JOURNAL OF POLITICAL STABILITY ARCHIVE

Online ISSN: 3006-5879 Print ISSN: 3006-5860
DOI: https://doi.org/10.63468/jpsa.3.3.58

Vol. 3 No. 3 (2025)
https://journalpsa.com.pk/index.php/JPSA/about

Recognized by: Higher Education Commission (HEC), Government of Pakistan

Predicting the Impact of AI Tools on Learning and Academic Performance: A Categorical Data Analysis Approach

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ABSTRACT

Understanding complex interrelationships within categorical data is essential across various research domains, particularly when traditional regression assumptions are not met. This study aimed to identify and model significant associations and predictive relationships among a set of exclusively categorical variables using advanced statistical techniques. Initially, five distinct log-linear models were developed to explore multidimensional dependencies among variables. These models were systematically evaluated and compared using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to determine the most parsimonious and best-fitting model structure. To further examine predictive relationships with a specified categorical outcome variable, binary, ordinal, and multinomial logistic regression models were applied. These models were assessed using key goodness-of-fit metrics, including pseudo R-squared, AIC, and BIC. Results revealed a statistically significant and interpretable log-linear model that captured critical interaction effects among the predictors. Among the logistic models, binary logistic regression consistently demonstrated superior performance,

providing the most robust and accurate predictions. This study underscores the value of integrating log-linear and logistic regression techniques for comprehensive analysis of categorical data. The combined approach enhances the understanding of complex variable interactions and supports informed decision-making for future research, policy formulation, and intervention strategies.
Keywords: Categorical Data, Logistic Regression, AI Tools.

INTRODUCTION

In the evolving landscape of education, particularly within the context of rapid digital transformation, the integration of Artificial Intelligence (AI) tools into academic environments has become a key area of research. Students across various disciplines are increasingly using AI-powered platforms such as ChatGPT, Grammarly, and DeepSeek for tasks like summarization, content generation, and skill enhancement (Zawacki-Richter et al., 2019; Dwivedi et al., 2021). These tools are reshaping learning experiences, yet their actual impact on academic performance, learning autonomy, and cognitive development remains a subject of critical inquiry (Luckin et al., 2016; Holmes et al., 2021). While several studies have suggested that AI enhances learning efficiency and academic achievement (Mhlanga & Moloi, 2020), others raise concerns about ethical implications, over-reliance, and reduced critical thinking (Tang et al., 2022; Bodily & Verbert, 2017). Moreover, individual differences—such as students' confidence in using AI, field of study, or academic level—as well as institutional context (e.g., public vs. private universities), may moderate the influence of AI tools (Smutny & Schreiberova, 2020; Zhang et al., 2020). Most survey-based studies in education produce data that are categorical in nature, such as AI usage frequency, perceived performance, and preferred tools. Analyzing such data requires advanced methods, as traditional linear regression techniques assume continuous variables and normally distributed errors—assumptions that are violated in categorical contexts (Agresti, 2013). Therefore, this study applies log-linear modeling, which enables the analysis of multidimensional associations among categorical variables by evaluating the structure of contingency tables without requiring a defined outcome variable (Christensen, 1997). To complement association analysis with prediction, this study also employs three types of logistic regression—binary, ordinal, and multinomial—each suited to different levels of categorical outcome variables (Hosmer et al., 2013). Model selection is guided by well-established fit indices such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), as well as pseudo-R-squared values (Burnham & Anderson, 2002), which support identifying the most parsimonious and explanatory model. This research adopts a dual-method strategy to investigate the academic implications of AI tools among university students in Lahore, Pakistan. First, five log-linear models are developed to explore associations among key variables such as institution type, primary AI usage, and skill development. Second, binary, ordinal, and multinomial logistic regression models are applied to predict academic performance using categorical predictors. Among these, the binary logistic regression model emerged as the most robust in terms of model fit and predictive accuracy. This integrated approach demonstrates the methodological strength of combining log-linear and logistic regression models in categorical data analysis. The findings offer valuable insights into the educational impact of AI tool usage and contribute to evidence-based policy-making, curriculum design, and student support strategies in technology-enhanced learning environments.

METHODOLOGY

This study employs a quantitative, cross-sectional design, utilizing survey data to explore both associative and predictive relationships among categorical variables related to AI tool usage and academic performance. The methodological framework integrates log-linear modeling and logistic regression analysis, enabling the examination of complex interactions as well as outcome prediction within a categorical data context (Agresti, 2013; Christensen, 1997).

The target population consisted of university students enrolled in public and private institutions across Lahore, Pakistan. A total of 100 students were selected using Simple Random Sampling (SRS) to ensure unbiased representation. All participants were Pakistani students, yielding a homogeneous sample in terms of national and educational background.

Data was collected through a semi-structured questionnaire, the questionnaire included items related to: Institutional type (public/private), Academic level (undergraduate, postgraduate), Field of study, Frequency and purpose of AI tool usage, Confidence in using AI, and Perceived impact on academic performance. All variables were coded categorically to align with the intended modeling techniques.(provided in end)

Prior to model fitting, non-parametric correlation analysis was conducted using Kendall's tau-b and Spearman's rho to screen for initial associations among variables. These techniques are suitable for ordinal and nominal data and are robust against violations of normality (Akoglu, 2018; Puth, Neuhauser, & Ruxton, 2014). Correlation strength was interpreted based on thresholds proposed by Dancey and Reidy (2007).

To explore multivariate associations, five distinct log-linear models were constructed using contingency tables. The models ranged from independent to saturated forms and included two-way interactions among key variables. Model selection was based on Likelihood Ratio Chi-square (G^2), AIC, and BIC, with the lowest values indicating the best-fitting model (Burnham & Anderson, 2002).

Mathematical Models:

1 Log-Linear Models

Independent Model: Assumes no associations between variables (only main effects). For three variables A, B, C: (e.g., for Institution Type, Primary AI Use & New Skills Development) is:

$$\ln(\mu_{ijk}) = \lambda + \lambda_A(i) + \lambda_B(j) + \lambda_C(k) \qquad (1)$$

Partial Independent Model: Includes main effects and specific two-way interaction terms.

$ln(\mu_{ijk}) = \lambda + \lambda_A(i) + \lambda_B(j) + \lambda_C(k) + \lambda_{AB}(ij) + \lambda_{AC}(ik) + \lambda_{BC}(jk)$ (2)

Saturated Model: Includes all possible main effects and interaction terms up to the highest order. This model perfectly fits the observed data but is often not parsimonious. For three variables A, B, C:

$ln(\mu_{ijk}) = \lambda + \lambda_A(i) + \lambda_B(j) + \lambda_C(k) + \lambda_{AB}(ij) + \lambda_{AC}(ik) + \lambda_{BC}(jk) + \lambda_{ABC}(ijk)$ (3)

Where:

- μ_{ijk} is the expected count in the cell corresponding to category i of variable A, category j of variable B, and category k of variable C.
- λ is the overall mean effect.
- $\lambda_A(i), \lambda_B(j), \lambda_C(k)$ are the main effects of variables A, B, and C, respectively.
- $\lambda_{AB}(ij), \lambda_{AC}(ik), \lambda_{BC}(jk)$ are the two-way interaction effects.
- $\lambda_{ABC}(ijk)$ is the three-way interaction effect.

Three types of logistic regression were applied to investigate the predictive relationships between categorical predictors and academic performance: Binary Logistic Regression (High vs Low), Ordinal Logistic Regression (4-level ordered categories), and Multinomial Logistic Regression (Most Used AI Tool: ChatGPT, Grammarly, DeepSeek, All Tools). Model performance was assessed using AIC, BIC, and pseudo R-squared values (Hosmer, Lemeshow, & Sturdivant, 2013)

2 Binary Logistic Regression: Let Y be the binary dependent variable (e.g., Y=1 for High Performance, Y=0 for Low Performance). Let $X=(x_1, x_2, \ldots, x_p)$ be the vector of independent variables (e.g., "Ethical_Concerns", "Institution_Type", "Primary_AI_Use", "New_Skills_Development", "AI_Usage_Frequency").

The probability of "High Performance" is modeled as:

$$P\left(Y = \frac{1}{X}\right) = \frac{e^{\beta_o + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p}}{1 + e^{\beta_o + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p}} \quad (4)$$

Alternatively, in terms of log-odds:

$$ln\left(\frac{P(Y=1|X)}{1-P(Y=1|X)}\right) = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p \quad (5)$$

3 Ordinal Logistic Regression: to model Academic Performance, which has ordered categories ("Below Average", "Average", "Good", "Excellent"). Ordinal logistic regression is cumulative in nature specifically; it often uses the cumulative logit model (also called the proportional odds model). Because instead of modeling the probability of a specific category, it models the cumulative probability of being in a category or below. Let Y be the ordinal dependent variable with K ordered categories (e.g., K=4 for academic performance levels). The model uses K–1 cumulative logit equations.

$$ln\left(\frac{P(Y \le k|X)}{1-P(Y \le k|X}\right) = \alpha_k - (\beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p) \quad (6)$$

4. Multinomial Logistic Regression: Let Y be the nominal dependent variable with K categories, choose one category as the reference category. Let's say category 1 is the reference. For each other category k (where k=2,…,K), a separate set of coefficients is estimated.

The log-odds of choosing category k versus the reference category 1 is modelled as:

$$ln\left(\frac{P(Y=k|X)}{(P(Y=1|X)}\right)=\beta_{k0}+\beta_{k1x1}+\beta_{k2x2}+\ldots+\beta_{kpxp} \qquad (7)$$

To derive the probabilities for each category:

$$P(Y=k|X)=\frac{e^{\beta_{k0}+\beta_{k1x1}+\beta_{k2x2}+\ldots+\beta_{kpxp}}}{1+\sum_{j=2}^{K}e^{\beta j0\quad+\beta j1\quad x1\quad+\ldots+\beta jp\quad xp}} \quad (k=2,\ldots,K) \qquad (7.1)$$

$$P(Y=1|X)=\frac{1}{1+\sum_{j=2}^{K}e^{\beta j0\quad+\beta j1\quad x1\quad+\ldots+\beta jp\quad xp}} \quad \text{(for reference category)} \qquad (7.2)$$

All analyses were conducted using R, Diagnostics and interpretation based on fitted values, odds ratios, and predictive probabilities.

RESULTS

Initial correlation analysis revealed several statistically significant, though weak, associations between variables such as Institution Type, Primary AI Use, and New Skills Development with academic performance. These were retained for model development.

Table 1: Correlated Variables with Academic Performance

Rank	Variable	Kendall's Tau-b	Spearman's Rho	P-value	interpretation
1	Ethical_Concerns	0.267	0.306	<0.05	Significant
2	Institution_Type	-0.225	-0.239	<0.05	Significant
3	Primary_AI_Use	0.191	0.230	<0.05	Significant
4	New_Skills_Development	0.165	0.180	>0.05	Insignificant

Table 1 shows weak but statistically significant correlation with academic performance. These correlation results were preliminary tests to screen relationships before running logistic regression. Only variables that showed potential influence are considered for model fitting.

Five log-linear models were compared. Model 4, which included Institution Type, Primary AI Use, and New Skills Development with all two-way interactions, showed the best fit with the lowest AIC and BIC values. It was also statistically significant, indicating strong variable interactions. Table 2 shows Lower deviance means better model fit. (likelihood ratio) All p-values > .05 so models show a good fit to the observed data.

Table 2. Log-Linear Model Comparison

Model	Variables	AIC	BIC	Deviance	DF	P-value
Model 1	Gender × AI Usage × Academic Performance	64.58	127.11	16.58	24	0.86595
Model 2	Field × AI Tool × AI Impact	91.30	185.09	19.30	36	0.98965
Model 3	Academic Level × Confidence × Ethics	57.61	120.14	9.61	24	0.99597
Model 4	Institution × Primary Use × Skills Development	**37.52**	**68.78**	13.52	12	0.33274
Model 5	Age Group × AI Dependency × Future AI	65.18	143.34	5.18	30	1.0000
Partial Log-linear Model	Ethics × Institution × Primary Use × Skills Development	270.303	543.846	60.303	105	0.9999

Mosaic Plot:

Colour Interpretation (Pearson Residuals):

Blue (positive residuals): More observations than expected under independence. *Red (negative residuals):* Fewer observations than expected. *Grey:* No significant deviation from expected. So,

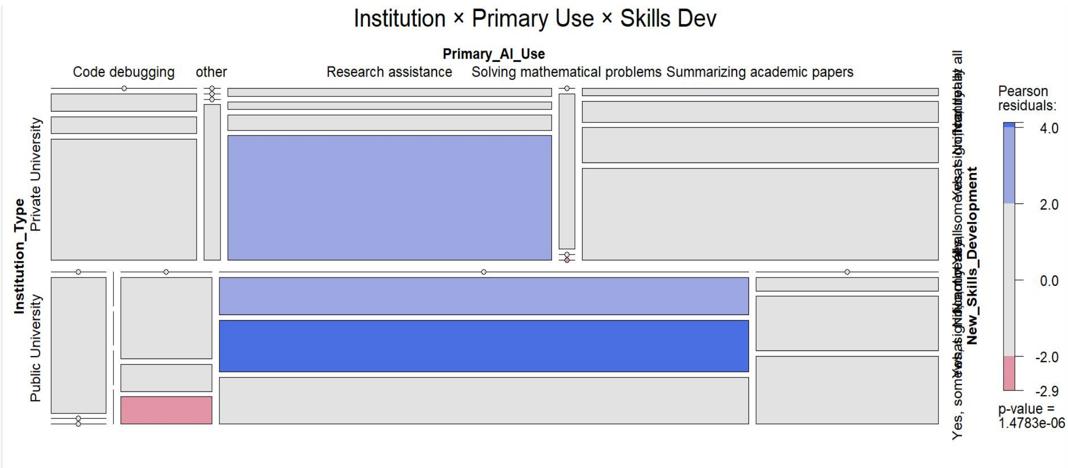
Dark Blue: Students in public universities who use AI mainly to solve math problems are more likely to report gaining new skills.

Light Blue: Students in private universities using AI for research assistance also report more skill development than expected.

Red : Those using AI for code debugging or other tasks in public universities are less likely to report skill development.

The plot shows that institution type and primary AI use are important in understanding how students perceive new skill development. Students in public universities, especially those using AI for problem-solving, seem to benefit the most in terms of developing new skills. There's a statistically significant dependency between the three variables.

There's a **statistically significant dependency** between the three variables.



Mosaic plot generated from R

The binary logistic regression model showed the strongest performance, with McFadden's R^2 = 0.393 and Nagelkerke's R^2 = 0.532.9 (table 3) Students from public universities were significantly less likely to report high academic performance, while those using AI for summarizing papers had much higher odds of high performance. (table 4)

Ordinal and multinomial logistic models were statistically significant but suffered from inflated odds ratios due to data separation, making interpretation unreliable. These models would benefit from a larger, more balanced sample.

Table 3. Pseudo R-Squared Comparison Across Models

Model Type	McFadden R^2	Nagelkerke R^2	Interpretation
Binary Logistic	0.393	0.532	Strong predictive fit
Ordinal Logistic	0.195	0.396	Moderate fit
Multinomial Logistic	0.3518	0.6100	Good fit, but less parsimonious
New Skills Dev ~ Performance	0.20	0.26	Weak but significant

Table 4. Binary Logistic Regression Summary

Predictor	**Odds Ratio**	**p-value**	**Interpretation**
Public University	0.031	0.017	Less likely to report high performance
AI Use: Summarizing Papers	32.61	0.044	More likely to report high performance

Table 5: Model Comparison by AIC and BIC

Model	AIC	BIC	Null Deviance	Residual Deviance
Binary Logistic	101.57	143.26	114.61	69.57
Ordinal Logistic	216.02	262.91	223.72	180.02
Multinomial Logistic	241.01	366.06	223.72	145.01

Binary logistics is the best model based on the lowest AIC and BIC. Indicates the best balance between fit and complexity. In ordinal Higher AIC/BIC suggests a poorer fit compared to the binary model. Multinomial is the worst fit among the three, especially penalized by BIC due to model complexity (table 5)

Overall, the best model is the Binary Logistic Regression due to the best combination of fit, simplicity, and clear interpretation.

DISCUSSION

This study combined log-linear and logistic regression techniques to explore the influence of AI tool usage on academic performance among university students. Significant interactions found in Model 4 suggest that the type of institution, purpose of AI use, and skill development are interconnected.

Binary logistic regression provided the most accurate predictions. Public university students were less likely to perform highly, and those using AI for summarizing showed improved performance, supporting previous findings that AI enhances productivity and comprehension when used meaningfully (Holmes et al., 2021).

Complex models like ordinal and multinomial regression were limited by small and unbalanced category sizes. This reinforces the importance of model parsimony and sufficient sample sizes when applying categorical regression techniques (Burnham & Anderson, 2002).

The combined modeling approach demonstrated here offers a replicable method for analyzing survey-based categorical data in education and can inform future research and institutional policy on AI tool integration.

CONCLUSION

This study investigated how students' use of AI tools affects academic performance using categorical data analysis. Log-linear modelling revealed significant interaction effects among institution type, AI use, and skill development, emphasizing the interconnected nature of these variables. Among the logistic regression models tested, binary logistic regression emerged as the most parsimonious and reliable model for predicting academic performance.

Key findings indicated that students who used AI primarily for summarizing academic papers had significantly higher odds of reporting high academic performance, whereas students from public universities were less likely to do so. These results highlight the dual importance of effective AI usage and institutional support systems in enhancing student outcomes

Recommendations

Based on the study's findings, the following recommendations are proposed:

Encourage Purposeful AI Usage

Educators should promote the strategic use of AI tools, especially for comprehension and synthesis tasks, such as summarizing academic content.

Bridge Institutional Gaps

Public universities should invest in digital infrastructure and student training to ensure equitable access to AI resources and support.

Simplify Model Selection in Categorical Data

Researchers working with categorical datasets should consider starting with simpler, well-fitting models like binary logistic regression, before using more complex alternatives.

Expand Future Research Scope

Future studies should incorporate **larger and more diverse samples** to validate findings across subgroups and enhance model stability, particularly for ordinal and multinomial analyses.

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Index: Semi-structured Questionnaire

Questionnaire: " Impact of AI Tools on Learning and Academic Performance"

Section 1: Demographic Information

1. What is your age group?

☐ 18-25 ☐ 26-35 ☐ 36-45 ☐ 46+

2. What is your gender?

☐ Male ☐ Female

3. What is your field of study?

☐ Science & Engineering ☐ Business & Management ☐ Arts & Humanities ☐ Social Sciences

4. What is your current academic level?

☐ Bachelors ☐ Master's /MPhil ☐ PhD

5. What type of institution do you attend?

☐ Public University ☐ Private University

Section 2: Use of AI Tools in Learning

6. How often do you use AI-powered learning tools (e.g., ChatGPT, Grammarly, DeepSeek, Gemini, Copilot, etc.)?

☐ Never ☐ Rarely (Once a month or less) ☐ Occasionally (1-2 times per week) ☐ Regularly (3-5 times per week) ☐ Daily

7. Which AI tools do you use most frequently for learning? (Select all that apply)

☐ ChatGPT ☐ Grammarly ☐ DeepSeek ☐ Other (Please specify: ________________)

8. For what purpose do you primarily use AI tools in your studies?

☐ Summarizing academic papers ☐ Code debugging ☐ Solving mathematical problems ☐ Research assistance

9. How confident are you in the accuracy of AI-generated responses?

☐ Very Confident ☐ Somewhat Confident ☐ Neutral ☐ Slightly Doubtful ☐ Not Confident at All

10. How do you usually verify the information provided by AI tools?

☐ Cross-checking with other sources ☐ Consulting instructors or peers ☐ Other (Please specify: _________)

Section 3: Academic Performance & AI Tools

11. How would you rate your overall academic performance using AI Tools in the past semester?

☐ Excellent (A-grade or equivalent) ☐ Good (B-grade or equivalent) ☐ Average (C-grade or equivalent) ☐ Below Average (D-grade or lower)

12. Do you feel that using AI tools has improved your academic performance?

☐ Strongly Agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly Disagree

13. How much time do you spend studying independently without AI assistance?

☐ Less than 1 hour per day ☐ 1-2 hours per day ☐ 3-4 hours per day ☐ More than 4 hours per day

14. Would you recommend AI tools for academic learning to other students?

☐ Yes ☐ No ☐ Maybe

15. Do you think AI tools have helped you develop new skills?

☐ Yes, significantly ☐ Yes, somewhat ☐ No, not really ☐ No, not at all

16. Do you think AI tools have helped you develop improve existing skills?

☐ Yes, significantly ☐ No, not really ☐ No, not at all ☐ Yes, somewhat

Section 4: Challenges and Ethical Considerations

17. Have you faced any challenges while using AI tools for learning?

☐ Yes, technical issues (e.g., tool not working properly) ☐ Yes, accuracy issues (e.g., incorrect information)

☐ Yes, over-reliance on AI tools ☐ No, I haven't faced any challenges

18. Do you think the use of AI tools in education raises any ethical concerns?

☐ Yes, plagiarism ☐ Yes, academic integrity ☐ Yes, over-reliance on AI ☐ Yes, bias in AI algorithms

☐ No, I don't think there are ethical concerns ☐ Other (Please specify: ________________)

19. Do you believe that AI tools could create a dependency among students?

☐ Yes, definitely ☐ Yes, somewhat ☐ No, not really ☐ No, not at all

Section 5: Future of AI in Education

20. How do you envision the role of AI tools in education evolving over the next 5-10 years?

☐ AI will replace teachers ☐ AI will complement teachers

☐ AI will have a minimal impact on education ☐ Other (Please specify: ______________________

21. What improvements or new features would you like to see in AI-powered learning tools?

☐ Better accuracy and reliability ☐ Integration with other educational platforms

☐ More personalized learning experiences ☐ Other (Please specify: ________________)