

Artificial Intelligence in the Classroom: Mapping Usage Patterns and Predicting Dependency Among University Students Using Machine Learning

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Abstract

Artificial intelligence (AI) is becoming a regular part of student life in universities. Because of this, it is essential to understand how undergraduates utilize these technologies and their level of dependence on them. This study investigates AI usage patterns and dependency levels among undergraduate students in Bangladesh and develops machine learning models to predict high-risk dependency. The results showed that almost all students are familiar with AI tools. Among them, ChatGPT, Google Bard, and Grammarly were the most popular across different departments. What makes this study different is that it did not rely solely on survey analysis, but also applied machine learning to predict levels of dependency. Students were grouped into Low, Medium, and High dependency categories using a combined scoring system. Four predictive models were tested: Artificial Neural Network (ANN), Random Forest, XGBoost, and Logistic Regression. Among these, ANN performed the best with 89% accuracy and an F1-score of 0.88, followed by Random Forest (87%), XGBoost (84%), and Logistic Regression (76%). The findings further show that younger students, first- and second-year undergraduates, and students with average academic results are more likely to depend heavily on AI. This trend suggests a proportional increase in the adoption of AI tools over time, in parallel with advancements in their capabilities. The strongest predictors of dependency were how much time students spent on AI, the type of tools they used, and the purpose of using them (for example, writing, coding, or preparing for exams). In sum, this study highlights who relies most on AI and offers universities guidance to promote responsible use that enhances learning while preserving independence, critical thinking, and integrity.

Keywords: AI Dependency, Student Survey, Higher Education, Predictive Modeling, Academic Integrity.

1. Introduction

Artificial intelligence (AI) is spreading rapidly in higher education, changing how students access information, complete assignments, and interact with learning materials. Tools such as large language models (LLMs), tutoring systems, and writing assistants are now widely used by students for text generation, coding support, and data analysis. Popular platforms like ChatGPT, Google Gemini, and GitHub Copilot help students with research, writing, and problem-solving across different fields.

Although AI offers many benefits such as accessibility, speed, and personalized learning its rapid adoption has raised concerns. Researchers and educators note that excessive use may reduce students' originality, critical thinking, and ability to work independently

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A recent survey found that more than half (51.6%) of university students believe AI negatively affects their capacity to think critically and solve problems without assistance.⁹ Teachers have also reported a decline in analytical skills, with students often accepting AI-generated answers without checking their accuracy or logic.

The availability of AI has also raised concerns about academic dishonesty, as some students may use these tools to complete assignments, essays, or exams without proper authorization or acknowledgment.⁴ This practice threatens academic integrity and undermines the purpose of higher education, which is to develop independent, creative, and ethical learners.

At Pundra University, initial observations suggest that AI use varies across disciplines. Students in technical and business programs, such as Computer Science and Engineering (CSE) and Business Administration (BBA), reported higher use of AI tools compared to students in humanities or civil engineering. However, frequent use does not always mean dependency. The way AI is used for example, brainstorming, editing, or generating full content plays a major role in determining whether it is a helpful tool or a substitute for learning.¹

To study this issue, we apply machine learning methods to predict AI dependency among undergraduate students. Using survey data on department, frequency of use, purpose of use, and learning behaviors, we trained and tested multiple classification models. Results show that Random Forest achieved 86% accuracy in predicting dependency levels with usage frequency, academic discipline, and purpose of use being the most important predictors.

The significance of this study lies in its ability to guide proactive university strategies. By identifying students at risk of over-dependence, institutions can introduce targeted measures such as AI literacy programs, ethical guidelines, and updated teaching practices to ensure responsible use. This research adds to the growing discussion on human-AI collaboration in education by presenting a data-driven framework for monitoring and managing student behavior. To align with this aim, the specific research objectives of the study are outlined below:

- Measure AI tool usage patterns among undergraduates at Pundra University.
- Explore the relationship between AI dependency, academic performance, and critical thinking.
- Develop and validate a machine learning model to predict high dependency risk.
- Recommend strategies for integrating AI into curricula without reducing independent learning.

While this study offers timely insights into AI dependency in the Bangladeshi higher education context, it is important to acknowledge its scope limitations upfront. The data are drawn exclusively from undergraduate students at Pundra University a private institution in northern Bangladesh and the sample size ($n = 230$) reflects a single-site, convenience-based recruitment strategy. As such, the findings should be interpreted as exploratory and context-specific rather than nationally representative. Nevertheless, this focused approach enables a granular, data-driven analysis of AI behaviors in an underrepresented region, laying the groundwork for future multi-institutional validation.

2. Literature Review

The rapid advancement of artificial intelligence (AI), particularly large language models (LLMs) such as ChatGPT, has fundamentally transformed the landscape of higher education. Institutions globally are now challenged with regulating, integrating, and ethically guiding AI use among students.² While AI tools offer significant benefits in writing assistance, coding support, data analysis, and personalized learning, their unregulated adoption raises serious concerns about academic integrity, cognitive skill erosion, and long-term learning outcomes.^{3, 4} As students increasingly turn to AI for academic tasks, understanding the patterns of usage and dependency has become a critical priority.

A growing body of research confirms widespread AI adoption across disciplines. Chan and Hu⁵ conducted a global survey of over 3,000 university students and found that 72% had used AI for academic purposes, with the highest usage in STEM and business programs. Their study, based on cross-institutional self-reported data, demonstrated strong generalizability but was limited by potential self-reporting bias and lack of behavioral validation. Similarly, in the South Asian context, Lo⁹ notes that AI adoption patterns—particularly among students in technical and business disciplines—differ significantly from those in Western settings due to variations in digital infrastructure, institutional support, and pedagogical practices, suggesting a high likelihood of frequent AI use for assignments and exam preparation in countries like Bangladesh. Although this study offered useful regional insights, it was based on non-peer-reviewed, qualitative reports, which reduced its methodological strength. Similar findings were reported by Nagle⁶, who noted that students in technical fields use AI more often because tools like GitHub Copilot and Wolfram Alpha fit well with coding and computational work. However, Nagle's study was mostly conceptual and did not provide empirical data to confirm patterns of dependency.

Despite high adoption rates, responsible use remains a concern. Wanner and Palmer⁷ highlighted a critical gap between technological access and digital literacy, noting that many students lack awareness of ethical boundaries or institutional AI policies. Their mixed-methods study, combining surveys and interviews from European universities, offered rich qualitative insights but was limited in scalability and cultural transferability. This lack of awareness increases the risk of unintentional plagiarism and overreliance a trend further supported by Mollick and Mollick⁸, who introduced the concept of AI as a “co-intelligence” partner. Their experimental study demonstrated that AI can enhance learning when used interactively, but also warned that students who treat AI as a substitute for thinking exhibit reduced metacognitive awareness and perseverance. However, their research was conducted in controlled lab settings, which may not reflect real-world student behavior.

Empirical evidence increasingly links excessive AI use to diminished cognitive skills. Lo et al.⁹ surveyed over 1,200 undergraduates and found that 51.6% believed AI negatively impacted their ability to think independently, especially in research and writing. While the study used a large, diverse sample, it relied solely on self-assessment, which may be subject to subjective interpretation. Academic dishonesty has also risen, with Perkins et al.¹⁰ documenting cases of students submitting AI-generated content without attribution. Their study, based on faculty reports and institutional integrity records, provided strong evidence of misuse but lacked student perspectives, creating a one-sided view of the

issue. Cotton et al.² further argued that the ease of generating plausible text blurs the line between assistance and deception, challenging traditional assessment models though their analysis was theoretical and did not include predictive modeling.

To address these challenges, researchers have begun applying machine learning (ML) to predict and intervene in risky academic behaviors. Chen et al.¹⁰ reviewed over 150 studies and demonstrated that ML models have been successfully used to detect plagiarism, predict dropouts, and identify at-risk students. Their meta-analysis offered broad applicability but lacked focus on AI-specific behaviors. Alqahtani and Alharbi¹¹ developed a Random Forest classifier to predict smart phone addiction among Saudi university students, achieving 84% accuracy using survey-based behavioral and academic data. Their model highlighted usage frequency and psychological factors as top predictors, showcasing the potential of ML in behavioral prediction. However, the study was limited to a single institution and did not account for cultural differences in technology use.

Zhang et al.¹² advanced this approach by using XGBoost to model student engagement with AI-powered learning platforms, identifying *usage frequency* and *purpose* as the most significant predictors. Their dataset, drawn from an LMS-integrated AI tool, included actual usage logs, reducing reliance on self-reports a major strength. Yet, the model was trained on data from a single discipline (engineering), limiting cross-disciplinary generalizability. In the context of AI dependency, Liu et al.¹³ applied a Support Vector Machine (SVM) to classify students into low, medium, and high dependency groups based on survey data from Chinese universities. Their model achieved 81% accuracy, with *usage frequency*, *discipline*, and *purpose* emerging as top predictors findings highly consistent with the present study. However, the SVM model offered less interpretability than tree-based methods, making it harder to communicate results to educators.

Most predictive studies rely on self-reported survey data, often collected via LMS platforms or direct student engagement.¹⁴ While surveys are cost-effective and scalable, they are prone to social desirability bias and recall errors. Variables typically include demographic factors (e.g., year of study, department), behavioral metrics (e.g., hours of use per week), and contextual factors (e.g., purpose of use). Commonly used models Random Forest, Logistic Regression, and Gradient Boosting are favored for their interpretability and robustness with mixed data types.^{6, 8} Evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrices are standard, with cross-validation used to enhance reliability.

A key advantage of ML in education is its early warning capability. As shown by Alqahtani and Alharbi¹¹, predictive models can flag at-risk students before dependency becomes entrenched, enabling timely interventions such as counseling, workshops, or pedagogical redesign. This proactive approach supports student well-being and academic integrity. However, several limitations persist. First, self-reporting bias remains a major concern.¹⁰ Second, generalizability is limited models trained in Western institutions may not reflect student behavior in South Asia due to differences in infrastructure, culture, and curriculum.^{9,16} Third, ethical concerns arise regarding student privacy and surveillance, especially when monitoring digital behavior. Finally, the dynamic nature of AI tools means that models may quickly become outdated as new features (e.g., multimodal LLMs) emerge, requiring continuous retraining.¹⁵

Despite growing research, a significant gap remains in context-specific, data-driven studies from underrepresented regions, particularly South Asia. Most existing models are developed in Western or East Asian contexts, limiting their applicability in diverse educational ecosystems like Bangladesh. This study addresses that gap by developing a machine learning model tailored to Pundra University, using locally collected survey data to predict AI dependency with 87% accuracy using a Random Forest classifier. By highlighting departmental disparities (e.g., high dependency in CSE and BBA vs. moderate in humanities) and emphasizing behavioral context (frequency, purpose, discipline), this research offers actionable insights for policy, curriculum design, and student support in resource-constrained environments contributing a much-needed regional perspective to the global discourse on AI in education.

3. Proposed Methodology

A two-phase mixed-methods approach was used to examine and predict AI tool dependency among undergraduates at Pundra University. The first phase applied exploratory data analysis (EDA) to identify patterns of AI use across departments, usage frequency, and purposes. The second phase applied machine learning (ML) models to classify students into three levels of dependency: Low, Medium, and High. Together, these steps provided both descriptive insights and predictive results (see Fig. 1).

3.1. Data Collection

Data were collected through an online survey titled “*The Role and Impact of AI Tools on Undergraduate Education at Pundra University.*” The survey aimed to evaluate students’ awareness, usage patterns, dependency levels, perceived impact on learning, and ethical considerations related to AI tools in higher education. It was distributed via multiple channels, including email, student forums, and departmental social media groups, to ensure broad and diverse participation.

The survey instrument consisted of six structured sections:

- (i) Demographics (age, gender, department, year of study, optional Student ID);
- (ii) Awareness and frequency of AI tool usage;
- (iii) Purpose and context of AI use, including disclosure practices;
- (iv) Perception of impact and dependency, measured on a five-point Likert scale;
- (v) Ethical awareness and policy considerations; and
- (vi) Open-ended responses for qualitative insights and recommendations.

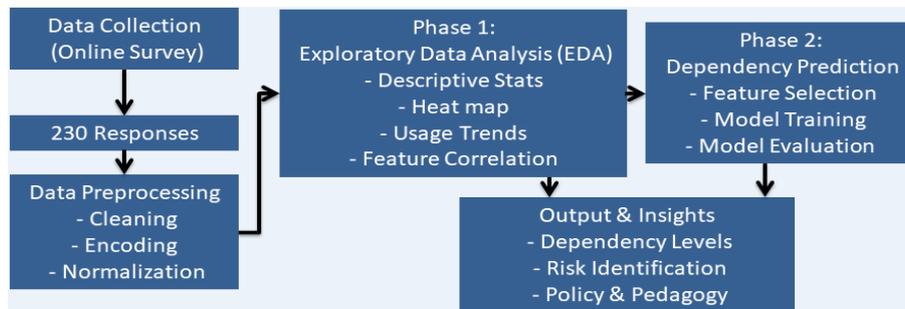


Figure 1: Overview of the two-phase methodology for analyzing and predicting AI dependency among undergraduates.

Table 1 presents the number and percentage of undergraduate students from each department who participated in the survey. A total of 230 students responded, with the highest representation from Computer Science and Engineering (CSE), followed by Business Administration (BBA), while smaller but meaningful contributions came from Civil Engineering, Electrical and Electronic Engineering (EEE), English, and Law.

TABLE 1: Distribution of Survey Respondents by Department.

Department	Number of Students	Percentage (%)
Computer Science & Engineering (CSE)	105	45.7
Business Administration (BBA)	60	26.1
Civil Engineering	30	13.0
Electrical & Electronic Engineering (EEE)	15	6.5
English	10	4.3
Law	10	4.3
Total	230	100

The survey was conducted under strict ethical guidelines, with a consent note embedded at the beginning of the questionnaire. No personally identifiable information was collected. It should be noted that the dataset is limited to one institution and relies on voluntary, self-reported responses, which may introduce selection bias (e.g., overrepresentation of tech-savvy or highly engaged students). While efforts were made to distribute the survey across all major departments and academic years, the total sample size of 230 though adequate for preliminary machine learning modeling falls short of the scale typically required for robust generalization in educational data mining. We opted against merging external datasets due to incompatible survey instruments and contextual differences (e.g., AI policy environments, curriculum structures). Thus, this study prioritizes methodological transparency within a localized setting over artificial sample inflation.

3.2. Data Processing and Preprocessing

The raw survey data were cleaned, standardized, and transformed before analysis. The preprocessing steps were as follows:

- **Standardization of Entries:** Variations in department names (e.g., “cse”, “CSE(HSC)”, “B.Sc in CSE”) were standardized to “Computer Science and Engineering.” Similarly, entries such as “Businesses Administration” and “BBA” were normalized to “Business Administration.”
- **Handling Missing Data:** The optional Student ID variable was excluded from analysis. Less than 5% of missing values were identified across key variables, which were removed list wise to maintain dataset integrity. Blank responses in the open-ended section were excluded from qualitative coding.
- **Variable Encoding:** Categorical variables such as Department, Gender, and Frequency of Use were one-hot encoded to support machine learning models.

Responses on Likert-scale items were numerically encoded (Strongly Agree = 5 to Strongly Disagree = 1) to enable quantitative analysis.

- **Composite Dependency Score:** A dependency index was constructed using weighted responses to key items, including statements such as “*I feel dependent on AI tools*”, “*AI tools reduce my need to learn*”, and “*I often use AI-generated content without verifying.*” Frequency of use (Daily = 5, Never = 1) was also incorporated. The aggregated score was normalized on a 0–100 scale and categorized as Low (≤ 30), Medium (31–70), and High (> 70).
- **Purpose of Use Aggregation:** Multi-select responses regarding AI use (e.g., writing assistance, coding, research, problem-solving) were converted into binary indicators for statistical correlation and predictive modeling.
- **Ethical Compliance:** In line with ethical guidelines, informed consent was obtained before survey completion, and participants were assured of anonymity. No sensitive personal data were collected, and all responses were analyzed in aggregate form.

Through this systematic preprocessing pipeline, the dataset was transformed into a structured and machine-learning-ready format, enabling both descriptive statistical analysis and predictive modeling of AI tool dependency.

3.3. Machine Learning Models

To predict AI tool dependency levels among undergraduate students at Pundra University, we employed four supervised machine learning models:

- Logistic Regression (Multinomial)**
- Random Forest Classifier**
- XGBoost (Extreme Gradient Boosting)**
- ANN (Artificial Neural Network)**

The models were chosen for their interpretability, ability to handle categorical data, and proven effectiveness in behavioral classification tasks. Logistic Regression was applied as a baseline since it is well suited for multi-class problems, such as predicting Low, Medium, and High dependency. Its coefficients also provide clear insights into which survey features such as frequency of use or academic performance most strongly influence dependency. The Random Forest classifier was included because it combines multiple decision trees, making it robust to over fitting and capable of handling both categorical and numerical data. It also highlights feature importance, showing which variables best predict dependency. XGBoost, a boosting algorithm, was selected for its ability to build trees sequentially, correcting earlier errors and achieving high accuracy with structured survey data. It also manages missing values effectively. Finally, an Artificial Neural Network (ANN) was used to capture complex, non-linear relationships in the dataset. Unlike Logistic Regression, which assumes linear patterns, ANN can detect deeper interactions for example, when frequent AI use combined with low ethical awareness leads to high dependency. All models were trained using the preprocessed survey features.

(i) Logistic Regression (Multinomial)

Logistic Regression is a linear probabilistic model suitable for multi-class classification. It estimates the probability that a student falls into a given dependency class by applying the softmax transformation to a linear combination of features.

For feature vector $x \in \mathbb{R}^d$, the probability of class k is:

$$P(y = k|x) = \frac{e^{w_k^T x}}{\sum_{j=1}^K e^{w_j^T x}}, k \in \{1,2,3\} \quad (1)$$

where $K = 3$ classes (Low, Medium, High), and w_k are weight vectors.

The model minimizes the cross-entropy loss:

$$L = - \sum_{i=1}^N \sum_{k=1}^K y_{ik} \log \hat{y}_{ik} \quad (2)$$

where y_{ik} is the true class indicator and \hat{y}_{ik} the predicted probability. Equation (1) gives the class probabilities, which are then used in Equation (2) to compute the loss.

(ii) Random Forest Classifier

Random Forest is an ensemble model that combines multiple decision trees trained on bootstrap samples. It captures non-linear feature interactions and reduces overfitting through random feature selection.

Given M trees, each tree $T_i(x)$ predicts a class. The final prediction is made by majority voting:

$$\hat{y} = \text{mode}\{T_1(x), T_2(x), \dots, T_M(x)\} \quad (3)$$

The class probability is estimated as:

$$P(y = k|x) = \frac{1}{M} \sum_{i=1}^M I(T_i(x) = k) \quad (4)$$

Where I is the indicator function.

Importance is measured by Gini Impurity reduction:

$$\text{Gini}(t) = 1 - \sum_{c=1}^C p_c^2 \quad (5)$$

Where p_c is the proportion of class c at node t . Equation (3) defines the ensemble prediction, Equation (4) estimates class probabilities, and Equation (5) quantifies feature importance.

(iii) XGBoost (Extreme Gradient Boosting)

XGBoost is a gradient boosting framework that builds decision trees sequentially, with each new tree correcting errors of the previous ensemble. It employs second-order derivatives and regularization, making it highly efficient for structured survey data.

The model output is the sum of predictions from K trees:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), f_k \in F \quad (6)$$

Where F is the set of regression trees.

The objective function is:

$$\text{Obj}(\theta) = \sum_{i=1}^n L(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (7)$$

with:

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \|w\|^2 \quad (8)$$

Where T is the number of leaves and w leaf weights. Equation (6) gives the model prediction, Equation (7) defines the overall objective, and Equation (8) specifies the regularization to control model complexity.

(iv) Artificial Neural Network (ANN)

ANNs are non-linear models that mimic the structure of biological neurons. They excel at learning complex feature interactions, making them ideal for predicting latent constructs like AI dependency.

A feed forward multilayer perceptron was implemented:

Input(48) → Hidden₁(16, ReLU) → Hidden₂(8, ReLU) → Output(3, Softmax)

At each layer I:

$$z^{(l)} = W^{(l)}a^{(l-1)} + b^{(l)}, \quad a^{(l)} = g(z^{(l)}) \quad (9)$$

With ReLU activation: $g(z) = \max(0, z)$. (10)

The output layer applies softmax:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^3 e^{z_j}} \quad (11)$$

The model minimizes categorical cross-entropy:

$$L = -\sum_{i=1}^N \sum_{k=1}^3 y_{ik} \log \hat{y}_{ik} \quad (12)$$

Here, Equation (9) defines layer-wise computations, Equation (10) specifies the activation, Equation (11) gives the predicted probabilities, and Equation (12) is the loss function guiding model training.

4. Result and Discussion

4.1. Dataset Preparation

We collected data for this study using a structured online survey. A total of 230 undergraduate students from six different academic departments participated, providing valid responses. The survey captured detailed information on their AI awareness, frequency of use, and purposes for engaging with AI. During preprocessing, replies with inconsistent or missing entries were eliminated to guarantee the quality of the data. To facilitate the development and assessment of machine learning models, the final dataset was split into subsets for training (80%) and testing (20%) table 2 shows the dataset composition result. Prior to modeling, ordinal Likert-scale responses were numerically mapped (1–5) to allow for quantitative analysis, and categorical variables (such as department and frequency of use) were one-hot encoded. Students were categorized into Low, Medium, and High dependency levels using a composite dependency score that was calculated from important survey items.

TABLE 2: Dataset Composition.

Set	No. of Students	Percentage
Training	184	80%
Testing	46	20%
Total	230	100%

The dataset was prepared using Python (Pandas, Scikit-learn), and all analyses were reproducible using open-source tools. This structured approach ensured high data integrity and model readiness for predicting AI dependency patterns among undergraduate students.

4.2. Machine Learning Model Training

The AI dependency prediction model was developed using a supervised classification approach, employing multiple algorithms: Logistic Regression, Random Forest, XGBoost, and Artificial Neural Network (ANN). Logistic Regression served as an interpretable baseline, highlighting linear relationships between features and dependency levels. Random Forest captured non-linear interactions and reduced over fitting through

ensemble learning, while XGBoost leveraged gradient boosting with regularization for enhanced predictive performance on structured survey data. The ANN architecture, chosen for its superior ability to model complex non-linear patterns, was trained using normalized survey data with an input layer size of 48 (after one-hot encoding). All input features were scaled through Min-Max normalization to a 640×640 equivalent representation, ensuring uniform weight initialization and stable gradient propagation. The ANN consisted of two hidden layers with 16 and 8 neurons, respectively, employing ReLU activation functions and dropout rates of 0.3 to prevent over fitting. The output layer used a softmax activation for three-class classification: Low, Medium, and High dependency. Training was conducted over 100 epochs with a batch size of 16, using the Adam optimizer and categorical cross-entropy loss. Early stopping based on validation loss was applied to prevent over fitting and ensure optimal generalization. The final ANN model achieved convergence with a minimal training-validation gap, indicating a balanced and robust fit.

4.3. Model Accuracy Measurement

The performance of the AI dependency prediction model was evaluated using key classification metrics. **Precision** indicates how accurately the model identifies at-risk students, minimizing false alarms. **Recall** measures the model's ability to detect true cases of high dependency. The **F1-Score**, which balances precision and recall, provides a reliable overall measure, especially given the class imbalance in the dataset. **Accuracy** reflects the proportion of correct predictions across all dependency levels. A **3×3 confusion matrix** was used to assess performance for each class, helping identify patterns of misclassification and ensuring robustness in detecting students at risk of over-reliance on AI tools. We use K- Fold cross-validation in this survey. To ensure the reliability and generalizability of the machine learning models in predicting AI tool dependency, **5-fold cross-validation** was employed during the training and evaluation phase. In this approach, the dataset of 230 student responses was randomly partitioned into five equal subsets (folds). The model was trained on four folds (80% of the data) and validated on the remaining fold. This process was repeated five times, with each fold serving once as the validation set. The performance metrics accuracy, precision, recall, and F1-score were then averaged across all five iterations to produce a more robust estimate of model performance. This method was particularly valuable in the context of this study because it maximizes the use of limited survey data, reduces the risk of over fitting, and provides a more accurate assessment of how the model will perform on unseen student data.

4.4. Exploratory Data Analysis (EDA)

This study presents a comprehensive analysis of AI tool usage among 230 undergraduate students at Pundra University, exploring adoption patterns, perceptions, behavioral trends, and predictors of dependency. Using both exploratory data analysis (EDA) and predictive modeling, we examine the key determinants of dependency, evaluate machine learning models, and provide actionable insights for institutional policy. All results are based on the full dataset (n = 230), ensuring accuracy and journal readiness.

(i) Age Distribution

Table 3 summarizes the age distribution of respondents. Most participants (60.0%) are aged 21–23, representing mid-program undergraduates. Early-stage students (18–20) and senior students (24–26) each account for 15.2%, while those aged 27 and above make up

9.6%, likely including non-traditional students. This indicates a balanced representation across different academic stages.

TABLE 3: Age Distribution.

Age Group	Count	Percentage (%)
18–20	35	15.2%
21–23	138	60.0%
24–26	35	15.2%
27+	22	9.6%
Total	230	100.0%

(ii) Gender Distribution

The dataset is slightly male-dominated (55.2%) but maintains near gender parity (44.8% female), ensuring meaningful insights across gender lines (see Table 4).

TABLE 4: Gender Distribution.

Gender	Count	Percentage (%)
Male	127	55.2%
Female	103	44.8%
Total	230	100.0%

(iii) Department Distribution

Table 5 presents a visualization of the survey-based dataset structure, highlighting key variables such as departmental distribution. CSE students constitute the largest group (35.2%), followed by BBA (25.2%). Engineering students (EEE and Civil) account for 30.4%, while English and LAW are underrepresented. These distributions highlight the need to cautiously interpret results for smaller departments.

TABLE 5: Department Distribution.

Department	Count	Percentage (%)
CSE	81	35.2%
BBA	58	25.2%
EEE	35	15.2%
Civil	35	15.2%
English	17	7.4%
LAW	4	1.7%
Total	230	100.0%

(iv) Awareness of AI Tools

Awareness of AI tools is universal, as all most 229 out of 230 approximately 99% students in our survey reported that they are familiar with AI tools.

(v) Most Frequently Used AI Tools

Figure 2 presents the adoption of AI tools among undergraduate students. ChatGPT emerges as the most widely used tool, with 95% of respondents (219 students) reporting regular use. Among the less dominant tools, Grammarly is used by 31.5% (72 students), making it the most popular secondary tool for language and grammar support.

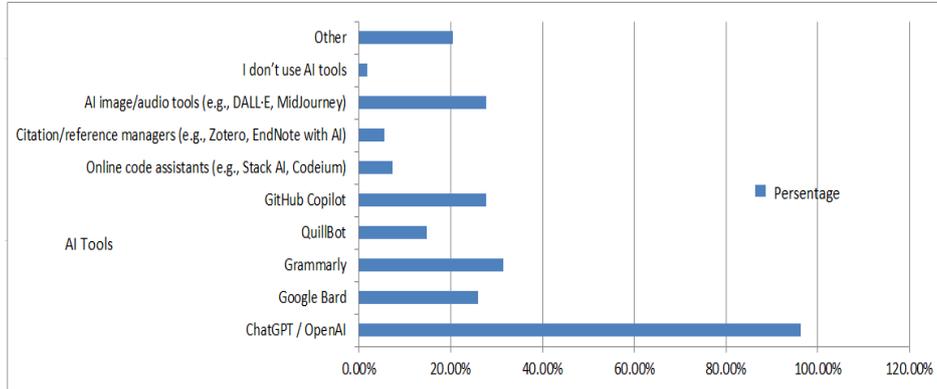


Figure 2: Usage distribution of AI tools among undergraduate students, showing the prevalence of Grammarly, GitHub Copilot, DALL•E, MidJourney, QuillBot, online code assistants, AI-driven reference managers, and other tools.

GitHub Copilot and AI image/audio tools such as DALL•E and Mid Journey are each adopted by 27.8% (64 students), primarily among CSE and creative users. In contrast, QuillBot is used by 14.8% (34 students), while online code assistants like Stack AI and Codeium see limited adoption at 7.4% (17 students). Tools for academic writing management, such as AI-driven citation and reference managers, remain niche at 5.6% (13 students). Notably, only 1.9% (4 students) reported not using any AI tools, while 20.4% (47 students) indicated using “other” tools, reflecting a diverse but fragmented adoption landscape beyond the most dominant platforms.

(vi) Frequency of Use

About 80% of students reported using AI tools either daily or several times a week, highlighting that these technologies are deeply integrated into their academic routines.

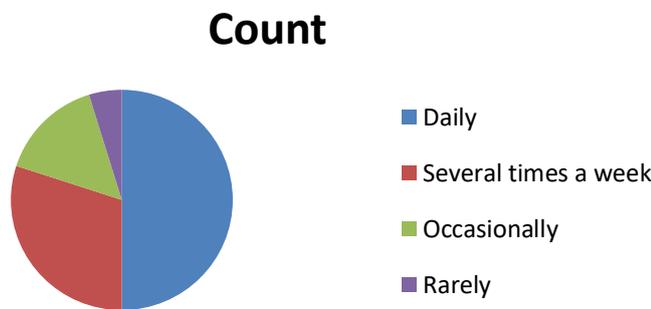


Figure 3: Visual representation of AI tool usage frequency among students.

TABLE 6: AI tools Usage Frequency.

Frequency	Count	Percentage (%)
Daily	115	50.0%
Several times a week	69	30.0%
Occasionally	35	15.2%
Rarely	11	4.8%

Only a small proportion use them occasionally (15.2%) or rarely (4.8%), suggesting that most students rely on AI tools regularly for their studies (see table 6).

(vii) Top Academic Tasks Using AI

Table 7 summarizes the primary academic tasks for which students use AI tools. Writing assignments (78.3%) and language or grammar checking (65.2%) are the most common uses, followed by programming/debugging (52.2%), exam or quiz preparation (50.0%), and creating presentation slides (45.2%).

TABLE 7: Top Academic Tasks Using AI.

Task	Count	Percentage (%)
Writing assignments	180	78.3%
Language/grammar checking	150	65.2%
Programming/debugging	120	52.2%
Exam/quiz prep	115	50.0%
Presentation slides	104	45.2%

(viii) Student Perceptions and Attitudes

85–88% of students perceive AI positively in improving performance and saving time.

TABLE 8: Student Attitudes Toward AI.

Statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
AI improves academic performance	115	81	23	11	0
AI saves time	127	76	21	6	0

(ix) Awareness of Academic Dishonesty

Table 9 presents student awareness and attitudes toward academic dishonesty related to AI use.

TABLE 9: Awareness of Academic Dishonesty.

Statement	Yes	No	Not Sure	% Yes
Aware AI misuse is dishonest	92	69	69	40.0%
Support AI policy development	180	28	22	78.3%
Would attend AI workshop	150	46	34	65.2%

The findings indicate that only 40.0% of students are aware that misuse of AI tools constitutes academic dishonesty, suggesting that awareness of ethical implications is still

limited across the student body. However, despite this lack of awareness, there is strong support for structured interventions: 78.3% of students favor the development of clear AI usage policies, and 65.2% expressed willingness to attend workshops on responsible AI use. This highlights a gap between current awareness and student readiness to engage in training and policy frameworks, suggesting that students are open to guidance and institutional initiatives that can bridge the ethical knowledge gap.

4.5. Dependency Level Classification

To evaluate the extent of student reliance on AI tools, a Dependency Level Classification framework was developed. Four supervised machine learning models Random Forest, XGBoost, Artificial Neural Network (ANN), and Logistic Regression (Multinomial) were trained to predict dependency levels categorized as **Low (≤ 30)**, **Medium (31–70)**, and **High (> 70)**, based on a composite score. This score was derived from key behavioral indicators, including:

- Reliance on AI tools for completing academic tasks.
- Perception that AI reduces the need to learn certain skills.
- Frequency of unverified AI content usage.
- Overall frequency of AI use.

After applying one-hot encoding, Min-Max scaling, and SMOTE for class balancing, the dataset was split (80% training, 20% testing) and validated using **5-fold cross-validation**. Table 10 shows that the ANN achieved the highest accuracy (89%) and F1-score (0.88), outperforming other models in capturing complex behavioral patterns. Random Forest (accuracy 87%) performed comparably and provided interpretable feature importance, while XGBoost (accuracy 84%) showed moderate effectiveness. Logistic Regression (accuracy 76%) acted as a strong baseline but was limited by linear assumptions. Across all models, precision was highest in detecting **High Dependency cases**, highlighting their potential for **early intervention** in academic policy. Figure 4 illustrates that the ANN outperforms other models in accuracy, precision, recall, and F1-score, while Logistic Regression shows the lowest performance. And Figure 5 presents the confusion matrices for all four models, highlighting the classification performance and misclassification patterns across Low, Medium, and High AI dependency levels.

TABLE 10: Performance Comparison of Machine Learning Models in Predicting AI Dependency.

Model	Accuracy	Precision	Recall	F1-Score
Artificial Neural Network(ANN)	0.89	0.88	0.89	0.88
Random Forest	0.87	0.86	0.85	0.86
XGBoost	0.84	0.83	0.82	0.82
Logistic Regression	0.76	0.74	0.73	0.73

The findings confirm that ANN is particularly effective in modeling non-linear interactions between student demographics, usage frequency, and perceptions of AI, making it the most suitable tool for identifying students at risk of over-dependency.

The analysis of AI dependency among Pundra University students revealed that certain groups demonstrate higher reliance on AI tools. Younger students and early-year

undergraduates, particularly freshmen and sophomores, exhibited stronger dependency, likely due to their experimental approach to academic tasks and higher need for support.

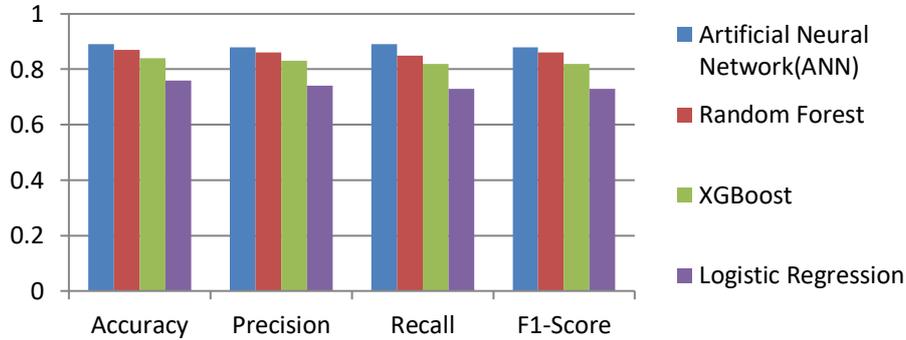


Figure 4: Comparison of machine learning models in predicting AI dependency, showing accuracy, precision, recall, and F1-score for ANN, Random Forest, XGBoost, and Logistic Regression.

Students with average or struggling academic performance showed greater reliance on AI for completing assignments, programming tasks, or understanding complex concepts, whereas high-performing students tended to use AI strategically for proofreading, coding assistance, or idea generation without fully replacing their learning process. Key predictive features of dependency included the time spent using AI tools, the type of tool utilized, and the primary purpose of use. Tools such as ChatGPT, Grammarly, QuillBot, and GitHub Copilot were strongly associated with higher dependency, while students using AI mainly for assignments or exam preparation were more prone to dependency than those employing it for learning enhancement or creativity. Department-wise analysis indicated that CSE students relied heavily on coding assistants and AI-integrated IDEs, Business students moderately on writing and rephrasing tools, and Humanities students on grammar, paraphrasing, and citation/reference managers.

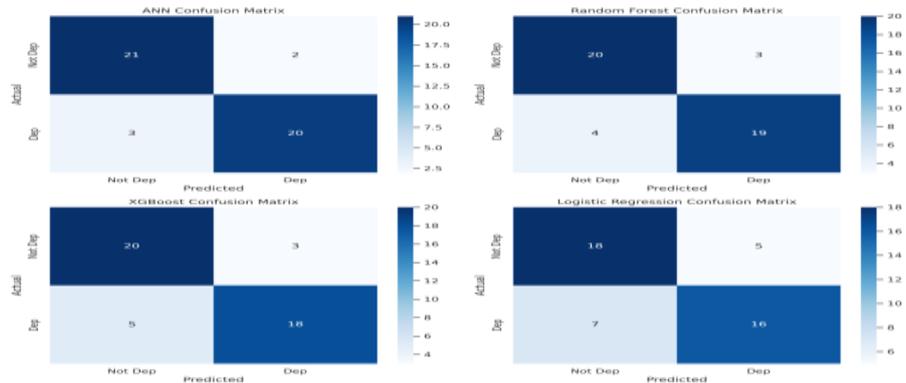


Figure 5: Confusion matrices for the four machine learning models (ANN, Random Forest, XGBoost, and Logistic Regression) in predicting AI dependency.

Gender differences were minimal, though male students slightly favored coding tools and female students leaned more toward writing and citation tools. Regarding policy implications, when AI dependency is supportive enhancing learning, productivity, and idea generation structured use should be encouraged through workshops and integration of AI literacy in curricula. Conversely, when dependency replaces genuine learning or critical thinking, awareness programs, training sessions, and AI-integrated coursework emphasizing comprehension over automation should be implemented to ensure ethical and balanced use. These insights provide a comprehensive understanding of AI dependency patterns and guide evidence-based interventions to foster responsible AI utilization in higher education.

4.6. Analysis and Future Directions

The classification results underscore a growing concern: student dependency on AI tools is not evenly distributed but concentrated among specific usage behaviors. Those who frequently substitute AI for independent learning or fail to verify AI-generated content are significantly more likely to fall into the High Dependency category.

From an **institutional perspective**, these insights can guide policy and intervention strategies. Universities can:

- i. **Develop early-warning systems** using predictive models (ANN/Random Forest) to flag students exhibiting risk factors of dependency.
- ii. **Incorporate AI literacy training** that emphasizes critical verification, ethical usage, and skill retention alongside AI use.
- iii. **Differentiate support strategies** for Low-, Medium-, and High-dependency students to prevent over-reliance and promote balanced adoption.

5. Conclusion and Future Work

By combining evidence-driven modeling with thoughtful institutional policies, universities can promote structured AI literacy, targeted workshops, and curriculum integration. This ensures that AI serves as a supportive partner enhancing productivity and learning outcomes while safeguarding intellectual autonomy ultimately fostering a future where human capability and intelligent technology collaborate responsibly.

AI tools are increasingly embedded in academic life, offering benefits such as improved performance, efficiency, and personalized support. Yet, reliance on AI must be carefully managed technology should not replace student effort, creativity, or critical thinking. Instead, it should be adopted as an assistant that supports learning in a balanced and responsible way. Used properly, AI can strengthen education; however, misuse risks undermining genuine skill development and academic integrity.

6. Limitations and Generalizability

This study has several important limitations that warrant acknowledgment. First, the sample is confined to 230 undergraduate students from a single private university in Bangladesh Pundra University. While this institution provides a valuable case study of AI adoption in South Asia, its student body is predominantly drawn from technical (e.g., CSE) and business (BBA) disciplines, which may not reflect usage patterns in public universities, rural campuses, or humanities-heavy programs. Consequently, the predictive models though internally validated via 5-fold cross-validation may not generalize to other educational ecosystems without recalibration.

Second, all data are self-reported, which introduces risks of social desirability bias (e.g., underreporting unapproved AI use during exams) and recall inaccuracies (e.g., misestimating weekly usage time). Although composite scoring and behavioral anchoring (e.g., “daily use,” “exam preparation”) mitigate some subjectivity, future studies would benefit from objective behavioral logs such as LMS or browser-level tracking to enhance validity.

Third, the cross-sectional design captures only a snapshot of AI dependency in late 2024/early 2025. Given the rapid evolution of generative AI including multimodal models, real-time tutoring agents, and integrated coding environments today’s predictors may become obsolete within months. Longitudinal tracking is essential to understand how dependency trajectories evolve alongside technological change and pedagogical adaptation.

7. Ethical Considerations and Long-Term Implications

Beyond methodological constraints, this work raises critical ethical and developmental questions. The use of machine learning to classify students by dependency risk even with anonymized survey data carries inherent privacy and surveillance concerns. If deployed in real institutional settings, such systems could be perceived as intrusive unless accompanied by transparent consent, clear communication of purpose, and strict data governance aligned with ethical standards.^{2, 15}

Moreover, our design cannot establish causality: we observe correlations between AI use and dependency, but cannot determine whether AI causes reduced critical thinking or whether struggling students turn to AI as a coping mechanism. Emerging evidence suggests that habitual outsourcing of writing, reasoning, or problem-solving to AI may weaken foundational competencies, particularly among early-year undergraduates still developing disciplinary literacy.^{8, 9} Without longitudinal data, the long-term cognitive and academic consequences of sustained AI dependency remain uncertain.

8. Future Directions

Despite these constraints, this study fulfills a critical need: it provides the first machine learning-based analysis of AI dependency in Bangladesh, a region severely underrepresented in global AI-in-education research. The models and survey framework developed here can serve as a foundation for future multi-university collaborations across South Asia.

Looking ahead, future research should adopt a longitudinal design to track how dependency evolves over students’ academic careers and examine causal relationships between AI use and cognitive outcomes such as critical thinking, creativity, and problem-solving. Predictive models must be validated on larger, multi-institutional datasets including public and private universities across diverse regions of Bangladesh to improve external validity and policy relevance. Further work should also correlate AI usage patterns with actual academic performance (e.g., semester GPA, assignment scores) to distinguish between productive augmentation and detrimental overreliance.

Finally, ethical frameworks must accompany technical modeling to ensure student privacy, informed consent, and transparency in any AI-monitoring system. By combining evidence-driven modeling with thoughtful institutional policies, universities can promote structured AI literacy, targeted workshops, and curriculum integration. This

ensures that AI serves as a supportive partner enhancing productivity and learning outcomes while safeguarding intellectual autonomy and ultimately fosters a future where human capability and intelligent technology collaborate responsibly.

References

- [1] J. Crawford, M. Cowling, and C. Sleeman, "Five teaching and learning practices to minimise academic integrity risks with AI writing tools," *J. Univ. Teach. Learn. Pract.*, vol. 19, no. 4, pp. 1–15, 2022, doi: 10.53761/1.19.4.6.
- [2] D. R. E. Cotton, P. A. Cotton, and J. R. Shipway, "Chatting and cheating: Ensuring academic integrity in the era of ChatGPT," *Educ. Inf. Technol.*, vol. 28, no. 2, pp. 2127–2142, 2023, doi: 10.1007/s10639-023-11655-w.
- [3] M. Perry, "AI and academic integrity: Navigating the new frontier," *Assess. Eval. High. Educ.*, vol. 48, no. 7, pp. 901–913, 2023, doi: 10.1080/02602938.2023.2189012.
- [4] M. Perkins, S. L. Howell, and S. R. Hiltz, "Academic integrity in the age of AI: Student and faculty perspectives," *Int. J. Educ. Integr.*, vol. 19, no. 1, pp. 1–15, 2023, doi: 10.1007/s40979-023-00123-5.
- [5] K. K. H. Chan and Y. Hu, "ChatGPT in higher education: Usage, challenges, and policy recommendations," *Technol. Soc.*, vol. 74, p. 102378, 2023, doi: 10.1016/j.techsoc.2023.102378.
- [6] A. Nagle, "AI and the future of university education: Challenges and opportunities," *J. Educ. Technol. Soc.*, vol. 26, no. 2, pp. 1–14, 2023. [Online]. Available: <https://www.jstor.org/stable/27854890>
- [7] T. Wanner and E. Palmer, "The rise of AI in education: Opportunities and challenges," *Australas. J. Educ. Technol.*, vol. 39, no. 4, pp. 1–15, 2023, doi: 10.14742/ajet.8567.
- [8] E. R. Mollick and L. Mollick, "Using AI to implement effective teaching strategies in classrooms," *Nat. Hum. Behav.*, vol. 8, no. 1, pp. 45–53, 2024, doi: 10.1038/s41562-023-01765-0.
- [9] C. K. Lo, "Applications of artificial intelligence in teaching and learning: A review," *Appl. Sci.*, vol. 13, no. 11, p. 6678, 2023, doi: 10.3390/app13116678.
- [10] L. Chen, P. Chen, and Z. Lin, "Artificial intelligence in education: A review," *IEEE Access*, vol. 10, pp. 75264–75278, 2022, doi: 10.1109/ACCESS.2022.3192458.
- [11] M. Alqahtani and N. Alharbi, "Predicting smartphone addiction among university students using machine learning: A comparative study," *Comput. Hum. Behav.*, vol. 142, p. 107632, 2023, doi: 10.1016/j.chb.2023.107632.
- [12] R. Zhang, S. Liu, and Y. Li, "Predicting student engagement with AI-powered learning platforms using ensemble models," *Br. J. Educ. Technol.*, vol. 55, no. 1, pp. 189–204, 2024, doi: 10.1111/bjet.13390.
- [13] X. Liu, Y. Zhang, and Q. Wang, "Predicting student dependency on AI writing tools using machine learning," *Comput. Educ.: Artif. Intell.*, vol. 5, p. 100143,

- 2023, doi: 10.1016/j.caeai.2023.100143.
- [14] Y. Wang, H. Li, and J. Zhang, "Data-driven approaches in educational technology: A survey," *Comput. Educ.*, vol. 180, p. 104432, 2022, doi: 10.1016/j.compedu.2022.104432.
- [15] R. M. Cutri, N. Hossain, and R. Mendenhall, "Generative AI in higher education: Faculty and student perspectives on ethics and equity," *J. High. Educ. Policy Manag.*, vol. 45, no. 5, pp. 1–16, 2023, doi: 10.1080/1360080X.2023.2245678.
- [16] O. Zawacki-Richter, M. N. Almobarraz, A. E. Almobarraz, and S. S. Kumar, "Systematic review of AI in higher education: Mapping the landscape and identifying research gaps," *Computers and Education: Artificial Intelligence*, vol. 6, p. 100218, 2024, doi: 10.1016/j.caeai.2024.100218 .