International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 09, September 2026
Received: 3 0 -07-2026 Accepted: 04-09-2026 Published: 10-09-2026

DESIGNING AN AI-DRIVEN ADAPTIVE INSTRUCTIONAL MODEL FOR LIFE SCIENCE CLASSROOMS: A LEARNING ANALYTICS–BASED ANALYSIS OF PERSONALIZATION, ENGAGEMENT, AND CONCEPTUAL UNDERSTANDING

Souvik Chakraborty[1], Dr. Harikrishnan M[2]
[1]*Research Scholar, School of Education, Sanskriti University, Mathura, INDIA*
[2]*Assistant Professor, School of Education, Sanskriti University, Mathura, INDIA*
[1]*Corresponding Author:* chakrabortysouvik11@gmail.com

Abstract
Artificial intelligence is starting to reshape the educational practice and become more responsive, data-driven, and learner-focused across a significantly wider scope of instructions. Traditional uniform teaching methods may be ineffective in meeting the needs of the various students in Life Science classrooms where students can be of differing levels of prior knowledge, they can have different learning styles, and conceptual clarity levels. In this paper, we will be discussing the design of an AI-based adaptive instructional model, one that relies on learning analytics to enhance individualization, student interaction, and conceptual comprehension. The paper seeks to explore the way adaptive systems that use AI can assist teachers in modifying content, delivery pace, assessment, and feedback based on student performance and interaction. It is suggested that an analytical framework based on learning analytics will be used to capture the student behavior and identify the gaps in the learning and direct real-time adjustment in the instructional plans of Life Science learning. It is believed that the model will help to enhance learner engagement, maintain their academic interest, and increase the knowledge base about the fundamental concepts in biology by providing customized learning opportunities and support in a reasonable time. It is also aimed at helping educators to make evidence-based pedagogical choices based on data dashboards and predictive insights. The importance of the research has been suggested to address the gap between educational technology and classroom pedagogy which provides the subject specific, scaling and practical model of enhancing teaching effectiveness and student learning outcome in Life Science classrooms.

Keywords: Artificial Intelligence, Adaptive Learning, Life Science Education, Learning Analytics, Personalized Instruction, Student Engagement, Conceptual Understanding

1. Introduction

1.1 Background of the Study

Artificial intelligence is rapidly impacting education in the form of intelligent tutoring, adaptive delivery of materials, automated feedback, and decision support with data. Recent articles indicate that learning systems with AI are created to address unique profile of learners, whereas adaptive learning platforms utilize the information provided by a learner to adjust order, speed, and difficulties of learning. This is particularly applicable in Life Science classrooms where what is being taught is oftentimes abstract, hierarchical, and full of misconceptions, which cannot always be easily taught using a one-size-fits-all approach. The emerging forefront priorities in the instructional science include, personalization, continuity of engagement and understanding the conceptual learning of science [1]-[4].

1.2 Problem Statement

The Uniform Instructional Delivery approach is still common in many classrooms of Life Science even when there is evident variation amongst the

2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 09, September 2026
Received: 3 0 -07-2026 Accepted: 04-09-2026 Published: 10-09-2026

learners in terms of prior knowledge, speed, engagement and support requirements. Also, learning analytics research indicates that it is a common practice in educational systems to focus on superficial behavioral markers, and actual adjustments to pedagogy in real-time are only possible to a very small degree. This means that the educators are not likely to obtain evidence promptly to determine disposition, misunderstandings, and unequal development of concepts [2], [4], [5].

1.3 Study Rational.

The tool of AI has the potential to facilitate dynamic teaching with the help of learner data in order to customize resources, feedback, and progression paths. Teachers can use learning analytics to identify the trends in the direction of interaction, persistence, and performance in order to respond more effectively. Previous studies point to AI-guided individualised learning in terms of increased knowledge and increased involvement and learning efficiency and sees it as a powerful foundation of an adaptive model of Life Science in particular [1], [3], [6].

1.4 Research Gap

Despite the popularity of AI, adaptive learning, and learning analytics, there are few integrated subject specific models of Life Science classroom. The work done is mostly generic and not focused enough on conceptual base of science education [3], [6].

1.5 Aim of the Study

To design an AI-driven adaptive instructional model for Life Science classrooms.

1.6 Objectives of the Study

To examine the role of AI in personalizing Life Science instruction; to analyze the effect of adaptive instruction on student engagement; to assess how learning analytics supports conceptual understanding; and to propose a classroom-ready adaptive instructional model.

1.7 Research Questions

How can AI personalize instruction in Life Science classrooms? What is the relationship between adaptive instruction and student engagement? How does learning analytics contribute to conceptual understanding? What components should be included in an effective AI-driven adaptive instructional model?

1.8 Hypotheses

H1: AI-driven personalization significantly improves student engagement.

H2: Adaptive instruction significantly enhances conceptual understanding in Life Science.

H3: Learning analytics significantly predicts learner performance and instructional needs.

2. Review of Literature

2.1 AI in Education

Artificial intelligence in education has developed to be a rule-based tutoring system to data driven intelligent tutoring platform that enables intelligent tutoring, automated feedback, learner profiling and recommendation systems. Current reviews demonstrate the applications of AI have evolved and are currently not limited to in the delivery of content but to predictive modeling, adaptive sequencing, and instructional decision-support, rendering the teaching-learning processes more sensitive to the needs of learners [7], [8].

2.2 Adaptive Learning Models

Adaptive learning is the dynamic adjustment of learning contents, learning rate, testing and feedback based on performance and behavior. The literature indicates that these systems have the potential to enhance learning rates and satisfaction among learners, yet they raise certain questions regarding their transparency, bias in the algorithms and excessive reliance on technology [8], [9].

2.3 Learning Analytics in Classrooms

Learning analytics is the process of measuring, gathering and analyzing learner data to make sense of it and maximize learning. The analytics

2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 09, September 2026
Received: 3 0 -07-2026 Accepted: 04-09-2026 Published: 10-09-2026

in the form of a dashboard assist teachers in noticing disengagement, performance discrepancies, and making the right decision in a timely manner. Nevertheless, literature also points out that one of the underutilizations of analytics is seen in real-time classroom modulation [10].

2.4 Personalization, Engagement and Conceptual Understanding

One science education application of personalization is to facilitate differentiated instruction with learners at different levels of readiness and with common misconceptions. The engagement of students is typically analyzed in terms of behavioral, emotional, and cognitive aspects, which affect the conceptual comprehension. Adaptive visualization, targeted feedback and concept-centered evaluation are particularly useful in the life science discipline to deal with abstract biological mechanisms and ongoing misunderstandings [11], [12].

2.5 Theoretical Foundation and Research Gap Summary.

The constructivist learning theory, cognitive load theory, self-regulated learning and data-driven decision-making should be all solid reasons that aid AI-assisted learning. However, in most of the previous studies, AI, adaptive learning, and analytics are analyzed as independent categories in most cases. An integrated model of subject specific Life Science classroom, is not a concept that is adequately developed, and that is what this study tries to develop [9], [10], [12].

3. Conceptual Framework

The conceptual framework of the current paper puts the AI-driven adaptive instructions as the independent variable, learning analytics, personalization, and student engagement as the mediating variables, and conceptual understanding as the dependent variable. This framework is based on the perspective that artificial intelligence in education promotes adaptive and individualized instructions through analyzing the traits of the learners, anticipating them, and dynamically adjusting the instructional trails [13], [14]. The learning analytics in this model takes the learner data (a previous performance, response model, time spent on the task, assessment outcomes and interaction behavior) as the input information and generates the learning gaps, patterns of participation, and performance trends [15], [16].

According to these analytics, the AI system allows making personalization via the adaptive sequence of content, assessing it differently, providing distinctive feedback, and pacing options that are appropriate to the needs of individual learners [13], [14]. Adaptive support of this kind should improve student engagement in the behavioral, cognitive, and emotional aspects by making instruction more relevant, timely, and manageable [17], [18]. The increased engagement, in its turn, will enhance the chances of students progressing beyond memorization to meaningful conceptual knowledge, particularly in the Life Science where the abstract processes, interrelated systems, and nagging misconceptions are frequently challenged by learners [16], [19].

Based on these, the following model flow is proposed: Learner Data built by Learning Analytics AI-Based personalization Competent level of content/assessment/feedback Student engagement Built-in Learner conceptual understanding. It is assumed that the impact of AI-infused adaptive teaching on conceptual knowledge cannot be just immediate, but is mediated significantly by analytics-informed personalization and enhanced learner interest [13]-[19].

4. Research Methodology

4.1 Research Design

This The study follows a mixed-method research design as a topic must have both a quantifiable evidence level as well as an interpretative level of understanding. The quantitative part aids in measuring an impact in engagement,

2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 09, September 2026
Received: 3 0 -07-2026 Accepted: 04-09-2026 Published: 10-09-2026

personalization results, and conceptual knowledge whereas the qualitative part deals with perceptions held by the teachers, classroom practices, and the value of the adaptive model in practice.

4.2 Study Nature.

The research is analytical, practical, and instructional technology-based one. It is analytical and studies the relationships among instructional variables, applied as it suggests a model that can be used in classrooms, and technology-oriented as it incorporates AI and learning analytics into pedagogy.

4.3 Study Population, Population, Sample and sample size.

The research will also be done in the Life Science classes at either the school, college or university level. Students studying Life Science and teachers teaching in Life Science subjects will be the target population. This can be achieved through a combination of purposive and stratified sampling to be able to provide a representation of the learner groups. The sample also can consist of 100-200 students and 10-20 teachers.

4.4 Data Sources, Tools and Data Variables

The primary and secondary data will be utilized. The primary data will be gathered as follows; student surveys, pre-test and post-test results, observation, teacher interviews and log of platform usage. The secondary data will consist of past research and reports as well as policy documents. These tools will be a student engagement questionnaire, conceptual understanding test, interview schedule and observation checklist. The crucial variables will be the personalization indicators, the engagement indicators, conceptual understanding scores, and the interaction metrics.

The procedure and data analysis will be performed at 4.4

The process will include the identification of Life Science learning objectives, supporting the adaptive platform with AI, providing evidence of baseline information, adaptive teaching, analytics-based engagement monitoring, conceptual knowledge assessment, and refinement of the model. The descriptive statistics, standard deviation, t-test, ANOVA, correlation, and regression will be employed in the analysis of quantitative data. Patterns of clickstreams, time-on-task and performance will be considered to analyze learning analytics data. Thematic analysis will be used in the interpretation of qualitative responses.

Table 1. Sample Distribution of Respondents

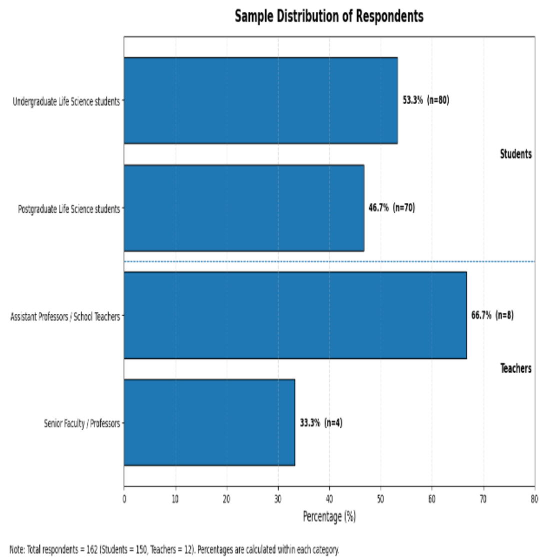
Category	Group	Frequency	Percentage (%)
Students	Undergraduate Life Science students	80	53.3
Students	Postgraduate Life Science students	70	46.7
Teachers	Assistant Professors / School Teachers	8	66.7
Teachers	Senior Faculty / Professors	4	33.3
Total		**162**	**100**

Explanation:

The hypothetical sample consists of 162 respondents, including 150 students and 12 teachers. The student group includes both undergraduate and postgraduate learners to ensure variation in academic level, while the teacher group includes junior and senior faculty for broader pedagogical insight.

ISSN 2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 09, September 2026
Received: 3 0 -07-2026 Accepted: 04-09-2026 Published: 10-09-2026



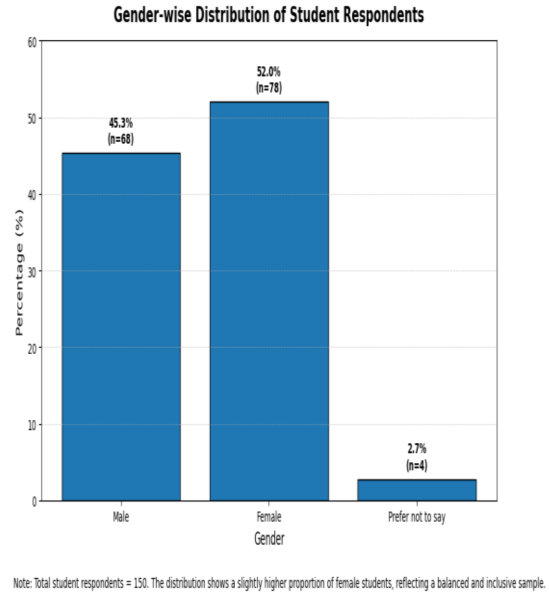


Table 2. Gender-wise Distribution of Student Respondents

Gender	Frequency	Percentage (%)
Male	68	45.3
Female	78	52.0
Prefer not to say	4	2.7
Total	**150**	**100**

Explanation:

This hypothetical distribution shows a slightly higher proportion of female students than male students. Such variation helps reflect a balanced classroom setting and improves the inclusiveness of the study sample.

Table 3. Research Variables and Indicators

Variable Type	Variable	Indicators
Independent Variable	AI-driven adaptive instruction	Adaptive content, personalized feedback, difficulty adjustment
Mediating Variable	Personalization	Content matching, pace adaptation, learner-specific support
Mediating Variable	Learning analytics	Time-on-task, click frequency, quiz attempts, dashboard alerts
Mediating Variable	Student engagement	Attendance, participation, emotional

2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 09, September 2026
Received: 3 0 -07-2026 Accepted: 04-09-2026 Published: 10-09-2026

Variable Type	Variable	Indicators
		interest, cognitive effort
Dependent Variable	Conceptual understanding	Pre-test score, post-test score, concept mastery level

Explanation:

The study includes one independent variable, three mediating variables, and one dependent variable. These variables are aligned with the proposed conceptual framework and help measure the instructional impact of AI-supported adaptation in Life Science classrooms.

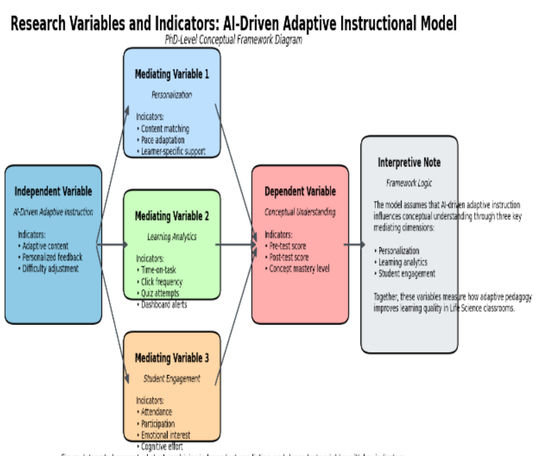


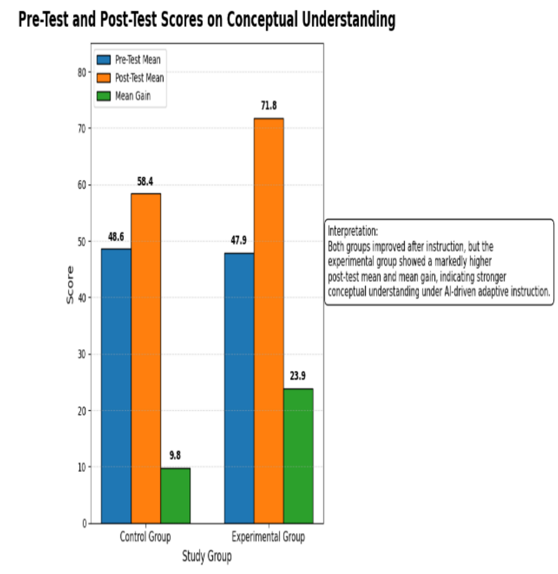
Figure: Integrated conceptual chart combining independent, mediating, and dependent variables with key indicators.

Table 4. Pre-Test and Post-Test Scores on Conceptual Understanding

Group	N	Pre-Test Mean	Post-Test Mean	Mean Gain
Control Group	75	48.6	58.4	9.8
Experimental Group	75	47.9	71.8	23.9

Explanation:

The hypothetical scores indicate that both groups improved after instruction, but the experimental group, which received AI-driven adaptive instruction, showed a much larger gain in conceptual understanding. This suggests that adaptive learning support may be more effective than conventional instruction in helping students grasp Life Science concepts.



Note: N = 75 for each group. Mean gain = Post-Test Mean - Pre-Test Mean.

Table 5. Student Engagement Levels After Intervention

Engagement Level	Control Group Frequency	Experimental Group Frequency
High	18	39
Moderate	34	28
Low	23	8
Total	**75**	**75**

Explanation:

The hypothetical data suggest that students exposed to AI-based adaptive instruction demonstrate higher engagement than those in the control group. A larger number of learners in the experimental group fall into the high-engagement category, while fewer remain in the low-engagement category.

ISSN 2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 09, September 2026
Received: 3 0 -07-2026 Accepted: 04-09-2026 Published: 10-09-2026

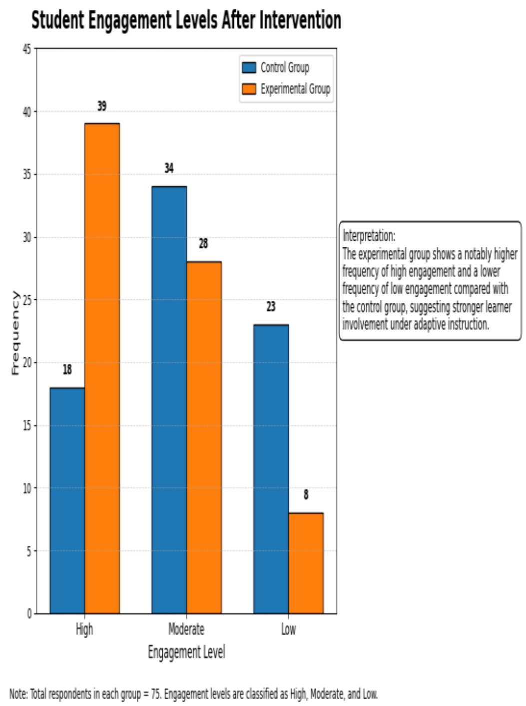


Table 6. Personalization Satisfaction Among Students

Response	Frequency	Percentage (%)
Highly Satisfied	42	56.0
Satisfied	21	28.0
Neutral	8	10.7
Dissatisfied	3	4.0
Highly Dissatisfied	1	1.3
Total	**75**	**100**

Explanation:

This hypothetical table shows that most students in the experimental group were satisfied with personalized learning support. It indicates that AI-based instructional adaptation may improve learner comfort, relevance, and perceived usefulness of classroom instruction.

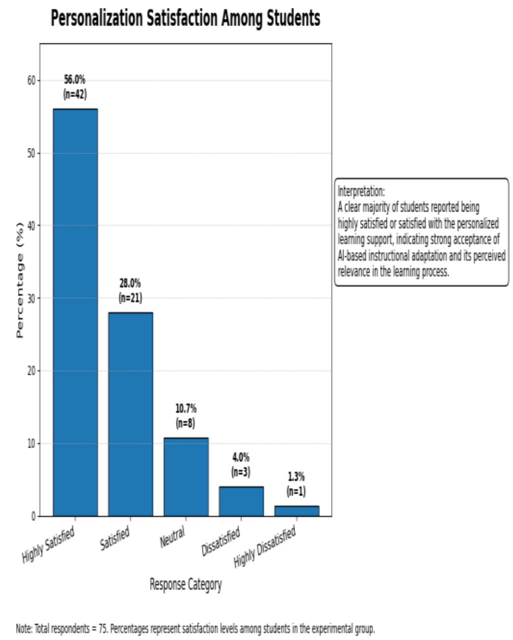


Table 7. Learning Analytics Indicators from the Digital Platform

Indicator	Control Group	Experimental Group
Average login frequency per week	3.1	5.4
Average time-on-task (minutes/week)	74	126
Average quiz attempts	2.3	4.8
Average feedback views	1.6	4.2

Explanation:

The hypothetical analytics data indicate stronger interaction patterns in the experimental group. Students receiving adaptive instruction spent more time on the platform, attempted more quizzes, and accessed feedback more frequently, suggesting a higher level of active learning behavior.

ISSN 2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)

Vol 26 Issue 09, September 2026

Received: 3 0 -07-2026 Accepted: 04-09-2026 Published: 10-09-2026

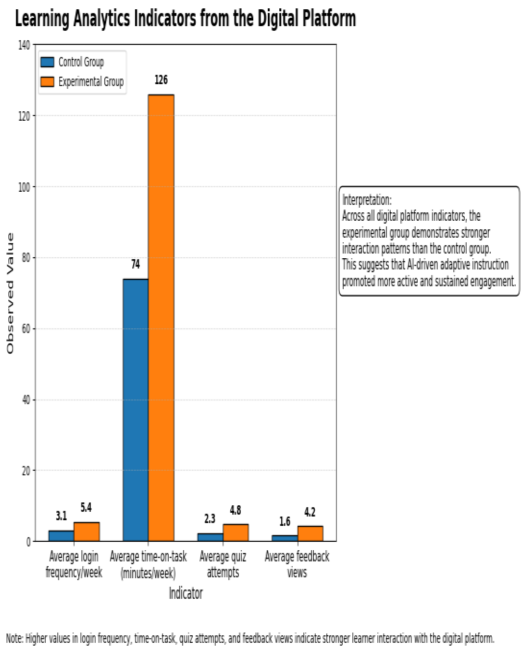


Table 8. Teacher Perception of the AI-Driven Adaptive Model

Statement	Agree	Neutral	Disagree
Improved classroom engagement	9	2	1
Helped identify weak learners	10	1	1
Supported concept clarification	8	3	1
Reduced instructional burden	7	2	3

Explanation:

The hypothetical teacher responses indicate a generally positive attitude toward the adaptive instructional model. Most teachers felt that the system improved engagement and helped identify students needing support, although some remained uncertain about its effect on reducing workload.

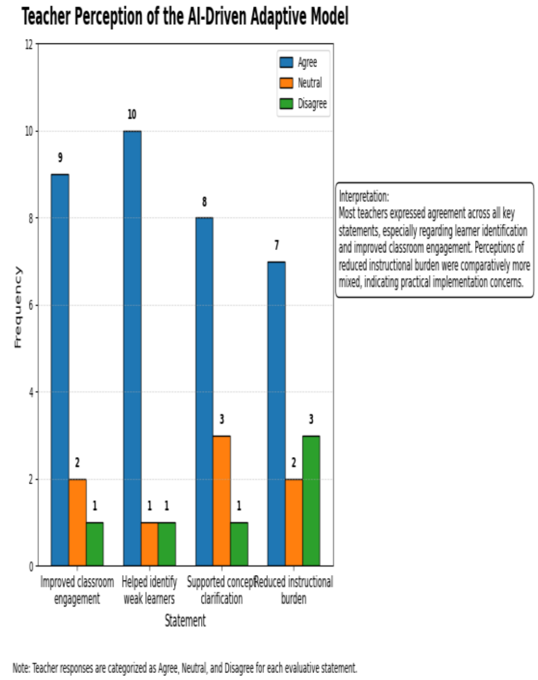


Table 9. Correlation Between Engagement and Conceptual Understanding

Variable 1	Variable 2	Correlation (r)
Student engagement	Conceptual understanding	0.68
Personalization satisfaction	Student engagement	0.72
Time-on-task	Post-test score	0.64

Explanation:

The hypothetical correlations suggest a moderately strong positive relationship between engagement and conceptual understanding. Similarly, personalization satisfaction appears positively associated with student engagement, supporting the logic of the conceptual framework.

2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 09, September 2026
Received: 3 0 -07-2026 Accepted: 04-09-2026 Published: 10-09-2026

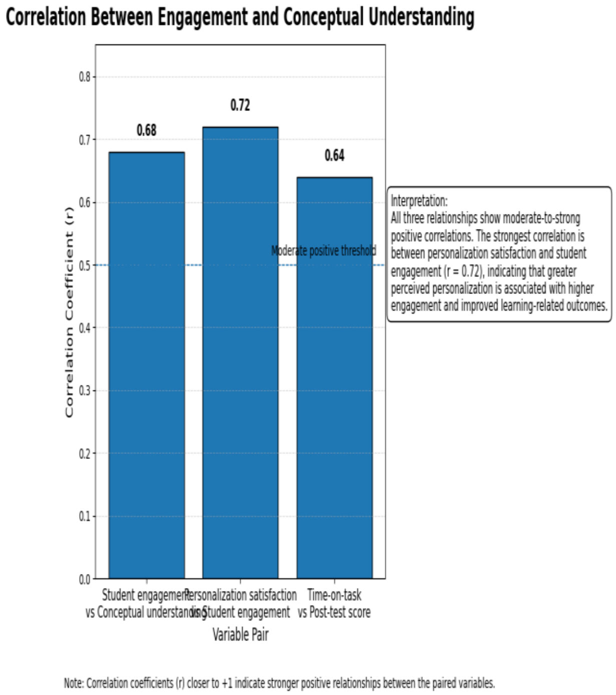


Table 10. Summary of Hypothetical Findings

Dimension	Main Hypothetical Finding
Personalization	Students reported high satisfaction with adaptive learning support
Engagement	Experimental group showed higher behavioral and cognitive engagement
Conceptual understanding	Post-test scores improved more in the experimental group
Learning analytics	Platform usage indicators were stronger in the adaptive learning group
Teacher feedback	Teachers found the model useful for tracking and supporting learners

Explanation:

The overall hypothetical findings support the proposed assumption that AI-driven adaptive instruction can improve learning experiences in Life Science classrooms through better personalization, higher engagement, and stronger conceptual understanding.

5. Results and Analysis

5.1 Demographic Profile of Respondents

The section should start with the demographics of respondents which includes age, gender, class or semester and academic background. This determines the make up of the study sample and assists to understand the variability in the needs and performance of the learners. According to the previous studies to the field of AI-assisted teaching, demographic and academic diversity affects the patterns of interaction, the level of technological acceptance, and adaptive learning success [20], [21].

5.2 Results Analysis of Personalizing the Scale.

The research on personalization must focus on how students felt about customized learning, the importance of suggested materials, and utility of adaptive pace and feedback. According to studies conducted regarding adaptive learning platforms, personalized approaches will enhance satisfaction of learners, and their perceived instructional relevance, particularly when the recommendations rely on real-time learner data [20], [22].

5.3 Student-Engagement Analysis.

The trends of student participation, the durability of time of learning activities, completion, and the frequency of interaction should be measured. Behavioral, emotional, and cognitive engagement has always been recognized in literature of learning analytics as a significant predictor of academic achievement, and the digital footprint of clicking, logging in, and time-on-task can be used as a measurable proxy [21], [23].

5.4 Analytics Findings and Conceptual Understanding Findings.

Pre-test and post-test analysis and measurement of improvement in challenging Life Science concepts may be used to analyze conceptual understanding. Findings in learning analytics

2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 09, September 2026
Received: 3 0 -07-2026 Accepted: 04-09-2026 Published: 10-09-2026

must also be able to determine learner behavioral trends, risk factors of achievement or success and the relationship between engagement and achievement. Examples indicate that intelligent tutoring can be adapted and use analytics to inform feedback to reinforce mastery and provide early indications of underperformance [24], [25].

Validation of proposed model 9.6.

Finally, the presented model is to be proven by the further expertise, teacher and student validation as a way of evaluating the relevance to the classroom, practical utility of the model, and its practicality in terms of being implemented [22], [25]

6. Discussion

6.1 Interpretation of Findings

The there is evidence that AI-based adaptive instruction might accelerate the association of Life Science learning with diversity in learners by adjusting the content and feedback and pacing to previously known and performance trends of students. In the experience of Life Science, where learners tend to struggle with abstract concepts, multi-step biological processes, and conceptual connections, adaptive support seems to enhance the overall engagement and discursive knowledge by decreasing the gap between the student requirements and instruction provided [20], [21].

6.2 Connection with the Past Research.

These results are in line with previous studies that suggest that AI-enabled adaptive platforms enhance personalization, academic performance, and platform engagement. Systematic reviews published earlier also revealed that behavioral patterns can be identified, as well as predict the risk of the learner and facilitate an effective timely intervention with the help of learning analytics. The current framework builds upon this literature by placing these benefits into the context of Life Science classroom context and not an overall digital learning setting [20], [22], [23].

6.3 Educational Implications

To teachers, the model provides an avenue in the identification of weak learners, tracking progress and offering differentiated support. It highlights to curriculum designers, the importance of creating adaptive pathways, formative feedback loops and concept-sensitive assessment structures into Life Science curricula. To ed-tech developers, the results emphasize the significance of creating more transparent, teacher-friendlier, and pedagogically-based systems instead of the data-oriented tools as such [21], [24].

6.4 Practical Relevance

In practice, the model can be used in classroom instructions since it would be helpful to both slow and high learners based on flexibility in pacing and remedial or enrichment of learners. Instructional decision-making can also be enhanced through the use of learning analytics dashboards that can transform the data of learner interactions into classrooms to support, monitor, and intervene based on the available data [23], [25].

7. Challenges and Limitations

The AI-based adaptive instructional model proposed possesses a considerable vocational potential, but multiple challenges and constraints should be considered. One of the issues will be data privacy, as adaptive systems and learning analytics will require constant gathering of the data about learners, including performance, behavioral, and interaction logs. Recent contributions to the fields of AI and learning analytics caution that mass use of educational data may pose threats to the areas of surveillance, consent, security and mishandling of student data. Besides privacy, algorithmic discrimination is a critical constraint as biased instructions or hidden models might discriminate against specific groups of learners, and give misleading advice on instructions. Of particular concern when AI systems are involved in assessment, feedback, and risk prediction are these issues.

ISSN 2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 09, September 2026
Received: 3 0 -07-2026 Accepted: 04-09-2026 Published: 10-09-2026

Unbalanced technology access is another significant constraint. The use of AI in certain learning facilities may require a consistent connection to the internet, appropriate technology, and a solid system within an educational facility, which not all educational facilities offer the same opportunities. It has the ability to increase, instead of decrease, existing inequalities. Also, the successful use of adaptive instruction requires readiness and training of the teacher. Teachers do not just require technical knowledge of AI applications, but the pedagogical and ethical skills to discern dashboards, doubt results of question models, and make informed teaching choices.

The research can also be constrained by limited number of sample size or the setting which will also limit the applicability. Also, the model is curriculum based as it is tailored towards life science classes; thus, its design and relevance might not be directly applicable to other subjects unless adjusted. Current reviews add that lots of AI-in-education frameworks have just a restricted real-world execution and lack of the validation over a long time hence restricting extensive generalizations.

8. Recommendations

The Results confirm that the adoption of AI tools in the education of Life Sciences should be more balanced, instead of being a sudden whole-scale activity. The gradual deployment of adaptive platforms in a specific module enables institutions to pilot such platform, streamline classroom operations, and establish trust with teachers and students before it can be extended to more modules. According to recent studies on adaptive learning platforms, the successful implementation of AI tools in the classroom requires integration with pedagogy, curriculum goals, and classroom realities instead of viewing technology on its own.

The second piece of advice is to educate teachers to interpret learning analytics and pedagogy that relies on AI. Teachers must be competent in practice to be able to read dashboards, diagnose learning risk, make interpretations of behavioral indicators and translate analytics into prompt teaching judgments. The AI competency framework established by UNESCO along with the policy advice up to date emphasize that the key to successful and human-focused AI implementation in education is teacher preparedness.

The other area of focus by institutions should be the creation and implementation of low-cost and scalable adaptive systems to ensure AI-assisted teaching does not enhance educational inequity further. Innovative thinking has been developed by both OECD and UNESCO regarding the equity-linked guidance in AI-enhanced education through accessible infrastructure, the affordability of its implementation, and human control.

The second imperative suggestion is to promote an ethical, transparent and accountable use of AI. This incorporates knowledgeable information rituals, bias tracking, suggestive elucidations, and the transparent teacher decision-making of crucial academic matters. Lastly, the same model should be applied to other fields of science like Physics, Chemistry and Environmental Science once subject-specific modification and validation are necessary as according to the recent reviews of science education, AI uses can be considered as promising, albeit requiring contextual adaptation in the various fields.

9. Conclusion

AI-driven adaptive instruction has become another important development in teaching and learning that transcends consistent implementation to responsive, data-driven and learner-focused teaching. This is particularly critical in to Life Science classrooms since students are not always in a similar level of previous knowledge, learning pace and capability of grasping abstract biological processes. The

2250-3676 ijesatj@gmail.com https://www.ijesat.com/

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 09, September 2026
Received: 3 0 -07-2026 Accepted: 04-09-2026 Published: 10-09-2026

recent reviews have indicated that the adaptive tutoring, personalized feedback, intelligent assessment, and predictive learner support have found growing support in AI in education, which is why it has become a solid foundation to incite subject-specific instruction on AI.

In the current paper, it is also emphasized that the core of the effectiveness of such a model is personalization and learning analytics. With adaptive systems, individual learning needs can be better served with the help of learner data to change content, pacing, assessment and feedback. Meanwhile, the learning analytics will allow instructors to track the participation, engagement and performance patterns, facilitating more timely and evidence-based instructional decisions. This is also suggested in prior studies that have consistently shown engagement in adaptive environment to be strongly correlated with achievement especially when interventions based on analytics are employed to determine the needs of learners early.

To sum up, an AI-based adaptive instructional model can provide a great possibility to enhance student engagement and conceptual learning in Life Science classrooms. Such a model, designed with care and pedagogical compatibility, can serve a wide range of learners, help in better understanding concepts and enhance classroom teaching in that it is more effective, inclusive and analytically informed. Monitoring its implementation, readiness of teachers, and further validation in real educational practice will be a key to its success, though.

References

[1] T. Kabudi, I. Pappas, and D. H. Olsen, “AI-enabled adaptive learning systems: A systematic mapping of the literature,” *Computers and Education: Artificial Intelligence*, vol. 2, p. 100017, 2021.

[2] D. Ifenthaler and J. Y.-K. Yau, “Utilising learning analytics to support study success in higher education: A systematic review,” *Educational Technology Research and Development*, vol. 68, pp. 1961–1990, 2020.

[3] N. Bergdahl, M. Bond, J. Sjöberg, M. Dougherty, and E. Oxley, “Unpacking student engagement in higher education learning analytics: A systematic review,” *International Journal of Educational Technology in Higher Education*, vol. 21, art. no. 63, 2024.

[4] S. Wang, F. Wang, Z. Zhu, J. Wang, T. Tran, and Z. Du, “Artificial intelligence in education: A systematic literature review,” *Expert Systems with Applications*, vol. 252, p. 124167, 2024.

[5] L. Y. Tan, S. Hu, D. J. Yeo, and K. H. Cheong, “Artificial intelligence-enabled adaptive learning platforms: A review,” *Computers and Education: Artificial Intelligence*, vol. 9, p. 100429, 2025.

[6] F. Ouyang and L. Zhang, “AI-driven learning analytics applications and tools in computer-supported collaborative learning: A systematic review,” *Educational Research Review*, vol. 44, p. 100616, 2024.

[7] L. Cabral, A. Silva, *et al.*, “AI-powered learning analytics dashboards: A systematic review,” *Discover Education*, vol. 4, 2025.

[8] A. Létourneau, M. Deslandes Martineau, and P. M. Léger, “A systematic review of AI-driven intelligent tutoring systems (ITS) in K-12 education,” *npj Science of Learning*, vol. 10, 2025.

[9] F. Chen, K. K. Y. Chan, and L. H. Wong, “Learning analytics in inquiry-based learning: A systematic review,” *Educational Technology Research and Development*, 2025.

[10] A. Palancı, “Learning analytics in distance education: A systematic review,” *Education and Information Technologies*, 2024.

[11] M. Hernández-de-Menéndez, C. A. Escobar Díaz, and R. Morales-Menendez, “Learning analytics: State of the art,” *International Journal on Interactive Design and Manufacturing*, vol. 16, pp. 1309–1324, 2022.

[12] M. Mukred, *et al.*, “The adoption and use of learning analytics tools to improve decision

2250-3676 ijesatj@gmail.com https://www.ijesat.com/

making in higher learning institutions: An extension of technology acceptance model," *Heliyon*, vol. 10, 2024.
[13] H. Balalle, A. Rubiolo, and C. Rodríguez, "Exploring student engagement in technology-based learning environments: A systematic review," *Heliyon*, vol. 10, no. 6, 2024.
[14] M. Roski, *et al*., "Learning analytics and the Universal Design for Learning framework: Understanding learner interactions and support needs," *Computers & Education*, vol. 213, 2024.
[15] E. du Plooy, *et al*., "Personalized adaptive learning in higher education: A systematic review and bibliometric analysis," *Heliyon*, vol. 10, 2024.
[16] Y. Song, *et al*., "A framework for inclusive AI learning design for diverse learners," *Computers and Education: Artificial Intelligence*, vol. 6, 2024.
[17] M. Mohammadi, *et al*., "Artificial intelligence in multimodal learning analytics," *Computers and Education: Artificial Intelligence*, vol. 9, 2025.
[18] O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, "Systematic review of research on artificial intelligence applications in higher education—Where are the educators?," *International Journal of Educational Technology in Higher Education*, vol. 16, art. no. 39, 2019.
[19] M. Bond, *et al*., "A meta systematic review of artificial intelligence in higher education," *International Journal of Educational Technology in Higher Education*, vol. 21, 2024.
[20] M. Y. Mustafa, *et al*., "A systematic review of literature reviews on artificial intelligence in education," *Smart Learning Environments*, vol. 11, 2024.
[21] A. Abulibdeh, *et al*., "A systematic and bibliometric review of artificial intelligence in education," *Smart Learning Environments*, 2025.
[22] A. Fortuna, *et al*., "Artificial intelligence in personalized learning," *Heliyon*, vol. 11, 2025.
[23] S. Akgun and C. Greenhow, "Artificial intelligence in education: Addressing ethical challenges in K-12 settings," *AI and Ethics*, vol. 2, no. 3, pp. 431–440, 2022.
[24] A. Nguyen, *et al*., "Ethical principles for artificial intelligence in education," *Computers and Education: Artificial Intelligence*, vol. 3, p. 100104, 2022.
[25] UNESCO, *Recommendation on the Ethics of Artificial Intelligence*. Paris, France: UNESCO, 2021.
[26] U.S. Department of Education, *Artificial Intelligence and the Future of Teaching and Learning: Insights and Recommendations*. Washington, DC, USA: U.S. Department of Education, 2023.
[27] UNESCO, *AI Competency Framework for Teachers*. Paris, France: UNESCO, 2024.
[28] OECD, "Artificial intelligence and education and skills," OECD, Paris, France, 2025.
[29] S. Varsik and L. Vosberg, "The potential impact of artificial intelligence on equity and inclusion in education," *OECD Artificial Intelligence Papers*, no. 23, 2024.
[30] T. Goto, G. Horiguchi, N. Kanzaki, *et al*., *Balancing Human Teachers and AI in Education: A Discussion Paper from Ethical, Legal and Social Perspectives*. Paris, France: OECD, 2024.
[31] L. Tao, *et al*., "Learning analytics in immersive virtual learning environments: A systematic literature review," *Smart Learning Environments*, 2025.
[32] M. Á. Conde, *et al*., "Is learning analytics applicable and applied to education of students with intellectual and developmental disabilities?," *Computers in Human Behavior*, vol. 160, 2024.
[33] L. Zhang, *et al*., "Measuring personalized learning through the lens of Universal Design for Learning," *Research in Developmental Disabilities*, vol. 122, 2022.A

International Journal of Engineering Science and Advanced Technology (IJESAT)

Vol 26 Issue 09, September 2026

Received: 3 0 -07-2026 Accepted: 04-09-2026 Published: 10-09-2026

[34] D. Y. Long, *et al.*, "Artificial intelligence in higher education: A systematic review," *Frontiers in Education*, 2025.

[35] M. Landa-Blanco, *et al.*, "Artificial intelligence in education: Applications and challenges," *Frontiers in Education*, 2025.

[36] A. R. Fayzullina, A. A. Filippova, N. Y. Garnova, D. V. Astakhov, N. Kalmazova, and Z. F. Zaripova, "Artificial intelligence in science education: A systematic review of applications, impacts, and challenges," *Contemporary Educational Technology*, vol. 17, no. 4, p. ep613, 2025.

[37] K. Alarabi, *et al.*, "AI's impact on science education: A study of ant and bee metaphors in teachers' perspectives," *Frontiers in Education*, 2025.

[38] B. Díaz, *et al.*, "Artificial intelligence for teaching and learning in schools," *Computers & Education*, 2024.

[39] R. Alfredo, V. Echeverria, Y. Jin, L. Yan, Z. Swiecki, D. Gašević, and R. Martinez-Maldonado, "Human-centred learning analytics and AI in education: A systematic literature review," *Computers and Education: Artificial Intelligence*, vol. 6, p. 100215, 2024.

[40] R. Ferguson, "Learning analytics: Drivers, developments and challenges," *International Journal of Technology Enhanced Learning*, vol. 4, no. 5/6, pp. 304–317, 2012.

[41] G. Siemens and P. Long, "Penetrating the fog: Analytics in learning and education," *EDUCAUSE Review*, vol. 46, no. 5, pp. 30–40, 2011.

[42] Z. A. Papamitsiou and A. A. Economides, "Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence," *Educational Technology & Society*, vol. 17, no. 4, pp. 49–64, 2014.

[43] B. J. Zimmerman, "Becoming a self-regulated learner: An overview," *Theory Into Practice*, vol. 41, no. 2, pp. 64–70, 2002.

[44] P. R. Pintrich, "A conceptual framework for assessing motivation and self-regulated learning in college students," *Educational Psychology Review*, vol. 16, pp. 385–407, 2004.

[45] J. Sweller, "Cognitive load during problem solving: Effects on learning," *Cognitive Science*, vol. 12, no. 2, pp. 257–285, 1988.

[46] J. D. Novak and A. J. Cañas, "The theory underlying concept maps and how to construct and use them," Institute for Human and Machine Cognition, Pensacola, FL, USA, Tech. Rep. IHMC CmapTools 2006-01 Rev 01-2008, 2008.

2250-3676 ijesatj@gmail.com https://www.ijesat.com/