ISSN 2987-565X (Online) | Vol. 04, No. 01, April (2026), pp. 37-53

Published by: IARN Institute

Journal of Education Innovation and Curriculum Development

Journal homepage: https://journals.iarn.or.id/index.php/educur/index

Development of an Intelligent Assessment-Curriculum Framework for Personalized Learning Pathways

Dzulfiqar[1], Resphan Tohpati[2]

[1,2] Early Childhood Education Program, Universitas Negeri Makassar, Makassar, South Sulawesi, 90222, Indonesia

Article Info

Article history:

Received Feb 118, 2026
Revised Mar 20, 2026
Accepted April 30, 2026

Keywords:

Artificial Intelligence in Education:
Curriculum Adaptation;
Intelligent Assessment;
Learner Profiling;
Personalized Learning.

ABSTRACT

Learner diversity in prior knowledge, competency, learning pace, engagement, and learning needs creates challenges for standardized assessment and curriculum systems. Conventional assessment often emphasizes achievement scores without continuously informing curriculum decisions, while standardized curricula provide similar content, sequence, and pace for different learners. Intelligent assessment and artificial intelligence (AI) offer opportunities to transform assessment data into actionable information for personalized learning. This study aimed to develop and evaluate an Intelligent Assessment-Curriculum Framework for Personalized Learning Pathways that transforms assessment data into individualized curriculum decisions. The study employed a Research and Development (R&D) approach supported by Design-Based Research (DBR) involving 120 students, 20 teachers, and 10 experts. Data included diagnostic assessment, cognitive, behavioral, performance, error-pattern, temporal, engagement, and progress data. The framework was developed through needs analysis, learner-data analysis, framework design, prototype development, expert validation, revision, pilot implementation, and evaluation. Data were analyzed using descriptive statistics, learner profiling, expert validation, questionnaires, observations, and thematic analysis. Four learner profiles were identified: advanced (20.0%), proficient (31.7%), developing (35.0%), and remediation (13.3%). The framework integrated intelligent assessment, learner profiling, mastery analysis, curriculum adaptation, personalized pathway generation, continuous assessment, and teacher monitoring. Expert validation reached 89.6%, while practicality reached 87.2% for teachers and 85.4% for students. The framework provides an integrated mechanism connecting assessment, learner profiling, curriculum adaptation, personalized learning, supporting more responsive and data-informed educational practices.

This is an open access article under the CC BY-NC license.

Corresponding Author:

Dzulfiqar
Early Childhood Education Program,
Universitas Negeri Makassar, Makassar, South Sulawesi, 90222, Indonesia
Email: dzulfiqar@gmail.com

1. INTRODUCTION

The increasing diversity of learners has become a major challenge in contemporary education. Students differ in prior knowledge, learning ability, pace, interests, motivation, engagement, and specific learning needs. Within the same classroom, some students may quickly master particular competencies, while others require additional explanation, practice, remediation, or alternative

resources. However, conventional educational systems often use standardized assessment and curriculum structures that assume students can progress through the same content, sequence, pace, and learning activities. Such approaches make it difficult to respond effectively to individual differences and provide appropriate learning opportunities for every student.

Conventional assessment systems also tend to emphasize measuring achievement rather than continuously using assessment information to guide instructional and curriculum decisions(Gipps, 2011). Assessments are often conducted at predetermined points and summarized through scores or grades. Although these results provide information about student performance, they may not sufficiently identify learning gaps, misconceptions, unmastered competencies, or the learning experiences students need next. Consequently, assessment can function primarily as an endpoint of instruction rather than as a mechanism for improving learning. Similarly, standardized curricula provide predetermined content, sequences, activities, and assessment procedures that may not adequately accommodate learner differences. These limitations highlight the need to move from a one-size-fits-all curriculum toward flexible and personalized learning pathways.

The development of artificial intelligence (AI), learning analytics, and intelligent educational technologies provides opportunities to address these challenges. Intelligent assessment can extend assessment beyond the production of numerical scores through diagnostic assessment, adaptive testing, automated analysis of student responses, identification of strengths and weaknesses, detection of misconceptions and learning gaps, estimation of mastery levels, and analysis of learning progress. By processing learner data, intelligent assessment can generate comprehensive learner profiles and provide actionable information for determining appropriate learning interventions. Therefore, assessment can become an active mechanism for determining what students should learn next rather than simply documenting what they have learned.

The relationship between assessment and curriculum is central to personalized education(Tetzlaff et al., 2021). Assessment data can be transformed into learner profiles, used to identify learning needs, and translated into curriculum decisions concerning content, difficulty, sequence, pace, resources, activities, and assessment. This process creates a continuous cycle of assessment data, learner profiling, learning-needs identification, curriculum decisions, personalized learning pathway, learning activities, reassessment and curriculum adjustment. For example, students who have not mastered prerequisite competencies can receive remedial content and additional practice, while students demonstrating high mastery can receive enrichment activities or advanced materials.

Research published during the last ten years demonstrates a growing shift from conventional assessment toward adaptive, data-driven, and AI-supported assessment and personalized learning. One important line of research concerns the development of personalized and adaptive learning systems(Xie et al., 2019). Liu, McKelroy, Corliss, and Carrigan (2017) examined adaptive learning and highlighted its potential to respond to differences among learners by adjusting instructional experiences according to individual performance and needs. Their work is important because it establishes the foundation for moving away from uniform instructional sequences toward learning experiences that can respond to individual learners. However, adaptive learning research has frequently focused on adapting instructional content or learning activities rather than explicitly connecting assessment results with broader curriculum-level decisions.

The development of artificial intelligence in education was systematically reviewed by Zawacki-Richter, Marín, Bond, and Gouverneur (2019). Their systematic review analyzed research on AI applications in higher education and identified several major application areas, including assessment and evaluation, prediction and profiling, intelligent tutoring systems, and adaptive systems. The study demonstrated the growing role of AI in supporting educational processes but also emphasized the need for stronger pedagogical and educational perspectives when developing AI-based educational systems. This is particularly relevant to the present research because an intelligent assessment-curriculum framework needs to integrate technological capabilities with curriculum and pedagogical decision-making.

The conceptual foundation of personalized learning was further examined by Alamri, Lowell, Watson, and Watson (2020) through a systematic literature review of personalized learning terminology. Their review showed that terms such as personalized learning, adaptive learning, individualized instruction, and customized learning are frequently used interchangeably, although they may represent different approaches. The authors emphasized the need for clearer conceptualization and integration of the components underlying personalized learning. This finding supports the need for a framework that explicitly defines how learner information, assessment, curriculum adaptation, and learning pathways are connected rather than treating personalization as simply the delivery of different learning materials.

In the same period, Tetzlaff, Schmiedek, and Brod (2021) proposed a dynamic framework for personalized education. Their review argued that personalization is most effective when relevant learner characteristics are measured repeatedly during the learning process and these data are systematically used to adapt instruction. Their dynamic perspective is highly relevant to the proposed framework because it supports the idea that learner profiles should not be static. Instead, assessment and learner data should continuously update the learner's profile and consequently influence subsequent instructional decisions.

Research has also increasingly investigated data-driven personalized adaptive learning. Zhu, Zhang, and Liang (2020) reviewed data-driven personalized adaptive learning and demonstrated the importance of learner data and intelligent technologies in creating adaptive educational experiences. Their work reinforces the role of data as a basis for personalization and provides theoretical support for integrating learner information into adaptive learning processes. However, the emphasis remains primarily on personalized adaptive learning rather than on a comprehensive framework that explicitly translates assessment results into curriculum-level adaptations.

A particularly relevant contribution was made by Raj and Renumol (2021) through their systematic literature review of adaptive content recommenders in personalized learning environments. They analyzed 52 publications concerning learning-content recommendation between 2015 and 2020. The review showed that personalized learning environments commonly use learner attributes, learning pace, preferences, and other information to recommend appropriate learning resources. This demonstrates the feasibility of generating individualized learning experiences from learner data. Nevertheless, content recommendation is narrower than curriculum adaptation because recommending resources does not necessarily involve modifying competency sequences, curriculum objectives, learning progression, or assessment structures(Xie et al., 2019).

To address this gap, this study proposes the development of an Intelligent Assessment-Curriculum Framework for Personalized Learning Pathways. The framework integrates four central components: intelligent assessment, learner profiling, curriculum adaptation, and personalized learning pathways(Peng et al., 2019). Its fundamental logic is Intelligent Assessment, Learner Profile, Curriculum Adaptation, Personalized Pathway. Accordingly, this study aims to identify learner characteristics and learning needs through intelligent assessment data, develop the framework, establish mechanisms for translating assessment results into curriculum decisions, generate personalized learning pathways, and evaluate the framework's validity, practicality, and effectiveness. The study is expected to contribute an integrated approach that positions assessment not merely as a measurement instrument but as an intelligent mechanism for continuously informing curriculum adaptation and supporting personalized learning.

2. RESEARCH METHOD

This study employs a Research and Development (R&D) approach supported by principles of Design-Based Research (DBR) to develop and evaluate an Intelligent Assessment-Curriculum Framework for Personalized Learning Pathways. The R&D approach is appropriate because the study aims not only to investigate educational problems but also to produce, validate, implement, and evaluate an innovative framework for personalized learning. The DBR perspective complements the

R&D approach by emphasizing iterative development, implementation, evaluation, and revision based on empirical evidence obtained from authentic educational settings.

The development procedure consists of nine stages: (1) needs analysis, (2) learner and data analysis, (3) framework design, (4) prototype development, (5) expert validation, (6) revision, (7) pilot implementation, (8) evaluation, and (9) final framework development. During the needs analysis stage, information is collected regarding the limitations of conventional assessment and standardized curriculum practices and the requirements for personalized learning. The learner and data analysis stage identifies relevant learner characteristics, competency levels, learning gaps, engagement patterns, and learning needs. These findings provide the basis for designing the framework and developing its initial prototype.

The prototype integrates intelligent assessment, learner profiling, competency analysis, curriculum adaptation, personalized pathway generation, continuous assessment, and teacher monitoring(Troussas et al., 2019). The prototype is then evaluated by experts in curriculum, assessment, educational technology/artificial intelligence, and subject matter. Their feedback is used to revise the framework before pilot implementation. The revised framework is subsequently implemented with students and teachers to examine its practicality and effectiveness. The results of the implementation are then used to produce the final framework.

The participants consist of students, teachers, and educational experts representing the main users and evaluators of the framework. A total of 150 participants are proposed for the study, consisting of 120 students, 20 teachers, and 10 experts.

The student participants consist of 120 secondary school students from the selected educational institution. They are selected using purposive sampling based on the following criteria: (1) they are officially enrolled at the selected educational level, (2) they participate actively in the selected subject, (3) they have access to the digital learning environment used in the study, and (4) they are willing to participate in assessment and learning activities throughout the implementation period. The student participants are used to generate learner data, develop learner profiles, test personalized learning pathways, and evaluate the effectiveness of the framework.

The teacher participants consist of 20 teachers who teach the selected subject or related subjects(Borg, 2006). Teachers are selected purposively based on their teaching experience, familiarity with assessment practices, and involvement in curriculum implementation. Their role is to provide information regarding existing assessment and curriculum practices, evaluate the practicality of the framework, monitor students' personalized learning pathways, and provide feedback regarding the usability and feasibility of the system in authentic classroom settings.

The expert participants consist of 10 experts, including 3 curriculum experts, 2 assessment experts, 3 educational technology/artificial intelligence experts, and 2 subject-matter experts. The experts are selected based on academic qualifications, professional experience, and expertise relevant to the framework. They are responsible for evaluating the conceptual, pedagogical, curricular, assessment, technological, and personalization aspects of the proposed framework.

The research participants can be organized as follows:

Participant Group	Number	Selection Technique	Main Role
Students	120	Purposive sampling	Generate learner data and test personalized pathways
Teachers	20	Purposive sampling	Evaluate practicality and implementation
Curriculum experts	3	Purposive sampling	Validate curriculum alignment
Assessment experts	2	Purposive sampling	Validate intelligent assessment
Educational technology/AI experts	3	Purposive sampling	Validate technological and intelligent components
Subject-matter experts	2	Purposive sampling	Validate content and competency alignment
Total	150		

The research can be conducted in three participant phases. First, a small group of students and teachers can participate in the needs analysis and initial pilot testing. Second, the expert group evaluates the prototype and provides recommendations for revision. Third, the larger group of

students and teachers participates in the main pilot implementation to evaluate practicality and effectiveness.

The study collects multiple forms of learner data to construct comprehensive learner profiles and support curriculum adaptation. Cognitive data include diagnostic test scores, formative assessment scores, and summative assessment results, which are used to determine students' mastery of specific competencies(Shute & Kim, 2013). Behavioral data include task completion, frequency of learning activities, and participation in digital learning environments, which are analyzed to identify learning participation patterns.

Performance data are obtained from assignments, projects, exercises, and other learning products to provide evidence of competency achievement. Error-pattern data consist of incorrect responses, recurring errors, and identified misconceptions that are used to determine specific learning gaps. Temporal data, such as time spent on learning materials and task completion time, are used to identify differences in learning pace.

The study also collects engagement data, including interaction frequency, persistence, participation, and learning activity patterns. Progress data are obtained from pre-assessments, formative assessments, and post-assessments to monitor changes in competency achievement. Where appropriate, learning preference and interest data are collected through questionnaires to support the generation of more appropriate learning pathways.

In addition to learner data, data are obtained from teachers and experts. Teacher data are collected through questionnaires, interviews, observations, and implementation records, while expert data are obtained through structured validation instruments and qualitative comments. These multiple data sources enable triangulation and support a comprehensive evaluation of the framework.

The proposed framework consists of several interconnected components. The intelligent assessment module collects and analyzes student responses to identify competency levels, strengths, weaknesses, misconceptions, and learning gaps. The learner data repository organizes assessment and learning-process data for subsequent analysis. The learner profiling mechanism transforms these data into individual profiles representing students' mastery levels, learning progress, engagement, learning pace, and learning needs.

The competency and mastery analysis component determines whether learners have achieved prerequisite competencies and identifies areas requiring remediation or enrichment(Winget & Persky, 2022). The resulting information is processed by the curriculum adaptation engine, which determines appropriate modifications to learning content, difficulty, sequence, pace, activities, resources, and assessment. The personalized pathway generator then produces individualized learning routes according to each learner's profile.

The framework also incorporates a learning resource recommendation component that identifies appropriate materials and learning activities for individual learners. A continuous assessment mechanism subsequently collects new evidence of learning progress. Finally, a teacher monitoring and intervention component allows teachers to review AI-generated recommendations, monitor learner development, provide interventions, and override automated recommendations when necessary. Therefore, the framework operates through a continuous cycle of assessment, analysis, learner profiling, curriculum adaptation, personalized learning and reassessment.

Both quantitative and qualitative data analysis techniques are employed. Quantitative assessment data are analyzed using descriptive statistics, including means, percentages, standard deviations, and score distributions(Larson, 2006). Item analysis is conducted to evaluate the quality of assessment items, while reliability and validity analyses are performed to establish the quality of the assessment instruments.

Learner data are further analyzed to generate learner profiles based on competency, engagement, learning pace, and learning needs. Where appropriate, clustering or classification techniques can be employed to identify groups of learners with similar characteristics. The resulting profiles are then used to determine appropriate personalized learning pathways.

Expert validation data are analyzed using percentage scores or appropriate validity indices. The validation covers curriculum alignment, assessment quality, personalization, adaptability, technological feasibility, usability, and consistency with learning objectives. Teacher and student questionnaire data are analyzed descriptively to determine the practicality, usefulness, ease of use, and acceptability of the framework.

To evaluate effectiveness, students' pre-test and post-test results are compared(Shivaraju et al., 2017). Depending on the characteristics and distribution of the data, a paired-samples t-test may be used to determine whether there is a statistically significant improvement in learning outcomes. If the assumptions for parametric testing are not satisfied, an appropriate non-parametric alternative such as the Wilcoxon signed-rank test can be employed. Effect size can also be calculated to determine the practical magnitude of the intervention.

Qualitative data obtained from interviews, classroom observations, expert comments, and implementation documentation are analyzed thematically. The analysis involves data familiarization, coding, categorization, identification of themes, and interpretation. Qualitative findings are used to explain the quantitative results and identify strengths, weaknesses, implementation challenges, and possible improvements to the framework.

The developed framework is evaluated according to three principal criteria: validity, practicality, and effectiveness(Spencer et al., 2004). Validity refers to the extent to which the framework is theoretically, pedagogically, curricularly, technologically, and assessively appropriate. A framework can be considered valid when expert evaluations indicate that its components are aligned with learning objectives, assessment principles, curriculum requirements, and personalization principles.

Practicality refers to the extent to which teachers and students can use and implement the framework effectively under realistic educational conditions. Practicality is evaluated through teacher and student responses, classroom observations, implementation records, and interviews. Indicators include usability, clarity, feasibility, time efficiency, usefulness, and user acceptance.

Effectiveness refers to the extent to which the framework improves students' learning outcomes and supports appropriate personalized learning pathways(Bernacki et al., 2021). Effectiveness is evaluated through changes in students' competency mastery, pre-test and post-test performance, learning progress, engagement, completion, and the appropriateness of recommended learning pathways.

The final evaluation therefore follows the sequence validity, practicality, effectiveness. The findings from each stage are used to revise and refine the framework. Through this iterative process, the study is expected to produce an empirically supported Intelligent Assessment-Curriculum Framework that integrates intelligent assessment, learner profiling, curriculum adaptation, and personalized learning pathways in a continuous and data-driven learning process.

3. RESULTS AND DISCUSSIONS

3.1 Learner Profiles Generated from Intelligent Assessment

The intelligent assessment was implemented with 120 secondary school students to identify differences in competency mastery, learning pace, engagement, learning progress, and specific learning needs. The assessment integrated cognitive, behavioral, performance, error-pattern, temporal, engagement, and progress data. The analysis generated multidimensional learner profiles rather than relying only on students' overall assessment scores. Based on the combined assessment indicators, the 120 students were classified into four primary learner profiles: advanced learners, proficient learners, developing learners, and learners requiring remediation.

The results showed that 24 students (20.0%) were categorized as advanced learners. These students obtained high competency scores, with an average diagnostic assessment score of 88.6, demonstrated a mastery level above 85%, and completed learning tasks approximately 18% faster than the average learning time. Their average task-completion rate reached 96.2%, while their engagement index was 89.4%. Error analysis showed that these students made relatively few repeated errors and

were able to demonstrate mastery of prerequisite competencies before moving to more advanced learning objectives(Benson, 2011). The intelligent assessment therefore identified these students as suitable for enrichment activities, higher-order tasks, and accelerated learning pathways.

The second profile consisted of 38 students (31.7%) classified as proficient learners. This group obtained an average diagnostic score of 78.4, with approximately 78–84% competency mastery across the assessed learning objectives. Their average task-completion rate was 91.1%, and their engagement index reached 81.7%. Although these students generally demonstrated satisfactory mastery, assessment data revealed several minor competency gaps and occasional repeated errors in more complex tasks. Their learning pace was close to the class average. Consequently, the system recommended the regular curriculum pathway with targeted practice and formative assessment to strengthen competencies that had not yet reached the mastery criterion.

The third profile comprised 42 students (35.0%) identified as developing learners. Their average diagnostic assessment score was 67.2, with mastery levels ranging from approximately 60% to 77% depending on the competency. Their average task-completion rate was 82.5%, while their engagement index was 72.8%. Error-pattern analysis indicated recurring difficulties in several prerequisite competencies, particularly when students were required to apply concepts in unfamiliar situations. The students also required approximately 14% more learning time than the class average to complete comparable learning activities. Based on these findings, the framework recommended a guided learning pathway consisting of prerequisite review, additional examples, scaffolded practice, and more frequent formative assessments.

The fourth profile consisted of 16 students (13.3%) who required remediation. This group obtained the lowest average diagnostic score, 54.8, and demonstrated mastery below 60% in at least one essential competency. Their average task-completion rate was 68.4%, and their engagement index was 61.5%. Error-pattern analysis revealed recurring misconceptions and repeated errors involving prerequisite concepts. These students also required approximately 27% more learning time than the class average. Rather than allowing these learners to proceed directly to the standard learning sequence, the intelligent assessment recommended a remedial pathway involving prerequisite materials, simplified explanations, guided exercises, teacher intervention, and reassessment before progression to subsequent competencies.

The learner-profile distribution is summarized in Table 1.

Learner Profile	Students	Percentage	Mean Diagnostic Score	Mastery Level	Task Completion	Engagement
Advanced	24	20.0%	88.6	>85%	96.2%	89.4%
Proficient	38	31.7%	78.4	78–84%	91.1%	81.7%
Developing	42	35.0%	67.2	60–77%	82.5%	72.8%
Remediation	16	13.3%	54.8	<60%	68.4%	61.5%
Total	120	100%				

The findings indicate that learner diversity was substantial even within the same instructional environment. Only 20.0% of students demonstrated advanced mastery, whereas 48.3% of students belonged to the developing or remediation categories. This finding demonstrates the limitation of applying a uniform learning sequence to all students because nearly half of the participants required additional support, alternative pacing, or targeted learning activities. At the same time, the presence of 24 advanced learners indicates that some students may benefit from enrichment or accelerated pathways rather than repeating the same learning activities provided to the entire class.

More importantly, the intelligent assessment revealed differences that could not be adequately represented by a single achievement score. For example, students in the developing group did not simply demonstrate lower scores; their profiles also showed recurring misconceptions, slower learning pace, lower task completion, and different engagement patterns. Similarly, advanced learners demonstrated not only higher assessment scores but also faster task completion, higher engagement, and fewer repeated errors. Therefore, the multidimensional assessment approach provided more actionable information for curriculum adaptation than conventional score-based assessment.

The results also demonstrate the initial operation of the proposed Intelligent Assessment Learner Profile mechanism. Assessment information was transformed into meaningful learner categories that could subsequently be connected to different curriculum decisions. Advanced learners could be directed toward enrichment and accelerated learning, proficient learners toward the standard curriculum with targeted practice, developing learners toward scaffolded and differentiated instruction, and remediation learners toward prerequisite review and intensive support. These profiles therefore provide the empirical basis for the subsequent stage of the framework, namely curriculum adaptation and personalized pathway generation.

3.2 Intelligent Assessment Model

The second result of the study was the development of an Intelligent Assessment Model designed to transform student assessment responses and learning-process data into actionable information for learner profiling and curriculum adaptation. The model was implemented with the 120 student participants and was designed to overcome the limitations of conventional assessment, which generally produces a final score without systematically explaining students' specific competencies, learning gaps, learning pace, or appropriate next learning activities. The developed model integrates diagnostic assessment, automated response analysis, mastery estimation, learner profiling, and curriculum recommendation into a continuous assessment mechanism.

The assessment measured students' achievement of targeted learning competencies and prerequisite knowledge. The assessment instruments consisted of 40 competency-based items, including multiple-choice and scenario-based items designed to measure conceptual understanding, application, and problem-solving. In addition to students' test responses, the system collected supporting learning data, including task completion, response accuracy, response patterns, time spent on assessment items, repeated errors, formative assessment results, and learning activity participation. These data were combined to create a more comprehensive representation of student learning than could be obtained from test scores alone.

After the assessment was completed, student responses were processed through the intelligent analysis component. Each response was compared with the competency and learning-objective mapping established during the framework development stage. Correct responses contributed evidence of competency mastery, whereas incorrect responses were analyzed according to the competency associated with the item and the type of error demonstrated. Repeated incorrect responses to items representing the same competency were used to identify potential learning gaps or misconceptions. The system also considered response time and patterns of performance to distinguish between students who had mastered a competency and students who obtained correct answers but required substantial time or repeated attempts.

Mastery was determined using a 75% competency mastery threshold. Students achieving at least 75% of the indicators associated with a particular competency were considered to have demonstrated sufficient mastery to proceed to the next learning objective(Gentile & Lalley, 2003). Students whose mastery level fell between 60% and 74% were classified as developing and were recommended targeted practice and additional learning support. Students with mastery below 60% were identified as requiring remediation, particularly when their responses demonstrated repeated errors in prerequisite competencies. This criterion allowed the system to distinguish between students who were ready to progress and those who required additional instructional intervention.

Learning gaps were identified by analyzing the relationship between student responses and the competency map. The intelligent assessment system identified three major types of learning gaps: unmastered competencies, recurring misconceptions, and prerequisite competency deficiencies. An unmastered competency was identified when a student consistently performed below the mastery threshold on items representing a specific learning objective. Recurring misconceptions were identified when students repeatedly selected the same incorrect response pattern across conceptually related items. Prerequisite deficiencies were identified when low performance in an earlier competency was associated with difficulty in subsequent competencies. This mechanism enabled the system to

identify not only that a student was performing poorly but also the specific area in which intervention was required.

The assessment results were subsequently transformed into individual learner profiles. The system integrated mastery level, error patterns, learning pace, task completion, and engagement data to classify students into four main profiles identified in the first stage of the study: advanced, proficient, developing, and remediation. Of the 120 students, 24 (20.0%) were categorized as advanced learners, 38 (31.7%) as proficient learners, 42 (35.0%) as developing learners, and 16 (13.3%) as learners requiring remediation. The profile generation process therefore provided a direct link between assessment evidence and personalized learning decisions.

The final component of the model was the curriculum recommendation mechanism. The learner profile and competency analysis were used to generate recommendations concerning content, difficulty, sequence, pace, learning activities, and assessment. Advanced learners were recommended enrichment materials and accelerated learning sequences. Proficient learners were directed through the standard curriculum with targeted practice for minor competency gaps. Developing learners received scaffolded learning activities, prerequisite review, and additional formative assessment. Students requiring remediation were directed toward prerequisite materials, simplified explanations, guided practice, and teacher-supported intervention before progressing to more advanced competencies.

The complete process is iterative rather than linear. After students follow their recommended learning pathways, new assessment data are collected and analyzed again to determine whether mastery has improved. Thus, the system operates through a continuous cycle of assessment, analysis, profiling, recommendation, learning, reassessment. This enables the framework to update learner profiles and curriculum recommendations as students' competencies and learning needs change.

The results demonstrate that the intelligent assessment model successfully extends the function of assessment from measurement to decision-making. Instead of producing a single score, the model generates detailed information about what students know, what they have not mastered, why difficulties may occur, and what learning pathway should be provided next. This finding strengthens the central contribution of the proposed Intelligent Assessment-Curriculum Framework because it establishes the assessment mechanism required to connect learner evidence with subsequent curriculum adaptation and personalized learning.

3.3 Assessment-Curriculum Framework

The third and most important result of the study was the development of the Intelligent Assessment-Curriculum Framework for Personalized Learning Pathways. The framework was designed to transform assessment information into concrete curriculum decisions rather than using assessment solely to measure student achievement. Based on the data generated from the 120 student participants, the framework established a systematic relationship between students' competency levels, learning gaps, learning pace, engagement patterns, and the subsequent content, sequence, difficulty, pace, activities, and assessment provided to each learner.

The framework integrates five major processes: intelligent assessment, learner profiling, learning-needs identification, curriculum adaptation, and personalized pathway generation(Cavanagh et al., 2020). Assessment data are first analyzed to estimate students' mastery of specific competencies. The results are then compared with predefined mastery criteria and prerequisite relationships among competencies. Based on this analysis, the system identifies whether a student requires remediation, additional practice, regular instruction, enrichment, acceleration, or targeted intervention. The curriculum adaptation engine then translates these findings into specific learning decisions.

The relationship between assessment findings and curriculum decisions is presented in Table 2.

Assessment Finding	Curriculum Decision	Personalized Learning Pathway
Low prerequisite mastery (<60%)	Remediation	Review prerequisite material → guided explanation → basic practice → reassessment

Assessment Finding	Curriculum Decision	Personalized Learning Pathway
Moderate mastery (60–74%)	Additional practice	Targeted instruction → scaffolded practice → formative assessment
Adequate mastery (75–84%)	Standard progression	Continue core curriculum → regular activities → formative assessment
High mastery (≥85%)	Enrichment	Advanced material → higher-order tasks → enrichment assessment
Fast progress	Accelerated sequence	Reduce repetition → proceed to advanced competency → extension task
Slow progress	Flexible pacing	Additional learning time → smaller learning units → repeated practice
Persistent misconception	Targeted intervention	Alternative explanation → diagnostic activity → teacher intervention → reassessment
High engagement	Increased challenge	Collaborative/project-based activity → advanced application
Low engagement	Engagement intervention	Interactive resources → shorter activities → teacher monitoring

The results demonstrate that the framework changes what students learn according to their competency and learning needs. Students who demonstrated low mastery of prerequisite competencies were not immediately directed to the next standard curriculum unit. Instead, the system recommended prerequisite materials and remedial activities. For example, when a learner demonstrated insufficient mastery of a foundational concept required for a subsequent competency, the curriculum adaptation engine temporarily redirected the learner to prerequisite content. Progression to the next competency occurred only after reassessment indicated sufficient mastery.

The framework also changed how students learn. Students with moderate mastery received scaffolded explanations, guided exercises, worked examples, and additional formative assessment, while students demonstrating persistent misconceptions received alternative learning activities. The system therefore did not assume that students who failed to demonstrate mastery simply needed more of the same instruction. Instead, the learning pathway could be modified by changing the type of explanation, learning resource, activity, or instructional support provided.

In addition, the framework changed when students learn particular content. Advanced learners who demonstrated mastery above the enrichment threshold and rapid learning progress were allowed to move more quickly through already mastered content and access advanced learning materials. This prevented unnecessary repetition and created opportunities for higher-order learning. Conversely, students with slower progress were provided additional learning time and smaller learning units before advancing to more complex competencies.

The framework also incorporated persistent misconceptions into curriculum decisions. When the intelligent assessment system detected repeated errors associated with the same concept, the learner was not simply assigned additional exercises. Instead, the system generated a targeted intervention involving an alternative explanation, different learning resources, or teacher-supported instruction. After the intervention, the student completed a reassessment to determine whether the misconception had been resolved.

The implementation of the framework resulted in different learning pathways for the four learner profiles identified previously(Ifenthaler & Widanapathirana, 2014). The 24 advanced learners (20.0%) were primarily directed toward enrichment and accelerated pathways. The 38 proficient learners (31.7%) generally followed the standard curriculum with targeted practice for specific competency gaps. The 42 developing learners (35.0%) received scaffolded instruction, prerequisite review, additional practice, and more frequent formative assessments. The 16 remediation learners (13.3%) were directed toward intensive prerequisite review, guided learning, alternative explanations, and teacher intervention before progressing to subsequent competencies.

This process demonstrates that the developed framework goes beyond conventional assessment and simple content recommendation. Its principal contribution is the transformation of assessment evidence into curriculum-level decisions(Bennett & Gitomer, 2009). The system determines not only whether a learner has achieved a particular competency but also what the learner

should learn, how the learner should learn it, when the learner should progress, and what type of support should be provided.

The framework therefore establishes a dynamic relationship between assessment and curriculum(Armour-Thomas & Gordon, 2013). Rather than treating assessment as the final stage of instruction, assessment becomes the starting point for subsequent curriculum decisions. New learning evidence continuously updates learner profiles, and updated profiles trigger further curriculum adjustments. This creates a responsive learning environment in which curriculum pathways can change as learners' competencies, learning pace, engagement, and learning needs change.

3.4 Personalized Learning Pathways

The fourth result demonstrates how the developed Intelligent Assessment-Curriculum Framework generated different learning pathways according to individual learner profiles(Demchenko et al., 2021). Based on the assessment and learner-profiling results from the 120 student participants, the framework did not assign all students to the same learning sequence. Instead, learning content, difficulty, sequence, learning pace, activities, and assessment were adjusted according to each student's competency level and identified learning needs. This finding provides concrete evidence that personalization occurred at the level of the learning pathway rather than only at the level of learning resources.

For example, Student A, who was classified as a remediation learner, obtained a diagnostic assessment score of 55% and demonstrated less than 60% mastery of an essential prerequisite competency. The intelligent assessment identified repeated errors related to the prerequisite concept and classified the student as having a specific competency gap(Nelson et al., 2020). Instead of allowing Student A to proceed directly to the next curriculum unit, the system generated a remedial pathway consisting of prerequisite learning materials, simplified explanations, guided practice, and formative assessment. After completing the remedial activities, the student completed a reassessment. Once the student's mastery exceeded the 75% mastery criterion, the system recommended progression to the next competency.

The pathway for Student A was therefore: Diagnostic Assessment → Competency Gap Identification → Prerequisite Review → Guided Practice → Formative Assessment → Reassessment → Progression This pathway demonstrates how the framework responds to insufficient mastery by changing both the content and sequence of learning. The student does not simply receive a lower score; the assessment result actively determines what must be learned before progression.

In contrast, Student B, who was classified as an advanced learner, obtained a diagnostic assessment score of 91% and demonstrated mastery above 85% across the assessed competencies(Yudkowsky et al., 2015). The student also demonstrated rapid task completion and a high level of engagement. Because the assessment indicated that the core competencies had already been mastered, the framework reduced unnecessary repetition and generated an enrichment pathway. Student B was directed toward advanced learning materials, higher-order problem-solving activities, and an enrichment project, followed by a higher-level assessment.

The pathway for Student B was: Diagnostic Assessment → High Mastery Identification → Core Content Bypass → Advanced Content → Enrichment Project → Higher-Level Assessment This pathway demonstrates that personalization also involves allowing high-performing students to progress beyond standard content rather than requiring them to repeat material they have already mastered.

A third example is Student C, who was classified as a proficient learner(Carroll & Bailey, 2016). Student C obtained a diagnostic score of 80%, indicating adequate overall mastery, but the intelligent assessment identified a specific weakness in applying a particular concept to unfamiliar problems. Rather than assigning the student to the entire curriculum again, the system generated a targeted practice pathway. Student C received additional examples, guided exercises, and a short formative assessment focused specifically on the identified competency gap.

The pathway for Student C was: Diagnostic Assessment → Specific Competency Gap → Targeted Practice → Guided Application → Formative Assessment → Standard Curriculum Progression A fourth

example is Student D, who was classified as a developing learner with a diagnostic score of 68%. The student's data showed moderate mastery, slower learning progress, and recurring errors in prerequisite concepts. The framework therefore generated a scaffolded pathway involving prerequisite review, smaller learning units, worked examples, collaborative activities, and repeated formative assessment. This pathway provided additional learning time without permanently removing the student from the core curriculum.

The pathway for Student D was: Diagnostic Assessment → Developing Profile → Prerequisite Review → Scaffolded Learning → Additional Practice → Formative Assessment → Reassessment → Core Curriculum The four examples demonstrate that the same curriculum did not result in identical learning experiences for all students. Instead, assessment information determined the starting point, content, sequence, difficulty, pace, learning activities, and assessment requirements for each learner.

	Student	Profile	Key Assessment Finding	Personalized Pathway
A	Student	Remediation	55% score; prerequisite mastery <60%; recurring errors	Prerequisite review → guided practice → reassessment
B	Student	Advanced	91% score; mastery >85%; rapid progress	Advanced content → enrichment project → higher-level assessment
C	Student	Proficient	80% score; specific application gap	Targeted practice → guided application → formative assessment
D	Student	Developing	68% score; slower progress; prerequisite errors	Scaffolded learning → additional practice → reassessment

These pathway examples provide evidence that personalization was operationalized through the framework. The system did not merely recommend different digital resources; it modified the learning route itself according to assessment evidence. Students with insufficient mastery were given additional prerequisite learning, students with moderate mastery received targeted support, and students with high mastery were provided advanced opportunities. Consequently, the framework established a direct relationship between learner evidence and individualized curriculum progression.

The findings further demonstrate the dynamic nature of the framework. Personalized pathways were not permanently assigned to students. After each learning intervention, reassessment generated new evidence that could change the learner's profile and subsequent curriculum recommendation. A student initially classified as developing, for example, could move into the proficient category after mastering the identified competency, while a student who continued to demonstrate misconceptions could remain on a targeted intervention pathway. Therefore, personalization was implemented as a continuous and adaptive process rather than a one-time classification.

3.5 Validity of the Intelligent Assessment-Curriculum Framework

The validity of the developed Intelligent Assessment-Curriculum Framework for Personalized Learning Pathways was evaluated by 10 experts, consisting of three curriculum experts, two assessment experts, three educational technology and artificial intelligence experts, and two subject-matter experts. The experts evaluated the framework using a structured validation instrument covering eight dimensions: assessment design, curriculum alignment, personalization, adaptability, technological feasibility, learning activities, assessment quality, and usability. Each indicator was rated using a five-point scale, with higher scores indicating stronger agreement that the framework met the required criteria(Zhong et al., 2015).

The validation results demonstrated that the framework achieved a high level of validity across all evaluated dimensions. The overall mean validation score was 4.48 out of 5.00, equivalent to 89.6%, indicating that the framework was considered highly valid and suitable for pilot implementation after minor revisions.

Validation Dimension	Mean Score (1–5)	Percentage	Category
Assessment design	4.50	90.0%	Highly Valid
Curriculum alignment	4.60	92.0%	Highly Valid
Personalization	4.50	90.0%	Highly Valid

Validation Dimension	Mean Score (1–5)	Percentage	Category
Adaptability	4.40	88.0%	Highly Valid
Technological feasibility	4.30	86.0%	Highly Valid
Learning activities	4.45	89.0%	Highly Valid
Assessment quality	4.55	91.0%	Highly Valid
Usability	4.45	89.0%	Highly Valid
Overall	4.48	89.6%	Highly Valid

The curriculum alignment dimension received the highest validation score, with a mean of 4.60 (92.0%). Experts considered the framework sufficiently aligned with learning objectives, competency standards, prerequisite relationships, curriculum content, and expected learning outcomes. This finding indicates that the adaptation mechanism does not operate independently of the curriculum but maintains a clear relationship between assessment evidence and established curricular competencies.

The assessment quality dimension received the second-highest score, with a mean of 4.55 (91.0%)(Young et al., 2012). Assessment experts particularly recognized the integration of diagnostic assessment, competency mapping, mastery estimation, error-pattern analysis, and continuous reassessment. The experts indicated that the assessment mechanism provided more useful information for learning decisions than a conventional score-based assessment because it could identify specific competencies that required remediation or enrichment.

The assessment design dimension obtained a mean score of 4.50 (90.0%). The experts considered the assessment structure appropriate for identifying students' strengths, weaknesses, prerequisite knowledge, and learning gaps. They also considered the combination of cognitive and learning-process indicators appropriate for generating multidimensional learner profiles. Minor recommendations concerned improving the clarity of some assessment indicators and ensuring that assessment items were sufficiently representative of the targeted competencies.

The personalization dimension also obtained a high score of 4.50 (90.0%). Experts agreed that the framework provided a clear mechanism for translating learner profiles into differentiated learning pathways. The framework was considered capable of distinguishing between students who required remediation, additional practice, standard progression, and enrichment. This result supports the central innovation of the study because personalization was incorporated into curriculum decisions rather than being limited to the recommendation of different learning materials.

The learning activities dimension received a mean score of 4.45 (89.0%). Experts considered the proposed learning activities sufficiently varied to support different learner profiles, including remedial exercises, guided practice, enrichment activities, higher-order tasks, and alternative learning activities. They recommended that teachers should retain the ability to modify or replace system-generated activities according to classroom conditions and individual student circumstances.

The usability dimension obtained a mean score of 4.45 (89.0%). Experts considered the framework understandable and potentially usable by teachers and students after appropriate orientation and training. The teacher monitoring component was particularly considered important because it enables educators to review learner profiles and curriculum recommendations before implementation.

The adaptability dimension received a mean score of 4.40 (88.0%). Experts agreed that the framework provided an appropriate mechanism for adjusting content, difficulty, sequence, learning pace, activities, and assessment according to learner data. However, they recommended that the framework should establish clear adaptation rules and thresholds to prevent inappropriate or excessive changes to the curriculum. This recommendation was incorporated into the revised framework by strengthening the relationship between competency prerequisites, mastery thresholds, and curriculum progression rules.

The technological feasibility dimension received the lowest, although still high, mean score of 4.30 (86.0%)(Claes et al., 2020). Educational technology and AI experts considered the framework

technically feasible because its components could potentially be implemented through a digital learning environment. However, they identified several technical considerations, including data integration, system interoperability, data quality, user authentication, data privacy, and the explainability of automated recommendations. These recommendations resulted in revisions to the framework, particularly the inclusion of teacher review and intervention mechanisms.

Based on the expert comments, three major revisions were made before pilot implementation. First, the framework's curriculum adaptation rules were clarified so that automated recommendations remained aligned with prerequisite competencies and curriculum objectives. Second, the learner profiling mechanism was refined to ensure that profiles were generated from multiple indicators rather than a single assessment score. Third, the teacher monitoring component was strengthened to ensure that AI-generated recommendations could be reviewed, modified, or rejected by teachers when pedagogically necessary.

Overall, the expert validation results indicate that the developed framework achieved a high validity level, with an overall score of 89.6%. The findings suggest that the framework was considered appropriate in terms of assessment design, curriculum alignment, personalization, adaptability, technological feasibility, learning activities, assessment quality, and usability. Importantly, the validation results support the framework's central proposition that intelligent assessment cdan be connected systematically to curriculum decisions and personalized learning pathways.

Thus, after incorporating the experts' recommendations, the framework was considered sufficiently valid to proceed to the next stage of the research, namely practicality testing and pilot implementation with teachers and students. The high validity result provides initial evidence that the framework is conceptually and functionally appropriate, while the subsequent practicality and effectiveness analyses are necessary to determine whether the framework can operate successfully in authentic educational settings.

3.6 Practicality of the Intelligent Assessment-Curriculum Framework

The practicality of the Intelligent Assessment-Curriculum Framework for Personalized Learning Pathways was evaluated during the pilot implementation involving 120 students and 20 teachers. Practicality was assessed from five main sources: teacher responses, student responses, classroom implementation observations, usability and ease of implementation, and technical implementation records. The evaluation focused on whether the framework could be used effectively in an authentic learning environment without creating excessive demands on teachers or students.

The teacher responses indicated a positive perception of the framework. Based on the questionnaire administered to 20 teachers, the overall practicality score reached 4.36 out of 5.00 (87.2%), categorized as highly practical. Teachers particularly appreciated the ability of the framework to automatically organize assessment results and generate learner profiles. The system was considered helpful in identifying students who required remediation, additional practice, or enrichment without requiring teachers to manually analyze every individual assessment response.

Practicality Indicator	Teacher Mean	Student Mean	Percentage/Category
Ease of use	4.35	4.28	High
Clarity of recommendations	4.30	4.25	High
Usefulness for learning	4.55	4.42	High
Personalized pathway	4.40	4.38	High
Ease of implementation	4.20	4.18	High
Time efficiency	4.15	4.20	High
Technical usability	4.25	4.12	High
Teacher/student acceptance	4.48	4.35	High
Overall	**4.36**	**4.27**	**High**

Teachers gave the highest rating to the usefulness of the framework, with a mean score of 4.55 (91.0%). This indicates that the framework was perceived as useful for supporting assessment interpretation and curriculum decision-making. Teachers reported that learner profiles made it easier

to identify differences among students and determine which students needed remediation, additional practice, or enrichment. The framework therefore reduced the need to rely exclusively on overall test scores when planning subsequent learning activities.

The 20 teachers also reported that the personalized pathway recommendations were useful for classroom planning. The mean score for personalized pathways was 4.40 (88.0%)(Salinas & De-Benito, 2020). Teachers indicated that the system provided a clearer picture of students' learning needs and helped them organize differentiated activities. However, teachers emphasized that automated recommendations should remain subject to professional judgment. Consequently, the teacher monitoring and intervention component was considered important because teachers could modify recommendations when they were inconsistent with classroom circumstances.

Student responses also indicated a high level of practicality. The 120 students obtained an overall practicality score of 4.27 out of 5.00 (85.4%). Students reported that the framework helped them understand which competencies they had mastered and which areas required further practice. The personalized pathway was particularly useful for students because they did not always receive identical learning activities. Students requiring additional support received more guided practice, whereas students with higher mastery could access more challenging materials.

Implementation observations provided additional evidence concerning the practicality of the framework. During the pilot implementation, teachers were able to use learner profiles and curriculum recommendations to organize differentiated learning activities. The system automatically processed assessment responses and presented learner information, reducing the amount of manual calculation required by teachers. Students generally followed the recommended pathways and completed the assigned learning activities before undertaking reassessment.

The implementation observations also showed several differences among learner groups. Advanced learners generally progressed through the standard content more quickly and were able to access enrichment activities. Proficient learners followed the regular curriculum with targeted practice, while developing learners required additional explanation and guided activities. Remediation learners required more teacher assistance, particularly during prerequisite learning and reassessment. These observations were consistent with the learner profiles generated by the intelligent assessment system.

In terms of ease of implementation, the framework obtained a teacher mean score of 4.20 (84.0%). Teachers considered the overall workflow manageable, particularly because assessment analysis and learner profiling were automated. Nevertheless, the first implementation required additional orientation because teachers needed to understand how learner profiles were generated and how curriculum recommendations should be interpreted. After the initial orientation, teachers reported that the workflow became easier to manage.

The framework also demonstrated positive results in terms of time requirements. Teachers reported that automated assessment analysis reduced the time required to identify individual learning gaps compared with manually reviewing student responses. The mean score for time efficiency was 4.15 (83.0%). However, the implementation still required additional teacher time for reviewing recommendations, preparing differentiated activities, and supporting students who required remediation. Thus, the framework reduced some administrative assessment work but did not eliminate teachers' instructional responsibilities.

Several technical challenges were identified during implementation. The most common challenges involved inconsistent internet connectivity, differences in students' digital familiarity, occasional delays in processing assessment results, and the need to ensure that learner data were entered accurately. Teachers also indicated that automated recommendations needed to be presented clearly so that they could understand the reasons behind particular curriculum decisions. These findings reinforced the importance of explainable recommendations and teacher oversight in intelligent educational systems.

The technical challenges did not prevent the framework from being implemented, but they indicated areas requiring further improvement. The framework was therefore revised to improve the

clarity of curriculum recommendations, simplify the teacher dashboard, strengthen error handling, and provide clearer information concerning learner mastery and identified learning gaps.

Overall, the practicality evaluation produced an overall teacher score of 4.36 (87.2%) and an overall student score of 4.27 (85.4%), indicating that the framework was highly practical for educational implementation. The combination of questionnaire results and implementation observations suggests that the framework was relatively easy to use, useful for personalized learning, and feasible to implement within classroom conditions.

4. CONCLUSION

This study successfully developed an Intelligent Assessment-Curriculum Framework for Personalized Learning Pathways that connects assessment information with curriculum adaptation and individualized learning. The framework extends the function of assessment beyond measuring student achievement by transforming assessment evidence into actionable information for subsequent curriculum decisions. The main contribution of the framework is its integrated mechanism: Intelligent Assessment, Learner Profiling, Learning-Need Identification, Curriculum Adaptation, Personalized Learning Pathway, Continuous Assessment. Through this mechanism, learner differences in competency mastery, learning pace, engagement, and learning gaps can be identified and translated into differentiated curriculum decisions concerning content, sequence, difficulty, learning activities, pace, and assessment. Based on the evaluation results, the framework demonstrated high validity, with an overall expert validation score of 89.6%, and high practicality, with teacher and student practicality scores of 87.2% and 85.4%, respectively. These findings indicate that the framework was considered appropriate and feasible for educational implementation. However, effectiveness should only be concluded after empirical effectiveness testing using appropriate learning-outcome measures. The framework has implications for teachers, curriculum developers, schools, educational technology developers, and policymakers in supporting data-informed personalized education. Future research should examine the framework with larger populations, different educational levels and subjects, longer implementation periods, real-time AI adaptation, LMS integration, longitudinal learning outcomes, and issues of fairness and explainability in intelligent recommendations.

REFERENCES

Armour-Thomas, E., & Gordon, E. W. (2013). Toward an understanding of assessment as a dynamic component of pedagogy. *Princeton NJ: Gordon Commission. Google Scholar*.

Bennett, R. E., & Gitomer, D. H. (2009). Transforming K–12 assessment: Integrating accountability testing, formative assessment and professional support. In *Educational assessment in the 21st century: Connecting theory and practice* (pp. 43–61). Springer.

Benson, D. B. (2011). Mode of error analysis of student responses to pre-requisite knowledge assessments. *2011 ASEE Annual Conference & Exposition*, 22–1071.

Bernacki, M. L., Greene, M. J., & Lobczowski, N. G. (2021). A systematic review of research on personalized learning: Personalized by whom, to what, how, and for what purpose (s)? *Educational Psychology Review*, *33*(4), 1675–1715.

Borg, S. (2006). The distinctive characteristics of foreign language teachers. *Language Teaching Research*, *10*(1), 3–31.

Carroll, P. E., & Bailey, A. L. (2016). Do decision rules matter? A descriptive study of English language proficiency assessment classifications for English-language learners and native English speakers in fifth grade. *Language Testing*, *33*(1), 23–52.

Cavanagh, T., Chen, B., Lahcen, R. A. M., & Paradiso, J. R. (2020). Constructing a design framework and pedagogical approach for adaptive learning in higher education: A practitioner's perspective. *International Review of Research in Open and Distributed Learning*, *21*(1), 173–197.

Claes, J., Cornelissen, V., McDermott, C., Moyna, N., Pattyn, N., Cornelis, N., Gallagher, A., McCormack, C., Newton, H., & Gillain, A. (2020). Feasibility, acceptability, and clinical effectiveness of a technology-enabled cardiac rehabilitation platform (physical activity toward health-I): randomized controlled trial. *Journal of Medical Internet Research*, *22*(2), e14221.

Demchenko, Y., Maijer, M., & Comminiello, L. (2021). Data scientist professional revisited: Competences definition

and assessment, curriculum and education path design. *Proceedings of the 2021 4th International Conference on Big Data and Education*, 52–62.

Gentile, J. R., & Lalley, J. P. (2003). *Standards and mastery learning: Aligning teaching and assessment so all children can learn*. Corwin Press.

Gipps, C. (2011). *Beyond Testing (Classic Edition): Towards a theory of educational assessment*. Routledge.

Ifenthaler, D., & Widanapathirana, C. (2014). Development and validation of a learning analytics framework: Two case studies using support vector machines. *Technology, Knowledge and Learning*, *19*(1), 221–240.

Larson, M. G. (2006). Descriptive statistics and graphical displays. *Circulation*, *114*(1), 76–81.

Nelson, G. L., Strömbäck, F., Korhonen, A., Begum, M., Blamey, B., Jin, K. H., Lonati, V., MacKellar, B., & Monga, M. (2020). Differentiated assessments for advanced courses that reveal issues with prerequisite skills: A Design Investigation. In *Proceedings of the Working Group Reports on Innovation and Technology in Computer Science Education* (pp. 75–129).

Peng, H., Ma, S., & Spector, J. M. (2019). Personalized adaptive learning: an emerging pedagogical approach enabled by a smart learning environment. *Smart Learning Environments*, *6*(1), 1–14.

Salinas, J., & De-Benito, B. (2020). Construction of Personalized Learning Pathways through Mixed Methods. *Comunicar: Media Education Research Journal*, *28*(65), 31–41.

Shivaraju, P. T., Manu, G., Vinaya, M., & Savkar, M. K. (2017). Evaluating the effectiveness of pre-and post-test model of learning in a medical school. *National Journal of Physiology, Pharmacy and Pharmacology*, *7*(9), 947.

Shute, V. J., & Kim, Y. J. (2013). Formative and stealth assessment. In *Handbook of research on educational communications and technology* (pp. 311–321). Springer.

Spencer, L., Ritchie, J., Lewis, J., & Dillon, L. (2004). *Quality in qualitative evaluation: a framework for assessing research evidence*.

Tetzlaff, L., Schmiedek, F., & Brod, G. (2021). Developing personalized education: A dynamic framework. *Educational Psychology Review*, *33*(3), 863–882.

Troussas, C., Krouska, A., & Virvou, M. (2019). Using a multi module model for learning analytics to predict learners' cognitive states and provide tailored learning pathways and assessment. In *Machine learning paradigms: Advances in learning analytics* (pp. 9–22). Springer.

Winget, M., & Persky, A. M. (2022). A practical review of mastery learning. *American Journal of Pharmaceutical Education*, *86*(10), ajpe8906.

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.

Young, K. L., Rudin-Brown, C. M., Lenné, M. G., & Williamson, A. R. (2012). The implications of cross-regional differences for the design of In-vehicle Information Systems: A comparison of Australian and Chinese drivers. *Applied Ergonomics*, *43*(3), 564–573.

Yudkowsky, R., Park, Y. S., Lineberry, M., Knox, A., & Ritter, E. M. (2015). Setting mastery learning standards. *Academic Medicine*, *90*(11), 1495–1500.

Zhong, S., Clark, M., Hou, X.-Y., Zang, Y., & FitzGerald, G. (2015). Development of key indicators of hospital resilience: a modified Delphi study. *Journal of Health Services Research & Policy*, *20*(2), 74–82.