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Ordinal Logistic Regression Analysis of Factors Influencing University Students' Use of AI Technologies in Education

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Abstract
Artificial intelligence (AI) has become one of the fields that are increasingly used in universities and the higher education sector. However, the factors affecting student use are still unclear in the universities of the Kurdistan Region. Thus, this research aims at exploring the determinants of students' acceptance of artificial intelligence (AI) in universities in Iraqi Kurdistan. Study with a sample size of 240 students, was conducted in the universities of the Kurdistan Region of Iraq using a structured questionnaire and ordinal logistic regression analysis.
The model adequately fit ($Nagelkerke\ R2 = 0.421$) data with a correct classification rate of (73.8%). The economic situation of the family, the perception that artificial intelligence tools are designed for students and would solve their problems, facilitation to use educational programs, and interest in using AI-based tools ranked as one of the significant effects on artificial intelligence usage by university students. Conversely, low self-confidence in personal skills and concerns of an ethical nature had a negative impact on its use.
The findings highlight economic, technological and behavioural aspects influencing the adoption of AI by university students. The researchers suggests that increasing its use would include building digital literacy and addressing ethical concerns. This work has more general theoretical relevance for academic practitioners and college policy makers; It attempts to offer practical guidance on how university and policy sectors could facilitate ethical use of artificial intelligence tools.

key words: *Ordinal Logistic Regression, Artificial Intelligent, Technology Adoption, Higher Education, Digital Literacy*

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تحليل الانحدار اللوجستي الترتيبي للعوامل المؤثرة على استخدام طلاب الجامعات لتقنيات الذكاء الاصطناعي في التعليم

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المستخلص

أصبح الذكاء الاصطناعي أحد المجالات التي تُستخدم بشكل متزايد في الجامعات وقطاع التعليم العالي. ومع ذلك، لا تزال العوامل المؤثرة على استخدام الطلاب له غير واضحة في جامعات إقليم كردستان. لذلك، تهدف هذه الدراسة إلى تحديد أهم العوامل المؤثرة على تبني الذكاء الاصطناعي بين الطلاب في جامعات إقليم كردستان العراق. اختار الباحثون عينة عشوائية بسيطة من 240 طالبًا من جامعات إقليم كردستان العراق، باستخدام استبيان منظم لجمع البيانات، إلى جانب تحليل الانحدار اللوجستي الترتيبي. كان ملاءمة النموذج كافية ($Nagelkerke\ R^2 =$ 0.421)، بدقة تصنيف .(73.8%). من بين أهم العوامل التي تؤثر سلبًا على استخدام الذكاء الاصطناعي الوضع الاقتصادي للأسرة، وتصور الطلاب لأدوات الذكاء الاصطناعي كأداة للتعلم وحل المشكلات، ومدى ملاءمة استخدام البرامج التعليمية، والاهتمام بالأدوات القائمة على الذكاء الاصطناعي. على العكس من ذلك، أثر انخفاض الثقة في المهارات الشخصية والمخاوف الأخلاقية سلبًا على استخدامه. تُشدد النتائج على العوامل الاقتصادية والتكنولوجية والسلوكية التي تُسهم في استخدام الذكاء الاصطناعي بين طلاب الجامعات. ويشير مؤلفو الدراسة إلى أن تعزيز استخدامه يتطلب تحسين الثقافة الرقمية ومراعاة الاعتبارات الأخلاقية، ولهذا العمل آثار نظرية أوسع نطاقًا على الممارسين في المجال الجامعي وواضعي سياسات التعليم العالي، إذ يسعى إلى توفير إرشادات جوهرية حول كيفية دعم الجامعات وواضعي السياسات للاستخدام المسؤول لأدوات الذكاء الاصطناعي

الكلمات المفتاحية : *الانحدار اللوجستي الترتيبي، الذكاء الاصطناعي، تبني التكنولوجيا، التعليم العالي، محو الأمية الرقمية*

1. Introduction:

Our society is in the process of significant technological change, Artificial Intelligence (AI) technologically powered driven transformation across society, including education and higher education. AI has also brought intelligent tools and systems to the classroom such as adaptive learning environments, intelligent tutors, automated assessment tools and educational data analysis. This progress is a reminder to study how far the students are benefited with these technologies, and what triggers them to use, particularly in the universities of Kurdistan Region (Sajja et al., 2024) .

The technology adoption of university students one quarter of the most technologically sophisticated. Most teachers are reasonably digital-literate but that alone does not make them effective with AI in the classroom. Utilization depends on demographic, cognitive, psychological, and technical factors that may change in different contexts (Mansoor HMH, Bawazir A & AH, 2024).

Even though AI is becoming more common in the higher education, it remains unclear to what extent students actually utilize AI, particularly in non-Western contexts such as the Kurdistan Region of Iraq. The vast majority of the literature considers the intention but not observed use, and only a limited number of studies apply ordinal or proportional-odds models to modelling AI adoption frequency. This understanding is critical for guiding effective educational strategies and providing equitable access as the use of AI continues to expand and becomes increasingly integrated responsibly.

This paper fills these gaps by employing ordinal logistic regression to examine the impact of a range of demographic, subjective, environmental and skill-related factors on students' use of AI as part and parcel of their academic activities in Kurdistan Region. Theoretical and practical implications for universities to help increase the adoption of AI in higher education are presented.

1.1 Literature Review

Artificial Intelligence (AI) is increasingly penetrating into higher education through personalized learning, intelligent tutoring systems, Chabot and automatic evaluations. As much as these applications improve efficiency, engagement and outcomes, privacy bargain, high expensive, algorithm bias and ethical considerations in return highlight the need for transparent/non-discriminative mechanism such(Harry & Sayudin, 2023). Academic research has recently drawn attention to generative AI, and especially ChatGPT. In a study with 102 students, they reported frequent used of it for researching, project and assignments. While faculty have appreciated the convenience and ready helping-hand it provides, its plagiarism, overreliance, and loss of critical thinking components necessitate a judicious application(Valova et al., 2024).

In role of usability, adequacy of training and policy on adoption AI technology: evidence from Kurdish university students reveal likelihood to enhance or eliminate opportunities for productive use(Tiza et al., 2023). The study (Shareef, 2025) highlighted the critical role played by artificial intelligence with respect to enhancing teaching efficiency and student involvement for higher education. It found that they were generally optimistic about the usefulness of AI technologies for research and assignments but still had concerns about accuracy and ethics. These findings further reinforce the concept that perceptual and behavioral factors for cognitions in AI acceptance among undergraduates should be taken seriously, rather than examining only a single model.

Across all studies, the dichotomous criterion for measuring intention or average use in technology acceptance research has been most commonly used. The problem is that if the dependent variable is ordinal, say a respondent's level of AI use (never, rarely,...always), OLS is not justified but ordinal logistic regression (OLR) should be preferred. The OLR measure has been applied in educational research, for analyzing academic performance, satisfaction and technology use acceptance, demonstrating obtained stability and interpretability.

Another research had studied there with the research of regarding faculty perception where technological competency, previous experience and perceived usefulness were significant predictors to the behavioural intention to adopt AI preparedness (Gjermeni, 2024).

(Abdalla, 2025) explored the acceptance of ChatGPT by social science students in Oman applying UTAUT and ordinal logistic regression. The findings indicate that performance expectancy, self-efficacy and social influence are significant predictors of AI adoption.

Using OLR(Mahmood et al., 2018) applied OLR to analyze student academic performance in the Kurdistan Region, finding predictors such as study habits and parental education effective in modeling performance categories.

Additionally, logistic regression analysis was used by (Eratlı Şirin & Şahin, 2020) in a study with 360 Turkish physical education students and results revealed that gender, university preference, department preference, father's educational status and support from others and instructor were the predictors of achievement while age and mother' s educational background were not significant.

Extending this, (Hamid et al., 2022) employed OLR with a sample of 188 Saudi students, and reported age, GPA, duration of study (i.e., how many hours a student studies per week), absences (if any), anxiety before the exams, economic status … parental divorce and family involvement to be predictors.

These research demonstrate the usage of ordinal logistic regression in education field, yet none have utilized this method as a primary approach for examining AI adoption by university students and specifically such practice in Middle Eastern countries. This gap highlights the importance of this study which strives to further develop the applicability of ordinal logistic regression to explain what factors influence use AI in institutions of higher education.

1.2. Research Problem

Although the adoption of Artificial Intelligence (AI) in higher education has recently been taking shape, very little is understood about the enabling and inhibiting factors for student's successful use of AI-enabled learning applications when adopted in non-Western academic settings like Kurdistan Region of Iraq. Thus, the main question that this research will attempt to answer is: what are determining factors (demographics, perception of technology, environment or resources) of AI use for students enrolled at the universities in Kurdistan Region?

1.3 Research Objectives

The objective of this study is to develop a model indicating the interrelationships among various factors for the usage frequency of AI tools in education by university students using an Ordinal Logistic Regression. Specifically, the study seeks to:

1. Examine demographics (e.g., gender, age, department type, and economic background) affected students' use of AI tools.
2. Explore what students believe about AI and trust to uncover how perceptions and beliefs impact the use of AI.
3. Consideration of how various environmental factors (e.g., university rules, teacher recommendations, social or online exposure) influenced the use of AI tools.
4. Evaluate to what extent students' skills and available resources are predictive of their use of AI tools.
5. Construct an ordinal logits regression model to control for variations in how often the students use AI-related technology section wise.

1.4 Research Importance

This study makes an original contribution to the literature on AI adoption in Higher Education as it applies ordinal logistic regression to assess the actual level of usage. It offers a number of interventions for policy-makers and university heads in the Kurdistan Region to ensure fair access, better technical training, as well as ethical and infrastructural issues associated with AI implementation.

1.5 Study Concepts

- AI in Education Intelligent tools and technologies for learning, which include applications like digital teachers for teachers and students, an automatic assessment system or advanced content recommendation systems.

- Use Extent: It is a categorical (low; medium; high) variable indicating the degree to which students depend on tools for their learning.
- Ordinal logistic regression Ordinal logistic regression is a statistical technique that allows to fit models in which the effect of some independent variables on an ordinal dependent variable takes place.

2. Artificial intelligence (AI) in education

Fast digital movement has caused artificial intelligence (AI) to become one of the most considerable advancements and a very strong digital force that is transforming all industry even education sector. It supports the leaner and educator as well to put effective solutions by analyzing data, personalized content delivery, and individual operator intervention(Elsayed, 2025). In brief, this is the capability of computer systems to perform tasks that would require human intelligence, such as learning, reasoning and problem-solving. In education, AI is increasingly being used in recommendation systems, intelligent assistants and ‘chatbots’, adaptive assessments and the measurement of academic achievement enabling institutions to create more personalised pathways and courses for both ends of the learning spectrum(Otaibi & Al-Sawat, 2023). While AI improves academic quality and changes the role of teaching and learning in universities, it presents great ethical, technical And structural stakes(Saputra et al., 2023) and(Sahar & Munawaroh, 2025).

Moreover, the new research reveals that not only is learning methodology being altered by artificial intelligence, but so is administrative structure and higher education governance, which are becoming more presence on artificial intelligence-based decision-making as well as management frameworks(Katsamakas & Pavlov, 2024).

Artificial Intelligence is being developed by the leaps and bounds, so universities are trying to integrate them into courses in order to ensure both quality in learning as well as adaptive content delivery. Educational policy makers in United States and around the world view AI as basis for preparing students to learn in a 21st century that will be dominated by technologies already woven into our daily lives(Mita Banerjee et al., 2020). Besides the reinforcement of traditional methods, AI creates smart study place systems(An & Ma, 2024), such as report writing, homework management, e-learning platforms, smart assessments and guidance chatbots and automated scoring that advance not only engagement and effectiveness but also personalized learning(Alazemi T, Alkandari A, 2024). The AI leads forward to increased learning pattern with the provision of adaptive learning systems to analyze their students' preferences, interest and capabilities further automatically deliver customized contents, while retaining certain individual differences(Mita Banerjee et al., 2020). Smart platforms enable access to knowledge all the time and place, foment acquisition of capacity to learn for itself and life-long learning plus assisting teachers in activities such as log on, give marks, issue reports(BRUGLIERA, 2024). Furthermore, AI constantly monitors student performance for providing personalized feedback and enhancing result effectiveness while promoting motivation (Sari et al., 2024).

AI in education – Pros and challenges. The lack of infrastructure limitations such as internet and high-level hardware are still challenges, especially in resource-limited environments. The lack of digital proficiency within student and staff populations also inhibits successful implementation including limited access to online material(Saputra et al., 2023). At the same time, ethical and legal issues regarding privacy, algorithmic bias and data protection are also problematic in/as AI enters into the classroom work force albeit with a need for curricula and pedagogical developments to match the potential of the technology as well as ensuring good educational outcomes(Bond et al., 2024).

3. Ordinal Logistic Regression: Conceptual and Mathematical model

Ordinal logistic regression is an important statistical model applied to analyze data where the dependent variable takes an ordinal form, meaning it assumes multiple values with a logical order (such as low, medium, and high)(Adejumo & Adetunji, 2013). Using ordinal logistic regression is appropriate because the dependent variable in this study the level of artificial intelligence use is an ordinal variable (low, medium, high). This model is considered a natural extension of binary logistic regression, as it allows studying the effect of a set of independent variables on a dependent variable with more than two ordered categories(Mohammed et al., 2024). Ordinal logistic regression has gained wide attention in recent decades in fields such as social, psychological, educational, and medical studies, particularly when the aim is to explain the transition of individuals across ordered levels of a phenomenon (Irawan et al., 2023). For example, in education, it can be used to study students' levels of adoption of artificial intelligence technologies and their relationship with demographic or academic variable.

Several logistic models can be used for analyzing ordinal data, differing in their assumptions and the way they calculate probabilities. The most notable models include the Proportional Odds Model, the Partial Proportional Odds Model(Shereen A. Hussain & Saad K. Hamza, 2023) , and the Adjacent

Categories Logit Model. Among these, the Proportional Odds Model is the most widely used due to its simplicity in interpretation and suitability for a wide range of practical applications(Mathew et al., 2021).

The Proportional Odds Model, presented by McCullagh (1980) and also known as the Cumulative Logit Model, uses the cumulative probabilities of the dependent variable's categories. The resulting odds ratios can be interpreted as summaries of the odds derived from separate binary logistic regressions for each threshold of the categories(Arfan & Sherwani, 2017). The mathematical representation of the model is as follows:

$$\text{Logit}\,[\,P(Y \le j \mid X)\,] = \alpha_j + \beta_1 X_1 + \beta_2 X_2 + \cdots .. + \beta_p X_p \,, for\ j = 1,2, \ldots .., J-1 \quad \ldots \ldots \ldots .. 1$$

Where:

α_j: the thresholds (cut-points) for each category.

β_p :the regression coefficients of the independent variables.

β_k : the explanatory variables.

J: the number of categories of the dependent variable.

An equivalent formulation using the natural logarithm of the odds for each category can also be written as:

$$\text{Logit}\,[\,P(Y = j \mid X)\,] = \log \frac{(\,P(Y = j \mid X)}{(1 - P(Y = j \mid X)} = \alpha_j + \beta_1 X_1 + \beta_2 X_2 + \cdots .. + \beta_p X_p \quad \ldots \ldots \ldots 2$$

The Proportional Odds Model assumes the so-called Parallel Lines Assumption, which states that the impact of predictors on the log odds (logit) are equivalent across thresholds. This assumption should be battered appropriate with Parallel Lines tests in SPSS(Ari & Yildiz, 2014).

Conclusion Ordinal logistic regression, specifically the Proportional Odds Model, is a useful tool when estimating ordinal data and can be a flexible way to model how independent variables are related to an ordered-outcome in its clarity.

3.1 Parameter Estimation of Ordinal Logistic Regression

The Maximum Likelihood Estimation (MLE) is often employed to estimate the parameters of the ordinal logistic regression models, particularly in the Proportional Odds Model. As in all statistical modeling, this approach seeks to estimate the parameters θ (i.e., the thresholds α that define categories and regression coefficients β) that maximize the likelihood of seeing the data one actually observed, or put differently make outcomes "most likely"(AGRESTI, 2010).

The key of these assumptions is the Proportional Odds Model that sets β (the regression coefficients) to be identical across thresholds, so that is left after adjustment are just the intercept terms (α_c), for $C = 1,2,3 \dots . J - 1$. This property allows pooling of estimates across the different ordinal models to produce a single set of regression coefficients which indicates how predictors influencing cumulative probabilities(Reddy & Endale Alemayehu, 2015). To aid in interpretation, we exponentiated the regression coefficients (e^{β}) and reported adjusted odds ratios (ORs), which is the change in the odds of being at a higher level by one unit increase or any other comparison level (i.e., $Y \geq 3$) for predictor X_J .

And in a more formal sense, the likelihood for the independent and identically distributed observation is given by(Omar, 2019):

$$lik\ (\theta) = \prod_{i=1}^{n} f(X_i|\theta) \dots \dots \dots \dots \dots .. 3$$

However, the product cannot optimized directly. Otherwish we would have the average. Then, it is usual to work with the log-likelihood function: this change transforms the product into a sum, facilitating the maximization process:

$$l(\theta) = \sum_{i=1}^{n} \log\big(f(X_i|\theta)\big) \dots\dots\dots\dots\dots\dots\dots 4$$

magnitude, the log-likelihood approximation eases most of estimation albeit constituting a reference to calculate the MLE of model parameters.

3.2 Ordinal Logistic Regression Fitting.

Goodness of fit testing is an important aspect in judging whether the ordinal logistic regression model is valid, as it helps to examine how well the model fits actual data and test underlying statistical hypotheses. The most significant test is the likelihood-ratio chi-square that compared a null model (i.e., with no IVs) to a full model of administered tasks with IVs. It is calculated as(Fagerland & Hosmer, 2017):

$$\chi^2 = -2\ln(L_0) + 2\ln(L_1)) \dots\dots\dots\dots\dots 5$$

Where L_0 is the maximum likelihood of the null model and L_1 is the maximum likelihood of the full model. Now, a high value of χ^2 with statistical significance ($P < 0.05$) implies there is much gain brought to the model by adding independent variables.

In addition, the Pseudo R^2 statistics (e.g., Cox & Snell, Nagelkerke, and McFadden) are used for checking of model fit by indicating how much variance in the dependent variable is explained by the independent variables. One of the most frequently used R-squared is Nagelkerke's, it is computed by using the following Equation:(Adejumo & Adetunji, 2013) and(Ugba & Gertheiss, 2023):

$$Nagelkerke\ R^2 = \frac{1-(\frac{L_0}{L_1})^{\frac{2}{n}}}{1-(L_0)^{\frac{2}{n}}} \dots\dots\dots\dots\dots\dots\dots.6$$

where n is the number of samples. Values close to 1 represent greater explanatory ability of the model.

Two other important statistics are the Pearson Chi-Square and Deviance used to determine the discrepancy between observed and expected events. where the Pearson statistic is (Salh et al., 2021):

$$\chi^2 = \sum\sum(\frac{\theta_{ij}-E_{ij}}{E_{ij}})^2 \dots\dots\dots\dots\dots\dots\dots.7$$

the Deviance formula is (Jajang et al., 2022) :

$$D = 2\sum\sum\theta_{ij}\ln(\frac{\theta_{ij}}{E_{ij}}) \dots\dots\dots\dots\dots\dots\dots\dots..8$$

where θ_{ij} is the observed and is the expected frequency. These tests are considered ideal if their values are non-significant ($P > 0.05$), which means that the model is a good fit tothe data.

The Test of Parallel Lines is another key test that tests the Proportional Odds Assumption for ordinal models. This is an goodness-of-fit test that compares your constrained, proportional-odds model to one without the constraint in a way largely analogous to how you compare nested models using a statistic analogous to the likelihood ratio(Hosmer et al., 2013) and (Tutz, 2022):

$$\chi^2 = -2\ln(\text{L constrained}) + 2\ln(\text{L unconstrained}) \dots\dots\dots\dots\dots.9$$

An insignificant relation ($P > 0.05$) favors the null hypothesis of the proportional odds assumption.

They can be aggregated to fully validate the quality of your model: Likelihood Ratio Test assesses if there is a point in fitting with independent variables, Pseudo R^2s confirms explanatory power, Pearson & Deviance stats test for correspondence between our model and data while finally Trial of Parallel Lines but guarantees that some key assumptions are being met. When taken together these tests allow us to reasonably follow a statistical path from model development and afford an increased confidence in our conclusions using the analysis.

4. Results and Discussion

An ordinal logistic regression was employed to examine and quantify the predictors of university students towards the use of Artificial Intelligence (AI) tools in science application in Kurdistan Region. Methods A descriptive, quantitative design was used and survey data were obtained. Data were analyzed using descriptive statistics and logistic regression analysis.

Sampling The study sample consisted of 240 students recruited via an online questionnaire on Google Form. Participants were selected through a random sampling approach from the Kurdistan Region universities. This was sufficiently large for stable estimates in the ordinal logistic regression analyses.

The demographic independent variables tested were Gender, Age, Field of Study, Year Level and Family Economic Status. In the questionnaire, three additional factors that may influence attitude were considered: (1) perception of and trust in artificial intelligence, (2) environmental impact and (3) resource skills and resource availability. The independent variables were measured through a three-category Likert type scale (No – To some extent – Yes) or (Poor – Average – Good) based on the derived construct. Dependent Variable The frequency of use of the AI tool was measured at ordinal scale (Never-Sometimes-Always) SPSS version 26 was utilized to construct the ordinal logistic regression model and results from it are reported and discussed next.

A content validity index was performed in the three dimensions: Perceptions & Trust in AI, Environmental Influence along with Skills & Resource Availability as the first step. All 240 cases were incorporated with no exclusion. Internal consistency was found to be acceptable, at Cronbach's Alpha = (0.708). This result indicates that the questionnaire is sufficiently reliable and valid for subsequent statistical analysis.

4.1 Descriptive Demographics

Before conducting the data analysis, in demographic we applied descriptive statistics i.e., to present frequency distribution of the dependent variable along with field of study: (AI utilization) by both gender and the study field including two categories scientific and literary.

Table 1: Frequency of AI use by students' gender and field of study

		Frequency of AI use (DV)			Total
		Never	Sometimes	Always	
Gender of student	Male	13	74	16	103
	Female	28	93	16	137
Field of study	Scientific	17	84	23	124
	Literary	24	83	9	116
Total		41	167	32	240

Table 1 shows the prevalence of gender-specific use of AI amongst the students. Among male students $(n = 103)$ never users were (12.6%), sometimes users were 71.8% and always users for 15.5%. By comparison, of female students $(n = 137)$, (20.4%) never use AI and (67.9%)sometimes do, with only (11.7%)always using AI. These findings suggest that the males are slightly more interested in using AI compared to females, illustrated by a lower proportion of "never users" and a higher proportion of 'always users'.

In a science field sample ($n = 124$) (67.7%) reported they sometimes use AI, (13.7%)stated that they have never used it at all and 18.5% had always used AI. for reading-field students ($n = 116$), the corresponding percentages were 40%, 35.3%, and 24%. Taken together, these findings add weight to the argument that attitude towards AI for educational purposes is not uniform among disciplines and that students in scientific studies are more likely to claim regular use of AI than those in literary fields who favor a never response regarding their previous experience with such technologies. These patterns imply that student interactions with AI technologies may be influenced by a combination of academic environment and female factors. For a deeper insight into the dependent variable, its distribution is represented graphically using a bar chart.

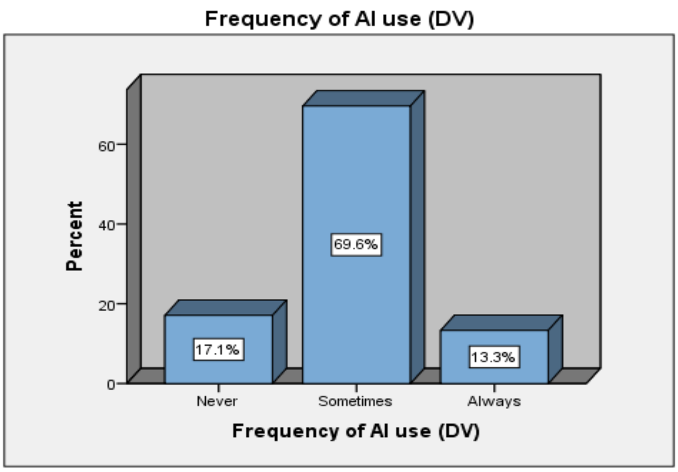

Figure 1: Bar graph of AI use by university students

As we can observe in Figure 1, out of the participants the large majority (167 participants = 69.6%) use AI just sometimes which stands for average behavior: rare use. Fewer participants: 41 (17.1%) had never used AI than the count of those who used AI all of the time; (32) 13.3%. Overall, it is therefore obvious that the actual use of AI on a regular basis remains rather low; however, participants are mostly in contact with AI systems.

It is important to understand this usage pattern to know why students are initially attracted to AI. If you are curious the following graph shows how and why AIs are taken up.

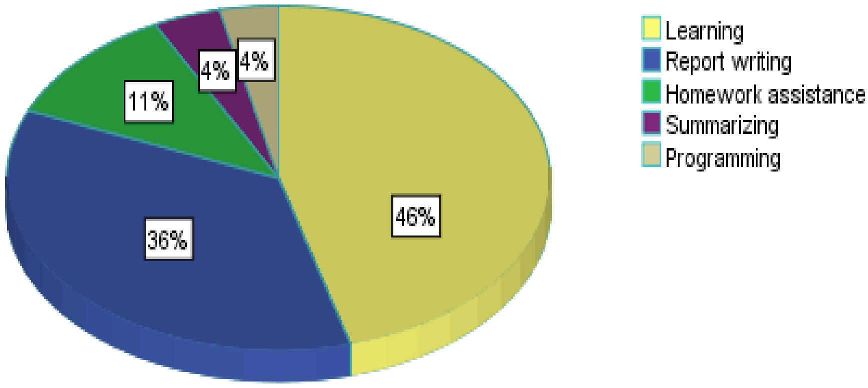

Figure 2: Pie graph of the main purpose of AI use by students

The pie demonstrates the application of AI in education by students. The largest percentage, (46%), reported using AI for learning, confirming it as a study tool. The second most common use is for report writing (36%), indicating that increasingly students are turning to AI when working on assignments or reports. Close behind is help with homework, cited by (11%), of respondents, while reflecting and programming are the least prevalent at (4%), apiece.

In Fig 2, the majority of students use AI to learn and produce report which imply they perceive AI as auxiliary technology in order to comprehend and achieve academic tasks. This is likely because of limited programming in interaction or summarization, the interactive utility knew that the students would not be explorative but rather task-authors. This highlights the need to educate students about artificial intelligence and its wider educational applicability beyond daily homework.

4.2 Multi-collinearity Test

To ensure that the independent variables were not highly correlated, a multi-collinearity test was conducted using the Variance Inflation Factor (VIF) and Tolerance values(Sesay et al., 2021), The results indicated that all VIF values were below 10 and all Tolerance values were above 0.1, suggesting that multi-collinearity was not a concern and the predictors could be safely included in the model.

Table 2: Tolerance and VIF of predictors variables

Questions	Collinearity Statistics	
	Tolerance	VIF
Q10	0.543	1.842
Q11	0.696	1.437
Q12	0.647	1.546
Q13	0.612	1.635
Q14	0.823	1.215
Q15	0.769	1.300
Q16	0.860	1.162
Q17	0.786	1.272
Q18	0.569	1.757
Q19	0.682	1.465
Q20	0.580	1.723
Q21	0.563	1.775
Q22	0.703	1.423
Q23	0.880	1.137
Q24	0.822	1.216
Q25	0.762	1.313

After confirming that multi-collinearity was not an issue, the next step was to estimate the ordinal logistic regression model to examine the predictors on the frequency of AI use in education by students.

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4.3 Ordinal Logistic Regression Results

4.3.1 Parameter testing

Table 3 presents the model fitting information for the ordinal logistic regression to compare the ordinal logistic regression model, which includes independent variables, with the baseline model, which includes only the constant term. The chi-square test was used according to the following hypotheses:

H_0 : The ordinal logistic regression model, which includes independent variables, is no better at predicting than the baseline model, which includes only the constant term.

H_1: The ordinal logistic regression model, which includes independent variables, is better at predicting than the baseline model, which includes only the constant term.

Table 3: Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	D.f.	Sig.
Intercept Only	394.977			
Final	295.452	99.525	22	0.000

From the previous table, the p-value is less than the significance level (0.05), which indicates the rejection of the null hypothesis that states that the ordinal logistic regression model that includes the independent variables is not better at predicting than the basic model that includes only the fixed term. This indicates that the included predictors collectively provide a better explanation of the variance in students' frequency of AI use. These results confirm that the model is suitable for studying the effects of independent variables.

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4.3.2 Model goodness - of- fit test

The goodness-of-fit test for the ordinal logistic regression model is based on two hypotheses:

H_0 : The model fits the data well
H_1: The model does not fit the data well

Table 4: Goodness-of-fit

	Chi-Square	D.f.	Sig.
Pearson	466.303	454	0.335
Deviance	295.452	454	1.000

Table 4 displays the goodness-of-fit statistics for the ordinal logistic regression model, including Pearson's and Deviance tests. Both tests assess how well the model fits the observed data, and since both p-values (0.335 and 1) are greater than 0.05, the null hypothesis that the proposed ordinal logistic regression model is a good fit to the data is accepted. This indicates that the model provides a good fit to the data and that the predictors used adequately explain the differences in students' frequency of AI use.

4.3.3. Pseudo R-Square:

The measures of Pseudo R-Square values for the ordinal logistic regression model indicate the proportion of variance in the dependent variable explained by the predictors.

Table 5: Pseudo R-Square

Cox and Snell	0.339
Nagelkerke	0.421
McFadden	0.252

The Cox and Snell value of (0.339), suggests that the predictors explain about (33.9%), of the variation in the dependent variable, while the

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Nagelkerke value of (0.421), , which is the commonly reported measure, shows an improved adjustment, indicating that approximately (42.1%) of the variance is accounted for by the model. Additionally, the McFadden value of (0.252)falls within the range considered a good fit for logistic models. Overall, these results demonstrate that the model provides a reasonable level of predictive capability.

4.3.4 Test of parallel lines

The test of parallel lines is considered one of the important tests in ordinal logistic regression analysis. This test aims to determine whether all independent variables have the same slope or not. This test depends on the following hypotheses:

$\boldsymbol{H_0}$ **:** All coefficients of the independent variables have the same slope across all levels of the response variable.

$\boldsymbol{H_1}$**:** All coefficients of the independent variables do not have the same slope across all levels of the response variable.

The table below presents the results of the parallel lines test obtained from the ordinal logistic regression model.

Table 6: Test of Parallel Lines

Model	-2 Log Likelihood	Chi-Square	d.f.	Sig.
Null Hypothesis	303.350			
General	286.116	17.234	16	0.371

In the previous table, it is clear that the value of $p - Value = 0.371$ is greater than the significance level 0.05, which means accepting the null hypothesis and fulfilling the assumption that the values of all coefficients of the independent variables have the same slope across all levels of the response variable.

4.3.5 Parameter Estimation:

Table 7: Parameter Estimates

		Estimate	Std. Error	Wald	d.f.	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[Q8_AI_use = 1]	1.353	1.938	0.488	1	0.485	-2.445	5.152
	[Q8_AI_use = 2]	6.405	2.011	10.141	1	0.001	2.463	10.347
Location	Q1_Gender	-0.089	0.345	0.066	1	0.797	-0.766	0.588
	Q2_Age	-0.191	0.170	1.259	1	0.262	-0.525	0.143
	Q3_Field	-0.210	0.348	0.364	1	0.546	-0.891	0.472
	Q4_Year	-0.058	0.172	0.112	1	0.738	-0.396	0.280
	Q5_Residence	-0.032	0.336	0.009	1	0.925	-0.691	0.628
	Q6_Fam_status	0.673	0.341	3.893	1	**0.048**	0.004	1.341
	Q10_AI_learning	1.802	0.347	26.908	1	**0.000**	1.121	2.482
	Q11_Lectures_missed	0.000	0.285	0.000	1	0.999	-0.557	0.558
	Q12_AI_Reliablity	-0.276	0.361	0.586	1	0.444	-0.984	0.431
	Q13_Complex_questions	0.657	0.300	4.807	1	**0.028**	0.070	1.245
	Q14_AI_ethics	-0.791	0.229	11.972	1	**0.001**	-1.239	-0.343
	Q15_AI_save	-0.030	0.318	0.009	1	0.924	-0.655	0.594
	Q16_Univ_support	0.052	0.228	0.051	1	0.821	-0.396	0.499
	Q17_Teacher_support	-0.001	0.241	0.000	1	0.996	-0.473	0.470
	Q18_peer_influence	-0.075	0.261	0.083	1	0.773	-0.587	0.436
	Q19_ads_influence	-0.120	0.233	0.264	1	0.607	-0.576	0.337
	Q20_comp_skill	0.783	0.290	7.308	1	**0.007**	0.215	1.351
	Q21_soft_skill	-0.643	0.315	4.180	1	**0.041**	-1.260	-0.027
	Q22_AI_interest	0.551	0.258	4.573	1	**0.032**	0.046	1.057
	Q23_AI_seminars	-0.056	0.223	0.062	1	0.803	-0.493	0.381
	Q24_internet	-0.113	0.289	0.152	1	0.696	-0.679	0.454
	Q25_devices	-0.292	0.316	0.853	1	0.356	-0.911	0.327
Link function: Logit.								

Several predictors were identified which had a significant impact on the degree to which students used the AI tools. Family economic status was one of the predictors influencing on AI tool using $\beta = 0.673$, $P = 0.048$ and it was positive effect which indicates that among those who used AI tool well in good economic status students were successful. The perception of AI to be useful for improving learning experience ($\beta = 1.802, P < 0.001$) and understanding difficult questions $\beta = 0.657, P = 0.028$ were significantly influenced the use artificial intelligence technologies as reported in Table-7. Perceived educational computer skills ($\beta = 0.783, P = 0.007$), and interest in learning AI-based tools ($\beta = 0.551, P = 0.032$) were also significant positive predictors of students' perceived AI adoption, indicating that the higher level of technical skill or more willingness to learn contributed positively to students' perception on uses of AI. Mitigating the negative effect, the students who opted not to use AI for ethical reasons were less likely to accept it $\beta = -0.791, P = 0.001$. Also, the negative prediction between soft skills $\beta = -.0643, P = 0.041$ and AI use was in a way, meaning that higher level soft skills would lead to the lower rate of using AI tools.

The findings indicate that family's economic status significantly influences how often AI tools are used by university students, for which access to (rich family) resources might play an important role in forming thinking patterns based on such short-term incentives. Likewise, the students who think that AI is useful to support their learning and solving difficult question are more likely to suggest using AI in academic activity emphasizing on the importance of positive perception of adopting AI. Skills with educational technology and attitudes towards tools based on AI were also significant predictors, therefore the technical self-efficacy and interest in new technologies are facilitating factors for exploring AI. In contrast, ethical concerns and the preference for personal (soft) skills negatively predict usage such that students who are worried about copyrighting, data privacy or challenging ethics might not use AI intentionally. They also suggest that universities should be concerned not just with offering their students access to AI tools but with developing both the skills and the morality necessary for using it appropriately. Enhancement of digital literacy course, training on AI and building awareness about ethical concerns would prepare students to use AI technologies in learning. The results from this study are somehow in line with (Jonathan, 2025), findings that suggested while perceived usefulness and facilitating conditions have significant influence on students acceptance of AI research tools. Regarding the case of students' recognition toward the use of AI, deploying tools and proficiency in educational software, a significant correlation was also noticed in our study participants as it was found in our whole cohort. However, in contrast to Jonathan, this research has found that the moral factor and perceived self-efficacy to control AI are both negative predictors of AI engagement. This variation could be attributed to a range of different contexts and culture between students who are based in Kurdistan Region versus India that highlight how economic, ethical and behavioural enablers tend to influence the patterns of AI adoption in higher education landscape.

4.3.6 Classification Accuracy

Table 8: Classification Table

		Predicted Response Category			Total
		Never	Sometimes	Always	
Frequency of AI use (DV)	Never	15	26	0	41
	Sometimes	7	156	4	167
	Always	0	26	6	32
Total		22	208	10	240

Model accuracy indicates how well the ordinal logistic regression that measures students AI use is being predicted.

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The classification table illustrates how often the students used AI on which model could make accurate predictions. This classifier made predictive results with an accuracy of 73.8% in total cases, a performance of the model also underperformance in 177 cases. For instance, 36.6% (15 out of 41) of never users were accurately predicted by the model as well as 93.4% (156 out of 167) the sometimes users and only 18.8% (6 out of 32) always users. Most of the misclassified instances were in "Always" but a lot of the cases under this category were predicted as "Sometimes". The model has a strong predictive performance for the common category (Sometimes), but limited for extreme categories (Never and Always), to be expected in ordinal logistic models with imbalanced categories.

5. Conclusion

The analyzation result of ordinal logistic regression showed the model was a good fit for the data, that it is correlated and able to explain a significant proportion of variance (R^2 Nagelkerke Value $= 0.421$) in use frequency amongst students' AI tool usage; approximately three-quarters cases 73.8% were correctly classified. Family Economic Status, contextual AI self-efficacy, complex problem solving, perceived relevance of AI tools and ability of computer use skills were positive predictors whilst ethical concerns or self-reported work-related skills negatively predicted use. Implications highlight the need for universities to ensure that AI-related education and digital literacy is embedded within curriculums, technology resources are equally available across all communities, and ethical use guidelines are established. Such observations can also be used to guide policy in shaping the future strategies for responsible and inclusive AI adoption in higher education.

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6. Recommendations

1. Because an awareness of AI ($\beta = 1.802 , P < 0.001$) leads to further frequent usage of AI tools among students, it is necessary to hold events for the introduction of these applications in universities and show their educational importance.
2. As the economic status of the family has a positive impact in relation to the use of AI ($\beta = 0.673 , P = 0.048$) these financial support programs or some free dissemination of these AIs tools should be beneficial for students with low economic status.
3. Due to the strong association between computer use ability ($\beta = 0.783 , P = 0.007$) and predicting factors, technical training courses need to be included in curricula in order to enhance students' digital competences.
4. Since students generally exhibit reticence due to ethical considerations with respect to the use of AI ($\beta = -0.791 , P = 0.001$), universities should conduct ethics modules in order for students' reluctance not to be too high for using it.
5. Lastly, the student education software skills were negatively related to AI use ($\beta = -0.643 , P = 0.041$), therefore, integrated training program should be developed to facilitate in which not the mutual substitution or rather complement of the students' interpersonal ability and how AI is being used.

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