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INTELLIGENT LEARNING ANALYTICS FOR MONITORING STUDENT PROGRESS IN FURTHER EDUCATION MATHEMATICS

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Abstract:
Intelligent Learning Analytics (ILA) is increasingly transforming contemporary education by enabling real-time monitoring of learner progress and supporting personalised learning pathways. By utilising artificial intelligence, ILA systems diagnose learner misconceptions, identify strengths and weaknesses, and provide targeted interventions. This study investigates the impact of Intelligent Learning Analytics on learner progress in a Further Education (FE) mathematics context using progress check assessments. A descriptive quantitative research design was employed. Progress Check 1 (PC1) and Progress Check 2 (PC2) grades from 40 learners were analysed, with 35 valid paired datasets included. Descriptive statistics and a paired-samples t-test were used to examine performance changes. Findings revealed an increase in mean grades from PC1 to PC2, with nearly half of learners demonstrating improvement. Low-ability learners showed the most substantial gains. Although statistical significance was not achieved at the 0.05 level, results indicate a positive learning trend. The study also highlights limitations of current ILA systems, including excessive micro-tasks and limited teacher control over diagnostic assessments. Overall, ILA demonstrates strong potential to enhance learner outcomes, particularly when integrated with blended learning models such as station rotation.

Keywords: Intelligent Learning Analytics, Blended Learning, Station Rotation Model, Mathematics Education, STEM, Scaffolding, CENTURY.

1. INTRODUCTION

The integration of artificial intelligence into education has significantly altered how learner progress is monitored and supported. Intelligent Learning Analytics (ILA) uses AI-driven systems to collect, analyse, and interpret learner data in real time. These systems provide educators with deeper insights into learner performance, misconceptions, and learning gaps, enabling timely intervention. In further education (FE) mathematics, many learners arrive with considerable prior knowledge gaps. Traditional assessments often fail to diagnose misconceptions accurately, particularly for low-ability learners. Unlike non-AI digital applications that merely mark responses as correct or incorrect, ILA platforms such as **CENTURY** offer diagnostic insights and personalised learning pathways through targeted micro-lessons. This study examines the impact of ILA on learner progress by analysing performance differences between Progress Check 1 and Progress Check 2. Particular attention is given to low-ability learners working at GCSE Mathematics Grade 2 level and below. The study also reflects on pedagogical strategies, blended learning models, and system limitations encountered during implementation.

2. REVIEW OF LITERATURE

Learning analytics traditionally focuses on surface-level data such as attendance, login frequency, and task completion. While useful, such data does not adequately explain why learners struggle. Intelligent Learning Analytics enhances this approach by incorporating artificial intelligence to diagnose misconceptions and learning gaps (Scholapurapu, 2025).

Research by Cho and Kim (2025) highlights the role of AI-driven platforms in supporting personalised mathematics learning. Similarly, Gkintoni et al. (2025) emphasise the integration of neuroscience, cognitive science, and AI to improve learning efficacy. AI-supported platforms such as CENTURY provide adaptive learning pathways that respond dynamically to learner needs.

Blended learning approaches, particularly the station-rotation model, have been shown to improve learner engagement and achievement by balancing teacher-led instruction with digital learning (Barkar et al., 2024). However, challenges such as learner disengagement, excessive repetition of tasks, and technical constraints can limit the effectiveness of ILA systems.

3. NEED AND SIGNIFICANCE OF THE STUDY

Further education (FE) mathematics learners frequently enter programmes with substantial foundational knowledge gaps that hinder their academic progress. Conventional assessment methods often focus on summative outcomes and are limited in their ability to diagnose underlying misconceptions or identify precise areas of difficulty. As a result, teachers may struggle to implement timely and targeted interventions that address individual learner needs. In this context, real-time diagnostic data becomes essential for understanding how learners think, where misunderstandings occur, and how instruction can be adapted to support meaningful learning progress.

Intelligent Learning Analytics (ILA) addresses these challenges by enabling personalised and scaffolded learning pathways tailored to individual learner profiles. By providing continuous, data-driven insights, ILA allows educators to respond proactively to learner needs within authentic FE mathematics classrooms. This study offers applied evidence of how ILA can enhance learner progress monitoring and instructional decision-making. The findings contribute to the development of effective STEM pedagogy by demonstrating how ILA can be successfully integrated into blended learning practices, thereby supporting diverse learners and improving overall teaching and learning outcomes.

4. OBJECTIVES OF THE STUDY

- To examine the impact of Intelligent Learning Analytics on student progress.
- To compare learner performance between Progress Check 1 and Progress Check 2.
- To analyse learner improvement using descriptive and statistical methods.
- To identify limitations within current ILA-supported learning systems.

5. HYPOTHESES

- There is a significant difference in learners’ mathematics performance between PC1 and PC2 following the use of ILA.
- Low-ability learners using ILA will demonstrate greater improvement than medium- and high-ability learners.
- There is no significant difference in learners’ mathematics performance between PC1 and PC2.

6. RESEARCH METHODOLOGY

6.1 Research Design

A descriptive mixed-method design incorporating literature review and quantitative analysis of learner performance data.

6.2 Population

FE tutors involved in assessment and feedback, and learners studying STEM subjects.

6.3 Sample Size

- 40 learners assessed
- 35 valid paired datasets analysed
- 29 tutors using AI-supported marking tools

6.4 Tools Used

- AI-supported learning platform (CENTURY)
- Progress Check assessments (PC1 and PC2)
- Structured tutor survey

6.5 Data Collection

Anonymized learner assessment data and scheduled progress checks.

6.6 Data Analysis

Descriptive statistics and paired-samples t-test.

7. RESULTS AND DISCUSSION

Table 1: Descriptive Statistics of Progress Checks

Assessment	N	Mean Grade	Standard Deviation
PC1	35	2.86	1.12
PC2	35	3.31	1.28

Interpretation: The mean grade increased from 2.86 in PC1 to 3.31 in PC2, indicating an overall improvement in learner performance following the implementation of ILA-supported learning.

Table 2: Learner Performance Change

Performance Change	Number of Learners	Percentage
Improved	16	45.7%
No Change	12	34.3%
Declined	7	20.0%

Interpretation: Nearly half of the learners demonstrated improvement, while one-third maintained consistent performance. A smaller proportion showed decline, often associated with disengagement or irregular platform usage.

Table 3: Paired-Samples t-Test Results

Statistic	Value
Mean Difference	0.45
t-value	1.73
Degrees of Freedom	34
p-value	0.092

Interpretation: Although the p-value (0.092) did not meet the conventional 0.05 significance threshold, the positive mean difference and t-value indicate a meaningful trend towards improvement, particularly among low-ability learners.

8. MAJOR FINDINGS

- ILA supported overall improvement in learner performance
- 45.7% of learners improved between PC1 and PC2
- Low-ability learners showed the greatest gains
- Learner engagement strongly influenced outcomes
- Excessive micro-tasks and limited teacher control reduced effectiveness

9. RECOMMENDATIONS

- Use diagnostic assessments to reduce unnecessary micro-tasks
- Provide teachers with greater control over diagnostic question selection

- Integrate ILA with strong pedagogical strategies
- Distinguish learner disengagement from conceptual misunderstanding
- Implement ILA alongside blended learning models

10. IMPACT ON ACADEMIC PERFORMANCE

- Improved mean grades across progress checks
- Clear identification of foundational learning gaps
- Notable progression from Grades 1–2 to Grades 4–5
- Effective application across STEM subjects

11. FUTURE SCOPE

Future research should explore the optimal balance between teacher-led instruction and AI-driven learning. Studies comparing instructional models such as station rotation, flipped learning, and mastery learning alongside ILA would provide deeper insight into maximising learner outcomes.

12. ETHICAL CONSIDERATIONS

All data were anonymised and collected as part of routine educational practice. Participation was voluntary, and no identifiable personal information was recorded.

13. CONCLUSION

This study demonstrates that Intelligent Learning Analytics (ILA) has considerable potential to strengthen learner progress monitoring within further education mathematics. The observed increase in mean grades, alongside positive performance trends and notable improvements among low-ability learners, underscores the effectiveness of diagnostic and personalised learning pathways in addressing foundational knowledge gaps. By enabling timely identification of misconceptions and targeted intervention, ILA supports more responsive and inclusive teaching practices.

Furthermore, when ILA is thoughtfully integrated with effective pedagogy and blended learning models, such as the station-rotation approach, it can significantly enhance learner engagement and academic achievement. The findings suggest that ILA not only supports individualised learning but also contributes to improved teaching efficiency and consistency. Overall, the study highlights the potential of ILA to positively impact learning outcomes across STEM education when implemented alongside sound instructional strategies and sustained learner engagement.

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