"It Seems Promising, But Is It Practical?": Exploring Social Science Students' Adoption of AI in Active Learning Using the UTAUT2 Model

by

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Abstract:

Artificial intelligence (AI) is rapidly reshaping higher education, offering new ways to make learning interactive, efficient and engaging. However, we still know surprisingly little about how students embrace these tools, especially in active learning classrooms. This study explored the factors that drive social science students at Sultan Qaboos University in Oman to adopt AI in their learning, shedding light on an area that has often been overlooked in the literature. To understand these patterns, a survey was conducted with 475 students from a wide range of social science disciplines. Using a quantitative research design and ordinal logistic regression model, guided by a well-established framework termed the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), factors such as how useful students believe AI to be, how easy it is to use, the influence of peers and instructors, and whether AI makes learning more enjoyable or rewarding were examined.

The findings showed that most students were keen to use AI tools, with five key factors identified as strong motivators for their use. The biggest driver was effort expectancy; students were more likely to adopt AI if they felt that it was easy to learn and apply. Belief in its usefulness, the enjoyment it brings, encouragement from others, and having the right support systems also played important roles. Interestingly, routine habits did not seem to matter much, suggesting that many students are still in the early stages of exploring these technologies rather than using them automatically or habitually. This study offers novel insights for educators, university leaders, and policymakers seeking to incorporate AI into social science education in meaningful ways. By understanding what inspires students to try new technologies and what holds them back, institutions can create learning environments that not only keep pace with global innovation but also respect unique cultural and educational contexts.

Keywords: Artificial Intelligence, Active Learning, Technology Adoption, Social Science Education, UTAUT2 Framework.

استكشاف العوامل المؤثرة في تبني طلبة العلوم الاجتماعية للذكاء الاصطناعي في التعلم النشط باستخدام نموذج UTAUT2

الملخص:

تُعيد تقنيات الذكاء الاصطناعي تشكيل التعليم العالي بوتيرة متسارعة، حيث تتيح فرصًا جديدة لجعل التعلم أكثر تفاعلًا وفعالية وجاذبية. ومع ذلك، ما زال هناك غموض كبير يحيط بكيفية تفاعل الطلبة مع هذه الأدوات، خصوصًا في بيئات التعلم النشط. تهدف هذه الدراسة إلى استكشاف العوامل التي تدفع طلبة العلوم الاجتماعية في جامعة السلطان قابوس بسلطنة عمان إلى تبنّي تقنيات الذكاء الاصطناعي في عملية التعلّم، في محاولة لسد فجوة بحثية لم تحظَ بالاهتمام الكافي. حيث استندت الدراسة إلى استبانة شملت ٤٧٥ طالبًا وطالبة من مختلف تخصصات العلوم الاجتماعية. استخدمت الدراسة المنهج الكمي ونموذج الانحدار اللوجستي الترتيبي، واستندت إلى إطار نظري يُعرف بـ"النموذج الموحد الموسّع لقبول واستخدام التكنولوجيا ($UTAUT_2$)"، وذلك لتحليل عوامل متعددة مثل مدى إدراك الطلبة بفعالية الذكاء الاصطناعي، وسهولة استخدامه، وتأثير الأقران وأعضاء هيئة التدريس، إلى جانب مدى الإحساس بالمتعة المتحققة أو القيمة التعليمية الناتجة عن استخدامه.

أظهرت النتائج أن غالبية الطلبة متحمسون لاستخدام أدوات الذكاء الاصطناعي، وتم تحديد خمسة عوامل رئيسية تؤثر على قرارات التبني لديهم. كان أبرزها هو "الجهد المتوقع"، أي ميل الطلبة لتبنّي الذكاء الاصطناعي عندما يشعرون أنه سهل التعلّم والتطبيق. كما لعبت عوامل أخرى مثل: الأداء المتوقع، والدافع الترفيهي، والدعم الاجتماعي، وتوفر البنية التحتية المناسبة، أدوارًا مهمة في تعزيز التبني. في المقابل، لم يكن لعامل العادة تأثير يُذكر، مما يشير إلى أن الطلبة لا يزالون في مراحلهم الأولى من استكشاف هذه التقنيات، دون أن تتحول بعد إلى أدوات يستخدمونها بشكل تلقائي. توفر هذه الدراسة رؤى جديدة ومهمة للجهات التربوية والأكاديمية وصناع القرار، في سعيهم لتكامل الذكاء الاصطناعي مع تعليم العلوم الاجتماعية بشكل فعّال. فمن خلال فهم ما يُلهم الطلبة لتجربة التكنولوجيا، وما قد يُعيقهم، يمكن تصميم بيئات تعليمية تواكب الابتكار العالمي، وتظل في الوقت ذاته منسجمة مع السياقات الثقافية والتعليمية المحلية.

الكلمات المفتاحية: الذكاء الاصطناعي، التعلم النشط، تبنّي التكنولوجيا، تعليم العلوم الاجتماعية، إطار $UTAUT_2$.

Introduction:

The contemporary landscape of higher education is experiencing an unprecedented transformation as artificial intelligence (AI) emerges as a pivotal force reshaping pedagogical paradigms and active learning methodologies (López-Chila et al., 2024; Shamkuwar et al., 2023). This technological revolution represents what Kamalov et al. (2023) characterized as a "new era of artificial intelligence in education," marking a sustainable multifaceted revolution that fundamentally reconfigures traditional educational approaches. Recent systematic reviews examining AI in higher education from 2016 to 2022 reveal a dramatic expansion of research and implementation, with institutions globally recognizing AI's potential to enhance student engagement, collaborative knowledge construction, and experiential learning (Granić, 2022; Lim et al., 2023). This technological integration constitutes a fundamental reconfiguration of educational epistemologies that positions AI as a catalyst for transforming passive learning environments into dynamic, student-centered ecosystems of knowledge creation.

The proliferation of AI-enhanced educational technologies manifests through intelligent tutoring systems that dynamically adapt to student-directed inquiry processes, sophisticated feedback mechanisms that respond with unprecedented granularity to learner-generated content, and immersive simulation environments that transform passive observation into active participatory discovery (Zhou et al., 2024). Contemporary educational platforms deploy sophisticated algorithms capable of scaffolding collaborative problem solving, dynamically recalibrating experiential learning pathways to accommodate diverse cognitive architectures and providing just-in-time guidance at critical junctures of student-led investigations. These technological affordances demonstrate promise within active learning frameworks, where traditional teacher-centered approaches yield student-driven exploration, collaborative knowledge construction, and authentic problem-solving experiences (Palacios-Rodríguez et al., 2024).

Research on personalized adaptive learning has revealed significant potential for enhancing academic performance and engagement through customized learning pathways that respond to individual student needs and learning patterns (du Plooy et al., 2024). Comparative studies have demonstrated that adaptive learning systems can be as effective as teacher-led instruction when properly implemented. According to Wang et al. (2023), adaptive learning environments significantly improve student outcomes when aligned with pedagogical best practices. Contrino et al. (2024) demonstrated that adaptive learning tools enhance both student performance and satisfaction in online and face-to-face educational contexts, supporting a more personalized approach to learning.

Khamis et al. (2024) provide a systematic review revealing that immersive technologies can significantly improve student engagement and learning outcomes when appropriately integrated into pedagogical frameworks. These findings align with ElSayary's (2024) research on integrating generative AI into active learning environments, which demonstrated enhanced metacognition and technological skills development through carefully designed AI-enhanced learning experiences.

Research specifically examining humanities and social sciences students' intentions to use AI applications reveals complex patterns of acceptance and resistance among them. Lavidas et al. (2024) identified key determinants influencing students' willingness to adopt AI tools for academic purposes, highlighting the importance of perceived usefulness, ease of use, and alignment with academic values. Their findings suggest that social science students may have distinct adoption patterns compared to students in other disciplines, which are influenced by disciplinary cultures and pedagogical traditions.

Emerging research provides compelling evidence that AI, when aligned with active learning principles, can substantially enrich social science education. Studies examining AI applications in personalized learning environments reveal significant potential for enhancing student engagement and learning outcomes, particularly through conversational agents that facilitate student-driven dialogic inquiry, intelligent writing environments that enhance metacognitive reflection, and virtual ethnographic spaces that enable immersive engagement with social contexts previously inaccessible within conventional classroom parameters (Zhou et al., 2024; Bilquise et al., 2023).

Ouyang and Jiao (2021) proposed three paradigms for AI in education that are particularly relevant to understanding these applications: AI-directed learning (where AI makes decisions about learning content and pace), AI-supported learning (where AI assists human decision-making), and AI-empowered learning (where AI augments human capabilities). Within active learning contexts, AI-supported and AI-empowered paradigms show the greatest promise for maintaining student agency while enhancing learning experiences.

Nevertheless, significant barriers persist, including technical literacy deficits, faculty resistance to curricular reconfiguration, infrastructural inadequacies, and ethical considerations surrounding the algorithmic mediation of human interaction within educational contexts (Granić, 2022). Research in diverse cultural contexts reveals additional complexities in AI adoption patterns. Wafik et al. (2024) examined academics' perspectives on AI integration in Bangladesh's higher education, revealing both opportunities and challenges that may be culturally specific.

In higher education contexts, UTAUT2 has established itself as a significant model for technology acceptance, with applications extending to various educational technologies, including educational chatbots and e-learning platforms (Xue et al., 2024). The model’s multidimensional structure encompasses constructs particularly relevant to understanding AI adoption within active learning environments: performance expectancy, effort, facilitating conditions, social influence, hedonic motivation, and habitual engagement (Venkatesh et al., 2012; Kavitha & Joshith, 2024).

Recent studies have successfully applied UTAUT2 to examine AI adoption in educational contexts. Research on university students’ acceptance of ChatGPT using UTAUT2 revealed significant insights into behavioral intentions and usage patterns (Zhang & Aslan, 2024), while studies exploring Chinese university educators’ acceptance of AI tools demonstrated the model’s cross-cultural applicability (Chen et al., 2024). Additionally, investigations into pedagogical beliefs and generative AI adoption have provided valuable insights into the factors influencing technology acceptance in higher education (Palacios-Rodríguez et al., 2024). However, empirical research specifically addressing AI adoption in active learning environments, particularly in social science disciplines and Middle Eastern educational contexts, remains limited.

Sultan Qaboos University represents a compelling case study at the intersection of technological innovation and active learning philosophy in the Arab Gulf context. The institution’s pedagogical framework emphasizes the learner at the center of the learning process, epistemic construction of understanding through experiential engagement, and lifelong cognitive development through participatory experience. These principles demonstrate natural alignment with active learning approaches that promote collaborative knowledge construction, authentic problem-solving, and demonstrable competency development through practical applications.

The university's commitment to active learning is clarified through graduate attributes encompassing intellectual versatility, professional competence, ethical discernment and nurtured innovative potential. These aspirational qualities materialize through inverted classroom structures, inquiry learning and virtual simulation pedagogical approaches that are increasingly enhanced through AI integration.

This study addresses the following research question: What are the key factors influencing social science students' adoption of AI tools, specifically within active learning environments at Sultan Qaboos University, as examined through the UTAUT2 framework?

Theoretical framework and hypotheses

The integration of Artificial Intelligence (AI) into active learning environments presents transformative opportunities for educational practices, particularly within the social sciences. AI applications can deliver personalized feedback, simulate complex real-world scenarios, and facilitate interactive learning experiences, thereby fostering deeper cognitive engagement and cultivating independent critical thinking. As educational institutions increasingly embed AI technologies into pedagogical approaches, understanding the determinants of student acceptance and effective utilization is crucial for successful implementation.

This study employs the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) to examine the factors influencing AI adoption in active learning environments among social science students. UTAUT2, which builds upon the original model developed by Venkatesh et al. (2003), introduces three additional constructs: hedonic motivation, price value, and habit, providing a more nuanced framework for analyzing technology adoption behaviors (Venkatesh et al., 2012). The model's strength lies in its capacity to capture both the utilitarian and experiential dimensions of technology use, making it particularly suitable for investigating AI integration in educational contexts.

Performance Expectancy (PE)

Performance expectancy refers to the degree to which students believe that using a particular technology improves their academic performance (Venkatesh et al., 2003). In the context of active learning, AI tools can support analytical thinking, enhance classroom interaction, and streamline access to relevant content. For social science students, AI applications may assist in structuring arguments, generating discussion prompts, or analyzing qualitative data, all of which contribute to improved learning outcomes. Prior studies have consistently demonstrated a strong relationship between performance expectancy and behavioral intention in the context of educational technology adoption (Das & Datta, 2024; Kabra et al., 2017). Based on this, the following hypothesis is proposed:

H1: Performance expectancy has a statistically significant positive effect on students' behavioral intention to adopt AI in active learning.

Effort Expectancy (EE)

Effort expectancy reflects the ease of using a given technology and the level of cognitive effort required for its integration (Venkatesh et al., 2012). For AI tools in social science education, intuitive design, minimal learning curves, and accessible language interfaces are essential for encouraging student participation. Tools that simplify data interpretation, offer academic writing assistance, or simulate social scenarios must be easy to adopt to maximize their educational impacts. Research supports the role of effort expectancy as a critical factor influencing technology adoption, particularly among learners encountering new digital systems (Abdalla et al., 2024; Tamilmani et al., 2021). Therefore, the following hypothesis is proposed:

H2: Effort expectancy has a statistically significant positive effect on students' behavioral intention to adopt AI in active learning.

Facilitating Conditions (FC)

Facilitating conditions refer to the institutional and technical infrastructure that supports technology adoption (Venkatesh et al., 2003). These include access to reliable Internet, digital devices, institutional training, and supportive learning environments. In higher education, particularly in social science programs, access to well-integrated AI platforms, academic guidance, and responsive technical support is essential for successful adoption of AI. Studies have shown that robust facilitating conditions enhance users' confidence and reduce barriers to technology integration (Nikolopoulou et al., 2021; Strzelecki, 2024). Thus, the following hypothesis is proposed:

H3: Facilitating conditions have a statistically significant positive effect on students' behavioral intention to adopt AI in active learning.

Social Influence (SI)

Social influence represents the extent to which individuals perceive that others, such as instructors, peers, or institutions encourage or expect them to use a technology (Venkatesh et al., 2003). Among social science students, the promotion of AI use by professors, peer endorsement, and institutional initiatives can significantly shape behavioral intentions. For example, a course in which the instructor actively uses AI-supported simulations or reflection prompts can normalize and reinforce AI adoption. Research has emphasized the heightened role of social influence in collectivist and collaborative learning environments (Hoque & Sorwar, 2017; Mehta et al., 2019). Hence, the following hypothesis is proposed:

H4: Social influence has a statistically significant positive effect on students' behavioral intention to adopt AI in active learning.

Hedonic Motivation (HM)

Hedonic motivation is the perceived enjoyment or pleasure derived from using technology (Venkatesh et al., 2012). In active learning settings, AI tools that engage students through interactive simulations, scenario-based tasks, or real-time feedback systems can make the learning experience more enjoyable and intrinsically rewarding for students. When students find the learning process fun and stimulating, they are more likely to adopt and sustain AI tool use. Prior research has linked hedonic motivation to increased engagement and technology adoption in educational contexts (Al-Azawei & Alowayr, 2020; Nikolopoulou et al., 2021). Therefore, the following hypothesis is formulated:

H5: Hedonic motivation has a statistically significant positive effect on students' behavioral intention to adopt AI in active learning.

Habit (H)

Habit represents the extent to which individuals tend to automatically perform behaviors due to learning (Venkatesh et al., 2012). In educational technology research, habits reflect the degree to which students have integrated AI tools into their routine academic practices. As students repeatedly engage with AI applications for specific learning tasks, these behaviors may become increasingly automatic and less deliberate. Empirical studies have demonstrated that habits significantly predict continued technology use in educational contexts (Strzelecki, 2024; Tamilmani et al., 2021). Consequently:

H6: Habit positively influences students' behavioral intention to adopt AI in active learning.

Based on the theoretical framework and hypotheses outlined above, Figure 1 presents the conceptual model that guided this research. The model illustrates the proposed relationships between the six independent variables (performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, and habit) and the dependent variable (behavioral intention to adopt AI in active learning).

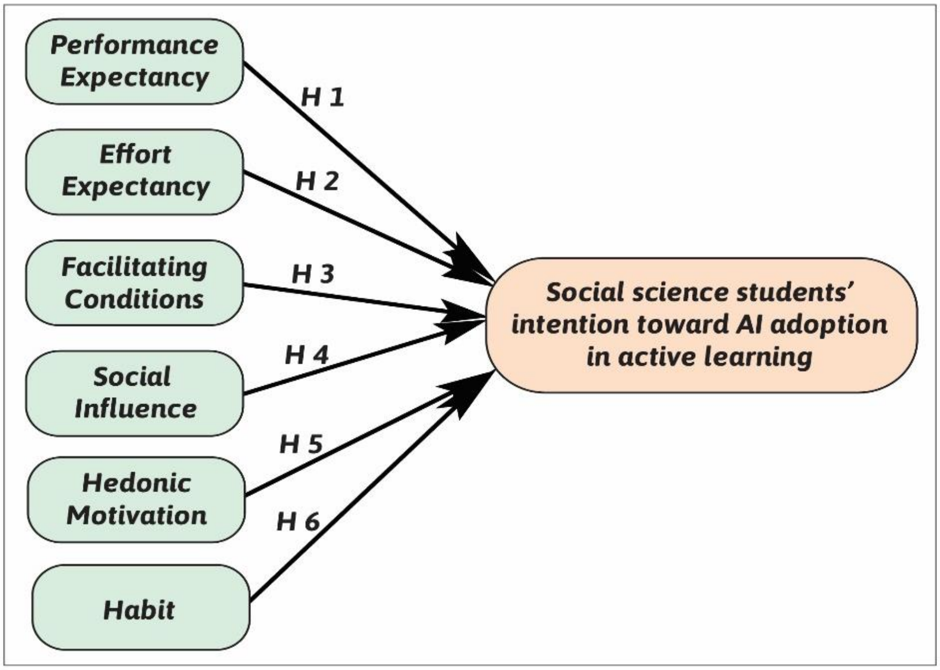

Figure 1. Conceptual Framework Based on the UTAUT2 Model

Methodology

Study design

This study employed a cross-sectional descriptive quantitative research design to investigate the primary research objective of identifying the key factors influencing the adoption of artificial intelligence (AI) tools in active learning environments among social science students. This methodological approach allowed for a systematic examination of the relationships between multiple predictor variables and AI adoption intentions within a natural educational context. Data were collected using a structured self-administered questionnaire developed based on established technology adoption frameworks, particularly the Unified Theory of Acceptance and Use of Technology (UTAUT).

Development of measurement framework

The measurement instrument was systematically developed through a rigorous process to assess students' engagement with artificial intelligence (AI) tools in active learning contexts and identify the psychological and contextual factors influencing their adoption behaviors. The final questionnaire was structured into two comprehensive sections, supplemented by demographic profiling items. The first section examines students' interaction patterns with AI tools in academic settings. This component incorporated multidimensional items that measured AI utilization across various educational activities: content summarization, interactive learning support, data-informed academic discussions, and engagement with intelligent platforms designed to enhance conceptual understanding and participation in the learning process. This section was designed to quantify the depth and breadth of AI integration into students' existing learning practices through behaviorally anchored response items.

The second section operationalized the determinants of AI adoption through six theoretically grounded constructs derived from the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh et al., 2012), with domain-specific adaptations to reflect the educational technology context. Performance expectancy assessed students' perceptions regarding AI's capability to enhance academic achievement, deepen conceptual understanding, facilitate knowledge retention, and support higher-order cognitive processes (sample item: "AI tools help me achieve better learning outcomes by providing personalized feedback on my academic work"; $\alpha = 0.87$). Effort expectancy measured the perceived usability, learnability, and cognitive load associated with AI tools, including the ease of integrating these technologies into existing academic workflows and learning processes (sample item: "I find that integrating AI tools into my coursework requires minimal additional effort"; $\alpha = 0.84$). Facilitating conditions evaluated the institutional, technical, and pedagogical infrastructure supporting AI implementation, encompassing hardware/software availability, technical support mechanisms, instructional scaffolding, and interoperability with existing learning management systems (sample item: "My institution provides adequate resources and support for effectively utilizing AI in my coursework"; $\alpha = 0.81$). Social influence captured the normative dimensions of AI adoption, quantifying the extent to which peers, instructors, academic mentors, and broader educational communities influenced students' perceptions and utilization patterns of AI technologies (sSample item: "My instructors actively encourage the responsible use of AI tools to enhance learning activities"; $\alpha = 0.83$). Hedonic motivation assessed the affective and engagement dimensions of AI use, focusing on perceived enjoyment, intellectual stimulation, curiosity satisfaction, and the capacity to enhance learning engagement through interactive and immersive experiences (sample item: "Using AI tools makes my learning experience more engaging and intellectually stimulating"; $\alpha = 0.85$). Finally, Habit examined the extent to which AI utilization had become automatized in students' academic routines, measuring frequency of use, technological dependence, and integration into established study patterns (sample item: "Consulting AI tools has become a natural part of my approach to addressing academic challenges"; $\alpha = 0.79$). All constructs demonstrated satisfactory convergent and discriminant validity, as evidenced by factor loadings exceeding 0.70 and average variance extracted values above the recommended threshold of 0.50.

Each construct was operationalized through 4-6 items rated on a five-point Likert-type scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The scale development process included content validation through an expert panel review (n=5) and preliminary cognitive interviews with students (n=12) to ensure item clarity, relevance, and comprehensiveness. The dependent variable, behavioral intention to adopt AI in active learning contexts was measured using a separate multi-item scale capturing students planned future engagement with AI across diverse educational activities.

Dependent variable

The dependent variable, "Adoption of AI in Active Learning," was assessed through an aggregate score derived from six principal constructs informed by the UTAUT2 model: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit. These constructs were selected to provide a comprehensive understanding of students' behavioral intentions and actual practices in utilizing AI tools in educational environments. Each construct was measured using a set of clearly defined items on a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), as presented in Section Three of the instrument. Responses across all items were averaged to generate a unified adoption score that reflected the overall level of engagement with AI-supported learning. Based on these scores, students were categorized into three levels of AI adoption: low (1.00–2.33), moderate (2.34–3.66), and high (3.67–5.00).

Table 1. Dimensions and measurement of ai adoption for active learning in social science education

Dimensioı	Definition	Measurement Item
Behaviora Intention to U AI Tools	The level of students' willingn and motivation to adopt AI tool enhance their learning experier	I am motivated to use AI tool: support my learning in socia science classes.
Perceived Engagement v AI-Enhance Learning	The degree to which students f committed to engaging AI tool enhance critical thinking anc problem-solving.	I am willing to invest time aı effort in using AI tools to strengthen my cognitive - learı skills.
Intention t Integrate AI i Academic Ta	The extent to which students p to incorporate AI tools into th academic tasks and study practi	I intend to integrate AI tools i my academic work to improve problem-solving and critica thinking skills.
Anticipate Frequency of Tool Usag	The frequency with which stud expect to use AI tools for diffe learning activities and assignme	I expect to use AI tools regula during coursework and stud sessions.

Independent variables

The independent variables presented in Section Three of the questionnaire were developed in alignment with the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), incorporating six primary constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit. Each construct was measured using multiple items (four to five per construct) designed to comprehensively capture students' perceptions of the integration of AI in active learning. Responses were recorded on a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), allowing for a nuanced assessment of agreement levels. These items were carefully constructed to ensure content validity, consistency, and clarity in reflecting the theoretical dimensions of the UTAUT2 Model. The detailed measurement structure is reflected in Section Three of the questionnaire, supporting a robust analysis of the determinants influencing students' adoption of AI technology in academic settings.

Table 2: Independent variables and their measurement items

1. Performance expectancy
1.1 AI tools help me achieve better learning outcomes.
1.2 AI enhances my deep understanding of subjects by providing customize content.
1.3 AI can support academic discussion.
1.4 AI helps me develop creative solutions for academic problems.
1.5 AI facilitates research and academic review in active learning.
2. Effort expectancy
2.1 I find AI tools easy to use in interactive learning processes.
2.2 I do not need extensive training to use AI in my studies.
2.3 I can easily integrate AI technologies into my academic activities.
2.4 AI user interfaces help me complete tasks easily.
2.5 I can learn how to use AI without assistance.
3. Facilitating conditions
3.1 The university provides a technological infrastructure that supports AI u in learning.
3.2 I can access technical support when facing difficulties using AI.
3.3 I have the necessary devices and software to use AI effectively.
3.4 The university offers appropriate training on how to integrate AI in studi
3.5 The university provides supportive policies and guidelines to facilitate A use in active learning.
4. Social influence
4.1 My peers encourage me to use AI tools in active learning.
4.2 My instructors motivate me to use AI in learning.
4.3 The university supports integrating AI as part of the modern learning environment.

4.4 My academic advisor guides me toward using AI tools in learning.

5. Hedonic motivation
   5.1 I find AI makes learning more enjoyable and interactive.
   5.2 AI helps me explore academic topics in creative ways.
   5.3 I enjoy interacting with AI applications that support active learning.
   5.4 I feel excited when using AI tools in my studies.
6. Habit
   6.1 Using AI has become an essential part of my learning style.
   6.2 I frequently rely on AI to complete my academic assignments.
   6.3 I automatically depend on AI when looking for new information.
   6.4 I feel comfortable using AI tools to accomplish academic tasks.

Data analysis procedure

The analytical strategy employed in this study is designed to address its two principal research objectives. The first objective, which seeks to explore the extent to which social science students engage with artificial intelligence (AI) tools in active learning environments, is addressed through the use of descriptive statistical analyses. These analyses provide a comprehensive overview of students' usage patterns and perceptions across the key constructs outlined in the UTAUT2 framework. The second objective, which focuses on identifying the underlying factors that influence students' adoption of AI technologies, is investigated using ordinal logistic regression (OLR). OLR is particularly well-suited for modeling dependent variables with ordinal outcomes, where response categories follow a meaningful sequence without assuming equal intervals between them (Sönning, 2024). This dual-method approach enables a holistic understanding of both the behavioral trends and the motivational drivers underpinning AI adoption among social science students.

Ordinal logistic regression is advantageous in its ability to accommodate a combination of categorical and continuous predictor variables, aligning well with the multidimensional nature of the constructs measured in this study (Vana-Gür, 2024). The primary goal of the OLR model is to estimate the probability that a given observation falls within a specific ordered category of the dependent variable. A critical assumption of this model is the proportional odds assumption, which asserts that the relationship between each predictor and the cumulative log odds of the outcome is consistent across all thresholds. This assumption simplifies the interpretation of results by allowing a single set of coefficients to describe the influence of predictors across all levels of the ordinal outcome. Positive coefficients indicate a greater likelihood of being classified into a higher level of AI adoption, whereas negative coefficients reflect a reduced likelihood (Gjermëni, 2024).

To facilitate meaningful interpretation, the coefficients obtained from ordinal logistic regression (OLR) are commonly transformed into odds ratios (OR), providing a more intuitive representation of effect sizes. An OR greater than 1 indicates an increased likelihood of being in a higher response category, whereas an OR less than 1 denotes a reduced likelihood. For instance, an OR of 1.25 corresponds to a 25% increase in the odds of higher-level adoption, while an OR of 0.80 reflects a 20% decrease. This transformation enhances the clarity and accessibility of statistical findings, particularly within applied educational research contexts (Wang, 2024). The analysis adopts a systematic procedure, commencing with an evaluation of the proportional odds assumption. This is assessed using the parallel lines test, where a non-significant p-value indicates that the assumption holds and supports the suitability of the ordinal logistic regression model (Borges & de Castro, 2024). Once this assumption is confirmed, the analysis proceeds to examine the estimated coefficients, corresponding odds ratios, and model thresholds to determine the key predictors influencing behavioral intention. The model's overall adequacy is subsequently assessed through fit statistics, including the Likelihood Ratio (LR) Test and pseudo R square indices. The LR Test evaluates whether the inclusion of independent variables significantly enhances model performance compared to the null model. Additionally, pseudo R square measures such as Nagelkerke and McFadden are reported to estimate the proportion of variance explained by the model, offering insight into its explanatory capacity (Ugba & Gertheiss, 2023).

Study participants

The study sample comprises 475 students enrolled in diverse social science programs at Sultan Qaboos University (SQU), including Arabic Language, English Language, Mass Communication, Social Work, Sociology, Music, Information Studies, Geography, History, and Tourism. This multidisciplinary cohort represents a comprehensive cross-section of social science disciplines, enabling a thorough examination of students' engagement with artificial intelligence tools in active learning environments. The inclusion of participants with both specialized linguistic training and broader social science backgrounds facilitates comparative analysis of AI adoption patterns across different academic specializations. Demographic distribution details regarding gender, field of study, and academic year are presented in Table 3. This diversity in participant characteristics enhances the study's generalizability and provides a robust foundation for analyzing students' perceptions, motivations, and behavioral intentions toward integrating AI technologies within active learning contexts.

Table 3: Demographic profile of study participants

Variable	Categories	N	(%)
Gender	Female	284	59.8%
	Male	191	40.2%
Discipline	Mass Communication	34	7.2%
	Sociology and Social Work	94	19.8%
	History	56	11.8%
	Tourism	31	6.٥%
	Information Studies	34	7.2%
	Geography	44	9.3%
	Music	24	5.0%
	English Language and Literature	76	16.0%
	Arabic Language and Literature	82	17.2%
Academic Year	First Year	74	15.6%
	Second Year	103	21.7%
	Third Year	118	24.8%
	Fourth Year	132	27.8%
	Fifth Year	48	10.1%

Results

Descriptive analysis of students' adoption of AI for active learning in social science education

Table 4 presents the descriptive statistics for the dependent variable, "adoption of AI for active learning," including its four core dimensions and the overall composite score. Statistical classification of the composite scores resulted in three adoption levels: high (77.9%), moderate (17.5%), and low (4.6%). Among the four dimensions, behavioral intention to use AI tools recorded the highest mean score of 9.07 (SD = 1.268), indicating strong motivation among students to engage with AI tools in their academic journey. This reflects a broad readiness to adopt AI as an integral part of active learning in social science education. Next, intention to integrate AI into academic tasks yielded a mean score of 8.40 (SD = 1.698), suggesting that students generally plan to incorporate AI into their routine study practices. However, the relatively higher standard deviation reflects variability in students' preparedness or ability to implement this intention consistently.

Perceived engagement with AI-enhanced learning recorded a moderate mean of 6.98 (SD = 1.325), highlighting that while many students are committed to using AI tools, a notable proportion may require more structured guidance or motivational support to deepen their engagement. Finally, anticipated frequency of AI tool usage received the lowest mean of 6.25 (SD = 1.479). This suggests that, despite strong behavioral intentions and planned integration, there is still uncertainty regarding how frequently students will engage with AI tools in practice. The overall composite score had a mean of 7.70 (SD = 1.308), indicating generally moderate to high levels of adoption among students. These findings reflect a positive attitude toward AI integration but reveal some variation in depth and consistency of use across dimensions.

Table 4: Summary statistics for dimensions and composite score of the dependent variable

Dimension	Min.	Max.	Mean	SD	Ordinal categories of the DV	N	%
Behavioral intention to use AI tools	5	10	9.07	1.268	Low adoption	22	4.6
Perceived engagement with AI-enhanced learning	2	9	6.98	1.325	Moderate adoption	٨٣	17.٥
Intention to integrate AI into academic tasks	3	10	8.40	1.69٦	High adoption	37٠	٧٧.٩
Anticipated frequency of AI tool usage	1	8	6.25	1.479			
Composite score	3.8	9.3	7.70	1.30٩			

Descriptive analysis of UTAUT2 predictors of AI adoption for active learning

Table 5 summarizes the descriptive statistics for the six independent variables derived from the UTAUT2 framework, which are hypothesized to influence students' adoption of AI tools for active learning in social science education. These variables reflect students' perceptions regarding the effectiveness, usability, support, motivation, social environment, and habitual engagement associated with AI-enhanced learning. Performance expectancy emerged as the most highly rated factor, with a mean score of 23.6 (SD = 1.566), representing 94.4% of the maximum score. This indicates that students strongly believe that AI tools enhance their academic performance and contribute to improved outcomes in understanding and applying social science concepts. Effort expectancy followed closely, recording a mean of 22.9 (SD = 1.353) or 91.6%, suggesting that students generally perceive AI tools as user-friendly and easy to incorporate into their learning routines. This high rating underscores the importance of usability in encouraging adoption.

Hedonic motivation reported a mean of 17.6 (SD = 1.435), which constitutes 88.0% of the maximum score. This reflects the enjoyment and interest students experience when using AI tools, highlighting the engaging and interactive nature of these technologies in the learning process. Facilitating conditions achieved a mean of 21.8 (SD = 2.603) or 87.2%, reflecting students' perception of the availability of institutional resources, infrastructure, and technical support necessary to adopt and use AI effectively in academic settings. Social influence had a mean score of 16.9 (SD = 1.467), equivalent to 84.5% of the maximum. This factor captures the extent to which students are influenced by peers, instructors, or institutional support in their decision to adopt AI tools. Lastly, habit recorded the lowest mean score of 15.3 (SD = 2.241), corresponding to 76.5% of the maximum. This indicates that regular and consistent use of AI tools is not yet fully established among many students. The greater variability also points to differences in how deeply AI usage has become integrated into students' academic routines.

Table 5: Summary of descriptive statistics for independent variables

Variable	M	M	M	Std	Mean
Performance expect	1		2	1	94.
Effort expectanc	1		2	1	91.
Facilitating condit	1		2	2	87.
Social influenc			1	1	84.
Hedonic motivati	1		1	1	88.
Habit			1	2	76.

Results of OLR analysis

Assessing the model's statistical adequacy and predictive strength

To determine the reliability and suitability of the Ordinal Logistic Regression (OLR) model in analyzing students' adoption of AI tools for active learning in social science education, several key validation procedures were performed. These assessments focused on model fit, assumption testing, and explanatory strength (Table 6). The model demonstrated a statistically significant improvement over the null model, as indicated by the Likelihood Ratio Chi-square value of 477.807 ($df = 6$, $p < 0.001$). This result confirms that the inclusion of UTAUT2-based predictors significantly enhances the model's ability to explain differences in students' adoption levels of AI tools for academic engagement.

To ensure the appropriateness of the OLR framework, the proportional odds assumption was tested using the parallel lines procedure. The non-significant result ($\chi^2 = 9.726$, $df = 6$, $p = 0.137$) indicates that this core assumption holds, validating the use of cumulative logits across ordinal response categories. The model's explanatory power was further demonstrated through pseudo R-square values. The Nagelkerke Pseudo R-square was 0.877, and the McFadden Pseudo R-square was 0.784, both of which indicate a strong capacity to account for variance in students' behavioral intentions to adopt AI for active learning purposes. In sum, these results confirm the OLR model's statistical soundness and predictive strength, affirming its appropriateness for exploring the key factors that shape students' engagement with AI-enhanced active learning in social science education.

Table 6. Summary of diagnostic tests for the OLR model

Validation Metric	Value
Likelihood Ratio (LR) Test Chi-square	Chi-square (df=6)= 477.807 (P-value = 0.000)
Proportional Odds Assumption (Parallel Lines Test)	Chi-square (df=6)= 9.726 (P-value = 0.137)
Nagelkerke Pseudo R-square	0.877
McFadden Pseudo R-square	0.784

Key predictors of AI adoption for active learning: results from the OLR model

The OLR model was employed to examine the impact of six UTAUT2-based predictors on students' adoption of AI tools in the context of active learning in social science education. Table 7 presents the estimated coefficients (β), standard errors, odds ratios (OR), 95% confidence intervals (CI), and p-values for each factor. Among all predictors, effort expectancy emerged as the strongest and most influential determinant of AI adoption. With a coefficient of 1.002 and an odds ratio of 2.72, the analysis shows that for every one-unit increase in students' perception of the ease of using AI tools, the odds of adoption increase by 172%. The corresponding confidence interval (1.837–4.043) confirms the consistency and statistical robustness of this relationship. Closely following was performance expectancy, with a coefficient of 0.998 and an odds ratio of 2.71. This suggests that students who believe AI tools enhance their academic performance are 171% more likely to adopt them. The confidence interval (1.856–3.966) further affirms the reliability of this predictor. While both variables are highly significant, the slightly higher odds ratio of effort expectancy indicates that perceived ease of use slightly outweighs perceived usefulness in influencing adoption behavior. Hedonic motivation also played a substantial role. A coefficient of 0.820 and an odds ratio of 2.27 imply that students who find AI enjoyable and engaging are 127% more likely to adopt it. The confidence interval (1.463–3.525) highlights the consistency of this motivational factor across the sample.

Social influence, representing perceived encouragement from peers, instructors, or institutions, demonstrated a statistically significant effect. With a coefficient of 0.760 and an odds ratio of 2.14, students who feel supported in their use of AI tools are 114% more likely to adopt them for active learning. The confidence interval (1.597–2.864) reinforces the reliability of this factor in promoting adoption behavior through social reinforcement. On the other hand, facilitating conditions, which reflect students' access to institutional and technical support, showed a more moderate but still significant influence. The coefficient of 0.410 and an odds ratio of 1.51 suggest that improved infrastructure and available resources increase the likelihood of adoption by 51%. The confidence interval (1.253–1.813) confirms that this predictor plays an important role in enabling AI adoption, though its impact is less pronounced compared to other leading factors.

In contrast, habit was not found to be a significant predictor in this context. Although its coefficient (0.111) and odds ratio (1.12) suggest a minor increase in adoption likelihood, the confidence interval (0.920–1.358) includes 1, and the p-value of 0.263 indicates that habitual use has not yet formed a consistent influence among students. In summary, the results highlight that students' adoption of AI for active learning is primarily driven by ease of use, perceived effectiveness, institutional support, enjoyment, and social encouragement. However, habitual use has not yet become a defining factor, pointing to the evolving nature of AI engagement in educational contexts.

The results of the estimated Ordinal Logistic Regression (OLR) model are visually presented in Figure 2. Each hypothesized relationship is represented with a directional line annotated by the corresponding odds ratio and significance level (in parentheses). Hypotheses that were not supported by the model are illustrated using dotted lines to indicate non-significant effects.

Table 7: Predictive factors of AI adoption in social science active learning: OLR model results

Predictor Variables	Coefficient (β)	S.E(β)	Wald	Odds Ratio (OR=Exp (β)	95% Confidence Interval for OR	p-value
Performance expectancy	.998	.194	26.531	2.71	1.856 – 3.966	<.001
Effort expectancy	1.002	.201	24.812	2.72	1.837 – 4.043	<.001
Facilitating conditions	.410	.094	18.949	1.51	1.253 – 1.813	<.001
Social influence	.760	.149	26.020	2.14	1.597 – 2.864	<.001
Hedonic motivation	.820	.224	13.359	2.27	1.463 – 3.525	<.001
Habit	.111	.099	1.255	1.12	0.920 – 1.358	.263

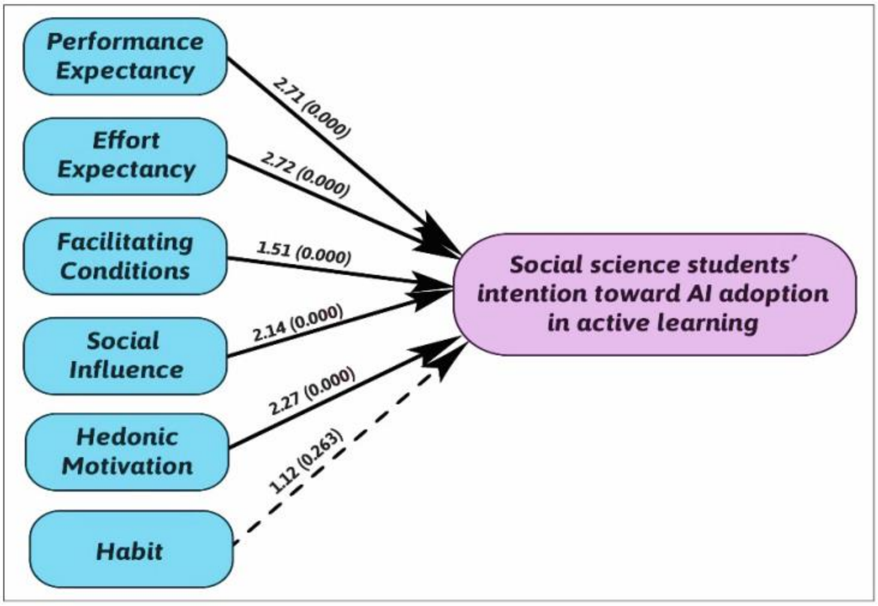

Figure 2. Results of the estimated Ordinal Logistic Regression

Discussion and Implications

This study examined AI adoption among social science students in active learning contexts through the lens of the UTAUT2. The findings reveal a complex interplay of individual, social, and institutional factors that shape student engagement with AI-enhanced learning environments. This discussion analyzes each UTAUT2 construct and elucidates its implications for pedagogical design, educational practice, and institutional policy in higher education.

Performance Expectancy: Integrating AI with Pedagogical Objectives

Performance expectancy emerged as the most significant predictor of AI adoption intentions, consistent with prior UTAUT2 research in educational contexts (Sasikala & Ravichandran, 2024; Yusuf, 2024). Students demonstrated clear recognition that AI tools could enhance academic performance through personalized learning pathways, streamlined research processes, and sophisticated analytical capabilities. However, within active learning frameworks, these perceived benefits must extend beyond operational efficiency to encompass higher-order learning outcomes.

The theoretical implications suggest that effective AI integration requires explicit alignment with constructivist learning principles that emphasize critical thinking, problem-solving, and learner autonomy (Rouzegar & Makrehchi, 2024; Szmyd & Mitera, 2024). Rather than positioning AI as a productivity tool, educators must demonstrate how these technologies facilitate deeper conceptual understanding through inquiry-based exploration and reflective synthesis. This pedagogical reframing necessitates comprehensive faculty development that bridges AI literacy with learning sciences, enabling instructors to model and communicate AI's role in promoting substantive learning outcomes.

From an institutional perspective, these findings underscore the importance of strategic alignment between AI capabilities and curricular objectives. Universities must invest in faculty training programs that emphasize pedagogical applications of AI rather than merely technical proficiency, ensuring that performance expectations are grounded in educational theory rather than technological determinism.

Effort Expectancy: Cognitive Load and User Experience Design

The significant influence of effort expectancy on student engagement aligns with cognitive load theory, which posits that learning is optimized when extraneous cognitive demands are minimized (Kanont et al., 2024). Students demonstrated greater willingness to engage with AI tools that featured intuitive interfaces and seamless integration into existing academic workflows, allowing cognitive resources to be allocated toward learning rather than technology navigation.

These findings have direct implications for educational technology design and implementation. AI tools deployed in active learning environments must prioritize user-centered design principles that minimize friction and cognitive overhead. This extends beyond interface design to encompass integration with learning management systems, compatibility with existing academic practices, and provision of contextual support resources.

Institutionally, universities must establish comprehensive support ecosystems that include robust onboarding programs, peer mentoring systems, and continuous technical assistance. Faculty development initiatives should specifically address strategies for scaffolding students' initial AI experiences, creating pathways that reduce barriers to entry while maintaining pedagogical rigor (Yan et al., 2025). The goal is to create conditions where technological engagement enhances rather than detracts from the cognitive processes central to active learning.

Facilitating Conditions: Systemic Infrastructure for Educational Innovation

The strong relationship between facilitating conditions and actual AI usage underscores that technology adoption transcends individual readiness to encompass broader organizational capabilities. Students’ engagement with AI tools was contingent upon reliable technological infrastructure, clear institutional guidelines, and responsive support mechanisms (Mohsin et al., 2024).

The context of Sultan Qaboos University, a leading national institution undergoing comprehensive digital transformation, provides valuable insights into the institutional factors that enable AI integration. The university's evolving infrastructure and support systems played a crucial role in facilitating students' capacity for technology-enhanced active learning, suggesting that institutional readiness is as critical as individual acceptance.

These findings advocate for a systems-level approach to AI adoption that recognizes technology integration as a component of broader organizational transformation (Abdurohman, 2025; Marais et al., 2024). Successful implementation requires coordinated investments across multiple domains: technological infrastructure, policy frameworks, faculty development, and student support services. Rather than treating AI adoption as an isolated initiative, institutions must cultivate collaborative, inquiry-driven learning environments that support sustained technological engagement.

The implications extend to higher education policy, suggesting that universities must develop comprehensive AI integration strategies that address technical, pedagogical, and organizational dimensions simultaneously. This holistic approach is essential for creating conditions that enable rather than constrain educational innovation.

Social Influence: Collaborative Learning and Individual Agency

Social influence demonstrated a moderate but nuanced impact on AI adoption, revealing a complex dynamic between peer learning and individual agency. While peer encouragement and instructor modeling positively influenced some students' attitudes toward AI, others maintained self-directed approaches to technology adoption, illustrating the heterogeneous nature of social learning processes.

In active learning contexts, these findings suggest opportunities to leverage collaborative structures, including peer mentoring, group projects, and discussion forums to facilitate constructive social influence around AI use (Gehreke et al., 2024; Le, Sok, & Heng, 2024). However, educators must also recognize and accommodate diverse learner trajectories, avoiding prescriptive or uniform expectations regarding AI engagement.

The pedagogical implications emphasize the importance of designing inclusive learning pathways that honor both socially influenced and independently motivated learners. This requires flexible instructional approaches that provide multiple entry points for AI engagement while maintaining coherent learning objectives. Faculty must be prepared to facilitate social learning processes while respecting individual learning preferences and autonomy.

Hedonic Motivation: Affective Dimensions of Technology-Enhanced Learning

The meaningful role of hedonic motivation in AI adoption highlights the affective dimensions of educational technology engagement. Students who experienced enjoyment and intrinsic interest in AI tools were more likely to integrate them into sustained academic practice, reflecting the emotional components of active learning environments (Lepp & Kaimre, 2025).

These findings call for intentional design of emotionally resonant learning experiences that leverage AI's capacity for interactive and creative applications. Gamified elements, immersive simulations, and innovative problem-solving applications can cultivate curiosity, motivation, and sustained engagement. However, such approaches must maintain academic rigor and alignment with learning objectives rather than prioritizing engagement for its own sake.

The implications for educational technologists and instructional designers emphasize the need to balance affective engagement with pedagogical effectiveness. AI tools should not only support academic goals but also contribute to positive, stimulating learning environments that foster intrinsic motivation (Alenezi, 2023; Luo, 2024). This requires sophisticated understanding of both user experience design and motivational psychology in educational contexts.

Habit: Temporal Dimensions of Technology Integration

The limited influence of habit in this study indicates that students had not yet developed routine patterns of AI engagement, distinguishing social science contexts from social science disciplines where digital tools are more deeply embedded in disciplinary practices. This finding suggests that students remain in exploratory phases of AI adoption, lacking the repetitive exposure necessary for habitual engagement.

These results highlight the temporal dimensions of technology integration and the importance of longitudinal curricular planning. Establishing regular, scaffolded AI applications across multiple courses and academic contexts is essential for fostering behavioral familiarity and confidence. Institutions must prioritize consistent reinforcement of AI applications to enable students' progression from initial exposure to autonomous, habitual use.

The implications extend to curriculum design and program-level planning, suggesting that AI integration should be conceived as a multi-semester developmental process rather than discrete course-based interventions. This longitudinal approach requires coordination across faculty, departments, and academic programs to ensure coherent and progressive AI engagement throughout students' academic trajectories.

Conclusion and future research directions

This study sheds light on how social science students in Oman are embrace artificial intelligence (AI) in active learning environments. Using the UTAUT2 framework, the research shows that students' adoption is driven mainly by perceptions of ease of use, usefulness, enjoyment, social support, and enabling conditions, while habitual use has not yet been developed. These findings highlight both the enthusiasm and early stage nature of AI integration in non-Western higher education. They underscore the importance of culturally responsive strategies that move beyond simply providing tools to fostering sustained engagement and meaningful learning experiences.

Future research should explore how students' initial experimentation with AI evolves into habitual practice through longitudinal studies. Cross-cultural comparisons could reveal how local norms and resources influence adoption patterns. Experimental interventions like targeted training or curriculum redesign may help identify effective ways to strengthen key motivators. Qualitative studies could capture deeper insights into students' perceptions and experiences, enriching quantitative results. Finally, assessing the impact of AI on academic outcomes and skill development will be essential to demonstrate its value and inform policy and investment decisions. Together, these directions can advance a more inclusive and effective vision for digital transformation in education.

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