0.2.

C. Data Analysis

Ten candidate metrics were extracted and calculated to model students' online engagement (TABLE I).

To answer RQ1, we conceptualized learning engagement as the mediator between learning context and learning outcomes [11]. The learning context involves factors including students' interactions with the course materials through Canvas, topics and types of learning materials in each module, topics and requirements of module assignments, and dynamics of peer interaction.

To situate the framework to our research context, factor analysis was conducted to explore the latent variables associated with the proposed metrics using the Psych package in R. The variables showing factor loadings greater than 1 or did not load were excluded after an iterative process of identifying the factor structure. Parallel analysis was conducted to select the appropriate number of factors and generate a random dataset of the same dimension for data analysis. Considering the relative normality of our data, standardized coefficients were estimated using maximum likelihood [30]. This process enables the computation of a wide range of goodness of fit indices and confidence intervals as well as tests for the significance of factor loadings and correlations.

TABLE I. CANDIDATE METRICS FOR ENGAGEMENT MODELLING

	Dimensions of Engagement			
	Behavioral	***Academic***	***Cognitive***	***Affective***
Focus	Analysis of students behavioral efforts	Measuring students learning efforts	Evaluating how students are cognitively engaged with assignments	Identifying how students are affectively engaged with assignment s
Metrics	Activities viewed Activities participated	Reading views Video views Assignment views Quiz vews	Cognitive process Analytical skills Authenticity	Positive tone Negative tone
Descrip tion	Diversity of activities students viewed Number of times that students participated in each activity	Number of times that students viewed each learning material	Evaluation of cognitive process, analytical skills, and authenticity of the assignments	Evaluation of emotional lexicon usage

To answer RQ2, we employed the state-space model (SSM) approach. This approach enables us to track the evolution of students' weekly engagement over the course of the semester, examine the complex interplay among the dynamic trajectory of each engagement type, identify factors influencing its temporal changes, and explore the dynamic associations between student engagement and learning outcomes on a weekly basis. SSM has been widely adopted to model state dependencies within time series data, capture the temporal dynamics across time steps in the series, quantify latent states from observed data, and forecast future states [31], [32].

Specifically, we used the State Equation to examine the temporal dynamics of students' engagement and the Output Equation to measure its effects on weekly learning outcomes.

To answer RQ 2.1, we considered the identified four dimensions of learning engagement (Cognitive, Affective, Behavioral, and Academic) as the state variable $\dot{x}$. The observed variables of students' learning behaviors, captured through the Canvas learning data, were defined as the input u. The State Equation can then be described as follows:

$$\dot{x}(t) = Ax(t) + Bu(t)$$

where x is the state vector representing the four dimensions of learning engagement at any given time t. $\dot{x}$ is the derivative of the state vector with respect to time, capturing how the levels of engagement evolve from one time step to the next. A is the state transition matrix which describes how the current state of engagement leads to its next state (In our research context, the next state refers to the corresponding engagement type in the subsequent week). The coefficients of the matrix represent the internal dynamics of the engagement dimensions, such as their growth rates and their influence on the change of other dimensions. B is the input matrix that determines how inputs (students' learning behaviors) affect the change of engagement.

To answer RQ 2.2, we considered students' weekly learning outcomes as the output variable $\boldsymbol{y}$. x is learning engagement and u is students' learning behaviors traced from Canvas. They were used to quantify how state variables (engagement) and input variables (observed learning behaviors) directly affected weekly learning outcomes. The Output Equation can then be described as follows:

$$y(t) = Cx(t) + Du(t)$$

where y represents the output vector corresponding to students' weekly grades. C is the output matrix that describes how different dimensions of engagement contribute to the observable outcomes (grades). D is the direct transmission matrix from inputs to outputs, indicating how students' learning behaviors independently affect the grades without mediation through the engagement states.

V. RESULTS

To answer RQ1, the analytical result suggests an 11-variable 4-factor model to be a moderate fit (TLI=0.93, RMSEA=0.08 with 90% CI: 0.05 - 0.09). TABLE II shows that the proposed model is applicable to the present context. Specifically, cognitive engagement (MR2) and affective engagement (MR3) are consistent with the proposed framework in that indicators like the authentic and cognitive process of students' assignments can be used to model cognitive engagement, and metrics like positive tone are highly associated with affective engagement.

TABLE II. FACTOR ANALYSIS STANDARDIZED LOADINGS

Metrics	Factor Loadings			
	MR1	***MR2***	***MR3***	***MR4***
Activities Participated	0.481			0.650
Activities Viewed	0.899	0.138	0.157	0.405
Reading Views	0.216	0.287		0.666
Video Views	0.549		0.490	0.312
Assignment Views	0.941			
Quiz Views	0.449			0.110
Cognitive Processes	0.121	0.563		
Analytical skills		-0.678	0.101	-0.159
Authenticit y		0.735	0.208	
Positive Tone			0.409	0.159
Negative Tone			-0.574	0.147

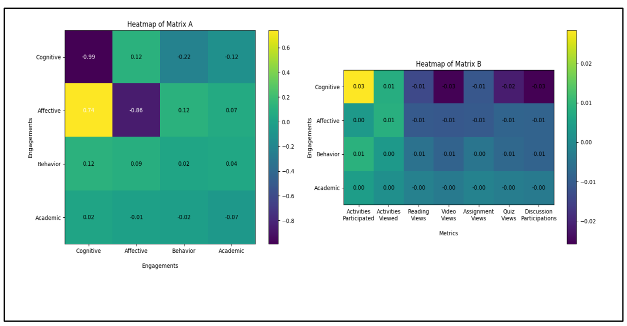

Fig. 1. Trajectory of Learning Engagement

(Matrix A: temporal dynamics of learning engagement, Matrix B: influence of learning behaviors on the trajectory of learning engagement)

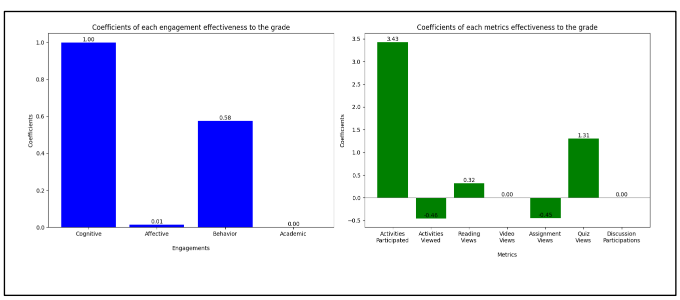

Fig. 2. Association of Learning Engagement with Weekly Learning Outcomes

In terms of RQ2, Fig. 1 shows how four dimensions evolve, interact, and influence each other over time. It can be found that students seem to consistently engage with the course in a behavioral manner. Activities participation positively contributes to the development of each engagement. Specifically,

Matrix A (state transition) presents how each dimension evolves and how they influence each other in a weekly manner. The diagonal elements (i.e., [−0.99, −0.86, 0.02, −0.07]) are particularly significant as they represent the internal decay or growth rates of each engagement type. Notably, cognitive, affective, and academic engagement show a negative decay, suggesting they diminish over time without external input or interventions. Conversely, the small positive value for behavioral engagement suggests a very slow intrinsic growth or maintenance over time. The off-diagonal elements indicate interactions between different types of engagement change. For example, a positive coefficient 0.74 from affective to cognitive engagement suggests that affective engagement largely boosts the development of cognitive engagement.

Matrix B (input influence) shows how different learning behaviors recorded in Canvas (metrics in this context) influence the dynamic trajectory of each engagement type. Each row of Matrix B corresponds to the influence of the seven metrics on individual engagement trends. Positive values suggest that the behavior positively affects the engagement change, while negative values mean the opposite. For example, 'Activities Participated' has a positive effect on all types of engagement, particularly on cognitive engagement (0.03), suggesting that participating in activities is crucial for enhancing the development of cognitive engagement over time. In contrast, metrics associated with content views ('Video Views', 'Assignment Views') tend to have negative coefficients, indicating that merely viewing materials without active participation may not be enough to maintain students' engagement with learning materials over time.

With regards to RQ 2.2, Fig. 2 shows that students' cognitive and behavioral engagement with the course strongly influences weekly learning outcomes. Their active participation in activities and viewing learning materials like quizzes and readings improve their learning outcomes.

The bar chart on the left quantitatively describes the influence of individual dimensions of engagement on students' weekly grades with 1.00, 0.01, 0.58, and 0.00 respectively.

The bar chart on the right reveals the direct effects of specific learning behaviors on weekly grades. Activities participated show the most significant positive impact, with a coefficient of 3.43, followed by quiz views at 1.31, and reading views at 0.32. Interestingly, video views and discussion participation showed negligible effects on learning outcomes.

VI. Discussion

The results indicate that the proposed framework is applicable to quantify learning engagement in our research context. Although the factor analysis showed a moderate fit, it is still consistent with the theorized quadripartite model in that it grouped the proposed metrics into four categories, which aligns with the four dimensions of learning engagement. For instance, MR3, which encompasses negative and positive tones, conceptually aligns with affective engagement. Likewise, MR2, composed of authenticity, analytic skills, and cognitive processes, aligns well with cognitive engagement. This result can be supported by the existing academic research that the artifacts produced by students in computer-mediated learning environments manifest their intellectual processing and understanding of the learning content [21], [33]. Therefore, the quality of the discourse can be perceived as the proxy for their cognitive engagement.

The decline observed in students' engagement with online courses over time is a common issue in undergraduate computing education [34], [35]. From our findings of how each engagement type interacts with one another, the changes in students' emotional attitudes towards their learning process strongly influence the cognitive engagement aspects such as the depth of cognitive processing and the assignment's relevance to the module topics. Similarly, affective engagement also positively interacts with behavioral and academic engagement. This observation aligns with the notion that changes in learners' cognitive and affective behaviors serve as precursors to their academic commitment and involvement in learning activities [18]. In other words, learners' cognitive and affective engagement mediate their behavioral and academic engagement.

With regard to the association between learning engagement and learning outcomes, it is not surprising to see that students' cognitive engagement such as intellectual efforts in their assignments strongly predicts their weekly performances. This is because the learning outcomes are indicated by weekly grades of assignments. Given the course objectives of our research context, a high level of intellectual effort in corresponding assignments is expected to correlate with better learning outcomes [36]. Additionally, behavior engagement not only positively influences the trajectory of all types of engagement but also is predictive of high learning performance.

Certain learning behaviors have been identified as the predictors of increased engagement and improved learning outcomes, such as active participation in learning activities, and frequent views of reading materials and quizzes. This insight is important since it provides instructors with actionable analytics on how to implement timely interventions tailored to individual students across various modules by leveraging activities that positively influence learning outcomes [37]. For example, to improve learning outcomes, instructors could encourage students to frequently engage with quizzes and reading materials. To maintain learning engagement, instructors could motivate students to actively participate in diverse learning activities, which includes timely responses to instructors' and graders' comments and feedback, as well as proactive posting of inquiries, rather than passively viewing materials. Additionally, more attention could be given to students' affective engagement such as encouraging students to express their thoughts and emotions in reflection papers alongside computing knowledge.

VII. Conclusion

The present study advances the research field of learning analytics in computing education from three aspects. Firstly, by adopting a multifaceted framework to model engagement as an indicator between learning context (an asynchronous computing course in Canvas) and outcomes (weekly grade), we investigated the temporal dynamics of students' learning engagement from a holistic perspective, behaviorally, academically, cognitively, and affectively. Secondly, we measured the effects of students' learning behaviors recorded in Canvas on the temporal change of their learning engagement throughout the semester. Thirdly, we explored how the longitudinal trajectory of learning engagement is associated with students' learning outcomes in a fine-grained manner.

In terms of the pedagogical practices, the study provides insights to educators and instructors about how to provide timely interventions and personalized learning experiences to enhance student's learning performances by 1) engaging students affectively to foster their cognitive engagement with the course over time, 2) encouraging active participation in course activities, 3) facilitating various interactions between students and instructors.

VIII. Limitations and Future Directions

The metrics we used to model cognitive and affective engagement in this study may not be comprehensive enough to capture students' cognitive processes and emotional states during the learning process. Future research could employ multimodal analytics to profile these dimensions in detail with tools such as eye-tracking and fMRI devices. Additionally, since the learning data used in this study to investigate learning engagement is specific to an asynchronous course delivered through Canvas, the results might not be universally applicable. Further studies can evaluate the generalizability of these findings across different settings in computing education, such as blended and in-person learning environments, as well as on different LMS, such as Blackboard and Moodle.

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