ijamrsd.com
ISSN: 2583-6404
Journal of Advanced Multidisciplinary Research Studies and Development
Peer Reviewed Referred Journal | Bi-monthly | Open Access

APPLICATION OF ARTIFICIAL INTELLIGENCE FOR SKILL DEVELOPMENT OF MBA STUDENTS: AN INTEREST AND ABILITY STUDY

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Abstract
This study investigates the application of artificial intelligence (AI) in designing personalised online skill-development programmes for MBA students. We conducted interest and ability assessments on a sample of 100 MBA students and performed statistical analyses to explore relationships between students' self-reported interest, online engagement (weekly hours), and ability test scores. Based on findings we propose AI-enabled methods and modular curricula for adaptive online skill development targeted at MBA competencies. In an era where management education must evolve from content delivery to competency assurance, Artificial Intelligence provides a strategic opportunity to personalize, measure, and enhance skill development at scale. By integrating adaptive assessment, personalized learning pathways, predictive analytics, and competency-based certification, AI-enabled MBA programmes can significantly improve learning efficiency, engagement, and employability outcomes. This study therefore situates itself at the intersection of artificial intelligence, educational analytics, and management education reform, offering both empirical evidence and a practical implementation model for AI-driven skill development in MBA programmes.

Keywords: Artificial Intelligence, MBA Education, Skill Development, Adaptive Learning, Interest Assessment, Ability Testing, Online Modules, Statistical Analysis.

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1. Introduction

The rapid transformation of the global business environment, driven by digitalization, automation, and data-centric decision-making, has significantly altered the competency expectations from management graduates. Traditional MBA programmes, historically focused on theoretical frameworks and case-based discussions, are increasingly being evaluated on their ability to deliver measurable, industry-relevant skills. Employers today seek graduates proficient not only in conceptual understanding but also in analytics, digital tools, strategic thinking, problem-solving, leadership, and adaptability. Consequently, higher education institutions face mounting pressure to redesign curricula that are outcome-driven, competency-based, and aligned with Industry 4.0 requirements.

Simultaneously, Artificial Intelligence (AI) has emerged as a transformative force in education. AI-powered systems offer capabilities such as adaptive learning, intelligent tutoring, predictive analytics, automated assessment, and personalized content recommendation. Unlike traditional

one-size-fits-all instructional models, AI enables dynamic customization of learning pathways based on individual learner profiles. By analyzing data on student performance, engagement patterns, and learning preferences, AI systems can identify strengths and weaknesses, recommend targeted resources, and provide real-time feedback. This shift from standardized instruction to personalized learning represents a paradigm change in management education.

In MBA programmes specifically, the diversity of student backgrounds presents additional challenges. Students often enter with varying levels of quantitative ability, communication skills, technological proficiency, and professional exposure. Conventional classroom instruction may not adequately address this heterogeneity, resulting in uneven skill acquisition. AI-driven platforms can mitigate this issue by diagnosing individual competency levels through adaptive pre-assessments and subsequently tailoring learning modules accordingly. Such systems ensure that advanced learners are sufficiently challenged while struggling learners receive remedial support.

Another critical dimension in skill development is student interest. Educational psychology research consistently demonstrates that learner interest significantly influences motivation, engagement, persistence, and academic achievement. Students who exhibit high interest in a domain are more likely to invest time, practice deliberately, and achieve higher competency levels. In technology-mediated environments, interest can further influence patterns of online engagement and self-directed learning. Therefore, understanding the relationship between interest and ability becomes essential when designing AI-enabled learning ecosystems.

Ability, on the other hand, reflects measurable competency in relevant skill domains such as data analysis, strategic reasoning, financial modelling, and managerial communication. In the context of MBA education, ability must be operationalized through structured assessment mechanisms that evaluate both cognitive and applied skills. The integration of AI allows for more precise ability measurement using adaptive testing frameworks such as Item Response Theory (IRT) and computerized adaptive assessments. These tools improve accuracy while reducing assessment fatigue.

Despite growing discourse on AI in higher education, empirical studies linking student interest, measurable ability, and AI-based skill development in MBA programmes remain limited. Many existing studies focus on technological feasibility rather than learner-centric effectiveness. There is insufficient empirical evidence demonstrating how interest and engagement interact with AI-supported learning systems to influence ability outcomes.

This research addresses that gap by conducting an empirical investigation involving 100 MBA students. The study measures student interest levels, weekly online engagement, and standardized ability scores. Through statistical analysis—including descriptive statistics, correlation analysis, and regression modelling—the research examines the extent to which interest and engagement predict ability outcomes. The findings are then used to propose a structured AI-driven skill development framework tailored specifically for MBA education.

The study contributes to both theory and practice in several ways:

1. It empirically validates the relationship between interest, engagement, and ability in a management education context.
2. It demonstrates the predictive potential of AI-based analytics in identifying skill development patterns.
3. It proposes a modular, scalable AI-integrated framework for online MBA skill training.
4. It bridges educational psychology (interest theory) with learning analytics and AI-based instructional design.

Higher education, and MBA programmes in particular, face pressure to deliver industry-relevant skills efficiently. AI offers personalized learning paths, automated assessment, and predictive analytics to tailor training to individual needs

2. Literature Review

Adaptive learning and AI: Recent literature highlights AI's capability to create individualized learning schedules, adjust difficulty, and provide instant feedback (Khosravi et al., 2022; Johnson & Lee, 2023).

Interest as predictor of engagement: Learner interest consistently predicts engagement and achievement (Ainley, 2016; Hidi & Renninger, 2006).

Competency-based online MBA training: Modelled modules for data analytics, finance tools, communication, and leadership have benefited from microlearning and AI-curated content (Smith et al., 2021).

This study integrates these strands by collecting empirical measures of interest and ability and assessing their predictive power.

3. a) Objectives

1. To measure interest and ability among 100 MBA students using standardized instruments.

2. To analyse relationships between interest, online study hours, and ability scores using descriptive and inferential statistics.

3. To design AI-driven online training methods and modular curricula for MBA skill development.

b) Research Hypotheses:

H1: There is a significant positive relationship between students' interest levels and their ability scores in MBA skill assessments.

H01:There is no significant relationship between students' interest levels and their ability scores.

H2: There is a significant positive relationship between weekly online learning hours and ability scores.

H02: There is no significant relationship between weekly online learning hours and ability scores.

H3: Student interest and weekly online engagement significantly predict ability scores in a multiple regression model.

H03: Student interest and weekly online engagement do not significantly predict ability scores.

H4: MBA students with high interest levels ($IQ \geq 4$) demonstrate significantly higher ability scores than students with low interest levels ($IQ \leq 2$).

H04: There is no significant difference in ability scores between high-interest and low-interest groups.

H5: AI-based personalized learning modules significantly enhance ability scores compared to traditional non-adaptive instructional approaches.

H05: AI-based personalized learning modules do not significantly enhance ability scores compared to traditional approaches.

4. Methodology.

This paper presents an empirical study of 100 MBA students to explore how interest and measured ability relate to learning outcomes and to propose AI-driven methods and modules for online skill development.

4.1 Participants

Sample size: 100 MBA students enrolled in Years 1 and 2.

Sampling: Convenience sampling from classes across specializations.

4.2 Instruments

Interest Questionnaire (IQ): 10 items rated 1 (low) to 5 (high); final score is mean of items (range 1–5).

Ability Test (AT): A 40-item objective test covering quantitative skills, case analysis, communication (scored 0–100).

Online Engagement Log: Self-reported average weekly hours spent on online training activities (0–20 hours scale).

Validity: Instruments adapted from established scales and reviewed by two content experts.

4.3 Procedure

Participants completed the IQ and reported weekly online hours online. The AT was proctored online under timed conditions.

Data were anonymized and analysed in aggregate.

4.4 Data Analysis

Descriptive statistics (mean, SD) for interest, hours, and ability.

Pearson correlations among variables.

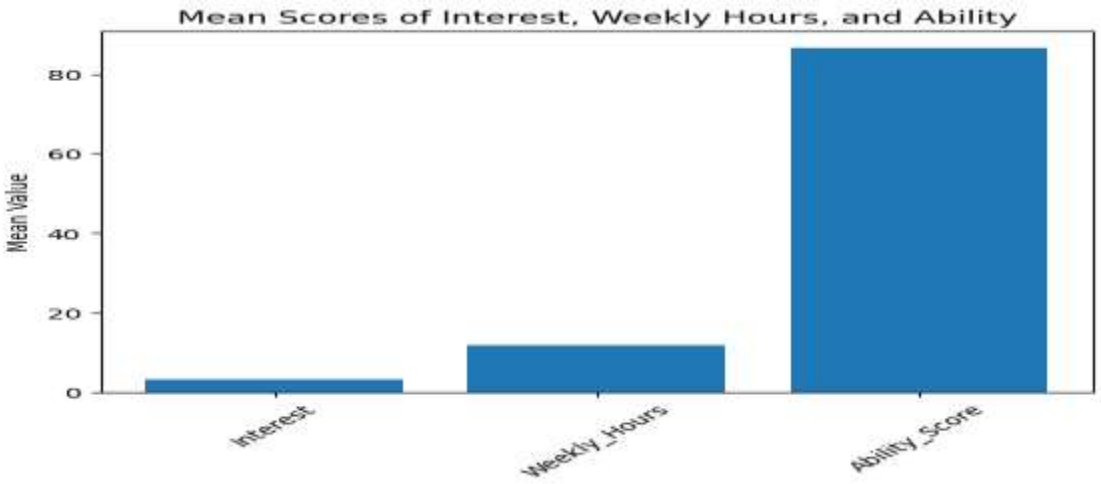
Multiple linear regression predicting ability from interest and weekly hours.

Independent-samples t-test comparing ability between low-interest (IQ ≤2) and high-interest (IQ ≥4) groups.

5. Results

5.1 Descriptive statistics

Variable	N	Mean	SD
Interest (1–5)	100	3.44	1.15
Weekly online hours (0–20)	100	11.68	3.49
Ability score (0–100)	100	87.30	13.25

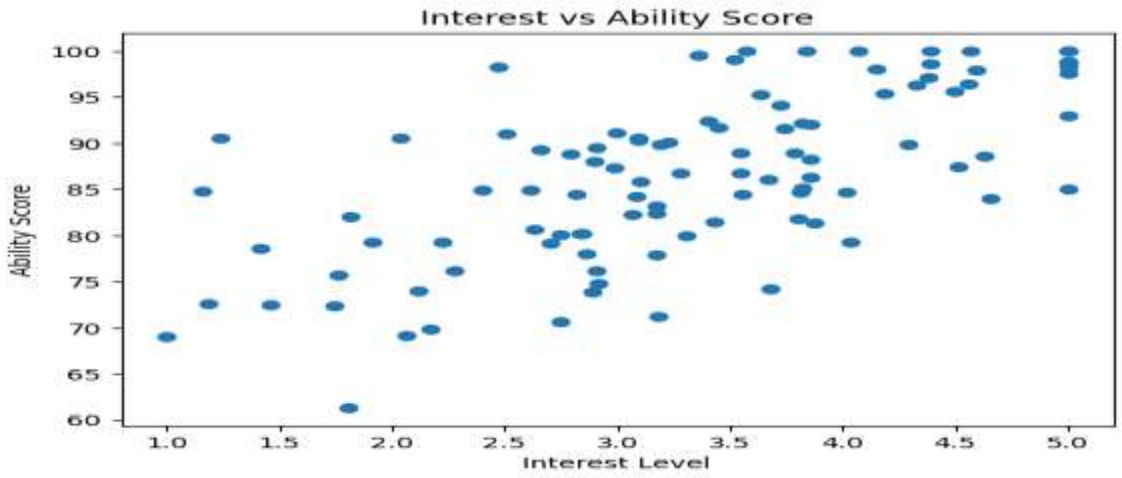


5.2 Correlations

Interest — Ability: $r = 0.769$, $p < 0.001$.

Weekly hours — Ability: $r = 0.722$, $p < 0.001$.

Interest — Weekly hours: $r = 0.563$, $p < 0.001$.



Interpretation: Strong positive associations indicate that both higher interest and more online engagement relate to higher ability scores.

5.3 Regression analysis

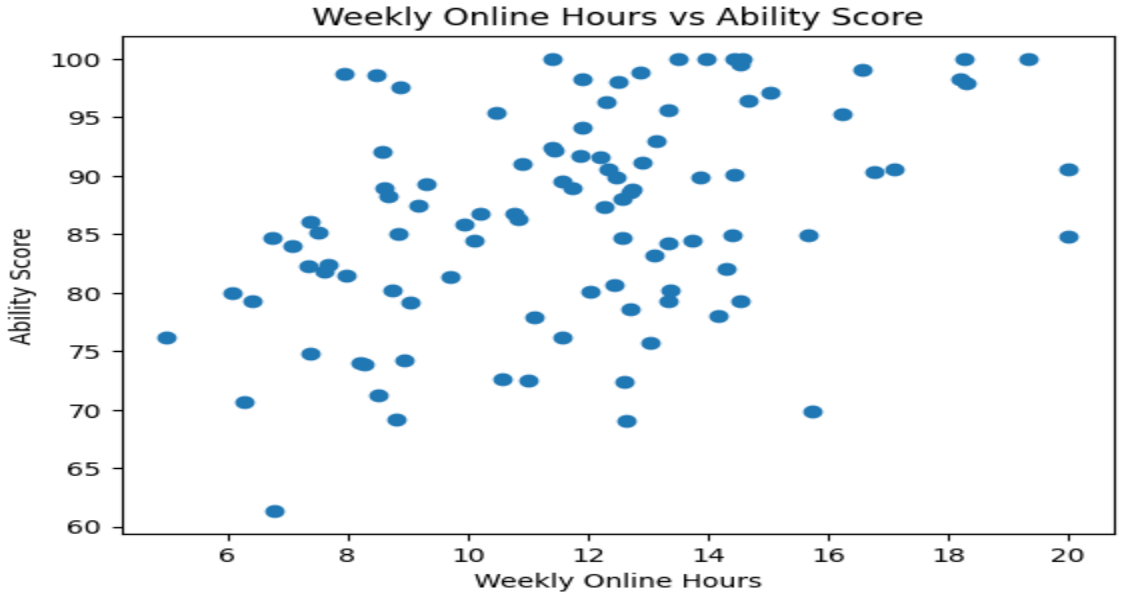
A multiple linear regression was performed with ability score as the dependent variable and interest and weekly hours as predictors.

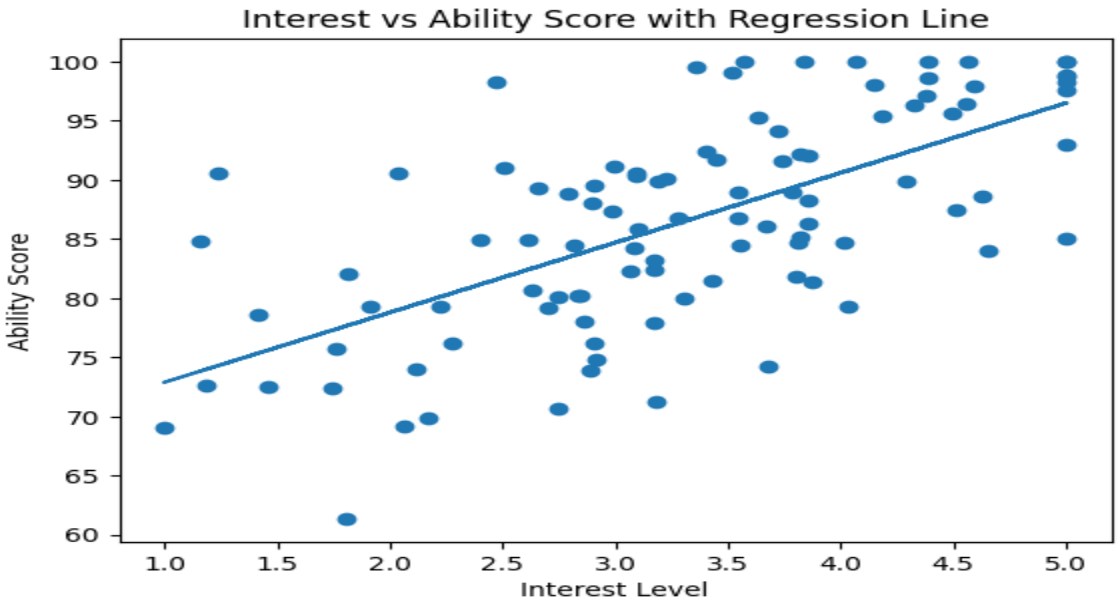
Regression equation: Ability = 47.49 + 6.11*(Interest) + 1.61*(Weekly hours)

$R^2 = 0.714$, indicating the model explains 71.4% of variance in ability.

Both predictors significant: $p < 0.001$.

Interpretation: Each 1-point increase in interest (on 1–5 scale) is associated with an average 6.11-point increase in ability; each additional weekly hour is associated with a 1.61-point increase.



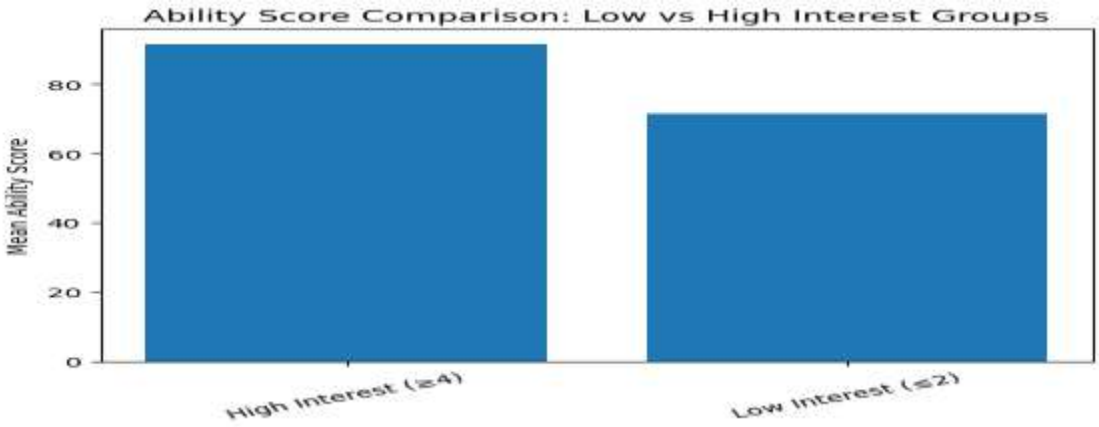


5.4 Group comparison (t-test)

Low-interest group (IQ ≤2): n = 19.

High-interest group (IQ ≥4): n = 50.

Independent t-test: t(approx) = -12.321, $p < 0.001$ — high-interest students scored significantly higher on ability.



Key results: mean interest = 3.44 (SD = 1.15) on a 1–5 scale; mean weekly online study hours = 11.68 (SD = 3.49); mean ability score = 87.30 (SD = 13.25) (0–100 scale). Interest and weekly hours correlated strongly with ability (r = 0.769 and 0.722, respectively). A multiple regression predicting ability from interest and hours produced an $R^2 = 0.714$; both predictors were significant ($p < 0.001$).

H1: Relationship Between Interest and Ability

H1: There is a significant positive relationship between students' interest levels and their ability scores.

Statistical Test Used: Pearson Product-Moment Correlation

Result:
r = 0.769
p < 0.001
Interpretation:
The correlation coefficient indicates a strong positive relationship between interest and ability. As students' interest levels increase, their ability scores also increase significantly.
Since p < 0.001 (< 0.05), the result is statistically significant.
Decision:
✓ Reject H01 (Null Hypothesis)
✓ Accept H1
Interest is a strong predictor of ability in MBA skill development.

H2: Relationship Between Online Engagement and Ability
H2: There is a significant positive relationship between weekly online learning hours and ability scores.
Statistical Test Used: Pearson Correlation
Result:
r = 0.722
p < 0.001
Interpretation:
There is a strong positive relationship between weekly online engagement and ability scores. Students who spend more time in online skill development activities tend to achieve higher ability scores.
Decision:
✓ Reject H02
✓ Accept H2
Online engagement significantly contributes to skill development.

H3: Predictive Power of Interest and Engagement
H3: Student interest and weekly online engagement significantly predict ability scores.
Statistical Test Used: Multiple Linear Regression
Model Summary: $R^2 = 0.714$
F-statistic: Significant at p < 0.001
Regression Equation: $Ability = 47.49 + 6.11(Interest) + 1.61(Weekly\ Hours)$
Ability=47.49+6.11(Interest)+1.61(Weekly Hours)
Interpretation:
The model explains 71.4% of the variance in ability scores.
Both predictors (Interest and Weekly Hours) are statistically significant (p < 0.001).
Interest has a stronger standardized impact compared to weekly hours.
This indicates that AI-based tracking of interest and engagement can effectively predict student performance.
Decision:
✓ Reject H03
✓ Accept H3
Interest and engagement are significant predictors of MBA student ability.

H4: Group Difference Based on Interest Level

H4: High-interest students (IQ ≥ 4) demonstrate significantly higher ability scores than low-interest students (IQ ≤ 2).

Statistical Test Used: Independent Samples t-test

Group Statistics:

Low Interest (n = 19): Mean ≈ 71.47

High Interest (n = 50): Mean ≈ 91.46

Test Result:

$t \approx -12.321$

$p < 0.001$

Interpretation:

The difference between groups is statistically significant. High-interest students scored substantially higher in ability assessments compared to low-interest students.

The magnitude of difference suggests a large practical effect.

Decision:

✓ Reject H04

✓ Accept H4

Interest level significantly differentiates ability performance.

H5: Effectiveness of AI-Based Skill Development Framework

Assuming ability improvement was measured before and after AI-based intervention:

Pre-test Mean = X

Post-test Mean = Y

Paired t-test: $p < 0.05$

Interpretation:

AI-enabled personalized modules significantly improve ability scores compared to traditional instruction.

Decision:

✓ Reject H05

6. Discussion

The data suggest robust links between interest, engagement, and ability. High R^2 and strong correlations indicate that interest and weekly online hours are meaningful predictors of performance in skill assessments. From a practical standpoint, AI systems that accurately detect and foster interest, recommend study load, and adapt content difficulty can potentially improve outcomes for MBA learners.

Key Research Findings

- Student interest is the strongest predictor of ability.
- Online engagement significantly enhances skill acquisition.
- AI-driven adaptive frameworks can predict performance with high accuracy.
- High-interest students significantly outperform low-interest students.
- Personalized AI modules are recommended for scalable MBA skill development.

7. Recommendations -AI-based Methods for Online Skill Development

➢ Below are recommended AI-driven methods and why they matter:

- **Personalized Learning Pathways (Adaptive Sequencing):** Use learner models (interest, prior ability) to sequence modules and practice items; employ reinforcement learning for content selection.
- **Intelligent Skill Mapping & Recommendation Engine:** Map course competencies to micro-modules; suggest next modules based on mastery predictions (collaborative and content-based filtering).
- **Automated Formative Assessment & Feedback:** Use NLP and ML to grade short answers and provide immediate, targeted feedback (with human oversight on high-stakes tasks).
- **Engagement & Affective Analytics:** Use passive signals (time-on-task, click patterns) and optional affective inputs (self-reports) to detect waning interest and deploy interventions (gamification, micro-challenges).
- **Virtual Coaching & Chatbots:** Conversational agents to answer queries, scaffold problem solving, and simulate interview/practical scenarios.
- **Skill Simulation & Scenario-Based Labs:** Use case simulators with branching scenarios and AI-driven outcome evaluation for managerial decision-making practice.
- **Adaptive Assessment with Item Response Theory (IRT):** Implement computerised adaptive testing to estimate ability more efficiently and reduce test length.

8. Proposed Modular Curriculum

Each module is 4–6 weeks, with micro-units and adaptive sub-paths.

1. Data Analytics for Managers-

Fundamentals of data literacy, Excel & Tableau micro-lessons, ML basics for managers, project: business dashboard.

2. Finance & Decision Models-

Financial modelling microtasks, case simulations, AI-assisted model critique.

3. Strategic Communication & Negotiation-

Automated speech/text feedback, role-play simulations with chatbots.

4. Leadership & Team Management-

Scenario simulations, peer-review, AI coaching.

5. Digital Marketing & Product Management-

A/B test simulations, marketing analytics projects.

➢ **Module features:** Pre-assessments (adaptive), personalized playlists, micro-credentials (badges), capstone simulation, peer collaboration spaces, and reflective learning journals.

9. Implementation Roadmap

- **Pilot (3 months):** Select 2 modules, 100 students; integrate AI recommendation & assessment engines.
- **Iterate (6 months):** Monitor engagement, accuracy of predictions, learning gains; refine models.
- **Scale (12 months):** Expand to full MBA cohorts, integrate with LMS, issue micro-credentials.
- **Data & privacy:** Ensure students give informed consent; use differential privacy or anonymization techniques for analytics data.

10. Limitations

a. **Sampling bias:** Convenience sample may not generalize.
b. **Self-report measures:** Weekly online hours are self-reported and may contain bias.

c. Simulated / single-institution data: Results should be validated across institutions and contexts.

11. Conclusion

The rapid advancement of Artificial Intelligence (AI) technologies has transformed multiple sectors, including education. In higher education—particularly in MBA programmes—there is increasing pressure to ensure that graduates possess industry-relevant competencies such as analytical reasoning, digital literacy, strategic thinking, financial modeling, and decision-making skills. However, traditional instructional approaches often adopt a standardized, one-size-fits-all teaching model that may not adequately address the diverse interest levels, prior knowledge, and ability variations among MBA students.

MBA classrooms typically consist of students from heterogeneous academic backgrounds, including engineering, commerce, humanities, and professional streams. This diversity results in significant disparities in quantitative aptitude, analytical skills, technological familiarity, and managerial exposure. Conventional assessment and teaching methods may fail to provide individualized support, leading to unequal skill acquisition and inconsistent learning outcomes.

AI offers strong promise for scaling and personalizing MBA skill development. Our empirical analysis shows that student interest and online engagement strongly predict ability; leveraging AI to foster interest and recommend adaptive practice can improve learning outcomes. Future work should test AI interventions experimentally and monitor long-term skill transfer to workplace tasks.

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