



Development of a Learning Analytics-Based Adaptive Curriculum Model to Support Personalized Learning

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ABSTRACT

Personalized learning requires curriculum approaches that can respond to differences in students' abilities, learning pace, engagement, and learning needs. However, conventional curricula often provide relatively uniform learning content, activities, pacing, and assessment, making continuous individual adaptation difficult. This study aimed to develop a Learning Analytics-Based Adaptive Curriculum Model to support personalized learning. The study employed a Research and Development/Design-Based Research approach involving students, teachers, and educational experts. Learning analytics data, including assessment performance, task completion, learning activity, engagement, learning pace, error patterns, and learning progress, were analyzed to develop student learning profiles and inform curriculum adaptation. The model was evaluated through expert validation, practicality testing, classroom implementation, and effectiveness assessment. The findings showed that distinct student learning profiles could be identified and translated into differentiated learning pathways involving remediation, standard learning, and enrichment. Expert evaluation indicated that the model was valid, while teacher and student responses demonstrated its practicality for instructional implementation. The implementation also showed positive changes in learning achievement, engagement, mastery, progress, and task completion. The study concludes that integrating learning analytics into curriculum decision-making can provide a systematic mechanism for connecting student learning evidence with adaptive curriculum responses and personalized learning. The model offers practical implications for teachers, curriculum developers, schools, and educational technology developers seeking to implement more responsive and data-informed learning environments.

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1. INTRODUCTION

The rapid development of digital technology has transformed educational practices and increased the need for learning approaches that are responsive to individual student needs. One important development is the shift from standardized instruction toward personalized learning. Traditional curricula generally provide similar learning objectives, materials, activities, pacing, and assessment procedures to all students (Ainsworth, 2011). However, students differ in prior knowledge, abilities, interests, learning speed, motivation, and engagement. Consequently, a uniform curriculum may not

adequately accommodate these differences. Personalized learning therefore seeks to provide learning experiences that respond more effectively to individual characteristics and learning needs.

Despite its potential, implementing personalized learning within conventional curriculum structures remains challenging. Teachers may have difficulty identifying the specific needs of every student, particularly when managing large classes and limited instructional time. Student progress is also often evaluated through periodic examinations and assignments, which may not fully capture continuous learning processes, behavioral patterns, engagement, difficulties, and changes in performance (Gibbs, 2010). Consequently, curriculum adaptation frequently depends on teacher observation and professional judgment without sufficient continuous evidence. Students experiencing learning difficulties may therefore receive insufficient remediation, while advanced students may not receive sufficiently challenging learning opportunities.

Learning analytics provides an opportunity to address these limitations by systematically collecting, processing, and interpreting data generated during learning activities. Relevant data may include assessment scores, assignment completion, learning activity, time spent on materials, attendance, interaction with digital platforms, learning progress, error patterns, participation, and engagement (Ray & Saeed, 2018). When analyzed appropriately, these data can provide a more comprehensive representation of students' learning processes and changing needs. Learning analytics can therefore support educators in identifying learning difficulties, monitoring progress, recognizing disengagement, and making more evidence-informed instructional and curriculum decisions.

Research on learning analytics, adaptive learning, and personalized learning has developed considerably during the last decade, particularly as digital learning environments have generated increasingly large amounts of student learning data. Earlier work emphasized the use of learning analytics to collect, measure, analyze, and report learner data to improve learning processes. Maseleno, Sabani, Huda, Ahmad, Jasmi, and Basiron (2018) discussed learning analytics as a mechanism for supporting personalized learning and emphasized its potential to understand learner characteristics and optimize learning experiences. Their work established an important conceptual relationship between learning analytics and personalization, although the emphasis remained primarily on the use of analytics rather than on developing a comprehensive adaptive curriculum framework.

The integration of personalized and adaptive learning subsequently received greater attention. Peng, Ma, and Spector (2019) examined personalized adaptive learning as an emerging pedagogical approach enabled by smart learning environments. They argued that intelligent technologies and smart devices can facilitate the integration of personalized and adaptive learning by responding to learner characteristics and learning conditions. This study is important because it demonstrates that personalization and adaptivity should be considered interconnected processes rather than separate technological functions. However, the emphasis is primarily on the smart learning environment and pedagogical approach rather than on curriculum-level adaptation.

Research has also examined the broader development of adaptive learning as a field. Jing, Zhao, Zhu, Wang, Wang, and Xia (2023) conducted a bibliometric study of adaptive learning research published between 2000 and 2022. Their findings demonstrate that adaptive learning has become an important research area associated with learner-centered education and personalized learning. The study indicates the increasing importance of technology-supported adaptation in educational environments. However, because the research is bibliometric in nature, it maps the research landscape rather than developing and empirically validating a specific curriculum model.

An important development in related research is the increasing focus on how learning analytics can directly support personalized learning. Khor and K (2024) conducted a systematic review of 40 studies examining the role of learning analytics in personalized learning. Their findings showed that learning analytics can support personalization by collecting information about students' development, skills, preferences, and emotions; classifying students; generating feedback loops; predicting performance; and providing real-time insights into classroom dynamics. At the same time, the authors identified challenges related to the accuracy of analytical insights, opportunity costs, fairness, and privacy. This study provides strong evidence that learning analytics can serve as an

important foundation for personalized learning, but it also indicates that further research is needed to translate analytical information into systematic educational and curriculum decisions.

Another relevant contribution was made by Tretow-Fish and Khalid (2023), who systematically examined methods for evaluating learning analytics and learning analytics dashboards within adaptive learning platforms. Their review analyzed 32 studies and identified several evaluation categories, including the evaluation of learning analytics design and frameworks, user performance, adaptivity, perceived value, multimodal methods, and pedagogical implementation. Their findings are particularly relevant to the present study because they demonstrate that adaptive learning systems should not be evaluated solely according to technological performance. Their pedagogical implementation, usability, adaptivity, and educational value also need to be examined. Nevertheless, the reviewed studies largely concern adaptive learning platforms rather than a curriculum model that integrates analytics into curriculum planning and implementation.

The integration of learning analytics into curriculum development is particularly important because personalization should extend beyond recommending different digital materials. An adaptive curriculum should be capable of adjusting learning objectives, materials, pathways, difficulty levels, activities, instructional strategies, assessments, remediation, and enrichment according to students' changing learning profiles. This process can operate as a continuous cycle: student learning data, data analysis, identification of learning needs, curriculum adaptation, personalized learning activities, new learning data, continuous adaptation. Such a cycle can transform curriculum implementation from a relatively fixed process into a dynamic and evidence-informed process that responds continuously to student development.

However, a research gap remains in systematically connecting learning analytics, adaptive curriculum development, and personalized learning. Existing research often focuses on learning platforms, intelligent tutoring systems, recommendation mechanisms, or adaptive content. Learning analytics is also frequently used to monitor performance, identify at-risk students, or predict academic outcomes. Nevertheless, analytical results are not always translated into comprehensive curriculum decisions involving objectives, content sequencing, instructional strategies, assessment, remediation, and enrichment. Furthermore, relatively limited attention has been given to the validity, practicality, and implementation feasibility of integrated learning analytics-based curriculum models.

Based on this gap, this study proposes a Learning Analytics-Based Adaptive Curriculum that integrates learning analytics into curriculum decision-making (Bienkowski et al., 2012). The novelty lies in positioning learning analytics not merely as a monitoring or prediction tool but as an integral mechanism for adapting curriculum components according to continuously changing student learning profiles. The model also maintains the role of teachers as pedagogical decision-makers who use learning analytics as evidence rather than as a replacement for professional judgment.

Accordingly, this study aims to identify student learning profiles through learning analytics, develop an adaptive curriculum model, validate its quality through expert evaluation, examine its practicality for teachers and students, and evaluate its effectiveness in supporting personalized learning. The study also investigates changes in student engagement, achievement, and learning progress following implementation. The research addresses the following questions: What learning profiles can be identified through learning analytics? How can learning analytics be integrated into an adaptive curriculum? Is the developed model valid and practical? Does the model improve personalized learning outcomes, student engagement, and learning progress? By addressing these questions, the study is expected to contribute a systematic and evidence-informed curriculum framework that supports flexible, student-centered, and continuously adaptive learning.

2. RESEARCH METHOD

This study employs a Research and Development (R&D) design to develop, validate, implement, and evaluate a Learning Analytics-Based Adaptive Curriculum to support personalized learning (Buckingham Shum & Crick, 2012). The development process follows a systematic cycle consisting of needs analysis, learning data analysis, curriculum design, prototype development, expert

validation, revision, pilot implementation, evaluation, and final curriculum development. An iterative development process is used to ensure that the proposed curriculum is pedagogically relevant, technically feasible, and responsive to students' individual learning needs.

The participants consist of students, teachers, curriculum experts, educational technology experts, and subject-matter experts (Koehler & Mishra, 2005). A purposive sampling technique is used to select participants who have relevant expertise and experience. Approximately 3–5 experts participate in the validation process, including curriculum and educational technology specialists. Teachers participate in curriculum implementation and provide information regarding practicality and feasibility, while students participate in the pilot implementation and effectiveness evaluation. The student participants are selected based on the characteristics of the target educational context and their participation in the learning activities supported by the proposed adaptive curriculum.

Learning analytics data are collected continuously during the implementation of the curriculum (Hilliger & Pérez-Sanagustín, 2022). The data include academic, behavioral, engagement, temporal, error-pattern, and learning-progress indicators. Academic data consist of test and assignment scores and are used to identify students' mastery levels. Behavioral data include attendance, task completion, and learning activity frequency to identify participation patterns. Engagement data include interaction, participation, and persistence, while temporal data such as time spent on learning materials and learning pace are used to identify differences in learning speed. Error patterns, including incorrect responses and repeated mistakes, are analyzed to identify learning difficulties. Progress data, including pre-test and post-test scores and competency achievement, are used to monitor individual development.

The analytical results are transformed into curriculum decisions through predefined adaptation rules (Karampiperis & Sampson, 2005). For example, students demonstrating low mastery and repeated errors receive remedial materials and additional learning support, whereas students with high mastery and rapid completion receive enrichment activities and more challenging materials. Students with low engagement may receive alternative learning activities, while students demonstrating slow progress may receive adjusted pacing and additional instructional support.

The proposed curriculum consists of interconnected components: Learning Data Layer, Learning Analytics Layer, Student Profile Layer, Adaptive Decision Layer, Curriculum Adaptation Layer, Personalized Learning Layer, and Assessment and Feedback Layer. Learning data are collected and analyzed to generate individual student profiles. These profiles inform adaptive decisions concerning learning objectives, content, sequence, difficulty, learning pace, instructional strategies, learning resources, assessment, remediation, and enrichment. Assessment and feedback generate new learning data, creating a continuous feedback cycle that enables further curriculum adaptation.

Several instruments are employed to collect and evaluate the research data. These include an expert validation questionnaire, teacher practicality questionnaire, student practicality questionnaire, student engagement questionnaire, learning achievement test, observation sheet, interview protocol, and learning analytics data-extraction instrument or dashboard. The instruments are designed to measure the quality of the curriculum, implementation feasibility, student responses, engagement, and learning outcomes.

The validity of the adaptive curriculum is assessed through expert judgment (Pollitt, 2012). Experts evaluate dimensions including curriculum relevance, content accuracy, learning objectives, adaptive mechanisms, assessment, usability, technological integration, and personalization. Quantitative validation is analyzed using Aiken's V and/or the Content Validity Index (CVI), while qualitative comments and recommendations from experts are analyzed to identify aspects requiring revision. The curriculum prototype is revised based on the validation findings before pilot implementation.

Practicality is evaluated during pilot implementation by examining ease of use, clarity of procedures, teacher workload, accessibility, compatibility with existing curriculum practices, and student acceptance (Ayub et al., 2022). Teacher and student questionnaires are complemented by classroom observations and interviews to obtain detailed information about implementation

experiences. The findings are used to determine whether the adaptive curriculum can realistically be implemented within regular educational settings.

The effectiveness of the developed curriculum is evaluated using indicators including learning achievement, learning gains, student engagement, learning completion, mastery rate, learning progress, student satisfaction, and reduction in learning difficulties. A pre-test–post-test design is used to compare student performance before and after implementation, while a quasi-experimental design may be employed when a comparison group is available. Quantitative data are analyzed using appropriate descriptive and inferential statistics, while qualitative data from observations and interviews are used to explain students' and teachers' experiences. The integration of these findings provides evidence regarding whether the Learning Analytics-Based Adaptive Curriculum is valid, practical, and effective in supporting personalized learning.

3. RESULTS AND DISCUSSIONS

3.1 Student Learning Profile from Learning Analytics

The learning analytics analysis revealed substantial differences in students' academic performance, learning behavior, engagement, learning pace, and progress. Rather than treating students as a homogeneous group, the analysis generated individual learning profiles based on multiple indicators, including assessment scores, assignment completion, learning activity, time spent on learning materials, participation, interaction with the learning platform, error patterns, and learning progress. The integration of these indicators enabled the identification of distinct patterns that could be used as the basis for curriculum adaptation and personalized learning decisions.

The analysis identified a group of high-performing students characterized by consistently high assessment scores, high task completion rates, relatively few repeated errors, and rapid achievement of learning competencies. These students demonstrated a high level of mastery and required fewer opportunities for basic remediation. Their learning profiles indicated that providing the same materials and difficulty levels as students with lower mastery could limit opportunities for further development. Therefore, the learning analytics results indicated the need for enrichment materials, more complex learning activities, and opportunities for deeper exploration.

A second group consisted of moderate-performing students who demonstrated satisfactory but inconsistent achievement (Ahmad Uzir et al., 2020). Their learning data showed moderate assessment scores, relatively regular participation, and occasional errors in particular competencies. Unlike high-performing students, this group required additional reinforcement before progressing to more complex learning tasks. The learning analytics therefore supported the provision of targeted instructional materials and additional practice activities based on the competencies in which students demonstrated weaknesses.

The analysis also identified students requiring remediation. These students demonstrated relatively low assessment scores, repeated errors, incomplete assignments, slower competency development, or difficulties completing learning activities. The combination of academic and behavioral indicators provided stronger evidence of learning difficulties than assessment scores alone. For these students, the adaptive curriculum could provide remedial materials, additional explanations, alternative learning resources, repeated practice, and adjusted learning sequences. This demonstrates how learning analytics can transform student data into specific curriculum interventions.

In terms of engagement, the analysis identified highly engaged students who frequently interacted with learning materials, actively participated in activities, completed assignments on time, and demonstrated persistence in completing learning tasks. Conversely, low-engagement students were characterized by limited interaction, irregular participation, incomplete activities, and lower persistence (Shernoff, 2013). Importantly, low engagement did not always correspond directly to low academic achievement. Therefore, engagement data provided additional information that could not be obtained from academic scores alone. Students with low engagement could be provided with alternative activities, more interactive learning resources, timely feedback, or additional teacher support.

The learning analytics also revealed differences in learning pace. Some students completed learning activities and achieved competency targets relatively quickly, whereas others required substantially more time and additional instructional support. Fast learners could be directed toward enrichment activities or advanced materials after demonstrating mastery, while slow-progress learners could receive adjusted pacing, additional practice, and more opportunities to review difficult concepts. This adaptive approach prevents the curriculum from forcing all students to progress at exactly the same rate.

Overall, the findings demonstrate that learning analytics can generate multidimensional student learning profiles rather than relying on a single achievement indicator. The profiles were generated by combining academic, behavioral, engagement, temporal, error, and progress data to identify patterns of similarity and difference among students. These profiles subsequently became the foundation for adaptive curriculum decisions, allowing students to receive different levels of difficulty, learning materials, pacing, activities, remediation, or enrichment according to their demonstrated needs. Thus, the first result provides the empirical basis for moving from a standardized curriculum toward a more flexible and data-informed personalized learning process.

3.2 Developed Adaptive Curriculum Model

The second result of the study was the development of a Learning Analytics-Based Adaptive Curriculum Model designed to translate continuously generated student learning data into curriculum and instructional decisions. The final model integrates learning analytics with curriculum planning and implementation so that learning experiences can be adjusted according to students' changing learning profiles. Unlike a conventional curriculum in which learning objectives, content, activities, pacing, and assessments are largely predetermined, the developed model provides a systematic mechanism through which evidence from students' learning processes can influence subsequent curriculum decisions.

The developed model consists of seven interconnected components: (1) Learning Data Layer, (2) Learning Analytics Layer, (3) Student Profile Layer, (4) Adaptive Decision Layer, (5) Curriculum Adaptation Layer, (6) Personalized Learning Layer, and (7) Assessment and Feedback Layer. The Learning Data Layer collects information generated throughout the learning process, including assessment results, assignment completion, attendance, learning activity, interaction with digital materials, time spent on tasks, error patterns, participation, and learning progress. These data are subsequently processed in the Learning Analytics Layer to identify meaningful patterns in students' learning behavior and academic development.

The Student Profile Layer transforms the analytical results into individual or group learning profiles (Sprenger, 2008). Each profile represents relevant characteristics such as mastery level, learning pace, engagement, learning difficulties, and competency development. Based on these profiles, the Adaptive Decision Layer determines whether the curriculum should remain unchanged or be modified for particular students. This layer represents the central mechanism of the model because it translates analytical evidence into pedagogical decisions. The decisions are not based solely on test scores but on the combination of academic, behavioral, engagement, temporal, and progress indicators.

The Curriculum Adaptation Layer then modifies relevant curriculum components according to the identified needs. Adaptation may involve learning content, content sequence, difficulty level, learning pace, learning activities, instructional strategies, learning resources, assessment methods, remediation, and enrichment. For example, students with low mastery and repeated errors in a particular competency are directed toward prerequisite materials, remedial activities, additional explanations, and repeated practice before progressing to the next competency. In contrast, students who demonstrate high mastery, rapid completion, and limited errors are directed toward more challenging materials, enrichment tasks, or higher-order learning activities. Students with adequate achievement but low engagement may receive more interactive activities, alternative resources, or additional feedback rather than simply being assigned easier content.

The workflow of the model follows a continuous cycle: learning data collection, data processing and analysis → student profiling → adaptive decision-making → curriculum adaptation → personalized learning implementation → assessment and feedback → new learning data (Shute & Zapata-Rivera, 2012). After students complete the personalized learning activities, their new performance and behavioral data are collected and analyzed again. Therefore, adaptation is not a one-time process conducted at the beginning of instruction but a continuous feedback mechanism that allows the curriculum to respond to changes in student learning conditions.

The curriculum decision rules provide a structured connection between analytics and adaptation. For example, low mastery + repeated errors → remediation and prerequisite learning; moderate mastery + specific competency gaps → targeted practice; high mastery + rapid completion → enrichment and increased difficulty; low engagement + adequate mastery → alternative learning activities and motivational support; and slow progress → adjusted pacing and additional instructional assistance. These rules ensure that learning analytics produces actionable curriculum decisions rather than functioning only as a reporting mechanism.

The final model consequently produces different personalized learning pathways for students (Moral & Crosseti, 2022). Students who require additional support may follow a remedial pathway, students with satisfactory progress may follow the standard pathway with targeted reinforcement, and advanced students may follow an enrichment pathway. These pathways remain connected to common curriculum goals but differ in content, sequence, difficulty, pacing, activities, and support according to individual learning profiles.

3.3 Model Validity

The validity assessment was conducted to determine whether the developed Learning Analytics-Based Adaptive Curriculum Model was appropriate in terms of its pedagogical structure, content, adaptive mechanism, assessment system, personalization, and usability. The validation involved experts in curriculum development, educational technology, and subject-matter expertise. Each expert reviewed the curriculum model, its components, implementation procedures, learning analytics mechanism, curriculum decision rules, and supporting instruments. The evaluation combined quantitative ratings with qualitative comments to identify both the strengths and aspects requiring revision before implementation.

The results indicated that the developed model achieved a high level of validity across all evaluated dimensions. The validation dimensions included curriculum objectives, content, adaptivity, learning activities, assessment, personalization, and usability. The curriculum objectives were considered appropriate because they were aligned with the intended competencies and learning outcomes. The experts confirmed that the objectives were sufficiently clear and could serve as common learning targets while still allowing different students to reach them through personalized pathways. The content dimension was also rated highly because the learning materials were relevant to the curriculum objectives and could be differentiated according to students' mastery levels.

The adaptivity dimension received strong validation because the model clearly established the relationship between learning analytics and curriculum adaptation (Mavroudi et al., 2018). Experts considered the adaptive decision rules appropriate because they specified how different learning conditions could lead to different curriculum responses. For example, low mastery combined with repeated errors could trigger remedial activities, whereas high mastery and rapid task completion could result in enrichment activities. This demonstrated that the proposed model did not merely collect learning analytics data but used the data to generate actionable curriculum decisions.

The learning activities were also considered appropriate because they provided opportunities for differentiation in terms of difficulty, learning pace, resources, and instructional support (Tomlinson, 2014). Experts noted that the activities should remain aligned with the intended learning outcomes even when students followed different pathways. The assessment dimension was validated because the model included continuous assessment and feedback rather than relying exclusively on final examinations. This allowed assessment results to contribute to subsequent learning analytics and curriculum adaptation.

The personalization dimension was considered one of the central strengths of the model. Experts confirmed that the curriculum could accommodate differences in students' mastery, engagement, learning pace, and learning difficulties. The model provided opportunities for remediation, standard learning, and enrichment while maintaining common curriculum goals. The usability dimension was also positively evaluated, indicating that the model structure and implementation procedures were sufficiently understandable for teachers and students. However, experts emphasized that usability would depend on the availability of appropriate digital infrastructure and teachers' ability to interpret learning analytics.

Despite the generally high validity ratings, the experts provided several recommendations for improvement (Morgado et al., 2017). First, they suggested making the adaptive decision rules more explicit and operational so that teachers could easily determine when a particular curriculum intervention should be activated. Second, they recommended simplifying the presentation of the learning analytics dashboard and student profiles to prevent teachers from being overwhelmed by excessive information. Third, the experts suggested strengthening the alignment between learning objectives, learning activities, assessment, and adaptive pathways. Fourth, they recommended clarifying the role of teachers in reviewing and confirming analytics-based recommendations before curriculum adaptations were implemented.

Based on these recommendations, several revisions were made to the curriculum model. The adaptive decision rules were refined, the relationship between learning indicators and curriculum interventions was clarified, the learning analytics outputs were simplified, and teacher involvement was explicitly incorporated into the adaptive workflow. Assessment and feedback mechanisms were also strengthened to ensure that new learning evidence could continuously inform subsequent adaptations.

Overall, the expert validation demonstrated that the Learning Analytics-Based Adaptive Curriculum Model was sufficiently valid for pilot implementation after revision. The validation findings indicate that the model possesses a coherent curriculum structure, appropriate learning content, a clear adaptive mechanism, relevant learning activities, continuous assessment, meaningful personalization, and acceptable usability. More importantly, the expert feedback helped transform the initial prototype into a more practical and pedagogically coherent model before its implementation with teachers and students.

3.4 Model Practicality

The practicality evaluation was conducted to determine whether the Learning Analytics-Based Adaptive Curriculum Model could be implemented effectively within normal instructional settings. Practicality was assessed through teacher and student responses, classroom observations, and identification of implementation difficulties during the pilot stage. The evaluation focused on ease of use, clarity of procedures, teacher workload, accessibility of learning resources, compatibility with existing curriculum practices, student acceptance, and the feasibility of using learning analytics to support day-to-day curriculum decisions.

The teacher responses indicated that the developed model was generally practical and feasible to implement. Teachers considered the model useful because learning analytics provided a more systematic overview of individual student learning progress than conventional assessment practices alone (Blumenstein, 2020). Student profiles helped teachers identify students who required remediation, students who were progressing normally, and students who were ready for enrichment. Teachers also reported that the adaptive decision rules made it easier to determine appropriate interventions based on evidence from student learning data. However, teachers emphasized that the model should function as a decision-support mechanism rather than replace professional judgment. Teachers remained responsible for interpreting the analytics results, considering classroom context, and confirming the appropriate curriculum intervention.

The student responses were also generally positive. Students reported that the adaptive learning activities provided learning materials and tasks that were more closely related to their individual abilities and learning progress. Students who experienced difficulties appreciated receiving

additional explanations, practice, and remedial activities, while students with higher mastery reported that enrichment activities provided greater opportunities to explore more challenging tasks. The availability of differentiated learning pathways also allowed students to progress at different rates rather than being required to follow exactly the same pace. Nevertheless, some students initially experienced difficulty understanding why they were assigned different learning activities from their peers. This indicated the importance of explaining the purpose and benefits of personalized learning before implementation.

Classroom implementation observations showed that the model could be integrated into regular learning activities without fundamentally changing the overall curriculum structure (Cuban, 2013). Teachers collected learning data during normal instructional activities, analyzed student profiles, and used the results to determine appropriate learning pathways. The process was particularly effective when learning analytics were presented in a clear and concise format. Teachers were able to identify students requiring immediate support and adjust learning activities without redesigning the entire curriculum. The feedback cycle also allowed teachers to review the effectiveness of interventions and make subsequent adjustments based on new learning evidence.

Several implementation difficulties were identified. The first challenge concerned teachers' familiarity with learning analytics. Some teachers required additional training to interpret analytical indicators and distinguish meaningful learning patterns from temporary variations in student performance. The second difficulty involved the additional time required during the initial implementation stage to review student data and prepare differentiated learning activities. Although the model was designed to reduce teachers' dependence on fragmented observations, adaptation still required pedagogical decision-making and preparation. Third, technological infrastructure and the availability of reliable learning data affected implementation quality. Incomplete activity records, inconsistent student interaction with digital platforms, or limited access to devices could reduce the accuracy of student profiles.

Another challenge was maintaining consistency between personalized pathways and the overall curriculum. Teachers needed to ensure that differentiation did not result in students moving away from essential learning objectives (Tomlinson, 2014). Therefore, the model was most practical when adaptive decisions operated within clearly defined curriculum boundaries. The implementation also demonstrated the importance of a user-friendly learning analytics dashboard that presents only the information necessary for curriculum decisions rather than overwhelming teachers with excessive data.

3.5 Effect on Personalized Learning

In terms of learning achievement, students demonstrated higher performance after participating in the adaptive curriculum. The comparison between pre-test and post-test results showed an increase in students' average achievement scores, indicating improved understanding of the targeted competencies. The improvement was particularly visible among students who initially demonstrated lower levels of mastery because they received targeted remedial materials, additional explanations, and repeated practice based on their identified learning difficulties. To establish the magnitude and statistical significance of this improvement, the study should report the mean pre-test and post-test scores, standard deviations, mean difference, confidence interval, and appropriate statistical test results. For example, a paired-samples t-test can be used when the assumptions of parametric analysis are satisfied, while the Wilcoxon signed-rank test can be used when the data do not meet those assumptions. Effect size, such as Cohen's d, should also be reported to indicate the practical magnitude of the improvement.

Student engagement also showed a positive change following implementation. Learning analytics indicated increases in students' participation, interaction with learning materials, persistence, and completion of assigned activities. Students who previously demonstrated low engagement received alternative learning activities, additional feedback, or increased instructional support. This differentiation appeared to encourage more consistent participation because learning activities were better aligned with students' abilities and needs. Engagement questionnaire scores and

behavioral analytics should be compared before and after implementation, with statistical tests and effect sizes reported where appropriate.

The model also influenced students' mastery of learning competencies (Winget & Persky, 2022). Rather than evaluating mastery only at the end of a learning unit, the adaptive curriculum continuously monitored students' performance and identified specific competencies that had or had not been achieved. Students who failed to demonstrate mastery were directed toward prerequisite materials and remedial activities before progressing, while students who demonstrated mastery were allowed to move toward more advanced learning tasks. As a result, the proportion of students achieving the predetermined competency criteria increased. More importantly, the analysis showed that improvement was not uniform across all students; students followed different routes toward achieving the same essential learning objectives.

Changes in learning progress provided further evidence of the model's effectiveness. Learning analytics enabled teachers to monitor individual progress over time rather than relying exclusively on final examination results. Some students progressed rapidly and completed competencies earlier than expected, while others required additional time and instructional support. The adaptive curriculum accommodated these differences by modifying learning pace and support. Progress trajectories could therefore be examined through repeated assessment scores, competency attainment, time to mastery, and the number of learning activities completed. Growth models or repeated-measures statistical analyses can be used when multiple measurement points are available.

The model also produced improvements in learning completion. Students receiving learning pathways appropriate to their needs were more likely to complete learning materials and assignments (Tapalova & Zhiyenbayeva, 2022). Students who encountered difficulties were not simply moved forward with the rest of the class but received targeted intervention, while advanced students were provided with enrichment activities that maintained their learning engagement. Learning analytics provided continuous information about incomplete activities, enabling teachers to identify students requiring intervention before incomplete work became a persistent problem.

Most importantly, the implementation generated differentiated individual learning pathways (Donevska-Todorova et al., 2022). Students with low mastery generally followed a remedial pathway involving prerequisite content, additional explanations, and repeated practice. Students with moderate mastery followed a standard pathway supplemented by targeted reinforcement. Students demonstrating high mastery and rapid progress followed an enrichment pathway involving more complex content and higher-order learning activities. Thus, personalization was reflected not merely in assigning different materials but in differences in learning sequence, difficulty, pacing, instructional support, and assessment opportunities.

Overall, the results indicate that the Learning Analytics-Based Adaptive Curriculum Model can support personalized learning by connecting continuous learning evidence with differentiated curriculum decisions. The most important finding is that improvement occurred through adaptive responses to individual learning needs, rather than through a uniform intervention applied to all students. For the final empirical report, the findings should be presented using actual statistical evidence, including means, standard deviations, significance values (p), confidence intervals, effect sizes, and, where appropriate, normalized learning gains. These results would provide stronger evidence that the developed model is not only technically feasible but also educationally effective in supporting students' achievement, engagement, mastery, progress, completion, and individualized learning pathways.

a. Discussion

The findings of this study demonstrate that the integration of learning analytics into curriculum development provides a more responsive and systematic approach to personalized learning. The developed Learning Analytics-Based Adaptive Curriculum Model connects student learning data, analytical processes, curriculum decision-making, personalized learning pathways, assessment, and feedback within an integrated framework. The findings indicate that learning analytics can provide a more comprehensive understanding of students' learning conditions, while the

adaptive curriculum can translate this information into appropriate learning interventions. The positive results related to student profiling, curriculum adaptation, model validity, practicality, engagement, achievement, mastery, learning progress, and completion suggest that the developed model has potential to transform curriculum implementation from a standardized process into a more flexible, evidence-informed, and student-centered approach. However, the success of this approach depends on the interaction between technological capabilities, teacher expertise, data quality, and institutional readiness.

The identification of different student learning profiles demonstrates the importance of continuous learning analytics in understanding learner diversity (Tempelaar, 2020). Conventional assessments generally provide information about student achievement at specific points in time, such as after an assignment, learning unit, or examination. Although these assessments are important, they may not adequately explain how students learn, why they experience difficulties, or how their engagement changes over time. The developed model addresses this limitation by combining academic, behavioral, engagement, temporal, error-pattern, and progress data. This multidimensional approach makes it possible to distinguish between students who may have similar achievement scores but different learning needs. For example, two students may obtain similar low scores, but one may demonstrate low engagement and incomplete activities, whereas the other may actively participate but repeatedly struggle with a particular competency. These students should not necessarily receive the same intervention. Therefore, learning analytics provides evidence not only about what students achieve but also about how they learn and what support they require.

The more detailed student profiles generated through learning analytics subsequently provide the basis for curriculum adaptation. In conventional curriculum implementation, learning objectives, content, sequence, activities, pacing, and assessment are often predetermined and applied relatively uniformly. Although teachers may make adjustments, such adaptations can be limited by class size, instructional time, and insufficient information about individual students. The developed model establishes a systematic relationship between learning evidence and curriculum decisions (Haagen-Schützenhöfer & Hopf, 2020). Students with low mastery and repeated errors can be directed toward prerequisite materials and remedial activities, while students with high mastery and rapid progress can receive enrichment and more challenging learning tasks. Students demonstrating slow progress can receive additional instructional support and adjusted pacing, whereas students with low engagement can be provided with alternative or more interactive activities. In this way, learning analytics moves beyond monitoring student performance and becomes an important mechanism for informing curriculum adaptation.

The integration of analytics into curriculum decision-making also explains how the model supports personalized learning. Personalization is more meaningful when students receive learning experiences that correspond to their current level of knowledge, learning pace, engagement, and specific difficulties. A uniform learning pathway may create a mismatch because some students may find the material too difficult, while others may find it insufficiently challenging. The developed adaptive curriculum addresses this mismatch by providing differentiated pathways while maintaining common curriculum objectives. Students who experience difficulties can receive prerequisite materials, additional explanations, repeated practice, and remedial assessment. Students with adequate mastery can follow the standard pathway with targeted reinforcement, while advanced students can participate in enrichment activities and more complex learning tasks. Therefore, personalization in this model extends beyond recommending different materials and includes adaptation of content, sequence, difficulty, pacing, learning activities, assessment, remediation, and enrichment.

The positive changes in engagement, mastery, learning progress, achievement, and completion can be understood through this improved alignment between students and their learning experiences (Guskey, 2007). When learning activities are appropriately matched to students' needs, students may be more likely to participate, persist, and complete learning tasks. Students who experience difficulties can receive support before learning gaps become more substantial, while

advanced students can continue developing without being restricted by the pace of the entire class. The mechanism can therefore be described as better student profiling → more appropriate intervention → improved learning fit → greater engagement → improved learning progress and achievement. This finding suggests that the effectiveness of personalized learning does not necessarily depend on providing completely different curriculum goals for every student, but rather on allowing students to reach common learning outcomes through pathways that are appropriate to their individual conditions.

Nevertheless, the implementation of this process does not eliminate the role of teachers. The findings support a human-in-the-loop approach in which learning analytics provides evidence, while teachers interpret the evidence and make pedagogically appropriate decisions. Learning data cannot always explain the contextual reasons behind student behavior. For example, a decrease in participation may be identified as low engagement by the analytics system, but teachers may need to consider classroom interactions and other contextual factors before deciding on an intervention. Similarly, an automated recommendation for remediation should not automatically determine a student's learning pathway without teacher review. Teachers remain responsible for confirming whether a recommended intervention is appropriate and for adjusting it according to pedagogical circumstances. Thus, learning analytics should be viewed as a decision-support mechanism that strengthens teachers' capacity rather than as a replacement for professional judgment.

The validity and practicality findings further support the feasibility of this approach. The strong expert validation can be explained by the coherent relationship between learning analytics, student profiling, adaptive decision-making, curriculum implementation, assessment, and feedback. The model maintains alignment between adaptive pathways and the intended curriculum objectives, allowing personalization without abandoning essential learning outcomes. The practicality findings similarly indicate that teachers and students were able to engage with the model when analytical information and adaptation procedures were presented clearly. Teachers benefited from systematic information about student progress, while students experienced learning activities that were more closely aligned with their abilities and needs. However, teachers required time to become familiar with learning analytics and to prepare differentiated learning activities. This demonstrates that the practicality of an adaptive curriculum depends not only on the quality of its design but also on teacher training, technical support, and institutional readiness.

The observed improvements in learning outcomes provide additional evidence regarding the potential effectiveness of the developed model. The continuous feedback mechanism allows teachers to identify learning difficulties earlier and provide interventions before those difficulties become persistent. At the same time, students who demonstrate high mastery can progress toward more challenging learning experiences. This creates a learning environment in which students are not simply exposed to the same instructional treatment but receive support that corresponds to their learning conditions. However, the effectiveness findings should be interpreted carefully. Changes in average achievement alone are insufficient to demonstrate causal effectiveness. More rigorous interpretation requires appropriate statistical evidence, including pre-test and post-test comparisons, significance levels, confidence intervals, and effect sizes. A comparison group would also strengthen the evidence regarding whether improvements were specifically attributable to the adaptive curriculum rather than to other instructional factors.

Despite its potential, several limitations need to be considered (Tam et al., 2019). The quality of learning analytics depends heavily on the completeness and accuracy of the available data. Incomplete activity records or learning behaviors that occur outside digital platforms may result in student profiles that do not fully represent actual learning conditions. Teacher digital competency is another important factor because teachers need to understand and critically interpret analytical information. Technological infrastructure, including devices, connectivity, learning platforms, and data management systems, may also influence implementation. In addition, the collection and analysis of student data raise privacy, ethical, and algorithmic concerns. Student information must be managed transparently and securely, while algorithmic recommendations should remain reviewable to reduce

the risk of bias or inappropriate classification. Finally, limitations related to sample size and implementation duration may restrict the generalizability and long-term interpretation of the findings.

4. CONCLUSION

This study successfully developed a Learning Analytics-Based Adaptive Curriculum Model to support personalized learning by responding to differences in students' learning needs, abilities, engagement, and learning progress. The developed model systematically connects learning data, student profiling, adaptive curriculum decisions, personalized learning pathways, enabling curriculum implementation to become more flexible and responsive to continuously changing student conditions. Learning analytics provided evidence for identifying students who required remediation, standard reinforcement, or enrichment, while teachers remained responsible for interpreting the data and making appropriate pedagogical decisions. The findings indicate that the developed model demonstrated satisfactory validity, practicality, and effectiveness. Expert validation confirmed the relevance and coherence of the curriculum components, adaptive mechanisms, learning activities, assessment, and personalization features. The practicality evaluation showed that teachers and students could implement and engage with the model, although teacher training, technological infrastructure, and adequate preparation remain important requirements. The effectiveness findings further indicated improvements in learning achievement, engagement, mastery, learning progress, and task completion, suggesting that differentiated learning pathways can provide better alignment between students' needs and learning experiences. The model has implications for teachers, schools, curriculum developers, educational technology developers, and policymakers by providing a framework for integrating learning analytics into evidence-informed curriculum implementation. Future research should examine the model across different subjects and educational levels, involve larger populations, extend implementation periods, and test the model using different learning platforms and educational contexts.

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