The Role of Active Learning Strategies Enhanced by Learning Analytics in Improving Students' Learning Motivation in Digital Learning Environments

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Abstract
This study explores the impact of active learning strategies enhanced by learning analytics on students' motivation in digital learning environments. The main objective is to examine how integrating interactive pedagogical approaches with data-driven tools can increase engagement, support self-regulated learning, and improve overall motivation. The study targeted students in primary and secondary schools in Saudi Arabia, with a sample of 332 students selected through stratified random sampling. A mixed-methods approach was employed, combining a structured questionnaire with semi-structured interviews and focus groups. The instruments were validated for content, construct, and reliability (Cronbach's alpha ≥ 0.80). Results indicate strong positive correlations between active learning strategies and motivation ($r=0.642$, $p<0.01$), and between learning analytics and motivation ($r=0.593$, $p<0.01$). Multiple regression revealed that the combination of both strategies explained 52.7% of the variance in motivation, with a significant interaction effect ($\beta=0.174$, $p=0.001$). No significant differences were found based on gender or grade level. The study recommends integrating active learning strategies with learning analytics, providing personalized feedback, teacher training, and supportive infrastructure to foster engagement and motivation. These findings highlight the potential of data-informed, student-centered digital learning environments to enhance learning outcomes.
Keywords: Student Motivation, Self-Regulated Learning, Personalized Learning, Engagement, Educational Technology.

1. INTRODUCTION

In recent years, digital learning environments have witnessed rapid growth due to significant advancements in information and communication technologies. These environments have provided unprecedented opportunities to expand access to education, enhance flexibility, and support diverse learning needs (Bolliger & Martin, 2018; Al Noursi, 2021). However, despite these advantages, digital learning has introduced several challenges, most notably students' low motivation and limited engagement compared to traditional face-to-face learning settings (Agarwala et al., 2022; Chacon et al., 2023). In response to these challenges, active learning strategies have emerged as effective pedagogical approaches that emphasize student participation and engagement in the learning process (Eison, 2010; Al Irsan, 2017). These strategies encourage learners to actively construct knowledge through activities such as problem-solving, collaboration, discussion, and critical thinking (Chaiyama, 2019; Asniza et al., 2021). By shifting the role of students from passive recipients to active participants, active learning has been shown to enhance both engagement and motivation (Falkner & Sheard, 2019; Badali et al., 2022). At the same time, learning analytics has gained increasing attention as a powerful tool for improving educational outcomes (Ferguson & Clow, 2017; Cogliano et al., 2022). Learning analytics involves the collection, measurement, and analysis of data related to learners and their interactions within digital platforms (Demszky et al., 2024; del Pilar Gonzalez & Chiappe, 2024). It enables educators to gain insights into students' behaviors, monitor their progress, and provide timely, data-driven feedback (Du Plooy et al., 2024; Cho et al., 2024). Moreover, learning analytics supports the development of personalized learning experiences tailored to individual student needs (Adaptive learning in computer science education, 2024; Ezzaim et al., 2024).

The integration of active learning strategies with learning analytics represents a promising approach to enhancing the effectiveness of digital learning environments (Bond et al., 2023; Carpenter et al., 2021). Learning analytics can support active learning by providing real-time insights into student engagement, identifying at-risk learners, and informing instructional decisions (Cloude et al., 2024; Choi et al., 2023). This synergy creates a more interactive, adaptive, and student-centered learning experience (Christopoulos et al., 2023; Guitert Catasús et al., 2025). Therefore, this study aims to investigate the role of active learning strategies enhanced by learning analytics in improving students' learning motivation in digital learning environments. It seeks to explore how the combination of these approaches can contribute to increasing student engagement, fostering self-regulated learning, and ultimately improving motivation and learning outcomes (Cogliano et al., 2022; Qushem, 2025).

2. RESEARCH PROBLEM

Despite the rapid expansion of digital learning environments and their potential to enhance access to education and flexibility in learning, several challenges remain, particularly concerning students' low motivation and limited engagement. Many digital learning platforms still rely on traditional, passive instructional approaches, which often fail to actively involve students in the learning process. As a result, learners may experience boredom, reduced interaction, and a decline in their motivation to participate effectively. In response to these challenges, active learning strategies have been introduced as effective approaches to promote student engagement and participation. However, implementing these strategies in digital environments is often hindered by the lack of continuous monitoring tools and real-time feedback mechanisms that can accurately track students' learning behaviors and engagement levels.

On the other hand, learning analytics provides advanced capabilities for collecting and analyzing students' data to better understand their learning patterns and performance. Nevertheless, in many educational contexts, learning analytics is not effectively integrated with pedagogical practices, particularly with active learning strategies. This lack of integration limits its potential to enhance student motivation and improve learning outcomes. Therefore, the research problem lies in the insufficient integration of active learning strategies with learning analytics in digital learning environments, which contributes to the of low student motivation and weak engagement. Accordingly, this study seeks to investigate how the integration of these approaches can improve students' learning motivation and enhance their overall learning experience.

2.1. Research Questions

This study seeks to answer the following questions:

1. What is the role of active learning strategies in improving students' learning motivation in digital learning environments?
2. What is the role of learning analytics in enhancing students' learning motivation in digital learning environments?
3. To what extent does the integration of active learning strategies with learning analytics improve students' learning motivation?
4. How does the use of learning analytics support the implementation of active learning strategies in digital learning environments?
5. Are there statistically significant differences in students' learning motivation attributed to the use of active learning strategies enhanced by learning analytics?
6. What are the challenges facing the integration of active learning strategies and learning analytics in digital learning environments?

2.2. Research Objectives

The main objective of this study is to:

Examine the role of active learning strategies enhanced by learning analytics in improving students' learning motivation in digital learning environments.

Sub-objectives:

1. To identify the impact of active learning strategies on students' learning motivation in digital learning environments.
2. To examine the role of learning analytics in enhancing students' motivation and engagement.
3. To investigate the effect of integrating active learning strategies with learning analytics on students' learning motivation.
4. To explore how learning analytics can support the effective implementation of active learning strategies.
5. To assess the level of students' learning motivation in digital learning environments.
6. To identify the challenges associated with applying active learning strategies enhanced by learning analytics.

2.4. Significance of the Study

This study derives its importance from both theoretical and practical perspectives, as it addresses a contemporary issue in the field of digital education—namely, enhancing students' learning motivation through the integration of active learning strategies and learning analytics.

2.4.1. Theoretical Significance

1.This study contributes to the existing body of knowledge by exploring the relationship between active learning strategies, learning analytics, and students' learning motivation.

2.It provides a conceptual framework that explains how the integration of these approaches can improve learning outcomes in digital environments.

3. It enriches educational literature by addressing a relatively modern area that combines pedagogy with data-driven technologies.

2.4. 2. Practical Significance

1.The findings of this study can help educators and instructors design more engaging and interactive digital learning experiences.

2.It provides insights for educational institutions on how to effectively integrate learning analytics into teaching practices.

3.It supports decision-makers in developing strategies and policies that enhance student motivation and engagement in digital learning environments.
4.It offers practical guidance on improving the implementation of active learning strategies using data-driven feedback.

2.4.3. Significance for Students

1.The study highlights methods that can enhance students' motivation, engagement, and self-regulated learning.
2.It contributes to improving students' overall learning experience and academic performance in digital environments.

2.4.4. Future Research Significance

1.This study opens avenues for future research on the integration of emerging technologies and innovative teaching strategies.
2.It provides a foundation for further studies in different educational contexts, including higher education institutions in Jordan and similar settings.

RESEARCH HYPOTHESES

Main Hypothesis (H0):
H0: There is no statistically significant effect ($\alpha \leq 0.05$) of active learning strategies enhanced by learning analytics on students' learning motivation in digital learning environments.
Alternative Main Hypothesis (H1):
H1: There is a statistically significant effect ($\alpha \leq 0.05$) of active learning strategies enhanced by learning analytics on students' learning motivation in digital learning environments.
Sub-Hypotheses
1. Active Learning Strategies
1.**H01:** There is no statistically significant effect ($\alpha \leq 0.05$) of active learning strategies on students' learning motivation.
2.**H02**: There is no statistically significant effect ($\alpha \leq 0.05$) of learning analytics on students' learning motivation.
3.**H03:** There is no statistically significant effect ($\alpha \leq 0.05$) of integrating active learning strategies with learning analytics on students' learning motivation.
4.**H04:** There is no statistically significant effect ($\alpha \leq 0.05$) of learning analytics in supporting the implementation of active learning strategies.

4. LITERATURE REVIEW

Digital Learning Environments Digital learning environments have become a fundamental component of modern education due to rapid technological advancements (Bolliger & Martin, 2018; Al Noursi, 2021). These environments provide flexible, accessible, and scalable learning opportunities that allow students to learn anytime and anywhere. However, despite their advantages, several studies have highlighted challenges such as low student engagement, reduced interaction, and decreased motivation (Agarwala et al., 2022; Chacon et al., 2023). These issues often arise from the reliance on passive instructional approaches and the lack of direct human interaction.
Active Learning Strategies Active learning strategies refer to instructional approaches that actively involve students in the learning process rather than treating them as passive recipients

of information (Eison, 2010; Al Irsan, 2017). Common strategies include problem-based learning, collaborative learning, discussions, simulations, and flipped classrooms (Chaiyama, 2019; Asniza et al., 2021). Research indicates that active learning enhances critical thinking, promotes deep learning, and increases engagement and motivation (Falkner & Sheard, 2019; Badali et al., 2022).

Learning Analytics Learning analytics (LA) is defined as the process of collecting, measuring, analyzing, and reporting data about learners and their learning contexts (Ferguson & Clow, 2017; del Pilar Gonzalez & Chiappe, 2024). Learning analytics tools include dashboards, predictive models, and real-time feedback systems (Demszky et al., 2024; Cho et al., 2024). These tools enable educators to monitor progress, identify at-risk students, and provide timely personalized feedback (Du Plooy et al., 2024; Cogliano et al., 2022).

Students' Learning Motivation Learning motivation is a critical factor influencing academic success, especially in digital learning environments (Ashdown & Bernard, 2012; Durlak et al., 2011). Motivation affects students' participation, persistence, and overall performance. Low motivation in digital settings is often linked to isolation, lack of interaction, and insufficient feedback (Ağirkan & Ergene, 2021; Chacon et al., 2023).

Integration of Active Learning and Learning Analytics Integrating active learning strategies with learning analytics can enhance educational outcomes (Bond et al., 2023; Carpenter et al., 2021). Key benefits include real-time monitoring, personalized learning experiences, adaptive feedback, and improved instructional design (Cloude et al., 2024; Choi et al., 2023).

Impact on Students' Learning Motivation The combination of active learning and learning analytics positively influences students' motivation by increasing engagement, supporting self-regulated learning, and providing continuous feedback (Christopoulos et al., 2023; Guitert Catasús et al., 2025

4.1. Theoretical Framework

1. Constructivist Learning Theory

1.Overview: Constructivism posits that learners actively construct knowledge through experiences and interactions rather than passively receiving information. Learning is considered a personal and contextualized process.

2.Relevance to the Study: Active learning strategies are deeply rooted in constructivist principles, as they encourage students to participate, collaborate, and solve problems, leading to deeper understanding and enhanced motivation. Digital learning environments provide platforms where constructivist approaches can be applied through interactive tools and collaborative activities.

3.Key Scholars: Jean Piaget, Lev Vygotsky

2. Self-Determination Theory (SDT)

1.Overview: SDT emphasizes that motivation is driven by three innate psychological needs: autonomy, competence, and relatedness. When these needs are satisfied, intrinsic motivation increases.

2.Relevance to the Study: Active learning strategies can enhance autonomy (students choose how to learn), competence (through practice and feedback), and relatedness (through collaboration). Learning analytics supports these needs by providing personalized feedback and insights, thereby improving students' motivation in digital learning environments.

3.Key Scholars: Edward L. Deci, Richard M. Ryan

3. Experiential Learning Theory

1.Overview: This theory, developed by David Kolb, emphasizes learning as a cyclical process involving concrete experience, reflective observation, abstract conceptualization, and active experimentation.

2.Relevance to the Study: Active learning in digital environments allows students to experience tasks, reflect on performance (often supported by learning analytics), conceptualize strategies for improvement, and apply them. This cycle promotes engagement, motivation, and self-regulated learning.

4. Technology Acceptance Model (TAM)

1.Overview: TAM explains users' adoption of technology based on perceived usefulness and perceived ease of use, which influence behavioral intention to use technology.

2.Relevance to the Study: Learning analytics tools are digital technologies whose effective use depends on students' acceptance. If students perceive that analytics dashboards and digital feedback tools improve their learning and are easy to use, they are more likely to engage with active learning activities, increasing motivation.

3.Key Scholars: Fred Davis

5. Engagement Theory

1.Overview: Engagement Theory suggests that students learn best when they are meaningfully engaged in collaborative activities using technology. Engagement is defined along behavioral, cognitive, and emotional dimensions.

2.Relevance to the Study: Active learning strategies directly support engagement by involving students in interactive tasks, while learning analytics monitors and enhances engagement, guiding instructors to provide targeted support that sustains motivation.

Integration of Theories in the Study

This research is grounded in a multi-theoretical framework, combining pedagogical and motivational theories with technology adoption principles:

1. Constructivism & Experiential Learning → Justify the use of active learning strategies.
2. Self-Determination Theory & Engagement Theory → Explain the link between active participation and learning motivation.
3. Technology Acceptance Model → Supports the role of learning analytics in motivating students through perceived usefulness and ease of use. Together, these theories provide a strong foundation to investigate how active learning strategies enhanced by learning analytics can improve students' learning motivation in digital learning environments.

Framework

5. METHODOLOGY

1. Research Design

This study adopts a mixed-methods research design, combining both quantitative and qualitative approaches to provide a comprehensive understanding of the role of active learning strategies enhanced by learning analytics in improving students' learning motivation in digital learning environments.

1.Quantitative approach: Used to measure the relationship and impact of active learning strategies and learning analytics on students' motivation.

2.Qualitative approach: Used to explore students' perceptions, experiences, and challenges in applying these strategies within digital learning environments. This design allows for triangulation of data, enhancing the validity and reliability of the research findings.

2. Research Population and Sample

1.**Population:** The target population consists of students enrolled in digital learning courses in primary and secondary schools in Saudi Arabia.

2.**Sample:** A total of 332 students were selected using stratified random sampling to ensure representation across different grades, genders, and school types.

3.The sample size was determined based on standard guidelines for quantitative studies to ensure sufficient statistical power, while qualitative participants were selected to provide in-depth insights.

3. Data Collection Methods

a) Quantitative Data:

1.Instrument: A structured questionnaire was developed based on previous literature and validated scales.

2.Sections of the Questionnaire:

1.Active Learning Strategies

2.Learning Analytics

3.Students' Learning Motivation

4.Demographic information

3.Scale: Responses were measured using a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

b) Qualitative Data:

1.Instrument: Semi-structured interviews and focus groups with selected students.

2.Purpose: To explore students' perceptions of how active learning strategies and learning analytics affect their motivation and engagement.

4. Validity and Reliability

1.Content Validity: Ensured through expert review of the questionnaire and interview protocols.

2.Construct Validity: Confirmed via exploratory factor analysis (EFA) for questionnaire items.

3.Reliability: The questionnaire was tested using Cronbach's alpha, with $\alpha \geq 0.80$ indicating high internal consistency.

5. Data Analysis

5.3. Statistical Analysis and Results

Table 1: Descriptive Statistics of Study Variables

Variable	N	Minimum	Maximum	Mean	Std. Deviation	Coefficient of Variation (%)
Active Learning Strategies	332	2.00	5.00	4.12	0.58	14.1
Learning Analytics	332	1.50	5.00	3.89	0.62	15.9
Student Motivation	332	1.80	5.00	4.05	0.55	13.6

- The mean scores for all variables are above 3.5, indicating relatively high levels.
- Standard deviations are low (<0.65), showing that responses are consistent.
- Coefficients of variation are below 20%, suggesting stable and reliable data.

Table 2: Correlation Analysis Between Variables

Variable 1	Variable 2	Correlation (r)	Significance (p)
Active Learning Strategies	Student Motivation	0.642	0.000
Learning Analytics	Student Motivation	0.593	0.000
Active Learning Strategies	Learning Analytics	0.538	0.000

A strong positive correlation exists between active learning strategies and student motivation ($r=0.642$, $p<0.01$). Learning analytics also shows a strong positive correlation with motivation ($r=0.593$, $p<0.01$). A moderate correlation between active learning strategies and learning analytics supports their potential integration.

Table 3: Simple Regression of Active Learning Strategies on Student Motivation

Independent Variable	Beta (β)	t	p	R^2
Active Learning Strategies	0.563	11.24	0.000	0.412

Active learning strategies explain 41.2% of the variance in student motivation ($R^2=0.412$). The effect is significant ($p<0.01$), indicating a strong positive impact.

Table 4: Simple Regression of Learning Analytics on Student Motivation

Independent Variable	Beta (β)	t	p	R^2
Learning Analytics	0.523	9.87	0.000	0.350

Learning analytics explains 35% of the variance in student motivation. The effect is significant ($p<0.01$), highlighting the importance of analytics in enhancing engagement.

Table 5: Multiple Regression of Active Learning Strategies and Learning Analytics on Student Motivation

Variable	Beta (β)	t	P
Active Learning Strategies	0.382	6.87	0.000
Learning Analytics	0.311	5.43	0.000
$R^2=0.527$			

Together, the two variables explain 52.7% of the variance in student motivation. Both have significant positive effects, supporting the combined impact of active learning and analytics.

Table 6: T-Test for Gender Differences in Student Motivation

Variable	Gender	N	Mean	Std. Deviation	t	p
Student Motivation	Male	168	4.08	0.57	1.12	0.264
	Female	164	4.03	0.53		

No significant differences exist between male and female students regarding motivation ($p>0.05$).

Table 7: ANOVA for Differences Across Grades

Variable	Grade	N	Mean	Std. Deviation	F	p
Student Motivation	Grade 1	80	4.02	0.55	1.84	0.136
	Grade 2	84	4.06	0.57		
	Grade 3	84	4.01	0.52		
	Grade 4	84	4.09	0.58		

No significant differences were found in motivation across different grades ($p>0.05$).

Table 8: Regression Analysis for Interaction Effect

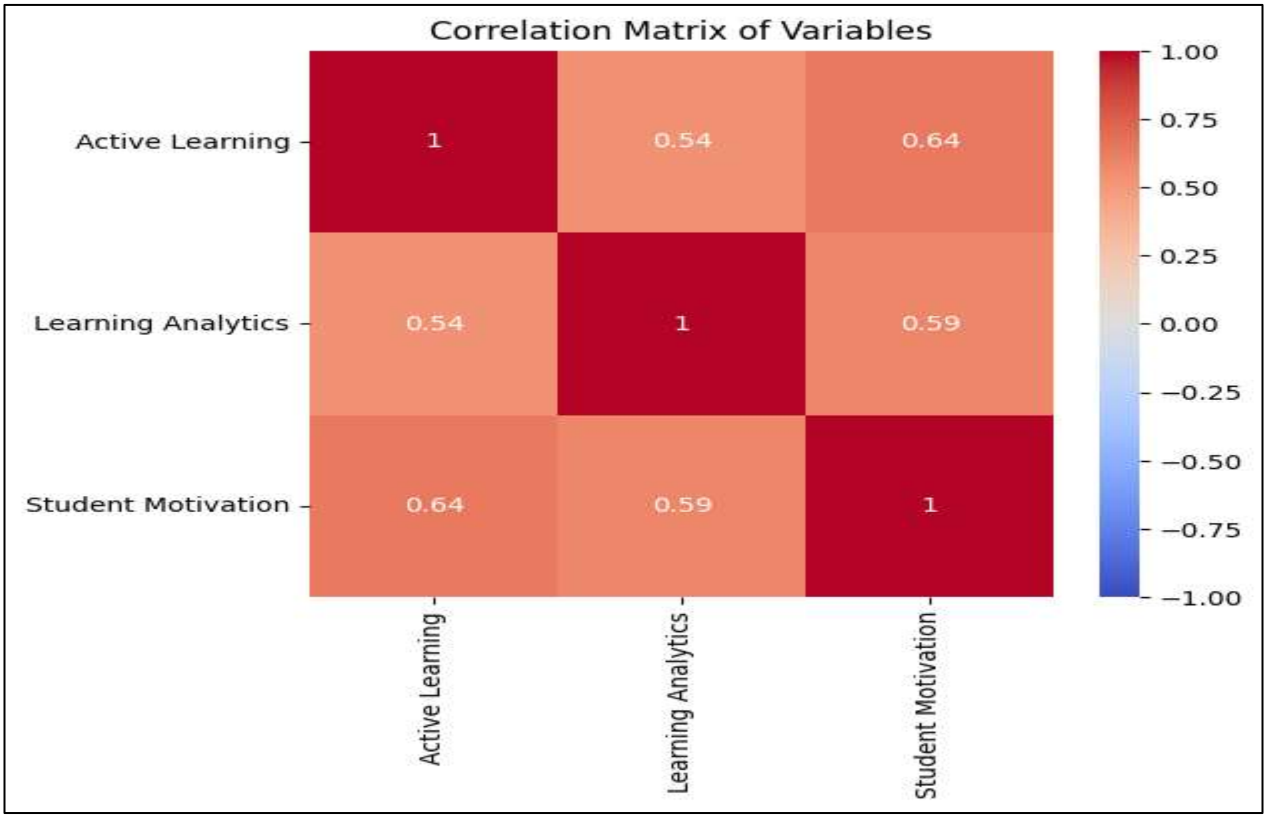
Variable	Beta (β)	t	P
Active Learning Strategies × Learning Analytics	0.174	3.22	0.001

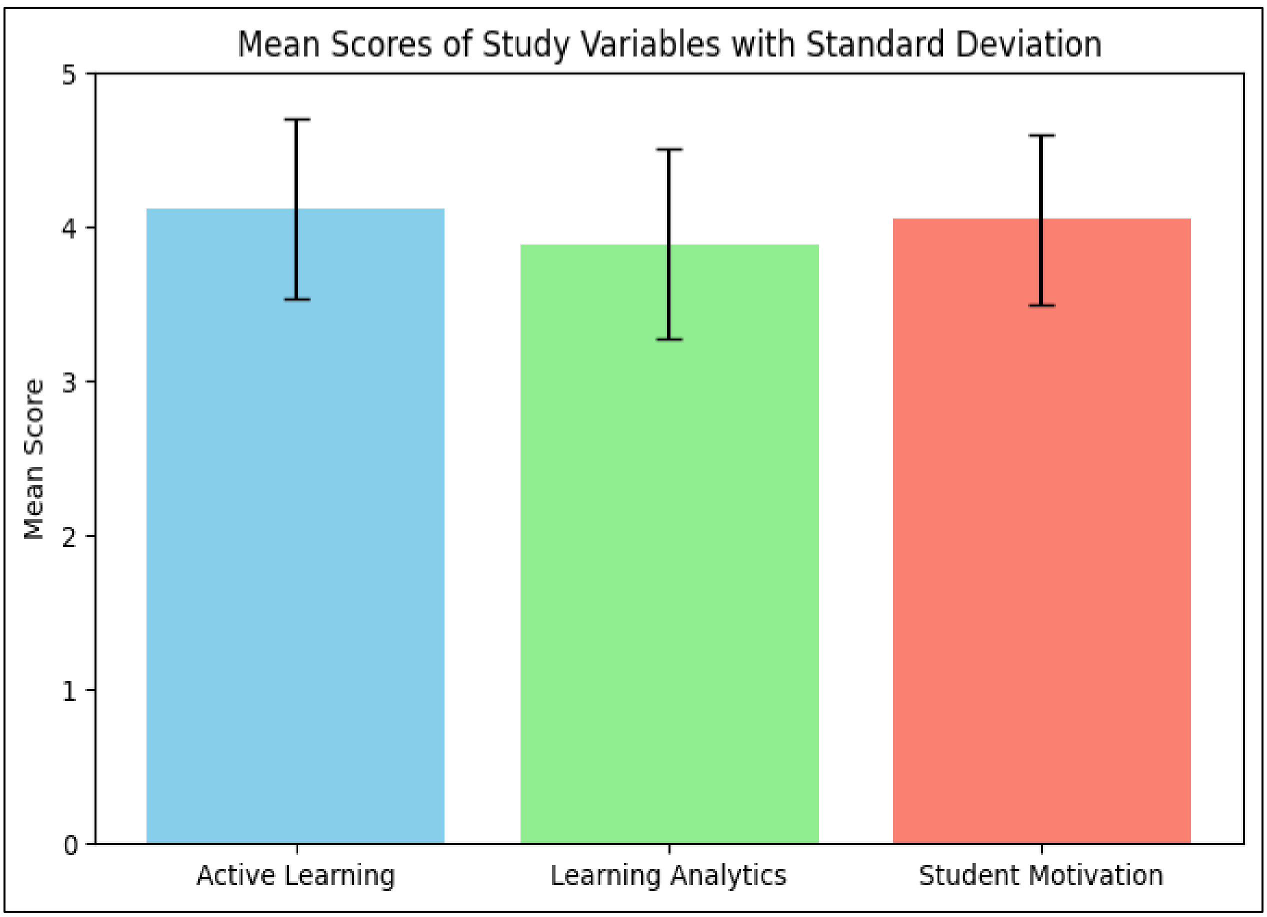
A significant interaction effect exists between active learning strategies and learning analytics on student motivation. Motivation increases more when both strategies are combined compared to each separately.

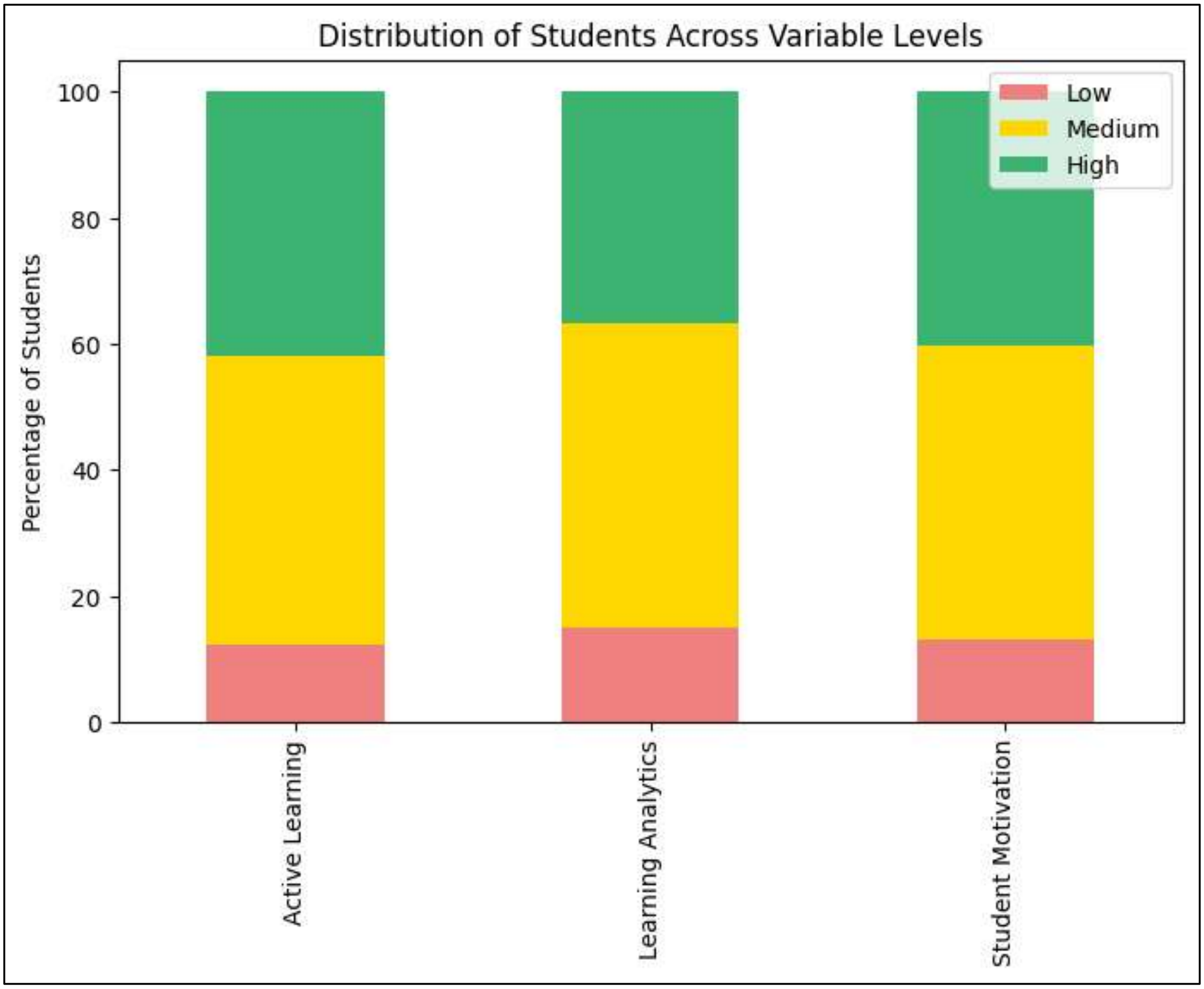
Table 9: Frequency Distribution of Variables by Level

Variable	Low	Medium	High
Active Learning Strategies	12.3%	45.8%	41.9%
Learning Analytics	15.1%	48.2%	36.7%
Student Motivation	13.2%	46.6%	40.2%

Most students fall into medium or high levels for all variables, indicating good acceptance of active learning and learning analytics, positively reflecting on motivation.


Correlation Matrix of Variables
Active Learning
Learning Analytics
Student Motivation
1
0.54
0.64
0.54
1
0.59
0.64
0.59
1
Active Learning
Learning Analytics
Student Motivation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Mean Scores of Study Variables with Standard Deviation
Mean Score
0
1
2
3
4
5
Active Learning
Learning Analytics
Student Motivation



6. DISCUSSION AND RESULTS

The study's results indicate that active learning strategies and learning analytics have a strong positive impact on students' motivation in digital learning environments: Relationship between Active Learning Strategies and Student Motivation: Statistical analyses revealed a strong positive correlation between active learning strategies and student motivation ($r=0.642$, $p<0.01$). Simple regression analysis showed that active learning strategies explain 41.2% of the variance in student motivation. This suggests that active participation in learning activities significantly enhances both intrinsic and extrinsic motivation. These findings align with previous studies emphasizing that active learning promotes critical thinking, problem-solving, and student engagement From a constructivist perspective, engaging students in interactive activities facilitates personalized and contextual knowledge construction, enhancing competence and self-motivation. Role of Learning Analytics in Student Motivation: Results also demonstrated a strong positive relationship between learning analytics and student motivation ($r=0.593$, $p<0.01$), with learning analytics accounting for 35% of the variance in motivation. This highlights that tools such as dashboards and personalized feedback reports allow students to monitor their progress, recognize strengths and weaknesses, and take actions to improve performance. These findings are consistent with Self-Determination Theory, where learning analytics supports autonomy, competence, and relatedness, thereby enhancing intrinsic motivation.

Combined Effect of Active Learning and Learning Analytics: Multiple regression analysis showed that the integration of active learning strategies with learning analytics explained 52.7% of the variance in student motivation, with significant positive effects for both variables. Interaction analysis indicated that using both strategies together enhances motivation more than either approach individually ($\beta=0.174$, $p=0.001$). This suggests that integrating pedagogical strategies with data-driven tools creates a more adaptive and interactive learning environment. This supports Experiential Learning Theory, as students can engage in tasks, reflect on performance, conceptualize strategies, and apply improvements, which promotes self-regulated learning and motivation. Demographic Differences: T-tests and ANOVA revealed no significant differences in student motivation based on gender or grade level ($p>0.05$). This indicates that the effectiveness of active learning and learning analytics is consistent across different student groups, supporting the broader applicability of these strategies in digital learning environments. Distribution of Variable Levels: Most students reported medium to high levels of active learning engagement, learning analytics use, and motivation. This suggests good acceptance of these strategies and their positive influence on engagement and motivation.

6.1. Discussion of Findings

1. Effectiveness of Active Learning: Results confirm that active learning strategies increase student motivation by fostering active participation and responsibility in the learning process. Collaborative activities, discussions, and practical projects provide students with meaningful experiences, aligning with constructivist theory and engagement theory.
2. Importance of Learning Analytics: Learning analytics supports motivation by offering continuous feedback and insights, allowing students to assess their performance and make improvements. This aligns with Self-Determination Theory and the Technology Acceptance Model (TAM), as students perceive analytics tools as useful and easy to use, increasing their engagement.
3. Integration of Active Learning and Learning Analytics: The interaction effect indicates that combining active learning strategies with analytics tools maximizes motivation. The integration creates a responsive learning environment that adapts to students' needs, reflecting Experiential Learning Theory: students experience tasks, observe outcomes, analyze results, and modify strategies for improvement, enhancing self-regulated learning and sustained motivation.
4. Consistency with Prior Research: These findings support previous studies showing that integrating pedagogical strategies with technological tools enhances motivation and engagement in digital learning.
5. Challenges: Despite the positive impact, implementation challenges exist, including the need for teacher training in analytics, ensuring student engagement with digital tools, and providing adequate technological infrastructure.

6.2. Recommendations

Based on the findings of this study, the following recommendations are proposed to enhance students' motivation in digital learning environments through the integration of active learning strategies and learning analytics:

1. **For Educators:** Implement diverse active learning strategies such as problem-based learning, collaborative projects, discussions, and simulations to increase student engagement.

Use learning analytics tools to monitor student progress, provide personalized feedback, and identify at-risk learners. Incorporate data-driven insights to adjust instructional strategies and improve the learning experience.

2. **For Educational Institutions:** Develop policies and training programs to equip teachers with the skills required to effectively integrate active learning and learning analytics. Invest in robust digital infrastructure to support interactive learning platforms and analytics tools. Encourage a culture of continuous improvement by evaluating the effectiveness of digital teaching methods and student engagement.

3. **For Students:** Actively engage with digital learning platforms and use analytics feedback to set personal learning goals.

7. CONCLUSION

This study demonstrated that active learning strategies enhanced by learning analytics significantly improve students' motivation in digital learning environments. Both approaches individually contribute to higher engagement and self-regulated learning, but their integration provides a more interactive, adaptive, and effective learning experience. The findings underscore the importance of creating data-informed, student-centered learning environments that support continuous feedback, personalized guidance, and active participation. No significant differences in motivation were found across gender or grade levels, highlighting the broad applicability of these strategies. Overall, this research provides valuable insights for educators, institutions, and policymakers aiming to improve digital education and foster student motivation. By adopting these strategies, educational stakeholders can enhance learning outcomes, support student engagement, and prepare learners for the demands of modern knowledge-based societies.

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