Journal of Culture and Values in Education

https://cultureandvalues.org

E-ISSN: 2590-342X

Volume: 9 Issue: 2 2026

pp.80-99

Promoting AI Learning Motivation for the Special English Program Students at Assiut University

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Article Info
Received: February 11, 2026
Accepted: April 11, 2026
Published: June 2, 2026

10.46303/jcve.2026.21

How to cite
Hamd, M. M. M., Abdellatif, M. S. Ahmed, S. A., & Assiry, B. (2026). Promoting AI Learning Motivation for the Special English Program Students at Assiut University. *Journal of Culture and Values in Education*, 9(2), 80-99. https://doi.org/10.46303/jcve.2026.21

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ABSTRACT
The objective of this study was to investigate and enhance the educational motivation of students within the Special English Language Program at the Faculty of Education, Assiut University, regarding the integration of Artificial Intelligence (AI) into their academic pursuits. As AI continues to reshape the landscape of higher education, understanding the psychological readiness of future educators is paramount. The research utilized a sample of 160 students and adopted a descriptive methodology, which was deemed the most appropriate approach for capturing the current state of student sentiment. The primary research instrument consisted of a scale specifically designed to measure motivation toward learning and utilizing AI applications. This tool was adapted and prepared by the researchers, undergoing rigorous psychometric verification to ensure the validity and reliability of the data collected. The findings revealed that students in the Special English Program generally possess a high level of motivation toward AI, indicating a positive disposition toward technological innovation in language learning. However, the results also highlighted a significant disparity between academic cohorts. Statistically significant differences were found between first-level and third-year students, with the latter showing markedly higher motivation levels. This finding is primarily attributed to the accumulated educational experience of the third-year students. Having been exposed to more specialized pedagogical training, these students have had greater opportunities to employ AI tools within practical classroom activities and authentic learning scenarios. Consequently, the study concludes with a set of recommendations aimed at integrating AI-driven activities earlier in the curriculum to ensure that all students, regardless of their year of study, are adequately prepared for the digital future of English language education.

KEYWORDS
Motivation; motivation and Learning; educational motivation for AI

INTRODUCTION

Artificial Intelligence (AI) is a rapidly evolving technology that has notably contributed to various fields. AI refers to the ability of computer systems to perform tasks that typically require human intelligence (Kaplan & Haenlein, 2019). Additionally, AI techniques have been designed to simulate fundamental aspects of human cognition, including reasoning, learning, perception, and problem-solving (Lieto et al., 2018).

One of the most remarkable benefits of this technology stems from its capacity to provide solutions for numerous challenges in our daily lives, with education being one of the most prominent fields because it heavily utilizes innovative AI applications. The advancement of AI and its implementation in education provide multiple advantages, such as enhancing the effectiveness, efficiency, and engagement of the educational process. Furthermore, AI enhances student success rates through personalized learning applications and reduce the cognitive and administrative burdens on both students and teachers (Chen et al., 2020; Wohlfart & Wagner, 2023; Yilmaz et al., 2023a). Because Artificial Intelligence has had a transformative impact on future workplaces, international organizations, including the OECD, the World Economic Forum (WEF), UNICEF, and UNESCO, have acknowledged the paramount importance of AI-related skills in the 21st century (Wang et al., 2023).

Furthermore, given the growing reliance on technology and the ongoing demand for AI-skilled professionals, higher education institutions and universities must enhance their graduates' capacity to respond to future developments. This enhancement may involve stimulating their motivation to explore AI concepts and applications while fostering their acceptance of new technologies. Indeed, the integration of Artificial Intelligence in education is closely associated with students' technology acceptance, notably impacting their motivation toward it (Kelly et al., 2023; Salas-Pilco & Yang, 2022; Velandia-Rodriguez et al., 2025).

Because the principle of excellence and student-centered learning are primary goals, the term ''Adaptive Learning'' has received substantial attention as an e-learning paradigm characterized by its flexibility in addressing individual differences among learners. It facilitates novel opportunities for engineering productive educational activities and developing superior technology-enhanced learning environments or applications. These environments support students by urging them to devise creative solutions for environmental problems (Xie et al., 2019).

Moreover, AI-based adaptive learning systems are highly technological and interdisciplinary. Without a clear understanding of the roles and techniques of Artificial Intelligence in education, educators cannot effectively implement its applications and activities (Huang et al.,2020). Artificial Intelligence is employed to create systems capable of absorbing and learning information, as well as utilizing deduction and structured logical reasoning (Mhlanga, 2023; Shabalala, 2024). Consequently, to fully capitalize on the advantages AI offers, students must acknowledge and implement AI, along with the motivation for advanced learning (Mohamed Sapawi & Nik Yusoff, 2025; Sezer & Yilmaz, 2019).

Furthermore, research has underscored factors that boost students' motivation to learn AI skills and applications, including peer and teacher support, which have a positive social impact. Humans are inherently social, and their environment offers cues for appropriate behavior. Therefore, when their peers view Artificial Intelligence as pivotal, students develop a stronger intention and, subsequently, a higher motivation to excel in it (Chai et al., 2022).

While learning Artificial Intelligence, students' expectancy beliefs are influenced by self-efficacy perceptions, which refer to an individual's judgment of their ability to learn AI. Simultaneously, the perceived benefits of learning AI shape value beliefs (Chai et al.,2020). Motivation to use AI applications is thus inherent in a student, who directs their behavior toward the educational situation until learning is attained. The Expectancy-Value Theory (EVT) is one of the helpful theories that has positively fostered students' motivation to use AI. This theory is broadly implemented in educational psychology to understand achievement-oriented motivations. Additionally, it provides a cognitive and emotional understanding of the processes that emphasize students' preferences, effort, and persistence in academic pursuits. This theory suggests two pivotal factors determine students' motivation, academic performance, and choices to use AI applications: Expectancy and Task Value. Task value comprises four dimensions: Attainment Value, Utility Value, Intrinsic Value (Interest), and Cost. These four dimensions collectively shape students' motivation toward AI tasks and activities (Eccles & Wigfield, 2020; Rosenzweig et al., 2019).

Guided by the Expectancy-Value Theory, Wang et al. (2023) underscored the vital role of supportive environments and expectancy-value beliefs in improving university students' acceptance of AI learning applications, which in turn shape their motivation toward them. For instance, Chiu et al. (2023) highlighted the importance of teacher support for students' motivation to learn with AI-based chatbots, which, in turn, fosters the use of other applications. This circumstance reinforces the importance of facilitating acceptance as a prerequisite for achieving authentic motivation to learn and engage with these technologies. In the current study, we adopt the Expectancy-Value Theory (EVT) as the fundamental theoretical framework. Consequently, the Motivation toward AI Applications Scale was constructed to align with the theory's dimensions, ensuring that the instrument accurately measures the psychological and educational constructs intended for this research.

Moreover, several demographic factors affect learning in Artificial Intelligence, including field of study (e.g., English language students in the current study), gender, and academic year. Findings from a study by Owens and Lilly (2017) demonstrated that students' intentions toward technology vary according to their diverse educational experiences. Similarly, Mei (2019) reported that students at higher academic levels exhibit substantially higher perceived utility value than those at lower levels.

Several factors impede student motivation toward Artificial Intelligence and its applications. Aldosari (2020), in a study exploring the potential impacts of AI on higher education at Prince Sattam bin Abdulaziz University, reported a low level of awareness

concerning AI implementation mechanisms. The study underscored the urgent need for students to integrate AI applications in education. Additionally, Harkut and Kasat (2019) revealed growing concerns regarding the spread of AI because AI relies on complex technologies and algorithms not known by many, which consequently undermines trust in these systems.

Usually, in Arab universities, and particularly in Egypt, Artificial Intelligence remains a relatively nascent topic. Therefore, these institutions primarily maintain traditional educational approaches, with varying levels of technological infrastructure. Consequently, theoretical and empirical research on AI is scarce, and its educational applications are limited compared to the extensive efforts in international universities. Research efforts have predominantly addressed the availability of educational technology rather than its integration. Nonetheless, future strategic plans for these universities reveal a potential to adopt AI as a primary tool for developing and supporting higher education. Notable exceptions include diligent efforts to implement AI applications within the Faculties of Education for English language students and to boost their motivation to use these technologies.

Accordingly, our study seeks to enhance students' educational motivation to use Artificial Intelligence in the Special English Language Program at the Faculty of Education, Assiut University. This objective addressed the specific needs of this group, taking into account the nature of their studies, innovative research activities, and projects that require creative solutions to educational challenges. This condition occurs within an educational system that increasingly relies on adaptive learning based on each student's self-paced learning. Accordingly, the focus of the learning process shifts from the teacher to the student, with the teacher serving as a facilitator.

Problem Statement and Research Questions

This research is designed to elucidate students' educational motivation to use Artificial Intelligence in the Special English Language Program at the Faculty of Education, Assiut University. This issue is particularly relevant in the current era of digitalization, where AI-based digital technologies and media have become increasingly pivotal, especially for this category of students. Because we selected participants from the Special English Language Program at the Faculty of Education, our findings provide a focused insight into a high-potential student category. Additionally, developing a specialized instrument to measure students' educational motivation while using AI helps them invest their unique capabilities in a broader educational advancement for society. Our research may serve as a foundation for researchers to conduct additional studies across various university disciplines to enhance students' motivation to acknowledge and adopt these emerging and critical technologies.

The research problem can be expressed in the following main question: How can we enhance the students' educational motivation to use Artificial Intelligence in the Special English Language Program at the Faculty of Education, Assiut University?

Then, the following sub-questions are derived:

1. What is the current level of students' educational motivation to use Artificial Intelligence in the Special English Language Program at the Faculty of Education, Assiut University?
2. Are there statistically significant differences in the educational motivation for using Artificial Intelligence between third-year and first-year students in the Special English Language Program?
3. What are the proposed recommendations to enhance the students' educational motivation to use Artificial Intelligence in the Special English Language Program at the Faculty of Education, Assiut University?

Literature Review

Theoretical Framework and Related Studies: Artificial Intelligence offers substantial benefits to learners, who are the true intellectual capital and the primary players in the educational process. Even though educators often face challenges in addressing students' diverse educational needs, AI technology offers versatile, customized solutions that cater to learners' diverse needs. Using these technologies, we can diagnose students' prior knowledge, individual abilities, and learning readiness.

Concept and Applications of Artificial Intelligence

Aldosari (2020) defines Artificial Intelligence as a diverse set of techniques, methods, and tools for problem-solving and for creating simulated models that mimic human behavior. Moreover, AI applications are computerized mental systems that can engage in human-like cognitive processes, including learning, adaptation, synthesis, and self-correction (Luckin et al., 2016).

AI applications are among the most effective strategies for preparing a generation capable of responding to advances in scientific and state-of-the-art knowledge. Ernie (2021) reported that managing digitization-based hybrid education as a strategy has enhanced learning motivation in higher education and reinforced the teacher-student motivational relationship. Likewise, Alghamdi et al. (2023) underscored the notable impact of AI applications on elevating selective attention in primary school female students in Saudi Arabia.

Educational AI applications encompass expert systems, language and character recognition, speech processing, and pattern recognition, as well as applications in special education. Additionally, Fryer and Nakao (2019) demonstrated the role of robots in facilitating students' interest in learning other languages and reshaping traditional learning methods.

Furthermore, AI applications have helped specialists in decision-making by augmenting observational analysis and behavioral data through machine learning programs that support conclusions based on complex algorithms (Popenici & Kerr, 2017). Even though AI is increasingly preferred in global education, its integration and prevalence in Arab universities depend on students' acceptance of technology (Baytak, 2023).

While the technical capabilities of AI provide a robust framework for decision-making and observational analysis the successful integration of these tools within the academic landscape of Arab universities is not merely a matter of infrastructure. As Baytak (2023) suggests

the prevalence of these technologies is deeply contingent upon the human element specifically. The degree to which students accept and engage with digital innovation. This shift from institutional availability to actual classroom adoption necessitates a focused examination of the psychological drivers that govern student behavior. Therefore, understanding the internal mechanisms that propel a learner toward or away from technology is essential. To analyze this dynamic, it is critical to define the dual nature of motivation intrinsic and extrinsic as the primary lens through which students evaluate the utility and appeal of Artificial Intelligence.

Motivation to Learn and Use Artificial Intelligence: Intrinsic Motivation refers to tasks students engage in for the sake of the task itself; the learner is internally driven without needing external incentives, including studying because of the inherent enjoyment of the process. Conversely, Extrinsic Motivation pertains to activities undertaken to attain outcomes associated with external factors, such as rewards.

To this end, Ryan and Deci (2000) categorized motivation into the following types:

1. Intrinsic Motivation: Lauermann et al. (2017) demonstrated that intrinsic motivation urges students to set academic goals and sustain their engagement in relevant activities, ultimately leading to the achievement of intended learning outcomes.
2. Functional (Utility) Motivation: This motivation arises when students engage in tasks they perceive as high in value for their future careers and successful performance in a specific subject (Eccles & Wigfield, 2023). For instance, students with a positive inclination toward STEM careers demonstrate high motivation to learn in these fields after perceiving their utility value (Hamd et al., 2025; Rozek et al., 2015). However, students who do not acknowledge these career paths lack the motivation to learn the associated fields (Rosenzweig & Wigfield, 2016).

Accordingly, future educators must develop strategies to improve students' skills by nurturing both intrinsic and functional motivation toward Artificial Intelligence. To achieve this, administrators should encourage students to excel in AI and its applications by reinforcing instructional design incorporated into these technologies.

Expectancy-Value Theory (EVT)

The Expectancy-Value Theory (EVT) has substantially facilitated the identification of the motivational factors impacting university students' use of Artificial Intelligence (AI). This theory provides a cognitive and emotional framework for understanding achievement-oriented motivations, student preferences, and their persistence in academic endeavors, and is broadly applied in educational psychology. This theory suggests that two essential factors determine students' motivation and their choice to adopt AI applications:

1. Achievement Expectations (Expectancy): Expectancy refers to the individual’s belief in their ability to succeed in a specific task.
2. Task Value: This factor comprises four distinct dimensions:

- Attainment Value: This dimension refers to the perceived importance of completing a task, based on its alignment with the individual’s identity and self-concept.

- Utility Value: This dimension denotes the degree to which the task aligns with the individual's future goals, serving as an assessment measure of its usefulness in attaining long-term objectives.
- Intrinsic Value (Interest): Intrinsic value refers to the satisfaction and enjoyment derived from engaging in the task, driven by curiosity and inherent pleasure.
- Cost: This dimension captures the perceived potential disadvantages of participating in the task, including the effort required and the risk of failure.

In the specific context of AI, an in-depth understanding of these sub-dimensions provides a robust foundation for specifying the motivational drivers of AI application use. Collectively, these dimensions offer a comprehensive understanding of the influences that direct an individual's decision to undertake a task (Barron & Hulleman, 2015; Eccles & Wigfield, 2020; Rosenzweig et al., 2019; Ryan & Deci, 2000). We adopt this theory as the theoretical foundation for defining students' AI learning motivation as the structural framework for the measurement scale developed in this study.

The Significance of Learning Motivation in AI Applications

The role of learning motivation in the use of Artificial Intelligence applications is evident across several dimensions. Motivation serves as a primary engine, directing an individual's behavior toward a specific goal. To this end, it facilitates behavioral change and diversity; every motive pertains to a specific objective that the individual strives to achieve to attenuate tension. Consequently, an individual's behavior improves after multiple attempts to satisfy that motive. Ideally, long-term functional stimulation sustains students' intrinsic motivation during instruction. Students choose career paths based on their inherent interests and the perceived value attached to their desired professions (Mohamed M., 2014; Scherrer & Preckel, 2019). Therefore, students' long-term engagement must be maintained in learning tasks. Curriculum designers must emphasize these motivational requirements throughout the learning process (Ryan & Deci, 2000).

Moreover, Banda et al. (2023) examined the impact of interactive simulation-based learning on motivation and academic achievement among physics students at the University of Malawi. The results demonstrated that the experimental group, which used simulations, significantly outperformed the control group (taught via traditional methods) in both motivation and academic achievement.

Furthermore, the ARCS Motivational Model—which comprises Attention, Relevance, Confidence, and Satisfaction—can serve as a pedagogical framework for providing satisfying learning experiences. Consequently, this model facilitates students' motivation to learn and use Artificial Intelligence applications through the following dimensions:

- Attention: Capturing and maintaining students' interest in the learning content.
- Relevance: Building a clear connection between the content and the students' personal or professional needs.

- Confidence: Nurturing positive learning experiences and building self-assurance within an AI-based environment.
- Satisfaction: Improving students' fulfillment with the learning processes or their outcomes.

These four factors of motivational design, when appropriately designed and implemented, result in rewarding learning experiences and uphold students' sustained interest and motivation to learn (Hong et al., 2017; Keller, 2010).

METHOD

We employed a descriptive methodology because it aligns well with the objectives of the current study. This approach was employed to assess the students' educational motivation to use Artificial Intelligence in the Special English Language Program at the Faculty of Education, Assiut University. Additionally, it served as the foundation for proposing recommendations to improve educational motivation for AI incorporation among the target student population.

To verify the normality of the data distribution, the Kolmogorov-Smirnov test was applied, yielding a non-significant result (P = 0.073), which suggests that the data does not significantly deviate from normality. Furthermore, descriptive statistics indicated that Skewness (-0.45) and Kurtosis (0.35) were well within the acceptable limits of +_1.96. These results, combined with the robustness provided by the Central Limit Theorem for our sample size (N=160), confirm that the data meets the assumptions required for parametric analyses, specifically the Independent Samples T-test.

Participants

The research population comprises undergraduate students in the Special English Language Program at the Faculty of Education, Assiut University, specifically those in the first and third years. The total number of participants is 252 (172 students from the first year and 80 students from the third year). The study focused exclusively on this group because this group is situated within an educational environment conducive to achieving the research objectives. As Salas and Zawacki-Richter (2019) noted, learning environments and motivational beliefs are fundamental in shaping students' motivation to learn and engage with Artificial Intelligence.

We administered the instruments to a pilot sample of 60 students (38 from the first year and 22 from the third year) from the Special English Language Program at the Faculty of Education, Assiut University, Egypt. We selected these students from the research population but excluded them from the main study. All participants in this group use AI applications in their educational activities. The purpose of this stage was to confirm the psychometric properties (validity and reliability) of the research tools before the final administration.

We administered the final instruments to the main sample of 160 students (95 from the first year and 65 from the third year) in the Special English Language Program at the Faculty of Education, Assiut University. The data collection for the main study occurred during the first semester of the 2024/2025 academic year.

Data Collection

The Questionnaire of AI Use Motives (QAIUM), developed by Yurt and Kasari (2024), was employed to specify the motivational determinants driving students to engage with Artificial Intelligence. Moreover, the scale addresses the interaction between motivation and attitudes toward AI in education.

We designed the scale based on the Expectancy-Value Theory (EVT). This theory comprises two main dimensions: Expectancy and Task Value. The task value is further divided into four sub-dimensions: Attainment Value, Utility Value, Intrinsic Value (Interest), and Task Cost. The questionnaire comprises 20 items, distributed equally across 4 dimensions, with 4 items per dimension.

We confirmed the scale's validity through a rigorous two-stage process:

- Exploratory Factor Analysis (EFA): This analysis was conducted on a sample of 524 university students in Turkey. Using oblique rotation (due to intercorrelation among dimensions), we confirmed the five-factor structure in the analysis.
- Confirmatory Factor Analysis (CFA): To evaluate the model's goodness-of-fit, we used a separate sample of 544 students. The results revealed that all fit indices were within the optimal range, strongly evidencing that the five-factor structure aligns well with the underlying motives for AI use.
- Reliability: We assessed internal consistency using Cronbach's Alpha coefficients, which yielded high values, indicating excellent reliability for the scale and its sub-factors.

Table 1.

Dimensions of the Educational Motivation Scale for AI Use and their Corresponding Item Numbers

No	Dimension	Item Numbers	Total Items
1	Achievement Expectations	1, 2, 3, 4	4
2	Attainment Value	5, 6, 7, 8	4
3	Utility Value	9, 10, 11, 12	4
4	Intrinsic Value (Interest)	13, 14, 15, 16	4
5	Task Cost	17, 18, 19, 20	4
Total		1 – 20	20 Items

We administered the scale online and in a group to students in the Special English Language Program at the Faculty of Education. We did not set any time limit for completion. Scoring: A 5-point Likert Scale was used, with responses ranging from *Strongly Agree* to *Strongly Disagree*. Scores were assigned values of 5, 4, 3, 2, and 1, respectively, for positive items.

We calculated internal consistency as an indicator of the construct validity for the AI Learning Motivation Scale among students of the Special English Language Program. This step was achieved by calculating the Pearson Correlation Coefficients between each item's score and

the total score of its corresponding dimension. We administered the scale to a pilot sample of 60 first-year students from the research population (excluded from the main study). Table 2 illustrates the results.

Table 2.

Correlation Coefficients between Individual Items and their Respective Dimensions (N = 60)

Dimensions	Item No.	Correlation	Item No.	Correlation	Item No.	Correlation	Item No.	Correlation
Achievement Expectations	1	.669**	2	.856**	3	.810**	4	.788**
Utility Value	9	.711**	10	.823**	11	.733**	12	.756**
Attainment Value	5	.820**	6	.669**	7	.659**	8	.710**
Intrinsic Value (Interest)	13	.699**	14	.689**	15	.702**	16	.720**
Task Cost	17	.752**	18	.700**	19	.663**	20	.792**

(**) Significant at the (.01) level.

The data in Table 2 indicate the following:

- Correlation coefficients for the Achievement Expectations items ranged from 0.669 to 0.856, all highly significant.
- Correlation coefficients for Utility Value items ranged from 0.711 to 0.823, all significant at the.01 level.
- Correlation coefficients for Attainment Value items ranged from 0.659 to 0.820, demonstrating strong internal consistency.
- Correlation coefficients for Intrinsic Value/Interest items ranged from 0.689 to 0.720, revealing significant item-to-dimension alignment.
- Correlation coefficients for Task Cost items ranged from 0.663 to 0.792, all of which are statistically significant at the .01 level.

To further verify the internal consistency of the AI Learning Motivation Scale, we calculated Pearson correlation coefficients between each dimension's score and the scale's total score. This analysis ensures that each dimension meaningfully supports the overall construct of motivation. Table 3 presents the findings.

Table 3.

Correlation Coefficients between Dimension Scores and the Total Score of the AI Learning Motivation Scale (N = 60)

Dimensions	Correlation Coefficient

Achievement Expectations	.850**
Utility Value	.832**
Attainment Value	.856**
Intrinsic Value (Interest)	.743**
Task Cost	.814**
Total Scale Score	.862**

(**) Significant at the (.01) level.

To ensure the reliability of the AI Learning Motivation Scale, we calculated Cronbach's Alpha and McDonald's Omega coefficients using the data from the pilot sample (**N = 60**). Table 4 presents the results, with high, statistically significant reliability values for both the individual dimensions and the total score.

Table 4.

Cronbach's Alpha and McDonald's Omega Reliability Coefficients for the AI Motivation Scale Dimensions (N = 60)

No	Dimensions	Cronbach's Alpha	McDonald's Omega
1	Achievement Expectations	.864	.877
2	Utility Value	.785	.801
3	Attainment Value	.842	.853
4	Intrinsic Value (Interest)	.873	.882
5	Task Cost	.789	.799
Total	Total Scale Score	.853	.884

Table 4 reveals that:

- All Cronbach's Alpha coefficients for the dimensions are high, ranging from .785 to .873, yielding a total scale reliability of .853.
- All McDonald's Omega values are also high and significant, ranging from 0.799 to 0.882, with a total score of 0.884.
- These values exceed the accepted threshold in the social sciences (0.70), strongly indicating the scale's internal consistency and stability.

Data Analysis

Descriptive statistics were used to Assess the students' educational motivation to use Artificial Intelligence in the Special English Language Program at the Faculty of Education, Assiut University. To analyze participants' views, Mean and standard deviation analysis was used. Similarly, to Identify the differences in their educational motivation between third-year and first-year students to use Artificial Intelligence in the Special English Language Program, Means, Standard Deviations, and T-value analysis was used.

We calculated means and standard deviations to determine the motivation levels. The levels were interpreted based on the following 5-point Likert scale.

RESULTS

This section first presents the current level of students' educational motivation to use Artificial Intelligence in the Special English Language Program at the Faculty of Education, Assiut University. Also, presents statistically significant differences in the educational motivation for using Artificial Intelligence between third-year and first-year students in the Special English Language Program.

Firstly, this section presents the findings regarding the current level of educational motivation among students in the Special English Language Program at the Faculty of Education, Assiut University, concerning the use of Artificial Intelligence.

Table 5.

Means and Standard Deviations for the AI Educational Motivation Scale (N = 160)

Dimension	Mean	SD	Approval Level	Rank
Attainment Value	4.28	0.39	Very High	1
Task Cost	4.01	0.42	High	2
Intrinsic Value (Interest)	3.97	0.39	High	3
Utility Value	3.56	0.48	High	4
Achievement Expectations	3.25	0.42	Moderate	5
Total Scale Score	3.95	0.49	High	-

Table 5 shows a high level of students' educational motivation to use AI, with an overall mean of 3.95.

Detailed Observations are as follows:

- Attainment Value: It is ranked first with a Very High level (4.28). This finding suggests that students strongly perceive AI proficiency as pivotal to their academic and professional identity.
- Cost and Intrinsic Value: Both fell within the High range. Interestingly, the high "Task Cost" score (4.01) indicates that even though students are motivated, they are acutely aware of the effort and investment required to master these tools.
- Achievement Expectations: This property ranked last with a Moderate level (3.25). This finding is critical because it suggests that despite their high motivation, students may still have some uncertainty about their actual ability to master complex AI systems without further training.
- Data Consistency: This property shows relatively lower standard deviations than the means indicate, suggesting low dispersion and enhancing the accuracy and reliability of these findings.

Results of the Second Question

Secondly, the second question sought to determine whether statistically significant differences exist between first-year and third-year students in the Special English Language Program regarding their educational motivation to utilize Artificial Intelligence

Table 6.

Means, Standard Deviations, and -t-value for First-Year and Third-Year Students in the Overall Score of Educational Motivation for Using AI

Variables	First Level (n= 95)		Third Level (n= 65)		-t-Value	Significance Level
Educational Motivation for AI Use	M1	SD1	M2	SD2	17.86	0.01**
	98.35	2.54	86.10	2.89		

According to Table 6, there was a significant difference in "Educational Motivation for AI Use" levels between first and third-year students ($p<0.05$). Based on the group averages, first-year students achieved higher "Educational Motivation for AI Use" scores compared to third -year students

DISCUSSION

The results revealed a high level of students' educational motivation to use AI, which can be attributed to the technical skills they acquired (e.g., Kahoot, Character.ai) during their studies. This exposure bridged the digital gap and elevated their readiness to face technological challenges. This finding aligns with Narayan (2020), who posits that AI serves as a "bridge" connecting learners, educators, and computer scientists to facilitate innovation.

The "Attainment Value" ranked highest (Very High), demonstrating that students perceive AI proficiency as a pivotal component of their academic identity and success. Interestingly, the high "Task Cost" score indicates a positive "sacrifice-benefit" ratio; students are willing to invest substantial time and effort, even at the expense of other activities, to master AI tools. Townsend and Hunt (2019) support this commitment, who view AI as a pioneering technology that reshapes entrepreneurial and academic dynamics.

The high "Interest" and "Utility Value" scores suggest that English language students are beyond passive users and are passionate about AI's potential to render learning enjoyable and professional. This sense of "Quality of Academic Life" is associated with the requirements of the future labor market. As underscored by Okonkwo and Ade-Ibijola (2021), the widespread use of generative AI, such as ChatGPT, has reshaped higher education environments into more interactive and supportive spaces.

The "Moderate" score in "Achievement Expectations" is pivotal, indicating that even though students are highly motivated (Value), they still feel a gap in their actual mastery of AI tools (Expectancy). This finding necessitates the following:

- Enhancing students' practical skills through targeted workshops.

- Facilitating professional development for faculty members to transfer technical expertise effectively.

Our discussion aligns with Mahalinga (2023) and McMurtrie (2023), who report that AI tools should be viewed like calculators or computers—essential instruments that enhance learning outcomes. Rather than fearing negative impacts, Shamsan et al. (2023) underscore the use of ChatGPT as a proactive educational tool.

The University should move beyond elective digital literacy and move toward "Embedded AI Lab Sessions" specifically for the Special English Language Program. This involves moving from theoretical awareness to Guided Mastery, where students move from being passive users of tools like Character.ai to creators of AI-prompted lesson plans.

The results of the third hypothesis indicated statistically significant differences in motivation between third-year and first-year students regarding the use of AI applications, favoring third-year students. This finding is attributed to third-year students' greater learning experience and their longer engagement with these applications than first-year students. Consequently, motivation levels rise as academic levels progress, because learning opportunities via AI applications increase.

Moreover, we attribute this finding to the students' acquisition of AI-related skills and concepts over the years of their study. Practicing various applications in the educational field, including expert systems, natural language processing (NLP), character recognition, automated tutoring, and pattern recognition, has substantiated their motivation. Specifically, the use of applications in English language learning, including Kahoot!, Character.ai, and others, has boosted their learning motivation, adaptation to technical requirements, and their ability to confront digital challenges linked to AI.

These findings align with Narayan (2020), who reported that incorporating digital technologies into educational activities improves learners' acceptance of performance expectancy, effort expectancy, facilitating conditions, and social influence. This finding aligns well with the expected value theory. This circumstance, in turn, stimulates technological learning motivation for performance expectations, utility value, and attainment value (Liebregts et al., 2019; Townsend & Hunt, 2019).

Furthermore, Goswami and Dutta (2016) found that increased AI use by a student’s peers, role models, or social circle boosts their own motivation to learn. Venkatesh et al. (2012) also underscored that indicators of technology acceptance models serve as motivational factors in driving students to master these applications.

The Faculty of Education can implement a Senior-Junior AI Mentorship Circle. Third-year students, who have already navigated the Task Cost and seen the Utility Value in their practicum, can lead workshops for incoming freshmen. This leverages the finding that social influence and peer success (Goswami & Dutta, 2016) are powerful motivators. It also positions Assiut University as a leader in collaborative, student-led digital transformation.

Assiut University's Measurement and Evaluation Center could spearhead a professional development series focused on Gen-AI Pedagogical Integration**.** If faculty members are not proficient in Natural Language Processing (NLP) or automated tutoring, they cannot effectively transfer that expertise to students. Institutionalizing a Digital Teaching Fellowship would ensure that the high Interest and Utility Value found in this study are met with high-quality, faculty-led innovation.

The research findings support the creation of an AI-Enhanced Language Lab within the Faculty. By creating a dedicated space where AI is treated as an essential instrument (similar to the views of Mahalinga, 2023), the university can reduce the perceived Task Cost. This would transform the sacrifice-benefit ratio into a seamless part of the academic workflow, ensuring that Assiut University graduates are not just English specialists, but AI-fluent educators ready for the international market.

CONCLUSION

Based on the research conducted at Assiut University regarding the promotion of AI learning motivation among Special English Program students, we reached the following conclusions:

First: High Intrinsic Motivation and Technological Awareness

The study concludes that students in the Special English Language Program have a strong educational motivation to use Artificial Intelligence applications. This finding suggests that students are no longer passive recipients of technology and are internally motivated to recognize AI's critical role in their academic and professional futures. This intrinsic drive is a pivotal indicator of technological readiness, indicating that students value AI as an essential tool for improving their linguistic and research capabilities rather than just a modern trend.

Second: The Impact of Academic Experience on Acceptance Our research vividly illustrates the "experience gap" between academic levels, with the third-year students demonstrating higher motivation than their first-year counterparts. This finding can be associated with the cumulative educational experience and increased exposure to AI tools in classroom activities and research projects, verifying that motivation is not static. It grows as students move from theoretical awareness to practical application, diminishing the perceived "cost" of effort and improving their confidence in handling complex digital systems.

Third: Transition Toward Student-Centered Adaptive Learning

Our study underscores a fundamental shift in the educational paradigm toward "Adaptive Learning" nurtured by AI. By enabling students to learn at their own pace and tailoring content to individual differences, AI reorients the educational process from the teacher to the student. In this new model, the teacher's role is reconceptualized as a facilitator and guide, reducing the administrative and cognitive burdens on both parties and fostering a more engaging, creative learning environment.

Fourth: The Role of Supportive Institutional Environments Finally, we underscore those social and institutional cues, such as teacher and peer support, deeply impact student motivation. A

university environment that prioritizes AI as a 21st-century skill notably boosts students' "expectancy-value" beliefs. We recommend that higher education institutions leverage this high level of motivation by formally incorporating AI into curricula and providing robust technical infrastructure, enabling graduates to be future-proofed and ready for a globalized, AI-driven job market.

Limitations

Despite the significant contributions of this study to the understanding of digital learning, several inherent limitations must be acknowledged. The design used in this research restricts the ability to draw causal inferences; therefore, it would be beneficial for future studies to investigate the combined effect of both variables.

The demographic scope of this study—centered on university students in Assiut University in Assiut city, Egypt—also presents a limitation regarding generalizability. Cultural and educational norms significantly influence how technology is adopted; therefore, cross-cultural replications are essential to determine if these mechanisms remain consistent in diverse global environments.

Recommendations

Based on the study's findings, we propose the following recommendations:

- Curriculum Integration: Integrate AI applications into the specialized courses of the Special English Language Program and establish a dedicated course on "AI in Education" for teacher preparation programs.
- Skill Development: Launch training programs addressing practical AI skills and robotics, offering a high-tech learning environment for both curricular and extracurricular activities.
- Motivational Workshops: Organize seminars to raise awareness about the ethical and optimal use of AI, emphasizing its utility value for career readiness.
- Innovation Incentives: Urge students to use AI tools for creative problem-solving and environmental initiatives to ensure the continuity of intrinsic motivation.

Funding

This research was funded with the project number (PSAU/2025/02/34269) at Abdulaziz University.

Acknowledgements

We extend our appreciation to Prince Sattam bin Abdulaziz University for funding this research work with the project number (PSAU/2025/02/34269).

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