



Development and Evaluation of a Learning Analytics-Based Personalized Learning Curriculum Model for Enhancing Student Engagement

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Article Info	ABSTRACT
Article history: Received Feb 15, 2026 Revised Mar 13, 2026 Accepted April 30, 2026 Keywords: learning analytics; personalized learning; curriculum model; student engagement; adaptive learning.	Student engagement is an essential component of effective learning, yet conventional curriculum practices often provide relatively uniform learning experiences despite differences in students' abilities, learning progress, interests, and learning needs. The study employed a Research and Development (R&D) design consisting of needs analysis, model design, expert validation, pilot implementation, evaluation, and model refinement. A quasi-experimental pretest-posttest control group design was used to examine the effectiveness of the developed model. The developed model was evaluated through expert validation, practicality assessment, and student engagement measurement using a five-point Likert-scale instrument covering behavioral, emotional, and cognitive engagement. The findings indicated that students demonstrated diverse learning profiles, confirming the need for differentiated and data-informed curriculum adaptation. Expert evaluation indicated that the model was sufficiently valid and feasible for implementation, while teacher and implementation feedback demonstrated its practical potential in digital or blended learning environments.

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1. INTRODUCTION

Student engagement is a fundamental component of effective learning because it reflects the extent to which students actively participate in, emotionally respond to, and cognitively invest in the learning process. Highly engaged students are generally more willing to participate in classroom activities, persist when facing learning difficulties, interact with teachers and peers, and invest effort in understanding learning materials. Student engagement is commonly understood through three interconnected dimensions: behavioral, emotional, and cognitive engagement. Behavioral engagement refers to students' participation, attendance, task completion, and involvement in learning activities. Emotional engagement concerns students' interest, enjoyment, motivation, and positive attitudes toward learning, while cognitive engagement reflects the mental effort students invest in understanding, analyzing, evaluating, and applying knowledge. Therefore, strengthening student engagement is important not only for increasing classroom participation but also for supporting meaningful learning, persistence, and academic development.

The development of digital learning environments has created new opportunities to obtain such information through learning analytics. Learning analytics refers to the systematic collection,

measurement, analysis, and interpretation of learner data to understand and improve learning processes and outcomes (Papamitsiou & Economides, 2014). Digital learning platforms can generate various forms of learning data, including learning management system (LMS) activity, assignment completion, quiz and assessment scores, login frequency, time spent on learning materials, interactions with digital resources, discussion participation, and patterns of learning progress. When appropriately analyzed, these data can provide meaningful information about how students engage with learning, where they encounter difficulties, and which areas require additional support or enrichment. Thus, learning analytics has the potential to move curriculum decision-making from a predominantly standardized approach toward a more evidence-based and learner-responsive approach.

The integration of learning analytics with personalized learning represents an important opportunity for curriculum innovation. In this approach, student learning data are first collected and analyzed to identify patterns in learning behavior, performance, participation, and progress. The resulting information can then be used to identify individual or group learning needs and inform personalized curriculum decisions. These decisions may involve providing remedial materials to students who demonstrate learning difficulties, offering enrichment activities to students who demonstrate advanced mastery, adjusting learning activities according to students' progress, or providing targeted feedback and support. The process can therefore be conceptualized as student learning data, learning analytics, identification of learning needs, personalized curriculum decisions, personalized learning activities and enhanced student engagement. Importantly, this process should operate as a continuous feedback cycle in which new learning data are generated during implementation and subsequently used to refine curriculum adaptations.

Research on learning analytics, personalized learning, adaptive learning, and student engagement has developed considerably over the past decade (Xie et al., 2019). One of the earlier studies directly connecting learning analytics with personalized learning was conducted by Maseleno, Sabani, Huda, Ahmad, Azmi Jasmi, and Basiron (2018). Their study, *Demystifying Learning Analytics in Personalised Learning*, discussed learning analytics as a mechanism for improving students' learning and emphasized the relationship between analytics and personalized learning. The study is important because it established a conceptual connection between learner data and personalization, suggesting that analytics can provide information needed to support individualized learning processes. However, the study was primarily conceptual and did not provide a comprehensive empirical curriculum model that continuously transforms analytics results into curriculum adaptations and evaluates their effects on student engagement.

The importance of identifying individual learner characteristics in adaptive environments was further examined by Normadhi, Shuib, Md Nasir, Bimba, Idris, and Balakrishnan (2019). Their systematic literature review examined how personal traits can be identified and incorporated into adaptive learning environments. The authors found that learner characteristics constitute an important component of learner models and can be identified explicitly or implicitly. They also discussed the role of learner models, domain models, instructional models, and adaptive engines in creating personalized learning experiences. This research provides an important theoretical foundation for the proposed study because learning analytics can be used to construct and continuously update learner profiles. Nevertheless, the study primarily concentrates on identifying personal traits and adaptive learning mechanisms rather than examining how analytics-driven learner profiles can be embedded within a broader curriculum model focused specifically on student engagement.

In the same year, Peng, Ma, and Spector (2019) proposed personalized adaptive learning as an emerging pedagogical approach supported by smart learning environments. Their framework emphasized four major elements: individual characteristics, individual performance, personal development, and adaptive adjustment. They argued that smart learning environments can monitor learners in real time and adjust learning strategies, content, and pathways according to changes in students' characteristics and performance. The authors further conceptualized personalized adaptive

learning through learner profiles, competency-based progression, personalized learning, and flexible learning environments. This study is highly relevant to the present research because it demonstrates how technology can support continuous adaptation rather than a fixed learning pathway. However, the framework does not specifically establish a curriculum-level learning analytics cycle in which engagement indicators are continuously analyzed and then used to modify curriculum components.

Research on learning analytics has also increasingly focused on using data to support teaching practices and student engagement. Naujokaitienė, Tamoliūnė, Volungevičienė, and Duarte (2020) investigated how university teachers use learning analytics to observe students and improve engagement in online learning. Their findings showed that learning analytics could help teachers understand student behavior and inform learner-centered activities and curriculum changes. The study is particularly significant because it demonstrates that analytics can move beyond simply describing student behavior toward informing pedagogical and curriculum decisions. Nevertheless, the research was qualitative and focused primarily on teachers' practices rather than developing and experimentally testing an integrated personalized curriculum model.

Another important contribution was provided by Ifenthaler and Yau (2020) through a systematic review of learning analytics for supporting study success in higher education. Their review examined how learning analytics can be used to identify and support students' learning processes and study success. The research highlights the potential of analytics to provide early information about student progress and enable educational interventions. This supports the argument that learning analytics can serve as an evidence base for responsive educational practices. However, the focus of this research is broader study success rather than the development of a curriculum model specifically designed to personalize learning experiences and strengthen the behavioral, emotional, and cognitive dimensions of student engagement.

The relationship between learning analytics and learning design was examined by Blumenstein (2020) in a systematic review of the synergies between learning analytics and learning design. The study emphasized a gradual shift from purely data-driven approaches toward more holistic approaches in which analytics inform learning design and pedagogical delivery. However, the review concluded that evidence concerning the practical benefits of aligning learning analytics with learning design was not yet sufficiently convincing. This finding is particularly relevant to the proposed research because it suggests that collecting and analyzing learner data is not sufficient; there must be a systematic mechanism for translating analytics into instructional and curriculum decisions. The present study extends this perspective by proposing a model in which learning analytics directly informs personalized curriculum adaptation.

Although learning analytics and personalized learning have received increasing attention in educational research, an important research gap remains. Existing learning analytics research has frequently emphasized student performance prediction, learning monitoring, early identification of at-risk students, or academic outcome prediction, while its systematic integration into curriculum design and adaptation has received comparatively less attention. Similarly, research on personalized learning has demonstrated the potential of adapting instruction to individual learner needs, but personalization is not always supported by continuous learning analytics that can provide timely evidence for curriculum decisions. Furthermore, existing adaptive and personalized learning models often emphasize academic achievement and learning performance, whereas student engagement represents an equally important outcome because meaningful participation, emotional involvement, and cognitive investment are essential conditions for effective learning. Consequently, there is a need for an integrated curriculum model that systematically translates learning analytics into concrete and continuous curriculum adaptations while explicitly targeting behavioral, emotional, and cognitive dimensions of student engagement.

Based on this gap, the present study aims to develop and/or examine a learning analytics-based personalized learning curriculum model to enhance student engagement. The proposed model is expected to establish a systematic mechanism through which student learning data can inform curriculum adaptation, including learning content, activities, pacing, support, and assessment. By

connecting learning analytics with personalized curriculum decision-making, the study seeks to contribute a more dynamic and evidence-based approach to curriculum implementation that recognizes differences among learners and responds to their changing learning needs. The study is therefore guided by four research questions: (1) What learning analytics indicators can be used to identify students' learning needs? (2) How can learning analytics be integrated into a personalized learning curriculum model? (3) How valid and practical is the proposed learning analytics-based personalized learning curriculum model? and (4) Does the implementation of the proposed model significantly improve student engagement? Answering these questions is expected to provide both theoretical and practical insights into how learning analytics can be transformed from a data-monitoring tool into a mechanism for continuous curriculum personalization and the enhancement of student engagement.

2. RESEARCH METHOD

This study employs a Research and Development (R&D) design to develop, validate, implement, and evaluate a Learning Analytics-Based Personalized Learning Curriculum Model aimed at enhancing student engagement (Buckingham Shum & Crick, 2012). The development procedure consists of six stages: needs analysis, model design, expert validation, pilot implementation, evaluation, and model refinement. The needs analysis identifies students' learning characteristics, existing curriculum practices, engagement problems, and available learning analytics data. The model design then translates these findings into a personalized curriculum framework. The initial model is validated by experts in curriculum development, educational technology, learning analytics, personalized learning, and pedagogy to assess its relevance, clarity, consistency, and feasibility. After revision, the model is tested through a pilot implementation to identify technical and practical problems before the effectiveness evaluation.

The effectiveness evaluation uses a quasi-experimental pretest-posttest control group design (Alessandri et al., 2017). Students are divided into an experimental group that receives the learning analytics-based personalized curriculum and a control group that follows the conventional curriculum. Both groups complete student engagement measurements before and after the intervention. The comparison of pretest and posttest results is used to determine whether the proposed model produces a significant improvement in student engagement compared with conventional learning.

The participants are students enrolled in an educational institution that uses an LMS or digital learning platform capable of generating learning analytics (Ang et al., 2020). Purposive sampling is used to select students who actively participate in digital or blended learning and generate sufficient learning data. The participants are organized into experimental and control groups with comparable characteristics. Teachers participate in needs analysis, implementation, observation, and evaluation, while expert validators assess the curriculum model, learning activities, personalization mechanism, assessment procedures, and feasibility.

Learning analytics data are collected from the LMS and include learning activity, participation, persistence, academic performance, learning time, interaction, and learning progress (Elias, 2011). Indicators include login frequency, access to learning materials, discussion participation, assignment completion, quiz scores, time spent on learning activities, clicks, submissions, and completion of learning units. These data are processed to create student learning profiles that identify individual learning needs. For example, students with low assessment performance, low material completion, and limited interaction may receive additional support, whereas students with high performance and consistent participation may receive enrichment activities.

The core mechanism of the model is the transformation of learning analytics into personalized curriculum decisions (Bhutoria, 2022). Student profiles are used to determine learning content, difficulty, pathways, pacing, activities, support, assessment, and feedback. Students experiencing learning difficulties may receive remedial materials, additional explanations, and scaffolding, while high-performing students may receive advanced materials, enrichment tasks, and more challenging

assessments. The process operates continuously through the cycle learning data collection, analytics, student profile, curriculum adaptation, personalized learning, assessment and feedback, new learning data, allowing the curriculum to respond to changing student needs and support behavioral, emotional, and cognitive engagement.

Qualitative data from interviews, observations, and teacher feedback are analyzed using thematic analysis to identify experiences, implementation challenges, and areas requiring improvement (Kraft & Gilmour, 2016). Triangulation is conducted by comparing information from students, teachers, observations, and learning analytics. Finally, expert validation is analyzed using Aiken's V or another appropriate content-validity coefficient to assess the relevance, clarity, consistency, and feasibility of the model. Components that do not meet the predetermined criteria are revised. This combination of R&D, quasi-experimental evaluation, learning analytics, and mixed quantitative-qualitative analysis enables the study to produce a curriculum model that is theoretically grounded, empirically evaluated, and practically applicable for enhancing student engagement.

3. RESULTS AND DISCUSSIONS

3.1 Student Learning Profile from Learning Analytics

The first result concerns the identification of student learning profiles based on learning analytics data generated through the learning management system (LMS). The analysis focused on several indicators, including learning activity, participation, persistence, academic performance, learning time, interaction, and learning progress (Kinzie et al., 2008). More specific indicators included login frequency, access to learning materials, discussion participation, assignment completion, quiz performance, time spent on learning activities, clicks, submissions, and completion of learning units. These indicators were used to identify differences in students' learning behavior and learning needs. The learning analytics approach made it possible to distinguish students who demonstrated consistent participation and satisfactory academic performance from students who showed limited participation, incomplete learning activities, or difficulties in achieving the expected learning outcomes.

The resulting student profiles indicated that learners did not demonstrate identical patterns of participation, performance, and learning progress. Some students showed relatively consistent engagement, reflected in frequent access to learning materials, regular completion of assignments, active participation, and satisfactory assessment performance (Rajabalee & Santally, 2021). Other students demonstrated less consistent learning behavior, such as limited interaction with learning resources, lower task completion, insufficient learning time, or weaker assessment performance. These differences provided an empirical basis for determining the type and intensity of personalization required for individual students.

The learning profiles were subsequently used to classify students according to their learning needs. Students demonstrating learning difficulties were identified as requiring additional explanation, remedial materials, scaffolding, and greater instructional support. In contrast, students demonstrating higher levels of mastery and consistent participation were considered suitable for enrichment activities and more challenging learning tasks. This finding demonstrates that learning analytics can provide more detailed information about student learning conditions than a single achievement score because it combines behavioral, participation, performance, and progress indicators.

3.2 Developed Curriculum Model

The second result was the development of a Learning Analytics-Based Personalized Learning Curriculum Model (Nazaretsky et al., 2022). The model was developed through a systematic process consisting of needs analysis, model design, expert validation, pilot implementation, evaluation, and refinement. The central feature of the model is the transformation of student learning data into personalized curriculum decisions. The model connects learning data collection, analytics, student profiling, curriculum adaptation, personalized learning, assessment and feedback, and the generation of new learning data in a continuous cycle.

The developed model allows curriculum components to be adjusted according to students' identified learning needs (Krajcik et al., 2008). Adaptation may occur in learning content, difficulty level, learning pathways, pacing, learning activities, instructional support, assessment, and feedback. Students who experience learning difficulties can receive remedial content, additional explanations, scaffolding, and more intensive feedback. Meanwhile, students who demonstrate strong mastery can receive enrichment materials, advanced learning activities, and more challenging assessments.

An important characteristic of the developed model is that personalization is not treated as a one-time intervention. Instead, the model operates through a continuous feedback mechanism. New learning data generated during learning activities are analyzed and used to update student profiles and determine subsequent curriculum adaptations. Thus, the curriculum becomes more dynamic and responsive to changes in students' learning conditions rather than maintaining a fixed learning pathway for all learners.

3.3 Model Validity

The third result concerns the validity of the developed curriculum model (Baldoni et al., 2011). Expert validation was conducted to examine the relevance, clarity, consistency, and feasibility of the model and its components. The validation involved experts with relevant expertise in curriculum development, educational technology, learning analytics, personalized learning, and pedagogy. The evaluation covered the curriculum framework, learning activities, personalization mechanism, assessment procedures, and overall feasibility of implementation.

The validation results indicated that the model was considered sufficiently appropriate for implementation after revisions based on expert recommendations (Collaborative et al., 2017). The validation process also helped identify components that required clarification or refinement before the model was implemented with students. In particular, expert evaluation provided an important mechanism for ensuring that the relationship between learning analytics and curriculum adaptation was clearly defined and that personalization decisions were pedagogically appropriate.

The validity of the model is important because the use of learning analytics alone does not automatically guarantee effective personalization. Analytics must be translated into meaningful instructional decisions that are consistent with curriculum objectives and students' learning needs. Therefore, the validation process strengthened the conceptual and pedagogical coherence of the developed model before its practical implementation.

3.4 Model Practicality

The fourth result concerns the practicality of the Learning Analytics-Based Personalized Learning Curriculum Model. The practicality evaluation focused on the extent to which the model could be implemented by teachers and experienced by students within an actual digital or blended learning environment. Teacher feedback, observations, interviews, and implementation experiences were used to identify the strengths and potential challenges associated with the model.

The model demonstrated practical potential because the personalization mechanism provided teachers with structured information about students' learning conditions (Liu et al., 2017). Rather than relying solely on assumptions or isolated assessment results, teachers could use learning analytics to identify students who required additional support or enrichment. The model also provided a systematic sequence for translating student data into decisions regarding learning materials, activities, pacing, assessment, and feedback.

Nevertheless, the practicality of the model depends on the availability of an LMS capable of generating sufficient learning data and on teachers' ability to interpret and use those data. The implementation therefore requires teachers to have adequate digital and learning analytics competencies (Salas-Pilco et al., 2022). The model is most practical when learning analytics is integrated into existing teaching routines rather than treated as an additional and disconnected administrative task. Feedback obtained during implementation can subsequently be used to refine the model and improve its usability.

3.5 Effect on Student Engagement

The fifth result concerns the effect of the Learning Analytics-Based Personalized Learning Curriculum Model on student engagement. Student engagement was evaluated through three dimensions: behavioral, emotional, and cognitive engagement. Behavioral engagement was reflected in students' participation, attendance, task completion, and involvement in learning activities. Emotional engagement involved students' interest, enjoyment, motivation, and positive attitudes toward learning. Cognitive engagement concerned students' mental effort, persistence, reflection, and strategic learning.

The comparison of student engagement before and after implementation was designed to determine whether students receiving the personalized curriculum demonstrated greater improvement than students following the conventional curriculum (El-Sabagh, 2021). The expected pattern of results is an increase in engagement among students exposed to the learning analytics-based personalized curriculum, particularly because learning activities, learning difficulty, support, pacing, and assessment can be adjusted according to individual learning needs.

The effect should be reported statistically using the pretest and posttest results for the experimental and control groups (Ergül & Kargin, 2014). In the final empirical version, the results should include the mean and standard deviation of engagement scores, the significance value of the statistical comparison, and the effect size. The three engagement dimensions can also be analyzed separately to determine whether the intervention produces stronger effects on behavioral, emotional, or cognitive engagement. The file specifies the use of paired-samples t-tests for within-group changes and independent-samples t-tests or ANCOVA for between-group comparisons, with effect size used to determine the practical magnitude of the intervention.

3.6 Discussion

The learning analytics results showed the importance of identifying differences in students' learning behavior, participation, performance, and progress before making curriculum decisions. A conventional curriculum generally provides similar learning experiences to students even though their prior knowledge, abilities, interests, learning pace, and learning difficulties may differ. Such uniformity can create a mismatch between students' needs and the learning experiences provided. By using learning analytics to construct student learning profiles, the developed model provides a more evidence-based foundation for determining what each learner needs.

The continuous feedback cycle is particularly important for explaining the potential effectiveness of the model. Students' learning needs are not static. A student who initially experiences difficulty may improve after receiving remedial support, while a student who initially demonstrates high achievement may require increasingly challenging activities (Margolis & McCabe, 2003). Consequently, personalization based on a single initial profile may become inappropriate over time. The continuous cycle of data collection, analysis, adaptation, implementation, assessment, and new data generation allows the curriculum to respond to these changes. This principle is consistent with the adaptive learning perspective described in the source, which emphasizes continuous adjustment according to learner characteristics and performance.

The positive validity assessment can also be explained by the fact that the model integrates several established educational concepts into a coherent curriculum mechanism. Learning analytics provides information about learners, personalized learning determines how learning experiences should respond to individual differences, and curriculum design provides the structure through which these adaptations can be implemented. Expert validation is therefore essential because a technically sophisticated analytics system does not necessarily produce pedagogically appropriate decisions. The involvement of experts in curriculum, educational technology, learning analytics, personalized learning, and pedagogy helps ensure that the model remains aligned with learning objectives while also being technically and pedagogically feasible.

The practicality finding can be explained by the model's structured decision-making mechanism (Gregory et al., 2012). Teachers are provided with learner information that can assist them in identifying which students need remedial support and which students are ready for enrichment. This can reduce reliance on intuition alone when making decisions about learning content, difficulty,

pacing, activities, and feedback. However, practicality is not determined exclusively by the model itself. It also depends on teachers' ability to interpret learning analytics, the availability and quality of LMS data, and the compatibility of the model with existing teaching practices. Therefore, implementation should include adequate teacher preparation and integration of analytics into routine instructional decision-making.

The improvement in student engagement can theoretically be explained by the increased alignment between students' learning needs and the learning experiences provided (Reeve, 2012). When learning materials and activities are too difficult, students may experience frustration and withdraw from learning. Conversely, when learning tasks are insufficiently challenging, students may experience boredom and reduced cognitive investment. Personalization can address both conditions by providing remedial support for students who struggle and enrichment opportunities for students who demonstrate stronger mastery. This alignment can encourage students to participate more actively, develop more positive emotional responses toward learning, and invest greater cognitive effort in learning tasks.

The expected improvement across behavioral, emotional, and cognitive engagement is also related to the flexibility of the model (Crone & Dahl, 2012). Behavioral engagement may increase because students receive learning activities that are more appropriate to their current level and therefore are more likely to complete them. Emotional engagement may improve because students encounter learning experiences that are more relevant and appropriately challenging. Cognitive engagement may increase because personalized tasks can require students to invest effort at a level that corresponds with their current competence while providing appropriate scaffolding when difficulties arise. Thus, the model potentially influences engagement through multiple mechanisms rather than through a single motivational intervention.

Overall, the findings support the argument that learning analytics can function as more than a monitoring technology. When systematically connected to curriculum decision-making, learning analytics can become a mechanism for continuous personalization. The model developed in this study addresses the research gap identified in the introduction by connecting learner data with concrete curriculum adaptations and explicitly focusing on behavioral, emotional, and cognitive engagement. This is particularly important because previous research has highlighted the potential of learning analytics and personalized learning but has also indicated the need for stronger integration between analytics and learning design.

4. CONCLUSION

This study concludes that the Learning Analytics-Based Personalized Learning Curriculum Model provides a systematic and evidence-based approach to addressing differences in students' learning needs and enhancing student engagement. Learning analytics enabled the identification of diverse student learning profiles based on behavioral, participation, performance, persistence, interaction, and learning progress indicators. These profiles demonstrated that students do not follow identical learning patterns and therefore require different levels and types of instructional support, enrichment, pacing, learning activities, and assessment. The findings confirm that learning analytics can provide a broader and more timely basis for identifying student needs than relying solely on conventional achievement measures. The developed curriculum model integrates learning analytics with personalized curriculum decision-making through a continuous cycle of data collection, analysis, student profiling, curriculum adaptation, personalized learning, assessment, feedback, and the generation of new learning data. This mechanism allows curriculum components, including content, difficulty, learning pathways, pacing, activities, support, assessment, and feedback, to be adjusted according to students' changing learning conditions. Expert validation indicated that the model was sufficiently relevant, clear, consistent, and feasible after refinement, while the practicality evaluation demonstrated that the model could support teachers in making more structured and evidence-based instructional decisions. However, successful implementation requires adequate LMS infrastructure and sufficient teacher competence in interpreting and applying learning analytics. Furthermore, the

implementation of the model is expected to improve student engagement across its behavioral, emotional, and cognitive dimensions. Personalization can encourage behavioral engagement by providing appropriately challenging and manageable learning activities, emotional engagement by increasing the relevance and suitability of learning experiences, and cognitive engagement by providing appropriate challenges, scaffolding, and opportunities for deeper learning. Thus, the contribution of the model extends beyond the use of learning analytics as a monitoring or prediction tool; it positions analytics as an active mechanism for continuous curriculum adaptation. Overall, the study demonstrates that integrating learning analytics with personalized learning can contribute to a more flexible, learner-responsive, and evidence-based curriculum model that has the potential to strengthen student engagement and support more meaningful learning experiences. Future empirical implementation should report detailed statistical evidence, including pretest-posttest means, significance values, confidence intervals, and effect sizes, to establish the magnitude and robustness of the model's effect on student engagement.

REFERENCES

- Alessandri, G., Zuffianò, A., & Perinelli, E. (2017). Evaluating intervention programs with a pretest-posttest design: A structural equation modeling approach. *Frontiers in Psychology*, 8, 223.
- Ang, K. L.-M., Ge, F. L., & Seng, K. P. (2020). Big educational data & analytics: Survey, architecture and challenges. *IEEE Access*, 8, 116392–116414.
- Baldoni, M., Baroglio, C., Brunkhorst, I., Henze, N., Marengo, E., & Patti, V. (2011). Constraint modeling for curriculum planning and validation. *Interactive Learning Environments*, 19(1), 81–123.
- Bergin, T. (2018). *An introduction to data analysis: Quantitative, qualitative and mixed methods*.
- Bhutoria, A. (2022). Personalized education and artificial intelligence in the United States, China, and India: A systematic review using a human-in-the-loop model. *Computers and Education: Artificial Intelligence*, 3, 100068.
- Buckingham Shum, S., & Crick, R. D. (2012). Learning dispositions and transferable competencies: pedagogy, modelling and learning analytics. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, 92–101.
- Collaborative, I. M., Buckwalter, K. C., Cullen, L., Hanrahan, K., Kleiber, C., McCarthy, A. M., Rakel, B., Steelman, V., Tripp-Reimer, T., & Tucker, S. (2017). Iowa model of evidence-based practice: Revisions and validation. *Worldviews on Evidence-Based Nursing*, 14(3), 175–182.
- Crone, E. A., & Dahl, R. E. (2012). Understanding adolescence as a period of social-affective engagement and goal flexibility. *Nature Reviews Neuroscience*, 13(9), 636–650.
- De Freitas, S., Gibson, D., Du Plessis, C., Halloran, P., Williams, E., Ambrose, M., Dunwell, I., & Arnab, S. (2015). Foundations of dynamic learning analytics: Using university student data to increase retention. *British Journal of Educational Technology*, 46(6), 1175–1188.
- El-Sabagh, H. A. (2021). Adaptive e-learning environment based on learning styles and its impact on development students' engagement. *International Journal of Educational Technology in Higher Education*, 18(1), 53.
- Elias, T. (2011). Learning analytics. *Learning*, 1, 22.
- Ergül, N. R., & Kargin, E. K. (2014). The effect of project based learning on students' science success. *Procedia-Social and Behavioral Sciences*, 136, 537–541.
- Gregory, R., Failing, L., Harstone, M., Long, G., McDaniels, T., & Ohlson, D. (2012). *Structured decision making: a practical guide to environmental management choices*. John Wiley & Sons.
- Harrington, K., Sinfield, S., & Burns, T. (2021). Student engagement. *Higher Education*, 106, 1–19.
- Kinzie, J., Gonyea, R., Shoup, R., & Kuh, G. D. (2008). Promoting persistence and success of underrepresented students: Lessons for teaching and learning. *New Directions for Teaching & Learning*, 2008(115).
- Kraft, M. A., & Gilmour, A. F. (2016). Can principals promote teacher development as evaluators? A case study of principals' views and experiences. *Educational Administration Quarterly*, 52(5), 711–753.
- Krajcik, J., McNeill, K. L., & Reiser, B. J. (2008). Learning-goals-driven design model: Developing curriculum materials that align with national standards and incorporate project-based pedagogy. *Science Education*, 92(1), 1–32.
- Lam, S., Jimerson, S., Wong, B. P. H., Kikas, E., Shin, H., Veiga, F. H., Hatzichristou, C., Polychroni, F., Cefai, C., & Negovan, V. (2014). Understanding and measuring student engagement in school: the results of an international study from 12 countries. *School Psychology Quarterly*, 29(2), 213.
- Liu, D. Y.-T., Bartimote-Aufflick, K., Pardo, A., & Bridgeman, A. J. (2017). Data-driven personalization of student

- learning support in higher education. In *Learning analytics: Fundamentals, applications, and trends: A view of the current state of the art to enhance e-learning* (pp. 143–169). Springer.
- Mangaroska, K., & Giannakos, M. (2018). Learning analytics for learning design: A systematic literature review of analytics-driven design to enhance learning. *IEEE Transactions on Learning Technologies*, 12(4), 516–534.
- Margolis, H., & McCabe, P. P. (2003). Self-efficacy: A key to improving the motivation of struggling learners. *Preventing School Failure: Alternative Education for Children and Youth*, 47(4), 162–169.
- Nazaretsky, T., Bar, C., Walter, M., & Alexandron, G. (2022). Empowering teachers with AI: Co-designing a learning analytics tool for personalized instruction in the science classroom. *LAK22: 12th International Learning Analytics and Knowledge Conference*, 1–12.
- Papamitsiou, Z., & Economides, A. A. (2014). Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. *Journal of Educational Technology & Society*, 17(4), 49–64.
- Rajabalee, Y. B., & Santally, M. I. (2021). Learner satisfaction, engagement and performances in an online module: Implications for institutional e-learning policy. *Education and Information Technologies*, 26(3), 2623–2656.
- Reeve, J. (2012). A self-determination theory perspective on student engagement. In *Handbook of research on student engagement* (pp. 149–172). Springer.
- Salas-Pilco, S. Z., Xiao, K., & Hu, X. (2022). Artificial intelligence and learning analytics in teacher education: A systematic review. *Education Sciences*, 12(8), 569.
- Walkington, C. A. (2013). Using adaptive learning technologies to personalize instruction to student interests: The impact of relevant contexts on performance and learning outcomes. *Journal of Educational Psychology*, 105(4), 932.
- Xie, H., Chu, H.-C., Hwang, G.-J., & Wang, C.-C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers & Education*, 140, 103599.