Students’ Cognitive Engagement in Blended Learning: Observations from Event-contingent Self-report and Log Data

Sabina Rako, Nina Begičević Ređep, Barbara Šlibar, Diana Šimić
University of Zagreb Faculty of Organization and Informatics
Pavlinska 2, 42000 Varaždin, Croatia
sabina.rako@student.foi.hr,{nina.begicevic,barbara.slibar,diana.simic}@foi.unizg.hr

Bart Rienties
Open University UK
Institute of Educational Technology
Walton Hall, Milton Keynes, UK
bart.rienties@open.ac.uk

Abstract. *Student engagement plays a crucial role in the learning process in higher education. This study aims to explore students’ cognitive engagement in a blended learning environment by combining data collected through event-contingent self-report and Learning Management System (LMS) log data. Participants were undergraduate students enrolled in a course on business decision making, specifically adapted for information technology students. Responses from 140 students revealed that students felt more actively involved during in-person learning, while concentration and focus levels were comparable between in-person and online modes. Polychoric correlation indicated a moderate positive relationship between concentration and passive-active items, whereas principal component analysis highlighted latent constructs. Analysis of LMS log data provided additional behavioral indicators, including time spent in the system, the number of distinct learning components accessed, and the type of activity performed (distinguishing between ’just view’ and ’more than view’ actions). Two distinct student profiles emerged from the combined dataset. This approach shows that combining self-reported and LMS log data provides a clearer picture of how students engage in blended learning.*

Keywords. cognitive engagement, self-reports, logs, higher education, decision making

1 Introduction

Blended learning, which combines classroom-based learning with online learning, is nowadays widely used in higher education (Vo et al., 2024). Blended learning offers flexibility and access to various learning resources, but keeping students consistently and meaningfully engaged is still a challenge (Bergdahl et al., 2024).

Tight (2020) argues, based on a comprehensive literature review, that research on student engagement in higher education has been largely driven by institutional efforts to improve student retention. A systematic literature review and meta-analysis of 137 studies published between 2003 and 2019, involving 158,510 students, by Wong et al. (2024) found that student engagement has a strong correlation with academic achievement and subjective well-being, but also emphasized that the construct of engagement is often overgeneralized in current research. While this meta-analysis (Wong et al., 2024) focused on elementary, middle, and high school education, engagement is also a widely discussed construct in the context of higher education (Lowe & El Hakim, 2020; T. D. Nguyen et al., 2018; Prananto et al., 2025; Tani et al., 2021).

Advances in educational technology and the widespread adoption of Learning Management Systems (LMS) in higher education have enabled the collection of detailed data on student interactions (Henrie et al., 2015; Ifenthaler & Yau, 2020). Furthermore, an analysis of studies using Learning Analytics (LA) published between 2011 and 2023 shows that student engagement in higher education is still predominantly measured through observable behaviors like clicks and time on task (Bergdahl et al., 2024). A deeper understanding of student engagement in higher education, supported by LA, could also improve learning design and provide more effective support for students (Q. Nguyen et al., 2022). Additionally, combining system data with self-reports, such as surveys or reflections collected shortly during or after the learning activity, could provide a more complete picture by capturing both actions and experiences, thereby contributing to Human-Centered Data Science (Aragon et al., 2022).

The variety of learning activities and the combination of in-person and online modes in blended learning create challenges for sustaining cognitive engagement (Halverson & Graham, 2019). Understanding variations in engagement is key to designing effective blended learning. Therefore, this study is driven by the following research questions:

- RQ1: In what ways does students' event-contingent self-reported cognitive engagement differ across learning modes (in-person and online) and activities in a blended learning environment?
- RQ2: How can LMS event logs help to explain or add to self-reported data about students' cognitive engagement in online learning?

To answer these questions, we collected and synchronized survey data based on a questionnaire grounded in the Experience Sampling Method (ESM) with LMS log data over a 22-day period in a higher education course, and then analyzed it. By integrating subjective and objective data sources (Tempelaar et al., 2020), this study contributes to a more granular understanding of cognitive engagement in higher education and blended learning environment.

2 Related Work

Skinner and Pitzer (2012) conceptualized the widely accepted model of engagement "grounded in self-determination theory, and organized around student engagement and disaffection with learning activities". In that model engagement is examined through three dimensions: behavioral, emotional, and cognitive. The behavioral aspect of engagement involves students' effort, persistence, and determination, especially when facing challenges. Emotional engagement refers to positive feelings such as enthusiasm, enjoyment, fun, and satisfaction, while cognitive engagement "encompasses attention, concentration, focus, absorption, “heads-on” participation, and a willingness to go beyond what is required "(Skinner & Pitzer, 2012).

Blended learning is considered to provide possibility for students to engage more in learning, and Halverson and Graham (2019) have recognized three main challenges regarding engagement in blended learning: (a) the concept of engagement is unclear, (b) blended learning is defined in many different ways, and (c) there is frequent confusion between indicators and facilitators of engagement. They proposed a conceptual framework that consists of indicators of cognitive and emotional engagement and takes into account the dynamics of learning in a blended learning environment.

Another frequently discussed aspect of engagement research is how it is measured. Ortega and Irala (2022) have reviewed various instruments that have been developed to assess student engagement in higher education. Concerning specifically cognitive engagement, Li (2022) provided an overview of various measurement methods of cognitive engagement such as self-report scales, observations, interviews, teacher ratings, experience sampling, eye-tracking, physiological sensors, trace analysis, and content analysis, as well as a summary of the advantages and disadvantages of each approach. The overview (Li, 2022) highlighted ESM as innovative method that measures students' cognitive engagement by asking them to report their thoughts during or closely after learning activities. Although it gives more accurate and timely data than traditional surveys, it can interrupt students, take time, and only allows short questionnaires.

3 Methodology

3.1 Setting and context

The participants in this study were first-year students enrolled in a university-level course, as part of an undergraduate study program conducted in Croatian language at the University of Zagreb. The topic of the course was related to business decision making adapted for information technology students. The course consists of 60 hours, divided equally between lectures (30 hours) and practice-oriented seminars (30 hours). Learning activities include both synchronous and asynchronous components and are supported through the e-course hosted on the institutional LMS.

After each learning activity, students were invited to complete a brief questionnaire. Participation was voluntary, and informed consent was obtained prior to questionnaire completion. Students could submit the questionnaire multiple times if they participated in multiple activities.

In the questionnaire, students were asked to specify the mode of learning (online or in-person), identify the learning activity they had participated in, and indicate the date on which the activity took place. The predefined learning activity options were:

- *lecture*
- *practice-oriented seminar*
- *interaction with colleagues* (e.g., student presentation, discussion, group work, collaborative project)
- *interaction with content* (e.g., reading course materials, reading articles, watching video content)
- *active learning* (e.g., taking knowledge tests, studying for assessment, working independently on a project)
- *other*.

The period for completing self-reports lasted from 7 April 2025 to 28 April 2025. Only complete responses were included in the final analysis, comprising 163 submissions from 140 unique students. After they participated in separate learning activities, responses were submitted twice by 23 students. The course had a total enrollment of 264 students.

3.2 Cognitive engagement

Cognitive engagement was measured using an adapted version of the ESM survey instrument previously validated in blended learning environment (Manwaring et al., 2017). Linguistic validation of the instrument was carried out in accordance with guidelines for the process of cross-cultural adaptation of self-report measures (Beaton et al., 2000). The survey was submitted for translation to two translators. One translator was familiar with concepts in the field of e-learning and has been a researcher in the area of digital education for over 15 years. Second translator was a professional translator with no prior knowledge of the concepts mentioned in the questionnaire (a translator from a company providing translation service). The translators were asked to include comments during the translation process in case of any ambiguities or additional suggestions.

After receiving the translations, one of authors of this paper, and subsequently a Croatian language proofreader, prepared a proofread version. Based on the proofread version, a back translation into the original language was conducted to verify the accuracy of the translation. The back translations were independently carried out by two certified translators.

Before implementing of the survey instrument, the final version of the questions were selected and additionally reviewed by two authors of this paper. The survey was implemented using LimeSurvey survey software (LimeSurvey Project Team / C. Schmitz, 2024).

The final instrument, translated and adapted from the EMS survey (Manwaring et al., 2017), included the following items:

- learning activity
- date when learning activity occurred
- learning mode
- three items about cognitive engagement:
  - *concentration*
    "How well were you concentrating?"
    (5-point scale, 1 = not at all to 5 = very much)
  - *passive to active*
    "Your involvement in the learning activity:"
    (7-point bi-modal scale)
  - *focused to distracted*
    "Your involvement in the learning activity:"
    (7-point bi-modal scale, opposite-worded).

In addition, supplementary data were collected by the survey software, including the date and time when the questionnaire was completed and the time spent completing it.

Students were asked to complete the self-report either at their own convenience, during lectures, or in practice-oriented seminars. At the beginning of the self-report, there was an introductory note: "People learn in different ways and in different places. Please choose a learning activity you have engaged in recently (or just completed) and fill out this short questionnaire. You can submit reflections for more than one learning activity.".

To ensure comparability, 5- and 7-point scales were rescaled to a 0–100 scale prior to analysis. The oppositely worded item (*focused-distracted*) was reverse-coded (*distracted-focused* to align with the direction of other items.

3.3 Event log data

For each participant who reported an online activity on a specified date, corresponding log data were extracted from the Moodle log data, including: *datetime*, *event context*, *component*, *event name*, *description*, and *origin*. In total, extracted log data contained 707 records.

In the event logs dataset, the verb representing student activity was extracted from the *description* field. For example, in the entry: "The user with id 'X' has submitted the submission with id 'Y' for the assignment with course module id 'Z'," the verb "submitted" was extracted. Similarly, from the *description*: "The user with id 'X' viewed the 'quiz' activity with course module id 'Y',"the verb "viewed" was obtained. The *component* field indicates the type of module involved in each activity (e.g., Forum, Quiz, Assignment), while *datetime* contains date and time of event.

A new dataset was created by aggregating event logs dataset by student ID and date. For each student and date, variables *activity*, *componentCount*, and *timeframe* were created.

If the only action student engaged in during a date was the "view" action, *activity* was set to "just view". If the student performed additional actions such as "submitted", "created", "uploaded", "saved", "updated", or "started" an activity, the value "more than view" was used.

For each student and date, the total number of distinct modules on which actions were performed was counted and stored in the variable *componentCount*.

The time spent on LMS was estimated by calculating the difference between the earliest and the latest time of event recorded for the student and date. This value was stored in variable named *timeframe*. It is important to note that this is an approximation, as it does not account for multiple login sessions throughout the day. This limitation arises from the structure of Moodle LMS logging system (Rotelli and Monreale, 2023).

The aggregated event log data and students' responses were merged using a composite key consisting of the variables *IDStudent* and *LADate* (learning activity date). The resulting dataset contained variables *concentration*, *passive-active*, *distracted-focused*, *activity*, *componentCount*, and *timeframe*.

3.4 Data analysis

Descriptive statistics were used to provide an overview of student responses. To compare mean scores between online and in-person learning modes, Welch's t-test was applied due to its robustness to unequal variances.

For correlation analysis, original responses on the 5- and 7-point scales were used, with the distracted–focused item reversed. Relationships among ordinal items were examined using polychoric correlations, and underlying constructs were identified through Principal Component Analysis (PCA) on the polychoric correlation matrix. Polychoric correlation is generally preferred for PCA when variables are ordinal, as it more accurately captures the relationships between the underlying continuous latent variables (Choi et al., 2010; Holgado–Tello et al., 2010). PCA was conducted using the `principal()` function from the *psych* package in R. Components with eigenvalue grater than 1 were retained and submitted to varimax rotation.

K-means cluster analysis was performed to identify distinct student profiles.

The analysis was conducted using R statistical software (R Core Team, 2024) and RStudio (Posit team, 2025), using packages *psych* (Revelle, 2025), *tidyverse* (Wickham et al., 2019), and *ggplot2* (Wickham, 2016).

4 Results

In total, 163 responses were collected from 140 unique students (78% male, 22% female). The number of responses by learning mode and activity is presented in Table 1.

Table 1. Number of responses (n = 163) by reported learning mode and learning activity

Reported learning mode	Reported learning activity
in-person (n=129; 79%)	lecture (n=35)
	interaction with content (n=29)
	active learning (n=26)
	seminar (n=17)
	other (n=16)
	interaction with colleagues (n=6)
online (n=34; 21%)	interaction with content (n=20)
	lecture (n=7)
	active learning (n=5)
	seminar (n=1)
	interaction with colleagues (n=1)

In this study, an event-contingent self-report approach was employed, where students were asked to reflect on their learning activity as soon as possible after its completion. The majority of responses (68.71%) were submitted within 24 hours of the learning activity. On average, students spent 1 minute and 13 seconds completing the questionnaire.

Student responses were aggregated by calculating the mean score per item when multiple responses were available for a single student. As shown in Fig. 1, the majority of students reported positive responses (scores above 50) across all three items (*concentration*, *passive-active*, *distracted-focused*). The *concentration* item had the highest number of scores above 50, suggesting that students generally felt confident in their ability to concentrate. A notable number of students reported the midpoint score of 50, ranging from 31 students (22%) on the *passive-active* item to 46 students (33%) on the *concentration* item. In contrast, scores below 50 were reported by 32 students (23%) on the *passive-active* item and 27 students (19%) on the *distracted-focused* item.

Figure 1. Frequencies of responses from 140 students for each cognitive engagement item, with score 50 highlighted

4.1 RQ1: Cognitive engagement across learning modes and activities

4.1.1 Learning modes

In terms of RQ1, when comparing scores across learning modes (Table 2), students have expressed noticeably higher activity during in-person sessions compared to online (*passive-active* item). Furthermore, Welch's t-test revealed a statistically significant difference in *passive-active* scores between in-person ($\bar{x}_{\text{in-person}} = 63.0$, $s = 23.1$) and online ($\bar{x}_{\text{online}} = 49.1$, $s = 20.1$) learning modes, $t(58.3) = 3.48$, $p = .001$, 95% CI $[5.89, 21.9]$. This suggests that students may feel significantly more actively involved during in-person sessions.

In contrast, scores on the *distracted–focused* item appear consistent across both modes, indicating similar levels of focus regardless of delivery format. Likewise, there was no significant difference in concentration scores between in-person and online modes.

As presented in Table 3, polychoric correlations revealed a moderate positive association between *con-*

Table 2. Mean and standard deviation (mean ± SD) by learning mode

Item	in-person	online
concentration	68.0 (±22.8)	63.2 (±19.7)
passive-active	63.0 (±23.1)	49.1 (±20.1)
distracted-focused	60.1 (±24.0)	60.4 (±22.4)

centration and *passive-active* items (r = 0.43). A weaker positive association was observed between *concentration* and *distracted-focused* items (r = 0.30), as well as between *passive-active* and *distracted-focused* items (r = 0.23). These results suggest that the underlying latent construct measured by these items are positively related, with the strongest relationship observed between *concentration* and *passive-active* items.

Table 3. Polychoric correlation matrix

	con	*pass-act*	*dist-foc*
con	1.00		
pass-act	0.43	1.00	
dist-foc	0.30	0.23	1.00

Fig. 2 shows PCA loadings plot as a result of PCA performed on polychoric correlation matrix. It can be seen that two principal components were retained, together explaining 81.3% of the total variance (RC1: 46.9%; RC2: 34.4%). This result shows that student cognitive engagement in not a unidimensional concept and that *concentration* and *passive-active* load on a different component than *distracted-focused*.

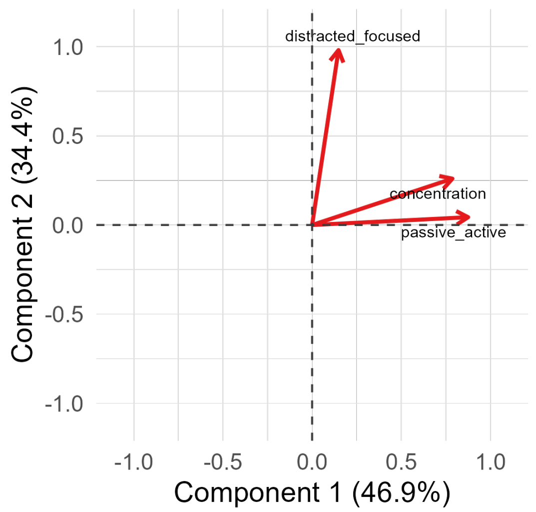

Figure 2. PCA loadings plot based on polychoric correlation matrix

4.1.2 Learning activities

Mean values and confidence intervals for various learning activities are displayed in the error bar plot (Fig. 3). "Interaction with content" (e.g., reading course materials, articles, or watching video content; n = 49) and "lecture" (n = 42) were perceived as the least engaging activities in terms of active involvement (*passive-active*). In contrast, "active learning" (e.g., taking knowledge tests, studying for assessment, working independently on a project, n = 31), was perceived as the most active learning activity. The highest mean concentration was reported for the "interaction with colleagues" activity, but this result is based on only 7 responses, which limits its comparability.

4.2 RQ2: Integration of event log data

Of the 34 reported online activities, 23 responses had corresponding LMS log data and those data were further processed and joined with self-report responses.

Two distinct student groups were identified through k-means cluster analysis (k = 2), as presented in Table 4. The optimal number of clusters was determined by inspecting the scree plot.

Table 4. Variables' means by cluster

Variable	Cluster 1	Cluster 2
activity	1.38	1.70
concentration	69.2	57.5
passive-active	51.2	38.4
distracted-focused	64.2	55.0
componentCount	3.00	4.10
timeframe	54.2	756.2

Cluster 1 represents students who are more cognitively engaged in their activities, but over a shorter period and with fewer components. Cluster 2 includes students with lower cognitive engagement, who participate in more activities and over a much longer timeframe. The distinction between the two clusters is further illustrated in the parallel coordinates plot (Fig. 4). Each line shows normalized variables for a single student. Cluster 1 is represented in black and cluster 2 in red.

5 Conclusions, limitations and future work

5.1 Conclusions

This study explored how students' self-reported cognitive engagement varies across different learning modes and activities in a blended learning environment (RQ1), and examined the extent to which LMS event logs can

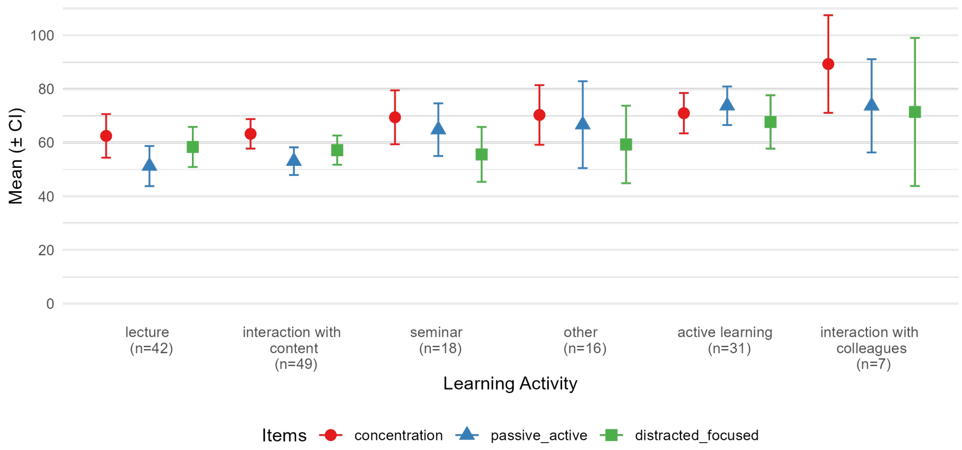

Figure 3. Mean and confidence interval (CI) by learning activity

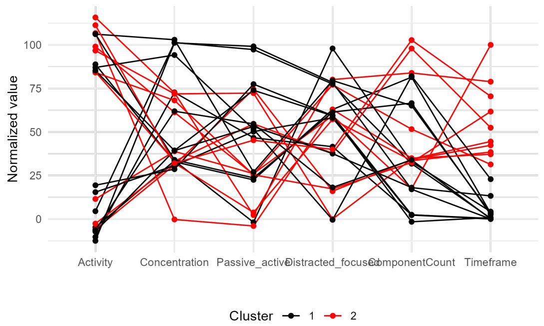

Figure 4. Parallel coordinates chart integrating self-report and event-log data by cluster (n=23)

complement and enrich self-reported cognitive engagement data in online learning settings (RQ2).

For RQ1, the results showed that students reported feeling more actively involved during in-person learning, while concentration and focus levels were similar across in-person and online modes. Among specific learning activities, "active learning" and "interaction with colleagues" were perceived as the most engaging, whereas "lectures" and "interaction with content" were rated lowest for active involvement. Previous studies have reported mixed results regarding levels of cognitive engagement in in-person and online activities (Huang et al., 2022; Manwaring et al., 2017). Our results also support findings that activities involving peer interaction positively influence cognitive engagement (Manwaring et al., 2017). In order to increase cognitive engagement instructional design in blended settings should offer content that requires active interaction.

For RQ2, integrating LMS log data with self-reports provided additional insights into student behavioral engagement. The combined data revealed two distinct student profiles: one group demonstrated higher cognitive engagement over shorter periods and with fewer learning components, while the other showed lower cognitive engagement but participated in more activities over a longer timeframe. This approach highlighted the value of merging behavioral log data with self-reported measures to capture a more comprehensive picture of student engagement in blended learning environments.

5.2 Limitations

The study primarily relied on one-time measurements of cognitive engagement. Although it adopted certain principles of ESM, data were mostly collected at a single time point. Consequently, the design does not support within-person or longitudinal analyses, limiting the findings to between-person comparisons.

Some bias may stem from the measurement instrument used to assess cognitive engagement. To address this, the instrument was translated using a standardized linguistic validation procedure. Another limitation of this study concerns the reliability of single-item measures. While such measures help reduce participant burden in experience sampling, they raise concerns about measurement accuracy. To address this, Dejonckheere et al. (2022) proposed two time-varying test–retest methods to estimate the measurement error of single-item assessments. In this study, the issue of reliability was only partially addressed.

The limited number of responses related to online learning, and consequently fewer LMS log data entries, may have contributed to the lack of observed differences between learning mode and learning activities. Although the number of responses was limited, the approach presented demonstrates the potential for combining self-reported data with LMS log data to capture complementary insights into learner engagement that would be difficult to obtain from a single data source alone.

5.3 Future work

Collecting data as close as possible to the learning activity offers new possibilities for capturing authentic and timely reflections. To enable longitudinal analysis, in future research self-reported data should be collected repeatedly over time, providing opportunities to explore inter-personal patterns and relationships. ESM offers a strong methodological foundation for this approach. Additionally, integrating event log data from various learning support systems could give deeper insights into learner behavior. Recently, Xie et al. (2024) have proposed framework of engagement where they mapped ESM methodologies, technologies, and statistical approaches to capture the characteristics of engagement in educational research. Another, more practical approach was published by Revol et al. (2024) on prepossessing of ESM data. Using these frameworks and tools could improve future studies.

Future research should also tackle Artificial Intelligence (AI) technologies. As identified by A. Nguyen et al. (2024), the use of AI tools in higher education may present new challenge for student engagement, particularly in terms of motivation, autonomy, and meaningful interaction with learning content. These emerging issues and their influence on engagement dimensions should be carefully examined and addressed in future work, highlighting the need for further theoretical conceptualization of engagement in blended learning environment.

Acknowledgments

The authors would like to thank Professor Nikola Kadoić for his support throughout this research.

References

Aragon, C. R., Guha, S., Kogan, M., Muller, M., & Neff, G. (2022). *Human-centered data science: An introduction*. The MIT Press.

Beaton, D. E., Bombardier, C., Guillemin, F., & Ferraz, M. B. (2000). Guidelines for the Process of Cross-Cultural Adaptation of Self-Report Measures: *Spine*, *25*(24), 3186–3191. https://doi.org/10.1097/00007632-200012150-00014

Bergdahl, N., Bond, M., Sjöberg, J., Dougherty, M., & Oxley, E. (2024). Unpacking student engagement in higher education learning analytics: A systematic review. *International Journal of Educational Technology in Higher Education*, *21*(1), 63. https://doi.org/10.1186/s41239-024-00493-y

Choi, J., Peters, M., & Mueller, R. O. (2010). Correlational analysis of ordinal data: From Pearson's r to Bayesian polychoric correlation. *Asia Pacific Education Review*, *11*(4), 459–466. https://doi.org/10.1007/s12564-010-9096-y

Dejonckheere, E., Demeyer, F., Geusens, B., Piot, M., Tuerlinckx, F., Verdonck, S., & Mestdagh, M. (2022). Assessing the reliability of single-item momentary affective measurements in experience sampling. *Psychological assessment*, *34*(12), 1138–1154. https://doi.org/10.1037/pas0001178

Halverson, L. R., & Graham, C. R. (2019). Learner Engagement in Blended Learning Environments: A Conceptual Framework. *Online Learning*, *23*(2). https://doi.org/10.24059/olj.v23i2.1481

Henrie, C. R., Halverson, L. R., & Graham, C. R. (2015). Measuring student engagement in technology-mediated learning: A review. *Computers & Education*, *90*, 36–53. https://doi.org/https://doi.org/10.1016/j.compedu.2015.09.005

Holgado–Tello, F. P., Chacón–Moscoso, S., Barbero–García, I., & Vila–Abad, E. (2010). Polychoric versus Pearson correlations in exploratory and confirmatory factor analysis of ordinal variables. *Quality & Quantity*, *44*(1), 153–166. https://doi.org/10.1007/s11135-008-9190-y

Huang, M., Kuang, F., & Ling, Y. (2022). EFL learners' engagement in different activities of blended learning environment. *Asian-Pacific Journal of Second and Foreign Language Education*, *7*(1), 9. https://doi.org/10.1186/s40862-022-00136-7

Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development*, *68*(4), 1961–1990. https://doi.org/10.1007/s11423-020-09788-z

Li, S. (2022). Measuring cognitive engagement: An overview of measurement instruments and techniques. *International Journal of Psychology and Educational Studies*, *8*(3), 63–76. https://doi.org/10.52380/ijpes.2021.8.3.239

LimeSurvey Project Team / C. Schmitz. (2024). *Limesurvey: An open source survey tool*. LimeSurvey Project. Hamburg, Germany. https://www.limesurvey.org

Lowe, T., & El Hakim, Y. (2020). *A handbook for student engagement in higher education: Theory into practice*. https://doi.org/10.4324/9780429023033

Manwaring, K. C., Larsen, R., Graham, C. R., Henrie, C. R., & Halverson, L. R. (2017). Investigating student engagement in blended learning settings using experience sampling and structural equation modeling. *The Internet and Higher Education*, *35*, 21–33. https://doi.org/https://doi.org/10.1016/j.iheduc.2017.06.002

Nguyen, A., Kremantzis, M., Essien, A., Petrounias, I., & Hosseini, S. (2024). Editorial: Enhancing Student Engagement Through Artificial Intelligence (AI): Understanding the Basics, Opportunities, and Challenges. *Journal of University Teaching and Learning Practice*, *21*(06). https://doi.org/10.53761/caraaq92

Nguyen, Q., Rienties, B., & Whitelock, D. (2022). Informing learning design in online education using learning analytics of student engagement. In B. Rienties, R. Hampel, E. Scanlon, & D. Whitelock (Eds.), *Open World Learning* (pp. 189–207). Routledge. https://doi.org/10.4324/9781003177098-17

Nguyen, T. D., Cannata, M., & Miller, J. (2018). Understanding student behavioral engagement: Importance of student interaction with peers and teachers. *The Journal of Educational Research*, *111*(2), 163–174. https://doi.org/10.1080/00220671.2016.1220359

Ortega, F. d. C., & Irala, V. B. (2022). The measurement of student online engagement of higher education: A scoping review in the international literature. *Texto Livre: Linguagem e Technologia*, *15*. https://doi.org/10.35699/1983-3652.2022.35747

Posit team. (2025). *Rstudio: Integrated development environment for R*. Posit Software, PBC. Boston, MA. http://www.posit.co/

Prananto, K., Cahyadi, S., Lubis, F. Y., & Hinduan, Z. R. (2025). Perceived teacher support and student engagement among higher education students – a systematic literature review. *BMC Psychology*, *13*(1). https://doi.org/10.1186/s40359-025-02412-w

R Core Team. (2024). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. Vienna, Austria. https://www.R-project.org/

Revelle, W. (2025). *Psych: Procedures for psychological, psychometric, and personality research*. Northwestern University. Evanston, Illinois. https://CRAN.R-project.org/package=psych

Revol, J., Carlier, C., Lafit, G., Verhees, M., Sels, L., & Ceulemans, E. (2024). Preprocessing experience-sampling-method data: A step-by-step framework, tutorial website, R package, and reporting templates. *Advances in Methods and Practices in Psychological Science*, *7*(4). https://doi.org/10.1177/25152459241256609

Rotelli, D., & Monreale, A. (2023). Processing and Understanding Moodle Log Data and Their Temporal Dimension. *Journal of Learning Analytics*, *10*(2), 126–141. https://doi.org/10.18608/jla.2023.7867

Skinner, E. A., & Pitzer, J. R. (2012). *Developmental dynamics of student engagement, coping, and everyday resilience* (S. L. Christenson, A. L. Reschly, & C. Wylie, Eds.). Springer US. https://doi.org/10.1007/978-1-4614-2018-7_2

Tani, M., Gheith, M. H., & Papaluca, O. (2021). Drivers of student engagement in higher education: A behavioral reasoning theory perspective. *Higher education*, *82*(3), 499–518. https://doi.org/10.1007/s10734-020-00647-7

Tempelaar, D., Rienties, B., & Nguyen, Q. (2020). Subjective data, objective data and the role of bias in predictive modelling: Lessons from a dispositional learning analytics application. *PLOS One*, *15*(6). https://doi.org/10.1371/journal.pone.0233977

Tight, M. (2020). Student retention and engagement in higher education. *Journal of Further and Higher Education*, *44*(5), 689–704. https://doi.org/10.1080/0309877X.2019.1576860

Vo, X. M., Do-Hong, C., Do, T. H. L., Ha, T. M. T., & Vu, C. T. (2024). An examination of blended learning in higher education over a two-decade period (2003-2022): Insights derived from scopus database. *Başlık*, *13*(4), 1821–1840. https://doi.org/10.12973/eu-jer.13.4.1821

Wickham, H. (2016). *Ggplot2: Elegant graphics for data analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., . . . Yutani, H. (2019). Welcome to the tidyverse. *Journal of Open Source Software*, *4*(43), 1686. https://doi.org/10.21105/joss.01686

Wong, Z. Y., Liem, G. A. D., Chan, M., & Datu, J. A. D. (2024). Student engagement and its association with academic achievement and subjective well-being: A systematic review and meta-analysis. *Journal of Educational Psychology*, *116*(1). https://doi.org/10.1037/edu0000833

Xie, K., Vongkulluksn, V. W., Heddy, B. C., & Jiang, Z. (2024). Experience sampling methodology and technology: An approach for examining situational, longitudinal, and multi-dimensional characteristics of engagement. *Educational technology research and development*, *72*(5), 2585–2615. https://doi.org/10.1007/s11423-023-10259-4