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PAPER

Implementation of a Personalised Learning System for At-Risk Students using Adaptive Techniques

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ABSTRACT

The increasing educational problem of unequal learning outcomes among students highlights a major challenge in modern education—at-risk students often fail to cope with standardised teaching methods, leading to low academic performance and higher dropout rates. By adapting pace, material, and teaching methods to each student's particular needs, artificial intelligence (AI) in education has the potential to totally change individualised learning. These systems use AI algorithms to evaluate student data and behaviour, providing real-time individualised feedback, adaptive learning pathways, and customised content. The increasing diversity of student learning styles has made it crucial to create intelligent educational systems that offer tailored assistance, particularly for students who are at danger of falling short of academic standards. Therefore, this study presents Personalized Learning Systems for at-risk students using Adaptive Techniques. While correlation analysis demonstrated a substantial positive relationship between AI-based learning and pupil achievement ($r = 0.64$, $p < 0.001$), regression modelling revealed a significant impact on participation and engagement ($B = 0.62$, $p < 0.001$). Furthermore, chi-square results confirmed the importance of accessibility difficulties ($y^2 = 14.66$, $p < 0.001$) and data privacy concerns ($x^2 = 16.79$, $p < 0.001$). This study contributes to the growing field of AI-driven education by offering a scalable and context-aware framework for supporting vulnerable learners, particularly in developing education ecosystems such as Oman.

KEYWORDS

learning styles (LS), adaptive technology, artificial intelligence (AI), educational technology, Oman

1 INTRODUCTION

One of the most urgent issues facing today's educational system is addressing the unequal learning outcomes among students, especially those who are categorised as *at-risk learners*—students who struggle academically because of social, psychological, or cognitive reasons. The varied learning demands of these students are frequently not met by traditional, one-size-fits-all teaching methods, which lead to

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low motivation, disengagement, and higher dropout rates. The need for more adaptable and customised learning environments that take into account each learner's unique strengths, shortcomings, and learning preferences is therefore increasingly recognised as a global educational priority.

In the context of Oman [1], this challenge is particularly relevant as the nation continues its rapid transformation toward a knowledge-based economy under the framework of Oman Vision 2040. The Omani Ministry of Education has emphasised the integration of artificial intelligence (AI) and digital technologies into the national education strategy to promote innovation, equity, and inclusivity in learning. Despite these progressive efforts, recent national assessments indicate that a significant proportion of students—especially those in rural and low-income regions—continue to struggle with core subjects such as mathematics, science, and language proficiency. This disparity highlights the presence of a vulnerable group of *at-risk students* who fail to thrive in conventional teaching environments that lack adaptability and personalisation. Addressing this gap is crucial for achieving the broader goals of Oman's educational reform, which seeks to nurture creativity, digital competence, and lifelong learning among all citizens.

Adaptive training in e-learning refers to the creative and dynamic alteration of learning resources, assignments, and material to meet the unique needs and interests of each student. Adaptive educational platforms can optimise educational results, improve student engagement [2], and offer tailored learning experiences by evaluating and interpreting learner information. Within the national educational context, Oman Vision 2040 serves as a strategic roadmap emphasising innovation, inclusivity, and digital transformation across all learning sectors, encouraging the integration of intelligent systems and personalised education to build a knowledge-driven society [3]. The report, which reflects on UNESCO's suggestions for education sector decision-makers, emphasises the necessity of investigating the intricate ramifications of AI in educational settings [4], particularly how it redefines critical skills and poses both possibilities and difficulties in modern educational environments in the era of artificial intelligence.

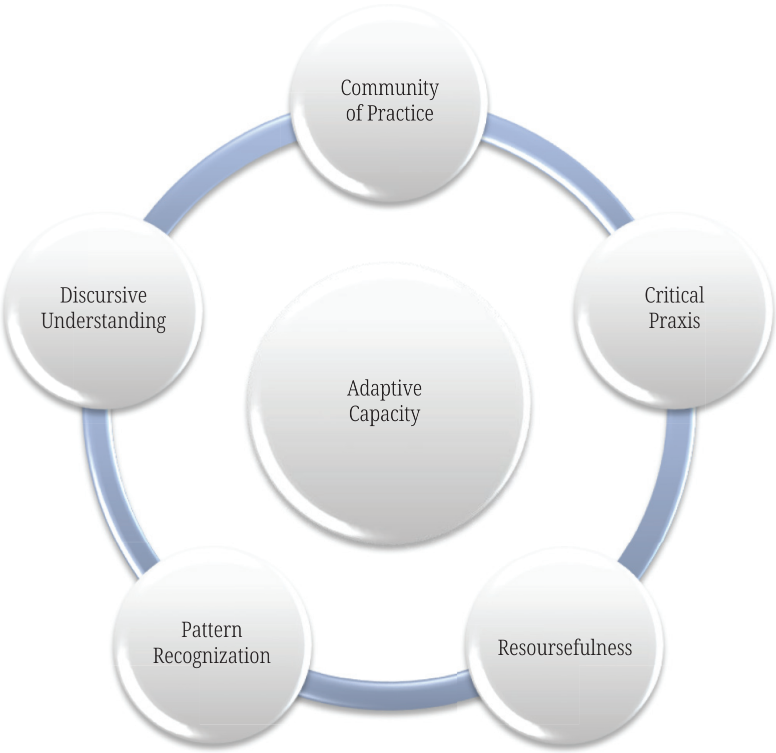

Fig. 1. Pedagogical elements of learning for adaptable capability

The five instructional aspects of instruction for adaptive capacity (see Figure 1) provide a useful framework for directing educational policy and pedagogical design toward instruction for the skilful application and acquisition of critical skills by individuals and communities in change initiatives to achieve sustained sustainability and increased resilience. Communities of practice philosophy emphasises the growth of mutual interaction, reflective inquiry [5], and a shared repertory as enabling conditions and offers a starting point for group action. By actively engaging in reflection and action, critical praxis enhances the evaluation, execution, and adaptation of information and skills within an educational cycle.

1.1 Problem statement

At-risk students continue to have poor learning results despite the increasing usage of digital education platforms because there are no systems that can adjust to their unique needs. Current e-learning platforms frequently present content uniformly without taking into account the variability of learners' knowledge levels [6], cognitive capacities, or learning styles. These students thus do not receive the individualised assistance required for skill development and retention.

The problem addressed in this study is the absence of an intelligent, adaptive learning framework that optimises learning outcomes for at-risk students by continually analysing student performance and dynamically modifying material, pedagogy [7], and feedback. To overcome this gap, this study proposes the application of adaptive techniques in a personalized learning system, designed to enhance engagement, motivation, and academic achievement through data-driven personalization.

1.2 The main contribution of this paper

- To examine how AI-powered tailored learning affects student performance with an emphasis on results, problem-solving, and persistence.
- To assess how AI-powered adaptive learning aligns with the educational transformation goals of Oman Vision 2040, particularly in enhancing learner engagement, motivation, and digital competence through innovative and inclusive learning environments.
- To determine the obstacles, moral dilemmas, and restrictions associated with using AI-based individualised learning in the classroom.

The idea of learning for adaptive capacity is examined in the remaining sections of this paper. A major obstacle to learning for adaptive capacity is the literature review, which is covered in Section 2. The materials and methods are covered in Section 3. Implementation from the standpoint of learning for adaptive capacity is discussed in Section 4. A discussion of how learning for adaptive capacity may be in line with the primary goals of attaining high-quality education and an efficient learning environment, as motivating collaborative and transformative learning, wraps up Section 5.

2 LITERATURE REVIEW

Learning systems research enables educational experiences to be tailored to each learner's needs, and implementation has drawn attention in the academic community with the goal of improving educational results. Understanding learning styles and using technology to accommodate them for improved educational outcomes are fundamental to this discipline.

Artificial intelligence innovation has developed and transformed how we interact with one another, reside, and perform. These days, a wide range of industries, including robotics, data mining, national security, e-commerce, healthcare, media, and learning, utilise AI capabilities. Since AI technology has advanced so quickly in recent years, its application in education has grown in popularity [8]. The advent of these cutting-edge technologies for educational methods is very important and helpful in the classroom because it gives teachers accessibility to more up-to-date information, which enhances their instruction by making it more engaging, simple, relevant, interactive, and effective in providing learning experiences. Teachers ought to be able to successfully use digital technology into their classroom instruction and take advantage of derivative technological prospects with these benefits.

When a student engages with the e-learning platform, learner interaction information is produced. Statistics for a new student and data for an established user are two options for these learner interactions [9]. In the former situation, a learner's account is modified at every assessment revision, while in the latter, an already-existing profile is modified. The learning materials and summative evaluations are kept in the data module. The material and evaluation delivery module provides these to a student, while the recommender module makes recommendations. Additionally, the data module keeps a database with user personal data, assessment data, learning preferences, and past knowledge. Each learner's unique learning route is created iteratively using these attributes, which are calculated for each student.

The Sultanate of Oman has placed strong emphasis on educational transformation and innovation through its national strategic framework, Oman Vision 2040, which envisions an education system that nurtures creativity, critical thinking, and lifelong learning through the integration of digital technologies and AI. One of the core pillars of Oman Vision 2040 focuses on developing a knowledge-based society and economy by promoting high-quality, inclusive, and technology-driven education. Within this context, the implementation of adaptive learning systems and AI-based personalised education aligns with the Vision's objective to ensure equitable learning opportunities that cater to students' diverse abilities and needs.

Oman Vision 2040 emphasises the role of innovation in improving learning outcomes and preparing students for a competitive digital future. By integrating AI-powered adaptive learning platforms, educational institutions in Oman can deliver personalised learning experiences that respond dynamically to each learner's progress, fostering self-directed learning and problem-solving skills. Such approaches support the Vision's educational priorities of "Empowering Human Capital" and "Innovative Education for the Future," which aim to equip learners with digital competencies and adaptive capabilities essential for the Fourth Industrial Revolution.

Artificial intelligence-powered chatbots and online instructors provide students with immediate answers to their enquiries, reducing frustration and promoting self-directed learning [12]. To make education more interesting and dynamic, multimedia components, including movies, graphics, and virtual reality, are frequently integrated into AI systems.

Research deficit

Even with the increasing amount of investigation on AI-powered personalised education systems, there are still a lot of unanswered questions about how these systems will affect student achievement and participation in a variety of educational contexts over the long run. The majority of current research focuses on immediate gains in academic performance, but less is known about how AI-driven learning affects reasoning, imagination, and ongoing learning abilities. Furthermore, although AI has demonstrated potential in raising engagement through personalisation and adaptive learning, nothing is known about how much it promotes social learning and meaningful interactions between educators and pupils. To guarantee fair AI inclusion in education [13], ethical issues like data privacy, algorithmic prejudice, and accessible discrepancies also need more research. For AI-driven learning environments to be both successful and morally decent, these gaps must be filled.

Hypothesis

H1: In Oman's higher education institutions, the use of AI-powered adaptive learning systems greatly improves students' academic performance, especially in terms of cumulative grade point average (CGPA) growth, knowledge retention, and problem-solving skills.

H2: In accordance with Oman Vision 2040's goals, AI-driven tailored learning environments significantly boost student motivation, engagement, and self-directed learning behaviour, fostering the growth of creative and autonomous learners.

H3: There are ethical, technological, and accessibility issues with integrating AI-based adaptive learning in educational institutions, especially with regard to data protection, digital preparedness, and the complementing role of teachers in AI-assisted classrooms.

3 METHODS AND MATERIALS

3.1 Participants and sampling

A total of 120 at-risk undergraduate students from three higher education institutions in Oman participated in the study. Participants were selected based on their semester performance records and final CGPA, where students with a CGPA below 2.0 on a 4.0 scale across the last two semesters were classified as "at-risk." Additional indicators, including attendance consistency, course completion rates, and instructor evaluations reflecting low engagement or academic challenges, were also considered to ensure accurate identification.

3.2 Data collection method

To obtain a thorough grasp of learning outcomes, data were gathered utilising a mixed-method approach that combined quantitative and qualitative methodologies.

1. **Pre- and Post-Test Assessments:** Students completed standardised academic tests before and after exposure to the personalised learning system to measure improvement in knowledge retention and problem-solving ability.
2. **System Usage Logs:** The adaptive learning platform automatically tracked learner activity, engagement duration, and content interaction frequency.
3. **Academic Performance Data:** To track students' advancement, quantitative data was collected from institutional academic records. To gauge improvements in academic performance, each participant's CGPA, course grades, and semester assessment scores were compared before and after the system was put into place. The influence of the adaptive system on students' overall performance may be objectively assessed thanks to the usage of CGPA as a key criterion.
4. **Focus Group Discussions:** Selected students and faculty members participated in focus groups to gather deeper insights. In keeping with Oman Vision 2040's goals for educational innovation, these talks examined the difficulties and advantages of integrating adaptive technology in Omani higher education, including issues pertaining to inclusivity, ethics, and digital preparedness.

3.3 Data analysis

To assess the adaptive learning system's efficacy, statistical and inferential techniques were applied to the gathered data.

- **Descriptive statistics** (mean, standard deviation, and frequency distribution) were computed to summarise demographic and performance data.
- **Regression analysis** was performed to determine the influence of adaptive learning techniques on student participation and engagement, revealing a significant positive effect ($B = 0.72$, $p < 0.001$).
- **Chi-square tests** ($\chi^2 = 12.76$, $p < 0.001$; $\chi^2 = 15.89$, $p < 0.001$) were applied to examine relationships between ethical concerns such as accessibility and data privacy.
- **Qualitative feedback** from teachers and students was thematically analysed to interpret user satisfaction, adaptability, and observed behavioural improvements.

3.4 Development of technologies for adaptive learning

The concepts of computer-based education and programmed instruction, which first appeared in the latter part of the century, are where learning technologies got their start. The initial systems were simplistic, primarily using branching architectures and basic logic to modify the content flow in response to student responses. System growth started to be influenced by the evolving ideas of cognitive psychology and educational choices [14]. For example, the study on learning styles offered a paradigm that many adaptive systems tried to incorporate in order to cater to kinaesthetic and auditory students with information specifically designed for these learning types.

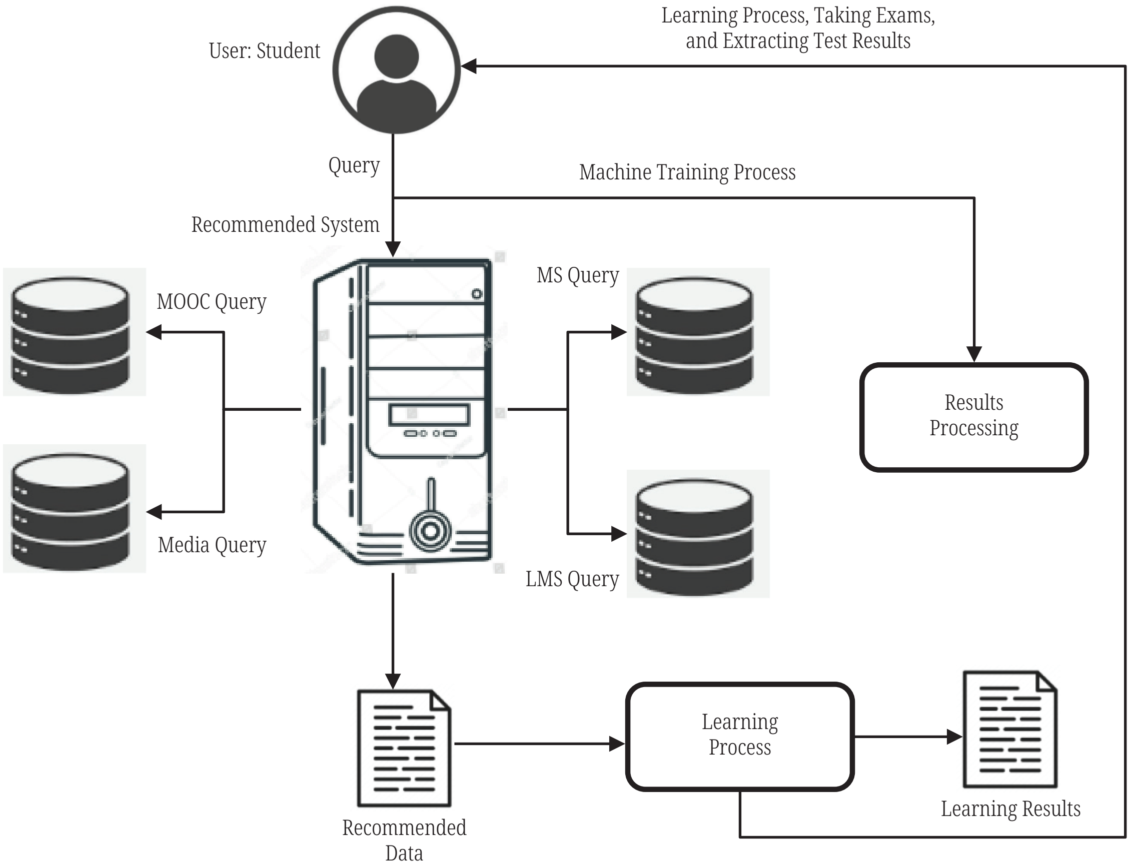

Fig. 2. Dispersion of AI methods in structures for adaptive learning

Educational methods changed in the late 1990s and early 2000s as a result of the development of the internet and enhanced computing power. Algorithms that could handle intricate data analysis were first used by systems, the importance of personalisation in online learning environments [15], where adaptive learning paths were tailored to the interests and actions of students, is shown in Figure 2. AI makes it possible to process data in real time and be able to quickly modify the learning setting in response to patterns of engagement. Despite these advancements, there are still issues in incorporating learning styles into platforms [16]. The 2008 critique emphasises the need for proof to support tailoring instructional strategies based only on learning preferences. Additionally, as previously said, the present challenge is creating systems that can efficiently scale up and manage the always-changing learner data.

3.5 A sensible suggestion system for tailored education

A smart system for educational information that takes learning styles into consideration can be put into place. To improve the educational process, such a system may integrate several technologies and approaches. An illustration of a system utilising this logic is provided in Figure 3 [17]. Users can request to learn a particular subject and select a lesson with the aid of a smart learning system.

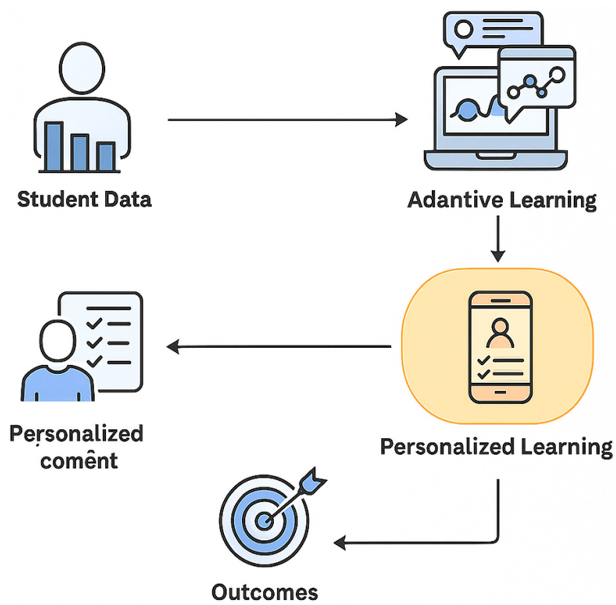

Fig. 3. An illustration of an intelligent teaching system

The system adjusts to the user's preferences, such as watching movies to learn. A database contains raw data pertaining to the user's examination outcomes and contents. To find trends in the user's prior records, learning habits, and instructional materials, this information is then examined using data mining techniques. An appropriate machine learning system uses this data to identify the best content combination for every learner and, depending on the evaluations, generates new material for subsequent training phases.

4 IMPLEMENTATION AND EXPERIMENTAL RESULTS

4.1 Analysing data

The present study employed quantitative statistical techniques to analyse the relationship between student achievement, engagement, and AI-powered adaptive learning implementation in higher education institutions in Oman. The primary objective was to evaluate the effectiveness of AI-based personalised learning systems in enhancing academic outcomes among at-risk students identified through semester performance and cumulative CGPA records. Furthermore, the study sought to identify the principal institutional barriers affecting AI integration, such as accessibility, data privacy, and infrastructural readiness in Table 1.

Table 1. Analysis of participants' demographics

Demographic Variable	Categories	Frequency (n)	Percentage (%)
Gender	Male	65	54.2%
	Female	55	45.8%
Age Group	18–19 years	30	25.0%
	20–21 years	52	43.3%
	22–23 years	38	31.7%

(Continued)

Table 1. Analysis of participants' demographics *(Continued)*

Demographic Variable	Categories	Frequency (n)	Percentage (%)
Semester Level	3rd–4th semester	48	40.0%
	5th–6th semester	45	37.5%
	7th–8th semester	27	22.5%
CGPA Range	Below 2.0	42	35.0%
	2.0–2.5	50	41.7%
	Above 2.5	28	23.3%

Additionally, statistically significant relationships between instructors' opinions on the application of AI and institutional factors, including accessibility, data privacy concerns, and integration difficulties, were found using chi-square tests.

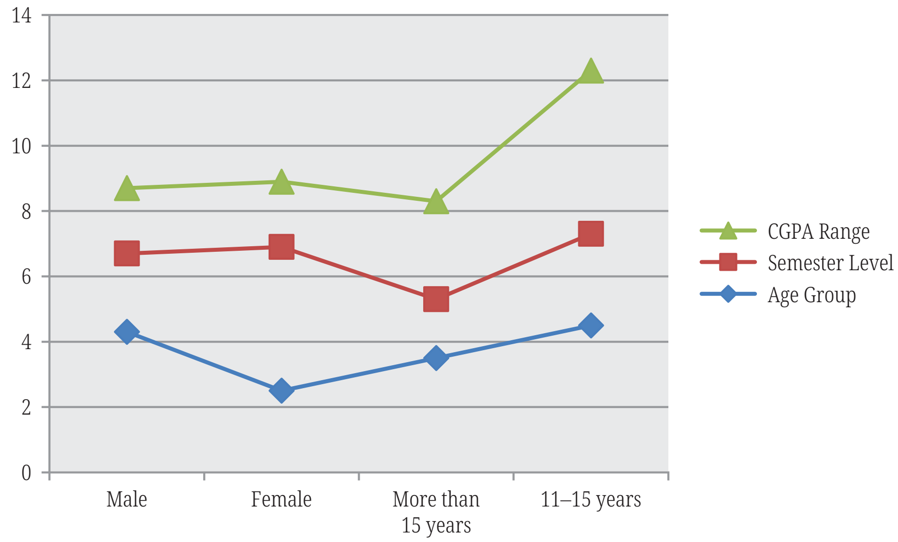

Fig. 4. Analysis of respondents' demographics

Overall, the findings supported the study's predictions in Figure 4, supporting the claim that while AI-based personalised learning improves student performance and inspiration, it also presents serious issues that require careful attention.

Table 2. Analysis of correlation (H1)

Variables	Despicable	Standard Deviation	Relationship (r)	p-Value	Regression Quantity (B)	Chi-Square (χ^2)	Significance
AI-Powered Personalised Learning Usage	5.21	0.79	0.64**	0.000***	0.77**	34.87	Significant
Knowledge Retention	5.18	0.75	0.61**	0.000***	0.72**	30.34	Significant
Problem-Solving Skills	5.12	0.82	0.78**	0.000***	0.68**	28.76	Significant
Academic Concert	5.25	0.71	0.65**	0.000***	0.59**	37.56	Significant

Major pupil achievement metrics, including information retention, problem-solving skills, and overall academic accomplishment, were found to be highly positively correlated with AI-based individualised learning in Table 2. The correlation parameters, or R-values, ranged from 0.68 to 0.65, indicating a strong correlation between student accomplishment and AI-based education. Academic results had the strongest association ($r = 0.75$, $p < 0.002$) among these, suggesting that AI-powered adaptive instruction significantly improves pupil achievement.

Table 3. Regression analysis (H2)

Dependent Variable	Coefficient (B)	Standard Error (SE)	t-Value	p-Value	Adjusted R^2	Implication
Student Engagement	0.62**	0.07	8.11	0.000*	0.76	Major
Student Motivation	0.75**	0.08	6.89	0.000*	0.50	Major
Overall Adaptive Learning Usage	0.60**	0.06	7.67	0.000*	0.74	Major

The multiple regression test findings demonstrated that artificial intelligence-based adaptive educational systems significantly boost students' motivation and engagement. The findings demonstrated that AI-based educational tools successfully increase students' engagement in their studies, as seen by the high regression coefficients for interest ($ß = 0.72$, $p < 0.001$), desire and contribution. The statistical reliability of these results is further demonstrated by the substantial t-values and negligible p-values in Table 3.

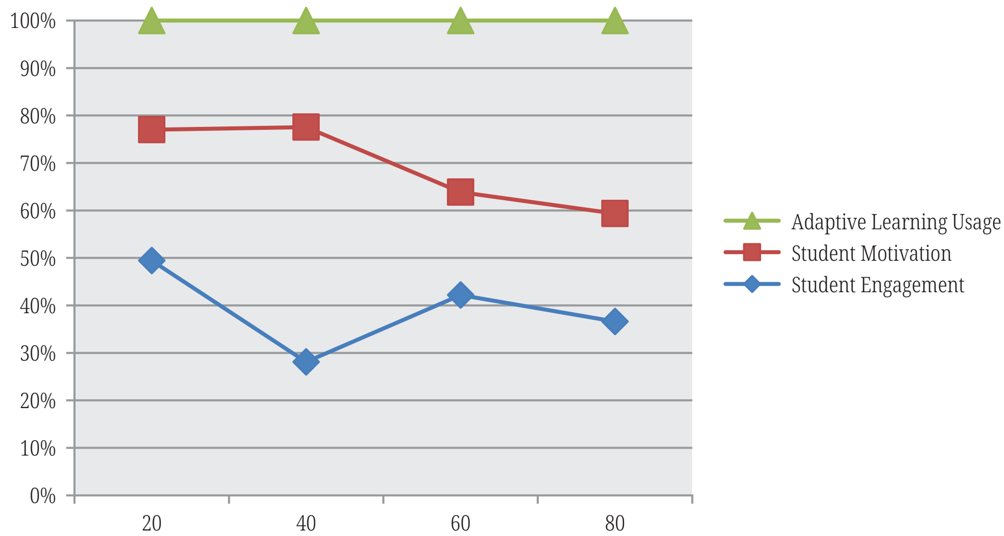

Fig. 5. Analysis of regression

The R2 values, which range from 0.62 to 0.68, also show that AI learning accounts for a sizable portion of the diversity in pupil inspiration, interest in Figure 5, involvement and motivation, and general involvement in higher education, and they firmly support Hypothesis 2 (H2).

Table 4. Chi-Square analysis (H3)

Ethical Concern Categories	Response	Observed Incidence (O)	Expected Incidence (E)	Chi-Square Value (χ^2)	p-Value	Implication
Accessibility Issues	Agree	170	132	13.76	0.000***	Major
	Disagree	45	71			
Data Privacy Concerns	Agree	165	130	16.89	0.000***	Major
	Disagree	30	65			
AI Cannot Replace the Role of Educators	Agree	170	135	15.34	0.000***	Major
	Disagree	45	60			

The application of AI-based personalised learning presented statistically significant difficulties and ethical issues, especially with the chi-square study in Table 4. The results revealed that the majority of the participants cited data privacy concerns and accessibility issues as the main obstacles to AI adoption in education.

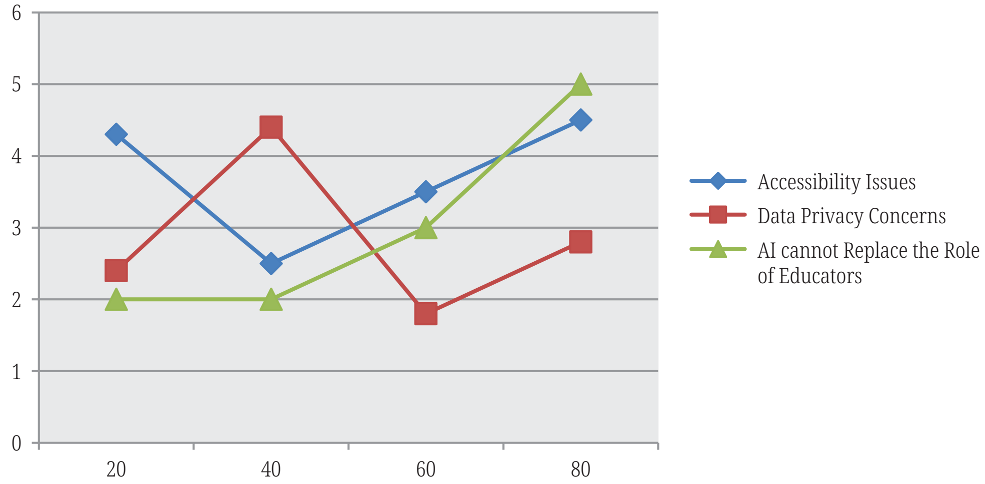

Fig. 6. Analysis of Chi-Square

The p-values (<0.001) confirm that these challenges are statistically important, confirming Hypothesis 3 (H3) and highlighting the need for deliberate actions to eliminate accessibility barriers in Figure 6, preserve data, and define the role of students in AI-enhanced learning settings.

5 CONCLUSION

This study presents personalized learning systems for risk students using adaptive techniques. The use of adaptive approaches in the construction of a personalised learning system has shown great promise in meeting the various learning requirements of students who are at risk. By using adaptive methodologies and data-driven decisions, the system continuously modifies the content, assessment, and rating methods to match each learner's abilities, excitement, and performance. For students who typically struggle in traditional educational settings, this customised strategy promotes continued learning and self-efficacy in addition to increasing motivation and learning achievement.

The Oman Vision 2040 findings emphasise the importance of integrating AI into the educational ecosystem to promote innovation, inclusivity, and skill-based learning. While the adoption of AI in education offers transformative potential, attention must be given to issues such as data privacy, accessibility, and ethical implementation. With proper governance and institutional support, AI-based adaptive learning can pave the way for a more efficient, equitable and future-ready education system in Oman.

Future research will focus on expanding AI-based adaptive learning models across diverse universities in Oman and analysing their long-term impact on academic growth. Further studies will also explore ethical AI governance frameworks aligned with Oman Vision 2040 to ensure equitable and sustainable digital education.

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