

Student perspectives on designing generative AI-based learning companions for higher education in Oman

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Article Info

Article history:

Received Feb 5, 2026

Revised May 24, 2026

Accepted May 30, 2026

Keywords:

AI assisted learning
Artificial intelligence
Design implications
Learning behavior
Learning companion

ABSTRACT

Artificial intelligence (AI) has rapidly permeated nearly every sector, from healthcare and finance to manufacturing, transportation, and communication. The emergence of generative AI (GenAI) applications, including intelligent assistants, recommendation engines, and predictive analytics, has further accelerated this transformation. Within education, these advances are reshaping teaching and learning, moving away from traditional instructor-centered models toward learner-centered ecosystems that emphasize adaptability, inclusivity, and self-directed growth. Despite the growing interest in AI-supported learning, existing literature reveals several important gaps that limit the effective integration of AI in educational contexts especially, students' learning behaviors, and preferred learning resources, have received limited attention. This study explores student's perceptions of AI-based educational tools to inform the design of an effective AI assistive learning companion for higher education. A structured survey was administered to 135 students across IT and business programs, examining demographics, language skills, learning habits, AI tool exposure, perceptions, concerns, and self-assessed learning confidence. The result of study highlights the need for AI learning companions that are adaptive, language-aware, discipline-specific, and ethically responsible, providing personalized scaffolding, practical skill reinforcement, and support for self-directed learning. These insights inform the design of AI tools that enhance learning confidence, inclusivity, and effectiveness in higher education.

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1. INTRODUCTION

The rapid pace of technological change, globalization, and the rise of knowledge-driven economies require learners to develop skills beyond memorization and standardized testing. Instead, students must cultivate critical thinking, creativity, adaptability, and problem-solving abilities to thrive in complex and uncertain environments. Transformative education shifts the focus from passive knowledge absorption to active engagement, encouraging learners to question assumptions, connect ideas across disciplines, and apply knowledge in real-world contexts [1], [2]. However, traditional educational models often struggle to support such transformation due to standardized curricula, limited instructional time, and unequal access to academic support [3]. Moreover, as lifelong learning becomes essential in modern societies, the relevance of transformative education continues to grow. In a world where industries evolve rapidly and new technologies

continually emerge, individuals must constantly reskill and upskill. Transformative education fosters autonomy and self-directed learning, empowering students to take ownership of their growth and remain adaptable throughout their careers [4], [5]. It also emphasizes inclusivity and equity, ensuring that diverse learners, regardless of background or language proficiency, can access meaningful educational opportunities. This focus on individual and inclusive growth naturally extends broader societal goals, including sustainability and global citizenship. It encourages learners to think critically about social, cultural, and environmental issues, preparing them to contribute responsibly to their communities and the world.

Transformative education is increasingly vital for students in computer science/information technology (IT) and business studies because these disciplines sit at the intersection of rapid technological change and organizational evolution. Traditional teaching approaches that emphasize rote learning and static curricula cannot keep pace with industries in which new tools, platforms, and business models continually emerge. Students in these fields must therefore cultivate adaptability, critical thinking, and lifelong learning skills to remain competitive in dynamic global markets [6]. This research work focuses on these two key specializations, evaluating learning habits, student readiness, and perceptions of artificial intelligence (AI)-assisted transformative learning. Within the domains of computer science and IT, learners must not only understand theoretical concepts but also apply them to complex, real-world problems, collaborate across disciplines, and continuously update their skills in response to evolving technologies such as AI, cloud computing, and cybersecurity. Transformative education supports this need by fostering reflective practice, experimentation, and self-directed learning, enabling students to move beyond procedural coding or tool-based training toward deeper conceptual understanding and innovation [7]. Similarly, business studies students face environments that demand strategic thinking, ethical decision-making, effective communication, and adaptability in global and digital markets [8]. Transformative learning equips these learners with the ability to evaluate business models critically, respond to uncertainty, and engage in lifelong professional development, which are essential competencies in modern business ecosystems.

AI-assistive learning is increasingly recognized as a catalyst for transformative education, enabling personalized, reflective, and adaptive learning experiences. As higher education institutions integrate AI companions into teaching and learning, it is essential to assess students' baseline readiness, confidence, and perceptions to ensure that such integration enhances learning outcomes while promoting equity across diverse learner populations [9], [10]. Within this evolving landscape, the rise of generative AI (GenAI) presents a significant opportunity to enhance personalized learning, practical problem-solving, and academic confidence [11], [12]. However, prior research works also highlights key challenges, such as limited long-term use, ethical concerns, poor integration into real learning contexts, and not fully considering individual differences including student confidence, language ability, and prior experience with AI. This study examines how insights into students' learning confidence, English proficiency, and prior experience with AI-powered tools can inform the design of a GenAI-based smart learning companion tailored for Omani higher education students. By identifying student's needs, learning challenges, and expectations regarding AI, the investigation aims to develop a smart, adaptive, and contextually relevant companion that enhances engagement, supports effective learning habits, and ensures equitable access to educational resources.

To achieve this, the study investigates students enrolled in four academic courses at the University of Technology and Applied Sciences–Shinas: principles of operating systems (diploma), applied machine learning (bachelor), strategic management (bachelor), and introduction to business (diploma). These courses were deliberately selected to represent varying levels of technical complexity, academic maturity, and application-oriented learning demands. It includes the contributions such as bridges gaps in existing research by directly connecting student needs to the design of AI learning tools, examines student's learning behaviors, confidence, and English proficiency in relation to AI-assisted learning, while accounting for academic level, program type, and language barriers to inform AI design and provides actionable design principles for adaptive, inclusive, and ethically responsible AI learning companions.

2. RELATED WORK

Bognar and Khine [13] report that the use of AI chat tools in higher education enhances student enthusiasm and provides timely, accessible academic support; however, these benefits do not consistently translate into sustained engagement or deeper learning practices. While some students experienced increased confidence and self-efficacy, others expressed concerns about overreliance on AI, the accuracy of generated responses, and their preparedness to use such tools effectively. Effective long-term use requires inclusive design, structured integration, and ongoing pedagogical support. A systematic review was carried out by Merino-Campos [14] to investigate the use of AI in higher education's individualized learning programs. The results indicate that AI-driven technologies improve instructional efficiency, student engagement, and adaptive learning by customizing feedback and content to meet the unique requirements of each student. On the other hand, ethical problems, concerns over data privacy, and the requirement for teacher training

highlight the significance of standardized evaluation frameworks and longitudinal research for the deployment of AI in a sustainable manner. Drawing on social cognitive theory and questionnaire responses from 204 students, Jeilani and Abubakar [15] investigate the ways in which students' perceptions of AI-supported learning in higher education are influenced by their perceptions of the support they receive from their institutions. The findings show that institutional support significantly enhances perceptions of AI learning and learning outcomes, with perceived learning outcomes partially mediating this relationship.

Technology self-efficacy plays a complex role: it is positively associated with outcomes but negatively moderates the impact of institutional support on perceptions of AI-supported learning, highlighting the need for supportive, well-structured AI integration strategies. Kumar *et al.* [16] investigated Indian higher-education students' perceptions and behavioral intentions toward AI-enabled learning using the unified theory of acceptance and use of technology (UTAUT) framework. Survey and qualitative data from 200 students reveal that performance expectancy and facilitating conditions strongly influence students' willingness to adopt AI tools, while effort expectancy and social influence have moderate effects. The findings emphasize the need for AI literacy initiatives, supportive infrastructure, and institutional support to ensure effective and equitable integration of AI in higher education. Jin *et al.* [17] examined global institutional policies and guidelines for integrating GenAI in higher education, analyzing adoption strategies across 40 universities from six regions using the diffusion of innovations theory. The study emphasizes the necessity of well-defined roles for teachers, students, and administrators to facilitate the collaborative and accountable incorporation of GenAI, providing practical recommendations for policymakers.

Furthermore, research by Maxwell *et al.* [18] examined how demographic factors, such as age, gender, and prior AI exposure, influence students' perceived readiness, perceived benefits, and perceived challenges of using GenAI in higher education. Findings show that while most students feel comfortable with GenAI and recognize its potential to enhance learning and productivity, concerns about academic integrity, overreliance, and data privacy persist. The study highlights equity gaps and underscores the need for AI literacy initiatives and differentiated support strategies to ensure inclusive and effective integration of GenAI. Giannakos *et al.* [19] emphasized ChatGPT and other GenAI based tools are reshaping learning by providing personalized feedback, adaptive support, and conversational engagement. These tools can help break down barriers that traditionally limit learning opportunities, enhances creativity, and support teachers in tailoring instruction. However, their role should remain complementary to human educators rather than a replacement.

Jabbour *et al.* [20] presented an AI-driven learning assistant that enhances education by making it more interactive, adaptive, and accessible through personalized clarifications, real-time support, and Socratic-style guidance. It highlights the system's ability to tailor learning experiences, boost engagement, and extend educational support beyond traditional settings. However, it can occasionally produce inaccurate responses and cannot fully replace the human interaction needed for effective learning. Mimoudi [21] examined how GenAI is reshaping education by offering adaptive tutoring, personalized feedback, and scalable resource creation. Drawing on a review of 75 studies and the result shows that most studies emphasize its potential to personalize learning (60%), assist teachers (51%), broaden inclusion (44%), and provide powerful analytics (33%). The authors highlight that ensuring fair and inclusive use of AI in education takes thoughtful planning, clear policies, and ongoing oversight.

Mirea *et al.* [22] presented a study on how GenAI, is influencing student's learning experiences and perceptions of academic improvement. Through a survey, the study found that students generally felt these tools helped enhance their understanding and grades. Building on these insights, the authors propose an adaptive learning system architecture that integrates GenAI, drawing from existing virtual assistant-based platforms, to create a more personalized, engaging, and supportive educational environment. Study by Wu and Gong [23] presented a low-code AI model that helps open and distance learning institutions bridge gaps between instructors and learners, offering instant, context-aware support through the intelligent learning companion. By integrating with learning management system (LMS) and communication platforms, it reduces isolation for students and provides a practical, scalable approach for sustainable AI-assisted education. However, student's perceptions and willingness to adapt to the AI system may vary. Li and Awang [24] studied how GenAI enhances student skills in higher education by acting as a mentor, assistant, and creative guide. They proposed a framework where AI-driven teaching, support, and feedback help develop digital, critical thinking, ethical, and self-directed learning skills.

Prior studies demonstrate the benefits of AI in higher education, including enhanced engagement, personalized learning, and improved instructional efficiency. But also revealed persistent challenges, including limited sustained use, ethical concerns, contextual integration, and insufficient attention to individual learner's characteristics, such as confidence, language proficiency, and prior AI experience. These gaps highlight that existing AI tools and institutional policies often lack the adaptability and cultural contextualization needed to meet diverse student needs. To address this gap, present study investigates the students' learning behaviors, challenges, and expectations regarding AI-based educational tools. It explores

the factors such as confidence, English language proficiency, academic level, and program type shapes the way students interact with AI. It also considers student's familiarity with AI-assisted learning and their perceptions of its role in education. By connecting these insights directly to design, the work offers practical principles for building adaptive, inclusive, and ethically responsible AI learning companions.

The main goal of this investigation is to examine student's learning behaviors, challenges, and expectations regarding AI-based educational tools in order to inform the design of an effective, adaptive, and inclusive AI assistive learning companion that supports transformative education. Thus, the research question of this study:

- What study habits and learning resources do students rely on most, and how frequently do they use AI tools compared to traditional resources? (RQ1)
- How confident are students in understanding subject concepts, solving problems, and applying knowledge to real-world projects? (RQ2)
- How do English language skills (reading, writing, and speaking) influence students' confidence and academic performance? (RQ3)
- How familiar are students with AI-powered educational tools before the course, and what specific forms of support do they expect from an AI learning companion? (RQ4)
- What concerns do students have about using AI in education (plagiarism, bias, privacy, and reduced critical thinking), and how do these concerns shape their willingness to adopt AI-assisted learning? (RQ5)

3. RESULTS AND DISCUSSION

3.1. Participants

The study involves N=135 students drawn from four academic program (principles of operating systems diploma, applied machine learning bachelor, strategic management bachelor, and introduction to business diploma). The student's demographic profiles, learning patterns, English language competency, and perspectives of AI-assisted learning were investigated through the use of a structured questionnaire that was constructed for the purpose of collecting data. The instrument was designed and comprised six thematic sections: Section A gathered demographic and academic information, including program of study, year level, and gender, providing contextual variables for subgroup analysis. Section B assessed English language proficiency and barriers, evaluating students' abilities in reading, writing, and communication, as well as challenges with vocabulary, grammar, and comprehension of academic texts. Section C focused on learning habits and academic support mechanisms, examining study frequency, preferred learning resources, and strategies used when facing difficulties, such as consulting peers, instructors, or AI tools. Section D measured exposure to and familiarity with AI tools, establishing a baseline for adoption readiness. Section E explored perceptions, expectations, and concerns regarding AI learning companions, including beliefs about their usefulness, expected support in clarifying concepts, exam preparation, language improvement, and concerns such as plagiarism, bias, privacy, and over-reliance. Section F captured self-assessment of learning confidence and preparedness, evaluating students' confidence in understanding subject concepts, solving practical problems, and applying knowledge to real-world projects, providing insight into perceived academic readiness.

Survey items employed multiple-choice formats and 5-point Likert scales, supplemented by open-ended options to capture qualitative insights. To ensure content validity and contextual relevance, the questionnaire was reviewed by two academic experts in educational technology and learning sciences. A pilot study with 20 students was conducted to evaluate clarity, reliability, and usability. Feedback from the pilot informed minor revisions to item wording and structure, thereby enhancing alignment with the research objectives and improving overall comprehensibility.

3.2. Data analysis approach

The study utilized a descriptive and comparative methodology, aligning with its cross-sectional framework. Descriptive statistics [25], [26] (frequencies, percentages, and mean scores) summarized trends across the whole sample (N=135). Cross-tabulation [27], [28] analyses examined subgroup differences based on program type (IT vs. business), year of study, gender, and English proficiency levels. Inferential tests (such as Chi-square tests, t-tests, and ANOVA) [29], [30] identified significant differences where applicable, highlighting how demographics and language skills influenced learning habits, AI familiarity, and perceptions.

3.2.1. Section A: demographic and academic information

Section A describes the demographic and academic profile of the respondents (N=135), providing essential context for interpreting learning behaviors, language proficiency, AI familiarity, and learning

confidence in subsequent analyses. As shown in Table 1, the respondent profile indicates that the sample comprises mainly diploma-level students (66.7% of participants), with a notable concentration in business-related program. By gender, female students constitute nearly two-thirds of the sample, indicating a higher female participation rate across the surveyed program. Additionally, a substantial proportion of respondents identified Arabic as their primary language, indicating a linguistically diverse student population. Given that instruction and academic materials are delivered predominantly in English, this linguistic background may pose challenges related to comprehension, academic writing, and classroom communication.

Table 1. Descriptive statistics-demographic and academic information

Variable	Category	Frequency	Percentage (%)
Course enrolled	Applied machine learning (bachelor)	21	15.6
	Strategic management (bachelor)	12	8.9
	Principles of operating systems (diploma)	48	35.6
	Introduction to business (diploma)	54	40.0
Year of study	I (diploma)	81	60.0
	II (diploma)	15	11.1
	Advanced diploma	9	6.7
Gender	Bachelor	30	22.2
	Male	41	30.4
Primary language	Female	94	69.6
	Arabic	60	44.4
Primary language	English	38	28.1
	Both equally	37	27.4

3.2.2. Section B: English language proficiency and barriers

Section B assessed students' self-reported proficiency in English reading, writing, and oral communication, as well as specific language-related barriers, including limited vocabulary, grammatical difficulties, and difficulties understanding academic texts. Table 2 shows that most students possess moderate confidence in their English language skills, including reading, writing, and oral communication. However, writing emerged as the weakest area, with nearly one-third of respondents reporting low confidence, highlighting persistent difficulties in written academic expression. In addition, more than half of the students identified challenges related to vocabulary, grammar, and comprehension of academic texts, suggesting that language-related barriers remain a significant concern and may adversely affect students' academic performance and learning engagement.

Table 2. Descriptive statistics-English language proficiency and barriers (N=135)

Variable	Category	Frequency	Percentage (%)
English reading confidence	High	42	31.1
	Moderate	63	46.7
	Low	30	22.2
English writing confidence	High	35	25.9
	Moderate	58	43.0
	Low	42	31.1
English oral communication confidence	High	39	28.9
	Moderate	61	45.2
	Low	35	25.9
Key language barriers	Academic vocabulary	78	57.8
	Grammar accuracy	72	53.3
	Understanding academic texts	69	51.1

3.2.3. Section C: learning habits and academic support mechanisms

This section explored students' study frequency, preferred learning resources, and strategies used when facing course difficulties. Understanding these habits is essential for designing an AI-assistive learning companion that complements students' existing strategies and promotes self-directed learning. In Table 3, most students study 2–3 times per week (44.4%), whereas a smaller proportion (19.3%) study daily. Lecture notes are the most frequently used resource (94.8%), followed by AI tools (83%) and online tutorials (70.4%). When encountering difficulties, students often combine strategies, such as consulting peers alongside AI tools (37%) or performing online searches. This pattern indicates that students adopt blended learning approaches that effectively integrate traditional resources, peer support, and digital technologies, including AI, to enhance their learning outcomes.

Table 3. Descriptive statistics-English language proficiency and barriers (N=135)

Variable	Category	Frequency	Percentage (%)
Frequency of studying outside class	Daily	26	19.3
	2-3 times/week	60	44.4
	Once/week	30	22.2
	Rarely	19	14.1
Strategies for addressing course difficulties*	Use AI tools	105	77.8
	Ask classmates/peers	95	70.4
	Search online (Google, YouTube)	70	51.9
	Ask instructor	60	44.4
	Refer to textbooks	45	33.3
Learning resources most relied upon*	Lecture notes	128	94.8
	AI tools	112	83
	Online tutorials/videos	95	70.4
	Textbooks	82	60.7
	Study groups	60	44.4

*Multiple responses allowed; percentages may exceed 100%

3.2.4. Section D: exposure to and familiarity with AI tools

This section assessed students' prior experience with AI-powered educational tools and their familiarity with such technologies. The data provides insight into readiness for AI-assisted learning. Table 4 shows that most students reported occasional use of AI tools (61.5%), whereas nearly a quarter (23.7%) reported frequent use, and a small proportion (14.8%) reported never using AI tools. The mean familiarity score of 2.86 (SD=0.91) indicates moderate familiarity, indicating that although students generally have positive exposure to AI educational technologies, their hands-on experience remains limited. This suggests a need for introductory guidance and support to ensure effective adoption of AI-assisted learning tools.

Table 4. Descriptive statistics-AI exposure and familiarity (N=135)

Variable	Category	Frequency	Percentage (%)
Prior experience using AI tools	Frequently	32	23.7
	Sometimes	83	61.5
	Never	20	14.8

3.2.5. Section E: perceptions, expectations, and concerns about AI learning companions

This section examined students' beliefs about AI learning companions, the types of support they expect, and concerns they hold. The data show that students are generally positive about AI-assisted learning, particularly regarding academic performance and personalized support, but cautious about ethical and reliability concerns. Table 5 shows that students hold a generally positive view of AI learning companions, expecting them to provide meaningful support in enhancing academic performance and offering personalized guidance tailored to their learning needs. They prioritize practical and conceptual assistance, such as help with assignments, clarification of complex concepts, and exam preparation, over language translation features. However, significant concerns about over-reliance, plagiarism, and the accuracy of AI outputs highlight the need for responsible, transparent, and ethically designed AI systems that promote independent learning while ensuring reliability and academic integrity.

Table 5. Descriptive statistics-AI perceptions and expectations (N=135)

Variable	Mean (%)	Description
Expected support-academic performance	93	The majority expect AI to improve grades and performance.
Expected support-personalized feedback	89	Students anticipate tailored study tips and feedback.
Expected support-assignments and exercises	84	AI is expected to assist with exercises and assignments.
Expected support-concept clarification	79	Students' desire facilitates understanding of complex concepts.
Expected support-exam preparation	74	AI assistance for revision and exam readiness is valued.
Concerns-over-reliance/reduced critical thinking	93	Most students are cautious about depending too much on AI.
Concerns-plagiarism/academic misconduct	88	Academic integrity is a major concern.
Concerns-accuracy/reliability of AI outputs	80	Students question the trustworthiness of AI information.
Concerns-privacy data security	67	Significant concerns exist regarding data protection.
Variable	Mean	Std. deviation
Belief AI companion improves learning	3.04	1.03
		Description
		Students moderately agree that AI companions can enhance learning outcomes.

3.2.6. Section F: self-assessment of learning confidence and preparedness

This section assessed students' confidence in understanding subject concepts, solving practical problems, and applying knowledge to real-world projects, providing insight into their perceived academic preparedness, as shown in Table 6. Students reported generally moderate-to-high confidence in understanding subject concepts and solving practical problems, indicating strong theoretical and problem-solving skills. However, their confidence in applying knowledge to real-world projects was noticeably lower, highlighting a gap in practical application and suggesting the need for targeted support, such as hands-on exercises, simulations, and guided practice, to strengthen students' ability to transfer learning to real-world contexts.

Table 6. Descriptive statistics-self-assessment of learning confidence

Variable	Mean	Std. deviation	Interpretation
SA1-confidence in understanding subject concepts	3.59	1.06	Moderate-to-high confidence in conceptual understanding.
SA2-confidence in solving practical problems	3.65	0.98	Students feel reasonably confident handling course problems.
SA3-ability to apply knowledge to real-world projects	2.87	1.00	Lower confidence in practical application, indicating a need for applied support.

3.3. Subgroup analysis

3.3.1. Section A: demographic and academic information

The subgroup analysis procedure involved examining the impact of independent variables, including course enrolled, year of study, gender, and primary language, on dependent variables such as learning confidence, English proficiency, study frequency, and AI familiarity. Statistical tests were selected based on data type, with the Kruskal Wallis H test applied to ordinal or non-normally distributed data, ANOVA used for continuous variables, and Chi-square tests employed to assess associations among categorical variables. A significance threshold of $p < 0.05$ was applied to determine meaningful differences. Table 7 presents the key findings of academic context (program type, year) influences learning confidence and English writing skills. gender has no significant effect. Primary language strongly affects English proficiency but does not influence familiarity of AI tools.

Table 7. Significant relationships-section A

Demographic variable	Outcome variable	Test	Result	Key insight
Course enrolled	Learning confidence (practical application, SA3)	Kruskal-Wallis H	$\chi^2=8.357$, $p=0.039$	Applied machine learning (bachelor) students report higher confidence
Course enrolled	English writing	ANOVA	$F=3.422$, $p=0.020$	Bachelor students demonstrate stronger writing skills
Year of study	Learning confidence (SA3)	Kruskal-Wallis H	$\chi^2=8.959$, $p=0.030$	Senior students show higher confidence in real-world applications
Year of study	English writing	ANOVA	$F=3.642$, $p=0.015$	Writing proficiency improves with academic progression
Year of study	Study frequency	Chi-square	$\chi^2=12.54$, $p=0.024$	Senior students study more regularly outside class
Primary language	English reading	ANOVA	$F=3.278$, $p=0.042$	English proficiency varies by language background
Primary language	English writing	ANOVA	$F=4.472$, $p=0.005$	Non-English speakers face writing challenges
Primary language	Oral confidence	ANOVA	$F=4.168$, $p=0.007$	Oral academic confidence differs by language

3.3.2. Section B: English language proficiency and barriers

The analysis examined the effects of independent variables, including year of study, gender, primary language, prior AI experience, and study frequency, on dependent variables measuring English proficiency in reading, writing, and oral confidence. Statistical tests were chosen based on data type, with ANOVA applied to continuous variables and t-tests used for comparisons between genders. A significance threshold of $p < 0.05$ was used. Table 8 indicate that the language support is a priority for non-native speakers.

Table 8. Significant group relationships–section B

Variable	Test	Result	Interpretation
Writing (EN2)×year of study	ANOVA	F=3.642, p=0.015	Senior students have higher writing proficiency
Reading/writing/oral×primary language	ANOVA	Reading F=3.278, p=0.042; writing F=4.472, p=0.005; oral F=4.168, p=0.007	English-native or bilingual students perform better
Writing×study frequency	ANOVA	F=3.058, p=0.031	Students who study more frequently perform better in writing

3.3.3. Section C: learning habits and academic support mechanisms

The analysis evaluated the effects of independent variables, including course enrolled, year of study, and primary language, on dependent variables such as study frequency, learning strategies, and learning resource preferences. Chi-square tests were used for categorical variables and ANOVA was applied to continuous variables, with a significance threshold of $p < 0.05$. Table 9 shows the frequent AI users and senior students demonstrate more self-directed learning habits and Learning resource preferences are largely consistent across languages and programs.

Table 9. Significant relationships–section C

Variable	Test	Result	Interpretation
Study frequency×prior AI experience	Chi-square	$\chi^2=28.277$, $p < 0.001$	Students who frequently use AI study more regularly
Study frequency×year of study	Chi-square	$\chi^2=12.54$, $p=0.024$	Senior students are more consistent in studying

3.3.4. Section D: exposure and familiarity with AI tools

This analysis assessed the impact of independent variables, including gender, year of study, course enrolled, primary language, and study frequency, on AI familiarity. The Kruskal Wallis H test was used for comparisons across more than two groups, the Mann Whitney U-test for two-group comparisons, and Chi-square tests for study frequency, with a significance threshold of $p < 0.05$. Table 10 indicates that the study habits are the strongest predictor of AI use, with slight trends indicating that applied machine learning students are more familiar with AI.

Table 10. Familiarity subgroup analysis–section D

Demographic	Test	Result	Interpretation
Study frequency	Chi-square	$\chi^2=28.277$, $p < 0.001$	Students who study more frequently use AI tools more often

3.3.5. Section E: perceptions, expectations, and concerns about AI learning companions

This analysis evaluated the impact of program type, year of study, gender, and primary language on perceptions and expectations of AI companions. The Kruskal Wallis H test was used for comparisons among multiple groups, and the Mann-Whitney test for two-group comparisons, with a significance threshold of $p < 0.05$. The results in Table 11 indicate that student's beliefs in AI companions are broadly consistent across demographics, indicating acceptance. Differences in adoption may be influenced more by academic context than by demographics

Table 11. Subgroup analysis–section E

Demographic	Test	Result	Interpretation
Program type, year, gender, primary language×belief in AI companion	Kruskal-Wallis/ Mann-Whitney	$p > 0.05$	Perceptions and expectations of AI companions are uniform across subgroups.

3.3.6. Section F: self-assessment of learning confidence and preparedness

This analysis assessed the effects of course enrolled, year of study, and gender on learning confidence. The Kruskal Wallis H test was applied for ordinal data, and Spearman's correlation was used to assess the relationship between conceptual and practical confidence, with a significance threshold of $p < 0.05$. Table 12 demonstrates the student's confidence in conceptual understanding and problem-solving, but less so in applying knowledge to real-world tasks. Confidence improves with academic progression and is higher in bachelor's programs in IT. Applied learning support is essential for lower-year students.

Table 12. Subgroup analysis—section F

Variable	Test	Result	Interpretation
Practical application (SA3)×course enrolled	Kruskal–Wallis H	$\chi^2=8.357, p=0.039$	Applied machine learning (bachelor) students report higher confidence
SA3×year of study	Kruskal–Wallis H	$\chi^2=8.959, p=0.030$	Senior students are more confident in applying their knowledge
SA1 and SA3	Spearman’s ρ	$\rho=0.253, p=0.003$	Small positive correlation: higher conceptual understanding→higher practical application ability

Table 13 provides a concise overview linking the key findings from each section of the study to actionable design recommendations for an AI assistive learning companion. Its purpose is to translate research insights—ranging from demographic and academic context, English proficiency, learning habits, AI familiarity, perceptions, and learning confidence—into practical, evidence-based features that address students’ diverse needs. By organizing the implications section-wise, the table highlights how different aspects of students’ learning experiences should inform adaptive scaffolding, language support, discipline-sensitive content, study habit facilitation, ethical safeguards, and personalized guidance within the AI system. This allows educators, designers, and developers to directly align AI functionalities with the specific challenges, strengths, and expectations identified in the study, ensuring that the AI companion is both student-centered and pedagogically effective.

Table 13. Section-wise AI companion design implications

Section	Key Findings	AI Companion Design Implications
Section A: demographic and academic info	Academic context and language background shape learning confidence; gender does not significantly affect learning needs.	<ul style="list-style-type: none"> - Adaptive scaffolding by academic level (diploma vs bachelor) - Discipline-sensitive support (IT vs business) - Language-aware assistance (simplified explanations, vocabulary support) - Inclusive, neutral interface - Customizable learning pathways
Section B: English proficiency and barriers	Primary language affects reading, writing, and oral confidence; gender and prior AI experience do not.	<ul style="list-style-type: none"> - Language-aware scaffolding (glossary, simplified explanations) - Adjustable language complexity - Writing support (grammar, sentence restructuring, model answers) - Reading comprehension support (summaries, keyword highlighting) - Equitable access focused on language inclusivity
Section C: learning habits and academic support	Senior students study more regularly; frequent AI users are more self-directed; learning strategies vary by program.	<ul style="list-style-type: none"> - Embed study scheduling and reminders - Multi-modal assistance (text, video, interactive exercises) - Blend with existing strategies (lecture notes, peer prompts) - Program-specific support (practical simulations for IT, case-based reasoning for Business) - Facilitate collaboration and access to resources
Section D: exposure and familiarity with AI tools	AI familiarity is consistent across demographics; study frequency predicts AI use; IT students are slightly more exposed to AI.	<ul style="list-style-type: none"> - Onboarding tutorials for beginners - Adaptive complexity in exercises and tips - Integration with self-study habits - Discipline-specific features (coding simulations for IT, case analysis for Business) - Progressive exposure to AI tools
Section E: perceptions, expectations, concerns	Students accept AI for learning; concerns include plagiarism, bias, privacy, and over-reliance; demographic differences are minimal.	<ul style="list-style-type: none"> - Provide academic performance support (assignments, exam prep) - Personalized feedback and adaptive learning plans - Concept clarification through interactive examples - Responsible AI use (hints, citation guidance, critical-thinking prompts) - Ethical and transparent AI outputs
Section F: learning confidence and preparedness	Confidence in practical application is lower than in conceptual understanding; senior/bachelor students are more confident.	<ul style="list-style-type: none"> - Targeted practical application exercises and simulations - Step-by-step problem-solving scaffolds - Course-specific modules (coding exercises for IT, business case analyses) - Progression-based challenges by year of study - Concept reinforcement linking theory to real-world projects

Table 14 and Table 15 synthesizes the study’s results, linking each research question to empirical evidence and actionable design recommendations for an AI assistive learning companion. By summarizing key findings from all sections of the study covering learning habits, confidence, English proficiency, AI familiarity, and concerns, the table highlights how students’ academic context, language background, and learning behaviors inform targeted AI features. This structured mapping allows researchers, educators, and designers to quickly identify which evidence supports specific design decisions, ensuring that the AI

companion is pedagogically sound, personalized, and responsive to students' needs while addressing ethical and accessibility considerations.

Table 14. Mapping research questions to key findings and AI companion design implications

Research question	Key findings	AI companion design implications
RQ1: study habits and learning resources	Study frequency and learning strategies vary by year; senior students exhibit more regular and self-directed study habits. AI tools complement traditional resources rather than replace them.	Provide study-planning tools, reminders, and guided learning pathways; encourage self-directed learning, particularly for diploma students.
RQ2: learning confidence and application of knowledge	Practical application confidence is higher among bachelors' students; diploma students report lower confidence in practical application.	Incorporate adaptive scaffolding, step-by-step problem-solving, and practice-based exercises tailored to academic level and program type.
RQ3: influence of English language skills	Primary language significantly affects English reading, writing, and oral proficiency. Language barriers impact academic communication but not AI familiarity.	Integrate language-aware features: simplified explanations, glossary support, adjustable language complexity, optional bilingual assistance, and writing/reading support.
RQ4: familiarity with AI tools and expected support	AI familiarity is consistent across programs, years, genders, and primary languages, suggesting baseline readiness for AI adoption.	Deploy a common AI platform with adaptive personalization based on learning needs (discipline, year, and confidence), rather than demographic characteristics.
RQ5: concerns about AI use in education	Student express concerns about plagiarism, bias, privacy, and overreliance, regardless of demographic background.	Embed ethical safeguards, transparency features, citation guidance, critical-thinking prompts, and explainable AI outputs to promote responsible and trustworthy use.

Table 15. Mapping key findings to AI companion design implications

Key finding	AI companion design implications
Senior/bachelor students study more regularly and are self-directed. Diploma (junior) students rely more on guidance.	Provide study-planning tools, reminders, guided learning pathways; encourage self-directed learning tailored to academic level and program type.
Confidence in practical application is lower than conceptual understanding. Diploma, and linguistically diverse learners report lower confidence.	Incorporate adaptive scaffolding, step-by-step problem-solving, practice-based exercises, and progression-based challenges by academic year and program.
Language barriers reduce academic confidence but do not affect AI familiarity.	Integrate language-aware features such as simplified explanations, glossaries, adjustable language complexity, writing/reading support, bilingual assistance.
AI familiarity is consistent across demographics; IT students slightly more exposed. Others have limited experience.	Include onboarding tutorials, adaptive complexity exercises, progressive exposure, and discipline (specialization)-specific features (coding simulations for IT, case analysis for business).
Students are positive about AI support but have concerns about plagiarism, bias, privacy, and over-reliance. They expect help with concept clarification, exam preparation, and language improvement.	Ensure ethical and transparent AI outputs, provide personalized feedback, critical-thinking prompts, citation guidance, and responsible-use safeguards.
Learning needs vary by academic level, program, and language proficiency, but not significantly by gender.	Design an inclusive, neutral interface with customizable learning pathways accommodating diverse backgrounds.

4. CONCLUSION

With the rapid rise of AI-based applications across all domains, education is undergoing a profound shift away from traditional instructor-led models toward dynamic, learner-centered ecosystems. In this changing landscape, the AI learning companion emerges not as a replacement for teachers but as a supportive catalyst, helping students navigate complex information, personalize their learning journeys, and build confidence in applying knowledge. This research examined students' learning behaviors, English language proficiency, learning confidence, and perceptions of AI-based learning companions within a cross-sectional framework.

The findings of the study show the need for an AI-assisted learning companion that is adaptive, language-aware, discipline-specific, and ethically responsible. Such a tool can provide personalized scaffolding, reinforce practical skills, support self-directed learning, and offer inclusive, flexible guidance, bridging gaps left by traditional teaching. Implementing these design principles ensures that the AI companion strengthens both learning confidence and practical competence, preparing students for success in an AI-driven academic and professional environment. The findings of this research provide a foundation for future studies to explore the long-term impact of AI-assisted learning on student performance and to extend experiments across diverse programs and institutions, offering broader insights into disciplinary and cultural differences in AI adoption and learning behaviors.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to the MoHERI and University of Technology and Applied Sciences, Shinas, for supporting this research.

FUNDING INFORMATION

This research work is supported by the Research Grant Program 2024, of the Ministry of Higher Education, Research & Innovation Oman (MOHERI), Sultanate of Oman.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nterpretation

R : **R**esources

D : **D**ata Curation

O : **O**riginal Draft

E : **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

Authors declare no conflict of interests.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [SRAS], upon reasonable request.





REFERENCES

- [1] G. H. van Rensburg and V. E. Matahela, "Transformative learning in open distance and e-learning: the critical role of nurse educators," *Discover Education*, vol. 4, no. 1, p. 308, Aug. 2025, doi: 10.1007/s44217-025-00772-4.
- [2] J. Mezirow, "Transformative learning: theory to practice," *New Directions for Adult and Continuing Education*, vol. 1997, no. 74, pp. 5–12, Jun. 1997, doi: 10.1002/ace.7401.
- [3] A. Asrifan, K. N. Tayibu, M. Muhayyang, S. S. Ingilan, and A. Mahfud, "Traditional learners vs. Non-traditional learners: bridging the educational divide," in *Mitigating Learner Disadvantages in Teaching and Learning*, S. Hai-Jew, Ed., Hershey, PA: IGI Global Scientific Publishing, 2025, pp. 59–90, doi: 10.4018/979-8-3693-8623-1.ch003.
- [4] V. Servant-Miklos and L. Noordegraaf-Eelens, "Toward social-transformative education: an ontological critique of self-directed learning," *Critical Studies in Education*, vol. 62, no. 2, pp. 147–163, Mar. 2021, doi: 10.1080/17508487.2019.1577284.
- [5] C. Mohiyeddini, "Self-directed teaching: a holistic framework for educator autonomy," *Frontiers in Medicine*, vol. 11, p. 1479885, Nov. 2024, doi: 10.3389/fmed.2024.1479885.
- [6] S. Yue, "The evolution of pedagogical theory: from traditional to modern approaches and their impact on student engagement and success," *Journal of Education and Educational Research*, vol. 7, no. 3, pp. 226–230, Mar. 2024, doi: 10.54097/j4agx439.
- [7] C. Bura and P. K. Myakala, "Advancing transformative education: generative AI as a catalyst for equity and innovation," *arXiv*: 2411.15971, 2024.
- [8] M. Kyambade, G. Nkurunziza, A. Namatovu, M. Tushabe, and G. Kwemara, "Enhancing critical thinking and ethical decision-making through learner-centered strategies in business education," *Cogent Education*, vol. 12, no. 1, pp. 1–21, Dec. 2025, doi: 10.1080/2331186X.2025.2588420.
- [9] A. Henukh, A. I. Irvani, A. Setiawan, E. M. Seme, and N. R. L. Raja, "AI and transformative learning in higher education: a systematic literature review and bibliometric insights," *Journal of Teaching and Learning*, vol. 19, no. 4, pp. 233–261, Oct. 2025, doi: 10.22329/jtl.v19i4.10096.




- [10] N. Abdallah, R. Katmah, K. Khalaf, and H. F. Jelinek, "Systematic review of ChatGPT in higher education: navigating impact on learning, wellbeing, and collaboration," *Social Sciences & Humanities Open*, vol. 12, p. 101866, 2025, doi: 10.1016/j.ssaho.2025.101866.
- [11] I. M. García-López, M. S. Ramírez-Montoya, and J. M. Molina-Espinosa, "Generative artificial intelligence in education: a systematic analysis of opportunities, challenges, and responses," *Interactive Learning Environments*, vol. 34, no. 3, pp. 1194–1217, Mar. 2025, doi: 10.1080/10494820.2025.2519133.
- [12] S. Benlakhdar, M. Rziza, and R. O. H. Thami, "Personalized learning in higher education: the impact of generative AI on deep learning project performance," in *Innovative Educational Assessment with Generative AI: Opportunities, Challenges, and Practical Case Studies*, M. Lahby, Ed., Cham: Springer Nature Switzerland, 2026, pp. 171–188, doi: 10.1007/978-3-032-05306-0_8.
- [13] L. Bognar and M. S. Khine, "Balancing enthusiasm and engagement: the impact of AI chat tools on student learning habits and perceptions in higher education," *Journal of Education and e-Learning Research*, vol. 12, no. 2, pp. 267–288, Jun. 2025, doi: 10.20448/jeelr.v12i2.6761.
- [14] C. Merino-Campos, "The impact of artificial intelligence on personalized learning in higher education: a systematic review," *Trends in Higher Education*, vol. 4, no. 2, p. 17, Mar. 2025, doi: 10.3390/higheredu4020017.
- [15] A. Jeilani and S. Abubakar, "Perceived institutional support and its effects on student perceptions of AI learning in higher education: the role of mediating perceived learning outcomes and moderating technology self-efficacy," *Frontiers in Education*, vol. 10, p. 1548900, Mar. 2025, doi: 10.3389/educ.2025.1548900.
- [16] M. Kumar, R. Tyagi, A. Gaumat, and J. Rani, "Students' perceptions and readiness for AI-enhanced learning: a UTAUT-based study in Indian higher education institutions," *Journal of Marketing & Social Research*, vol. 2, no. 3, pp. 495–500, 2025.
- [17] Y. Jin, L. Yan, V. Echeverria, D. Gašević, and R. Martinez-Maldonado, "Generative AI in higher education: A global perspective of institutional adoption policies and guidelines," *Computers and Education: Artificial Intelligence*, vol. 8, p. 100348, Jun. 2025, doi: 10.1016/j.caeai.2024.100348.
- [18] D. Maxwell, B. Oyarzun, S. Kim, and J. Y. Bong, "Generative AI in higher education: demographic differences in student perceived readiness, benefits, and challenges," *TechTrends*, vol. 69, no. 6, pp. 1248–1259, Nov. 2025, doi: 10.1007/s11528-025-01109-6.
- [19] M. Giannakos *et al.*, "The promise and challenges of generative AI in education," *Behaviour & Information Technology*, vol. 44, no. 11, pp. 2518–2544, Jul. 2025, doi: 10.1080/0144929X.2024.2394886.
- [20] J. Jabbour, K. Kleinbard, O. Miller, R. Haussman, and V. J. Reddi, "SocratiQ: a generative AI-powered learning companion for personalized education and broader accessibility," in *Proceedings of the Workshop on Computer Architecture Education (WCAE)*, Jun. 2025, pp. 1–10, doi: 10.1145/3743646.3750010.
- [21] A. Mimoudi, "Generative AI to bridge the educational divide: personalized learning and challenges," *Social Sciences & Humanities Open*, vol. 12, p. 102140, 2025, doi: 10.1016/j.ssaho.2025.102140.
- [22] C.-M. Mirea, R. Bologa, A. Toma, A. Clim, D.-D. Plăcintă, and A. Bobocea, "Transforming learning with generative AI: from student perceptions to the design of an educational solution," *Applied Sciences*, vol. 15, no. 10, p. 5785, May 2025, doi: 10.3390/app15105785.
- [23] D. Wu and Z. Gong, "Design and implementation of an AI learning companion," in *Proceedings of 2025 International Conference on Artificial Intelligence and Sustainable Development (ICAISD)*, 2025, pp. 252–255, doi: 10.1145/3786484.3786523.
- [24] X. Li and M. M. bin Awang, "Exploring the role of generative AI in developing student skills in higher education: a systematic literature review," *European Journal of Education*, vol. 61, no. 1, p. e70490, Mar. 2026, doi: 10.1111/ejed.70490.
- [25] Y. B. Rajabalee and M. I. Santally, "Learner satisfaction, engagement and performances in an online module: implications for institutional e-learning policy," *Education and Information Technologies*, vol. 26, no. 3, pp. 2623–2656, May 2021, doi: 10.1007/s10639-020-10375-1.
- [26] R. W. Cooksey, "Descriptive statistics for summarising data," in *Illustrating Statistical Procedures: Finding Meaning in Quantitative Data*, R. W. Cooksey, Ed., Singapore: Springer Singapore, 2020, pp. 61–139, doi: 10.1007/978-981-15-2537-7_5.
- [27] D. R. White, "A student's guide to statistics for analysis of cross tabulations," *World Cultures*, vol. 14, no. 2, pp. 179–193, 2004.
- [28] J. Fletcher, "Subgroup analyses: how to avoid being misled," *British Medical Journal*, vol. 335, no. 7610, pp. 96–97, Jul. 2007, doi: 10.1136/bmj.39265.596262.AD.
- [29] J. Paul and F. Jefferson, "A comparative analysis of student performance in an online vs. face-to-face environmental science course from 2009 to 2016," *Frontiers in Computer Science*, vol. 1, p. 472525, Nov. 2019, doi: 10.3389/fcomp.2019.00007.
- [30] P. Ranganathan, "An introduction to statistics: Choosing the correct statistical test," *Indian Journal of Critical Care Medicine*, vol. 25, no. S2, pp. S184–S186, May 2021, doi: 10.5005/jp-journals-10071-23815.

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