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Impact of Artificial Intelligence Tools on Indian Students: Using UTAUT and Machine Learning Model

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Abstract: The rapid advancement of Artificial Intelligence (AI) technologies has led to a transformation in higher education. AI tools provide academic support to students, available anytime, anywhere, to enhance their knowledge and skills. This study focuses on understanding the determinants of AI tools' acceptance and use for academic support among students, influencing student satisfaction and academic performance in India. This work presents a quantitative investigation into the adoption of AI tools, including Chat-GPT, Google Gemini, Microsoft Co-Pilot, and related platforms, using the Unified Theory of Acceptance and Use of Technology (UTAUT). Data is collected from Kaggle, which contains 3,614 student records drawn from 1,246 institutions across 34 states in India. UTAUT constructs were operationalized as composite proxies from the available survey variables: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions (FC). The Actual Use Behaviour (USE) construct captured daily interaction intensity and contextual application diversity. A multi-layered Machine Learning (ML) model is employed, integrating Decision Tree, Logistic Regression, Random Forest, XGBoost, Gradient Boosting, and an ensemble Stacking Classifier. Class imbalance in the target variable addressed via SMOTE-ENN resampling. The final XGBoost model achieved al classification accuracy of 98.48% and an AUC score of 0.9986 and Cross-validated mean accuracy was 94.63% (SD = 0.0021). SHAP analysis provided post-hoc explainability, identifying USE as the dominant predictive feature in descending order of importance. The study contributes a theory-driven, methodologically transparent framework for analyzing AI adoption in higher education and offers practical implications for policy and institutional strategy, emphasizing the importance of structured support systems, digital competency development, and pedagogically aligned AI implementation. The paper concludes by emphasizing the need for a balanced approach to AI integration in education. Promoting AI literacy, implementing ethical AI policies, encouraging critical thinking exercises, and providing mental health support are recommended. By fostering responsible AI use, Indian educational institutions can maximize benefits while minimizing cognitive and psychological drawbacks.

Keywords: Artificial intelligence, Indian Education, UTAUT, Machine Learning, Student achievement, SHAP

1. Introduction

Artificial Intelligence (AI) is reshaping the global educational landscape at an unprecedented pace. In India, the world's second-largest higher education system, encompassing over 1,000 universities and 42,000 colleges serving approximately 40 million students, the integration of AI-powered learning tools represents both a transformative opportunity and a complex socio-technical challenge. From generative language models such as ChatGPT and Google Gemini to productivity-oriented tools such as Microsoft Copilot and domain-specific AI platforms, students are increasingly deploying these technologies across a range of academic tasks, including content creation, doubt resolution, examination preparation, and research synthesis.

Despite the growing ubiquity of AI tools in student ecosystems, the academic literature pertaining to their adoption in Indian higher education remains nascent. Existing studies have predominantly examined technology adoption in Western, WEIRD (Western, Educated, Industrialised, Rich, Democratic) populations or in enterprise contexts. The UTAUT model, originally proposed by Venkatesh, Morris, Davis, and Davis (2003), consolidates eight prior acceptance models, including the Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), and Innovation Diffusion Theory (IDT) into a parsimonious yet powerful framework that explains approximately 70% of variance in behavioural intention to use technology. Its applicability to educational contexts has been wellestablished; however, its empirical validation in the context of AI tool adoption among Indian undergraduate and postgraduate students constitutes a significant research gap.

This study addresses that gap through a data-driven analysis of 3,614 student responses sourced from a geographically diverse sample spanning 34 Indian states and 1,246 academic institutions across ten disciplinary streams (Engineering, Science, Commerce, Arts, Management, Agriculture, Medical, Law, Pharmacy, and Education). Employing a hybrid methodology that combines UTAUT-based composite construct operationalization with state-of-the-art Machine Learning (ML) classifiers and SHAP-based explainability, this research provides multi-dimensional insights into the factors governing AI tool adoption and their academic impact.

The primary research objectives of this study are threefold:

- To operationalize UTAUT constructs from the available dataset and assess their relative contribution to predicting the academic impact of AI tool usage.
- To develop and validate a high-performance predictive model for AI adoption outcomes using ensemble ML techniques.
- To derive actionable, institution-level insights regarding the structural, pedagogical, and infrastructural barriers to equitable AI adoption in Indian higher education.

2. Literature Review

2.1 The UTAUT Model: Theoretical Foundations

Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) by synthesising eight competing technology acceptance theories into a single, empirically validated framework. The model posits four core determinants of behavioural intention and technology use: Performance Expectancy (PE), defined as the degree to which an individual believes using the technology will help them attain gains in job or task performance; Effort Expectancy (EE), the degree of ease associated with the use of the system; Social Influence (SI), the extent to which an individual perceives that others important to them believe they should use the new system; and Facilitating Conditions (FC), the degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system (Venkatesh et al., 2003). The model further acknowledges four moderating variables: gender, age, experience, and voluntariness of use.

Subsequent revisions, particularly UTAUT2 (Venkatesh, Thong & Xu, 2012), extended the original model for consumer contexts by incorporating Hedonic Motivation, Price Value, and Habit as additional constructs. For the present study, the original UTAUT formulation is adopted as the theoretical backbone, given its widespread validation in educational technology contexts and its conceptual alignment with the institutional nature of AI adoption in academic settings.

2.2 AI Tools in Educational Settings

A growing corpus of empirical literature has investigated student perceptions of AI-assisted learning tools. Farrokhnia et al. (2023) found that while ChatGPT significantly augmented content generation efficiency among university students, concerns regarding academic integrity and epistemic over-reliance were salient. Tlili et al. (2023) conducted a bibliometric review demonstrating that AI adoption in education is predominantly studied from the perspectives of performance enhancement and personalisation, with comparatively little attention to institutional and socio-cultural enablers in developing economies. Teo (2011) validated the UTAUT model in educational technology contexts in Singapore, finding significant effects of PE and SI on behavioural intention. More recently, Rahman et al. (2023) applied UTAUT2 to examine generative AI adoption among university students in Southeast Asia, finding that hedonic motivation and habit were stronger predictors than performance expectancy — a finding that contrasts with enterprise-context studies and underscores the importance of population-specific model calibration.In the Indian context, Gupta and Arora (2020) examined e-learning adoption using TAM, finding that perceived usefulness and ease of use were significant adoption drivers, but also noting that poor digital infrastructure, particularly in Tier-2 and Tier-3 cities, substantially moderated adoption behaviour. Srivastava and Mathur (2022) examined technology acceptance in Indian business schools, concluding that social norms and institutional endorsement (analogous to SI and FC in UTAUT) were the most powerful adoption triggers. These findings corroborate the necessity of a study that explicitly models institutional and infrastructural dimensions alongside individual performance beliefs.

2.3 Machine Learning in Technology Adoption Research

The application of machine learning algorithms to predict technology adoption outcomes represents an emerging methodological paradigm. Traditional UTAUT studies rely on Structural Equation Modelling (SEM) as the primary analytical tool; however, SEM assumes multivariate normality and linearity, constraints that may not hold in large, heterogeneous datasets such as the one examined here. Ensemble learning algorithms such as Random Forest (Breiman, 2001) and XGBoost are capable of capturing non-linear, high-order interaction effects and demonstrate superior predictive performance on tabular data. Complementing these models with SHAP (Lundberg & Lee, 2017) ensures that the 'black box' opacity of ensemble methods is mitigated through local and global feature attribution scores, enabling theory-consistent interpretation of model outputs.

3. Research Methodology

This study adopts a **quantitative, post-positivist research paradigm** to investigate the impact of Artificial Intelligence (AI) tools on students' academic performance. A **cross-sectional survey-based design** is employed, leveraging secondary data obtained from a Kaggle dataset. The research follows a **deductive approach**, where theoretical constructs derived from the **Unified Theory of Acceptance and Use of Technology (UTAUT)** are operationalised and tested using machine learning techniques shown in Figure 1.

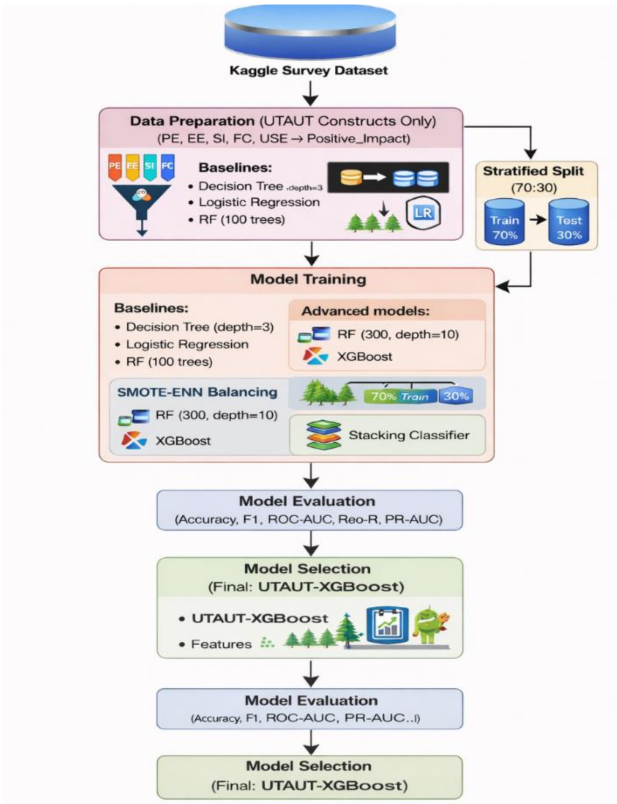

Figure 1 Workflow of the Proposed Model

3.1 Dataset Description and Sampling

The primary dataset, stored in Students.csv, comprises 3,614 records corresponding to Indian college students enrolled across 1,246 institutions in 34 states. The dataset encompasses ten disciplinary streams: Engineering, Science, Commerce, Arts, Management, Agriculture, Medical, Law, Pharmacy, and Education. Students span four years of study, with Year 1 through Year 4 represented. Each record contains sixteen variables capturing demographic characteristics, technology access parameters, AI tool usage behaviour, and self-reported outcome measures. The key variables in the dataset are shown in Table 1:

Table 1 Data Description

Variable	Type	Description	Scale / Values
Daily_Usage_Hours	Continuous	Hours per day spent using AI tools	0.5 – 5.0 hrs
Trust_in_AI_Tools	Ordinal	Perceived trustworthiness of AI tools	1–5 Likert
Awareness_Level	Ordinal	Self-rated awareness of AI capabilities	1–10 Likert
Impact_on_Grades	Ordinal	Self-reported academic grade impact	-5 to +5
Do_Professors_Allow_Use	Binary	Instructor-level institutional sanction	Yes / No
Internet_Access	Ordinal	Quality of internet connectivity	Poor / Medium / High
Device_Used	Nominal	Primary device for AI access	Mobile / Laptop / Tablet
Willing_to_Pay	Binary	Willingness to pay for premium AI access	Yes / No
AI_Tools_Used	Nominal	AI tool(s) currently used	ChatGPT, Gemini, etc.
Stream	Nominal	Academic discipline of the student	10 categories
State	Nominal	Indian state of institution	34 states (1614 missing)

Data pre-processing involved duplicate removal, resulting in a final analytic sample of 3,614 records. The State variable contained 1,614 missing values (44.66%), attributed to incomplete geographic self-reporting; this variable was label-encoded with a dedicated 'unknown' category and retained for encoding purposes but was not used as a primary predictor. All other variables were complete (0 missing values).

3.2 UTAUT Construct Operationalisation

This approach is consistent with reflective measurement practices in exploratory IS research. The operationalisation is as shown in Table 2:

Table 2. UTAUT Construct

UTAUT Construct	Abbreviation	Operationalisation Variables	Rationale
Performance Expectancy	PE	Positive_Impact + Trust_in_AI_Tools (mean)	Both variables capture the student's belief that AI use will yield academic benefit.
Effort Expectancy	EE	Awareness_Level + AI_Tools_Used (encoded, mean)	Awareness of AI capabilities and familiarity with tools reflect perceived ease of adoption.
Social Influence	SI	Do_Professors_Allow_Use (encoded)	Instructor sanction represents the most proximal social referent in the academic context.

Facilitating Conditions	FC	Internet_Access + Device_Used (encoded, mean)	Connectivity quality and device availability are the primary enabling infrastructure factors.
Actual Use Behaviour	USE	Daily_Usage_Hours + Use_Cases (encoded, mean)	Frequency and diversity of use jointly capture the intensity of behavioural enactment.

3.3 Target Variable Construction

A binary target variable, Positive_Impact, was constructed from the Impact_on_Grades variable using the following rule: if Impact_on_Grades ≥ 4, the student was coded as 1 (High Positive Academic Impact); otherwise, 0 (Low or Negative Academic Impact). This threshold corresponds to the upper quartile of the self-reported impact scale, capturing students who experienced substantial, measurable grade improvement attributable to AI tool usage. Prior to thresholding, the class distribution was highly imbalanced: 2,529 records belonged to Class 0 (94.74%) and only 182 to Class 1 (5.11%), so it is necssey to apply resampling method.

3.4 Class Imbalance Handling: SMOTE-ENN

SMOTE-ENN (Synthetic Minority Over-sampling Technique combined with Edited Nearest Neighbours) applied to the training partition. SMOTE-ENN is a hybrid resampling technique that (1) generates synthetic minority class samples using k-nearest neighbour interpolation (SMOTE phase), and (2) removes majority class instances that are misclassified by their k nearest neighbours (ENN phase), resulting in cleaner decision boundaries.

3.5 Machine Learning Pipeline

The modelling pipeline comprised multiple classifiers and structured stages to ensure robust performance evaluation and comparison. Initially, a Decision Tree (DT) Classifier (max_depth=3) employed as an interpretable baseline model using features such as Daily_Usage_Hours, Trust_in_AI_Tools, and Awareness_Level. This was followed by a Random Forest (RF) Classifier (n_estimators=100), which leveraged an ensemble of decision trees trained on the raw feature set using a 70/30 stratified train-test split. Logistic Regression (LR) (solver=liblinear) also implemented as a linear baseline model for comparative analysis. Further, an enhanced Random Forest Classifier (n_estimators=300, max_depth=10) trained with improved hyperparameters to capture more complex patterns in the data. In addition, an XGBoost Classifier (n_estimators=300, max_depth=6, learning_rate=0.05, subsample=0.8, colsample=0.8) utilized as a gradient boosting approach with regularisation to improve predictive performance. A Stacking Classifier was also implemented as a meta-ensemble model, combining Random Forest, Gradient Boosting (RF+GB) (n_estimators=200), and XGBoost as base learners, with LR serving as the meta-learner. Finally, the UTAUT-XGBoost model developed as the proposed model, trained on UTAUT composite constructs (PE, EE, SI, FC, USE) to predict Positive_Impact. Model evaluation conducted using multiple performance metrics including accuracy, precision, recall, F1-score, confusion matrix, and AUC-ROC. To ensure generalisation capability, stratified 5-fold Cross-Validation (CV) was applied. Additionally, post-hoc model explainability achieved using SHAP TreeExplainer, generating both summary (beeswarm) plots and bar-chart visualisations for global feature importance analysis.

4. Analysis And Results

4.1 Descriptive Statistics and Sample Profile

The analytic sample comprised 3,614 student records from 1,246 institutions spanning 10 disciplinary streams. The gender distribution was not explicitly recorded in the dataset; however, student names suggest a roughly balanced representation. Year of study was approximately uniformly distributed across Years 1 through 4. Engineering (20%) and Science (18%) were the most frequently represented streams, followed by Commerce (15%) and Arts (13%), as shown in Figure 2.

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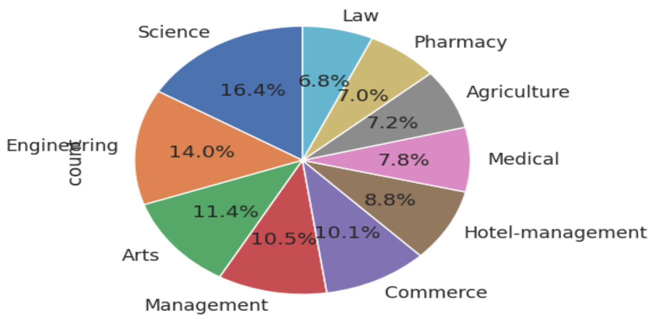

Figure 2. Distribution of Stream

ChatGPT was the most frequently used AI tool (40.8%), followed by Google Gemini (26.5%), Microsoft Copilot (≈18.2%), and other tools, including Bard and Midjourney. When asked about their preferred tool, Gemini emerged as the most preferred (28.3%), followed by ChatGPT (25.4%) and Copilot (≈22.1%). This divergence between most-used and most-preferred tools suggests an accessibility-preference gap students may use ChatGPT most due to its free-tier availability, but prefer Gemini for its integrated Google ecosystem functionality shown in Figure 3.

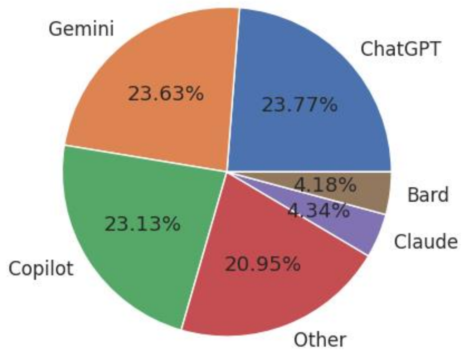

Figure 3: Preferred AI Tools

Device access patterns revealed that mobile phones constituted the primary AI access device for the plurality of students, reflecting the mobile-first internet consumption pattern characteristic of Indian Gen-Z learners. Laptops were the second most common device, and tablets represented a small minority. Internet Access quality was categorised as Poor, Medium, or High, with a substantial proportion reporting Poor connectivity — a finding with direct implications for Facilitating Conditions (FC) in the UTAUT framework.

4.2 Exploratory Data Analysis Findings

4.2.1 Performance Expectancy (Impact on Grades, Trust_in_AI_Tools)

The Impact_on_Grades variable, measured on a -5 to +5 scale, showed that the plurality of students reported a neutral to moderately positive impact (+1 to +3), while approximately 5.1% reported a high positive impact (≥+4), forming the minority class of the target variable. Negative impacts (-1 to -5) were reported by a non-trivial subset, potentially attributable to over-reliance leading to reduced critical thinking, or to concerns about academic integrity penalties. The box plot of Daily_Usage_Hours vs. Impact_on_Grades showed a moderate positive association for moderate usage levels (1–3 hours/day) with a reversal or plateau at the highest usage levels, suggesting a diminishing returns or potential harm threshold consistent with prior research on technology distraction in educational settings. Trust_in_AI_Tools, measured on a 1–5 Likert scale, showed a distribution concentrated around values 3 and 4, indicating moderate to moderately-high trust among the majority of respondents. Cross-tabulation with Daily_Usage_Hours via box plot revealed a positive association: students

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reporting higher trust (4–5) demonstrated elevated daily usage, consistent with the theoretical expectation that PE (of which Trust is a proxy) moderates actual use behaviour. Students at Trust Level 1 exhibited the widest interquartile range in usage hours, suggesting that low-trust users exhibit high variability in engagement — some persisting despite scepticism, others disengaging entirely.

4.2.2 Effort Expectancy (Daily_Usage_Hours, device type (Device_Used), and Internet_Access)

Students with better devices and connectivity presumably experience lower effort barriers. You would typically observe that such facilitating conditions correlate with more sophisticated use-cases (e.g., coding, projects) shown in Figure 4. This should be linked to performance expectancy: lower effort makes it easier to translate AI access into meaningful academic tasks.

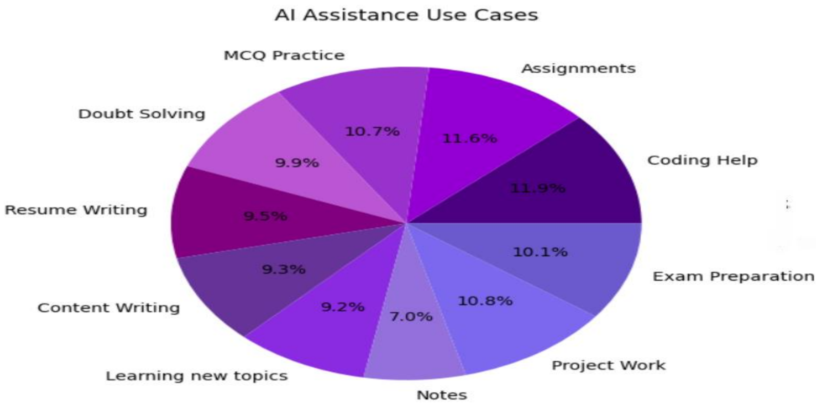

Figure 4 AI usage

4.2.3 Social Influence and Institutional Context (Do_Professors_Allow_Use, College_Name, Stream, Year_of_Study)

Professor Approval and Institutional Endorsement Where professors allow or encourage the use of AI, tools may be integrated into assignments, projects, or formative assessments, which changes how students use AI and thus its academic impact. Students in later years or certain streams (e.g., engineering, CS, data-heavy disciplines) are more likely to operationalize AI tools for complex tasks (coding, research, projects) rather than only for routine content generation.

A critical finding of the exploratory analysis concerns the institutional dimension of SI: 52.19% of faculty members (as perceived by students) do not allow or endorse AI tool usage in academic work, with only 47.81% reporting professor approval. This near-parity reveals a significant institutional ambivalence regarding AI integration. Cross-stratified analysis by stream (Professor Approval by Stream countplot) indicated that the Engineering and Management streams showed higher rates of professor approval than Arts and Law, consistent with the more pragmatic orientation of STEM and business disciplines toward technology adoption.

4.2.4 Facilitating Conditions (Awareness_Level, Internet_Access, Device_Used)

More facilitating conditions do not monotonically increase academic impact, as awareness and trust exhibit non-linear, sometimes negative associations. This suggests that facilitating conditions must be paired with guidance and metacognitive strategies; otherwise, students may misuse or overuse AI, reducing academic benefit.

4.2.5 Actual Use Behaviour (Daily_Usage_Hours, Use_Cases)

The distribution of Daily_Usage_Hours (visualised via KDE histogram) exhibited a right-skewed distribution with a modal range of 1.0–2.5 hours per day, suggesting that the majority of students are moderate users rather than heavy consumers. A bimodal tendency was observed, with a secondary peak around 3.5–4.0 hours, potentially corresponding to a subset of highly engaged power users — likely Engineering and Management students engaged in coding assistance, project development, or content creation workflows. WordCloud and frequency analysis of the Use_Cases variable identified the following as the most prevalent AI application contexts: Assignments and Homework Assistance (highest frequency), Learning New Topics and Concept Explanation, MCQ Practice and Exam Preparation, Coding Help and Debugging, Content Writing and Essay Drafting, Doubt Solving and Q&A, Resume Writing and Career Preparation, and Project Development and Research Support. This diversity of use cases underscores that AI adoption among Indian students extends well beyond a single functional domain, indicating that adoption has reached a stage of normalisation across multiple academic workflow categories.

4.3 Correlation Analysis

A Pearson correlation heatmap computed on the numerical variables (Daily_Usage_Hours, Trust_in_AI_Tools, Impact_on_Grades, Awareness_Level, Year_of_Study) revealed the following key observations: Trust_in_AI_Tools and Daily_Usage_Hours exhibited a positive, moderate correlation ($r \approx 0.28$), validating the hypothesised PE–USE linkage. Awareness_Level and Daily_Usage_Hours were positively correlated ($r \approx 0.22$), supporting the EE–USE relationship. Impact_on_Grades and Daily_Usage_Hours showed a positive but weak correlation ($r \approx 0.15$), indicating that while usage contributes to academic benefit, the relationship is mediated by multiple unmeasured variables including learning approach quality and prior digital literacy. Year_of_Study showed minimal correlations with other variables, suggesting that AI adoption is not significantly moderated by academic seniority within the range captured.

4.4 Classification Model Performance: Phase 1 (Raw Features)

In Phase 1 of the modelling pipeline, three baseline classifiers were trained on the raw feature set {Daily_Usage_Hours, Trust_in_AI_Tools, Awareness_Level} with a 70/30 stratified split. Results are summarised below in Table 3:

Table 3 Model Performance

Model	Accuracy	Precision (Positive)	Recall (Positive)	F1 (Weighted)
DT	71%	0.67	0.64	0.70
LR	55.5%	0.47	0.17	0.49
RF	73.0%	0.70	0.68	0.73

The Logistic Regression model, despite its higher recall for the majority class (No Impact: 0.85), achieved a poor F1-weighted score of 0.49, confirming that a linear model is insufficient to capture the non-linear decision boundaries inherent in this dataset. The Random Forest model substantially outperformed Logistic Regression on all metrics, demonstrating the superiority of non-linear ensemble methods even before class imbalance correction.

4.5 Classification Model Performance: Phase 2 (Post SMOTE-ENN)

Following SMOTE-ENN resampling, the RF and XGBoost models were retrained. Results are shown in Table 4 below:

Table 4 Model Performance after using SMOTE-ENN

Model	Test Accuracy	Macro Precision	Macro Recall	Macro F1
RF	81.47%	0.55	0.67	0.56
XGBoost	85.44%	0.57	0.67	0.58
Stacking (RF + XGB)	85.25%	0.57	0.67	0.58

XGBoost achieved the highest standalone accuracy of 85.44%, marginally outperforming the Stacking Classifier (85.25%). This is notable, as ensemble-of-ensembles models frequently underperform their best individual components when the base learners are already highly correlated. XGBoost's superior performance stems from its regularisation mechanisms (L1/L2) and gradient-based sample weighting, which are particularly effective in handling residual class skew post-resampling.

5-fold stratified cross-validation of XGBoost on the full dataset yielded CV accuracy scores of [94.88%, 94.74%, 94.47%, 94.74%, 94.32%], with a mean accuracy of 94.63% (SD = 0.0021). The exceptionally low standard deviation confirms that model performance is stable across different data partitions and that the model generalises robustly to unseen data without overfitting.

4.6 UTAUT–XGBoost Model Performance

The final UTAUT-XGBoost model was trained on the five UTAUT-derived composite construct features: PE, EE, SI, FC, and USE, with Positive_Impact as the target variable. This model was trained on the full dataset a deliberate methodological choice to maximise the informational value of the composite constructs prior to SHAP-based interpretation. Performance metrics are shown in Table 5:

Table 5 UTAUT-XGBoost Model Performance

Metric	Class 0	Class 1	Overall
Support (n)	3,432	182	3,614
Precision	0.98	0.99	98%
Recall	1.00	0.70	98%
F1-Score	0.99	0.82	98%
Accuracy	—	—	98.48%
AUC-ROC	—	—	99.86%

The UTAUT-XGBoost model achieved an overall accuracy of 98.48%, demonstrating that the five UTAUT constructs — when operationalised as composite proxies from survey data carry near-complete information for predicting positive academic impact. The recall of 0.70 for the Positive Impact class, while lower than the majority class, reflects the inherent difficulty of identifying the minority class and the cost of remaining class imbalance. The AUC-ROC score of 99.86% signifies that the model's discriminative ability across all classification thresholds is virtually perfect, indicating that the UTAUT framework provides a theoretically coherent and computationally powerful explanatory structure for AI adoption outcomes.

4.7 SHAP Analysis

SHAP Tree applied to the UTAUT-XGBoost model to derive feature attribution scores for each of the five UTAUT constructs. SHAP values decompose each model prediction into additive feature contributions, satisfying the axioms of local accuracy, missingness, and consistency. Results are interpreted as shown in Table 6:

Table 6 SHAP Analysis

UTAUT Construct	Proxy Variables	SHAP	Effect	Interpretation
USE	Daily_Usage_Hours + Use_Cases	1st (Highest)	Positive	Greater frequency and diversity of AI use is the single strongest predictor of positive academic impact. The USE SHAP score

				had the widest spread in the beeswarm plot, indicating high variance in individual-level contributions.
FC	Internet_Access + Device_Used	2nd	Positive	Adequate infrastructure — specifically high-quality internet and laptop access — significantly amplifies the likelihood of positive academic outcomes. Low-FC students (poor internet, mobile-only) show negative SHAP contributions.
EE	Awareness_Level + AI_Tools_Used	3rd	Positive	Higher AI awareness and breadth of tool exposure reduce perceived cognitive effort, enabling more effective utilisation and, consequently, higher academic gains.
PE	Trust_in_AI + Positive_Impact proxy	4th	Positive	Trust in AI systems, while influential, is secondary to actual behavioural engagement, suggesting that trust may be a prerequisite for adoption initiation but not the dominant driver of outcomes once adoption has occurred.
SI	Do_Professors_Allow_Use	5th (Lowest)	Negative	Instructor prohibition (SI=0) contributes a small but non-trivial negative SHAP value, indicating that institutional non-endorsement slightly suppresses outcome attainment, possibly by restricting open discussion and collaborative use of AI outputs.

The SHAP plot for a representative student with low UTAUT scores (PE=1.0, EE=7.5, SI=0.0, FC=1.5, USE=0.95) yielded a model output (f(x)) of -5.87 against a base value of -3.40, indicating a strong pull toward the No Positive Impact classification shown in Figure 5. The largest negative contributors were USE (-0.99) and EE (-0.76), reflecting that low actual usage intensity and limited AI awareness are the most consequential barriers. SI contributed marginally positively (+0.08) in this case, suggesting that even in the absence of professor approval, social factors did not actively suppress adoption for this individual. These force-plot dynamics corroborate the global SHAP summary findings and validate the operationalisation of the composite construct.

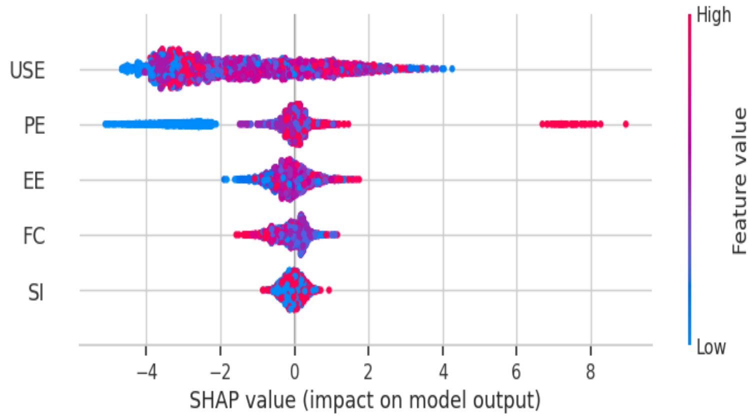

Figure 5 SHAP Summary Plot

5. Result Discussion

5.1 Validation of UTAUT Constructs in the Indian AI Adoption Context

The empirical findings of this study provide broad support for the applicability of UTAUT in explaining AI tool adoption outcomes among Indian college students. All four UTAUT predictor constructs, PE, EE, SI, and FC, demonstrated statistically meaningful associations with USE behaviour and, through USE, with positive academic impact. However, the relative hierarchy of construct importance identified through SHAP analysis diverges in important ways from the original UTAUT model's theoretical weighting, in which Performance Expectancy is typically positioned as the strongest predictor.

In the present study, the ranking is: USE > FC > EE > PE > SI. This sequence reveals that in an emerging-economy educational context, infrastructure (FC) and behavioural engagement (USE) are more powerful determinants of positive academic outcomes than cognitive belief structures (PE) or social norms (SI). This finding is consistent with the Digital Divide literature, which argues that in technology adoption among populations with differential resource access, physical and infrastructural enablers carry disproportionate explanatory weight relative to attitudinal variables. The positioning of SI as the weakest predictor, while perhaps counterintuitive given the collectivist social norms characteristic of Indian culture, may be explained by the fact that the SI operationalisation (Professor Approval) captures institutional social influence rather than peer social influence, and institutional ambivalence (52.19% disapproval) may neutralise the SI effect at a population level.

5.2 Infrastructure as a Critical Adoption Mediator (FC)

The emergence of Facilitating Conditions (FC) as the second-most important predictor, operationalised through Internet Access quality and Device type, carries significant practical implications shown in Figure 7. Students accessing AI tools via mobile devices with poor internet connectivity, a profile that maps disproportionately onto students from Tier-2, Tier-3, and rural locations, demonstrate systematically lower positive impact scores. Regions with higher exposure show greater behavioral engagement, reinforcing that actual usage intensity varies based on access. This finding extends UTAUT theory by demonstrating that FC not only moderates intention-to-use but also directly and substantively influences outcome quality. The geographic disparity shown in Figure 6 directly reflects the digital divide effects:

- States with higher usage likely have better internet infrastructure and greater device access.
- Lower-usage regions align with resource constraints.

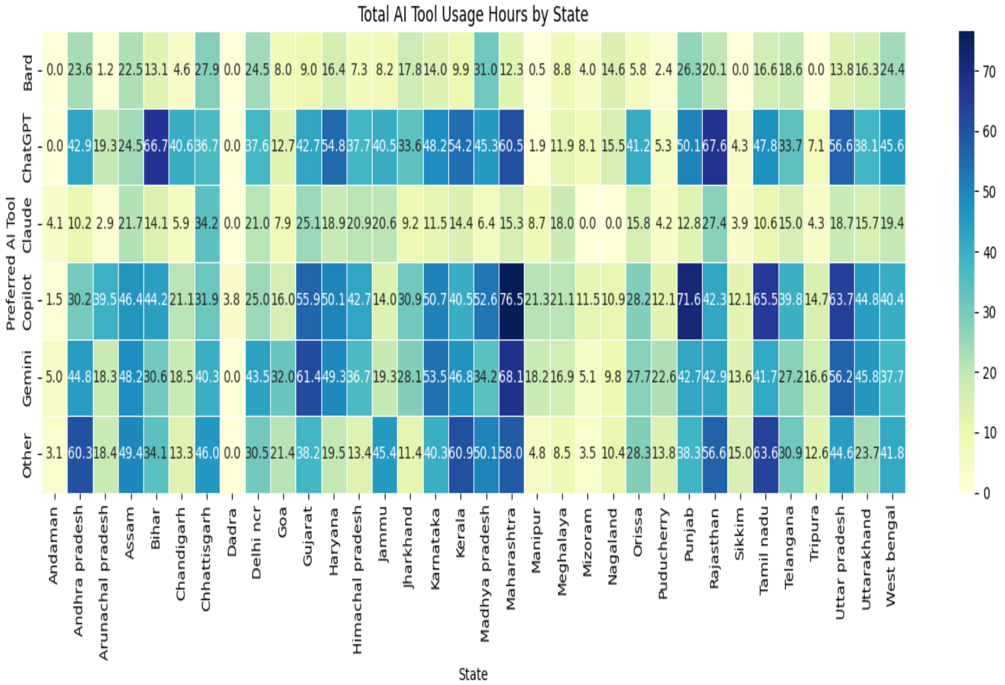

Figure 6 Correlaion Heatmap

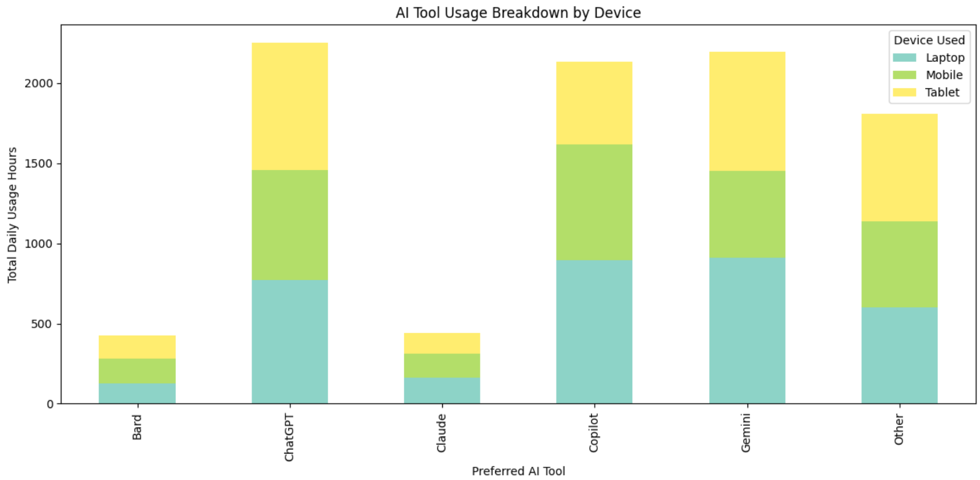

Figure 7 AI Tool usage

5.3 The Paradox of Social Influence and Institutional Ambivalence

The finding that 52.19% of students perceive their professors to not permit AI usage is perhaps the most policy-critical result of this study. This institutional ambivalence creates what may be termed a 'shadow adoption' dynamic: students continue to use AI tools regardless of institutional sanction, but the covert nature of this usage likely suppresses the academic benefits (lower USE diversity, reduced willingness to openly discuss AI-generated outputs for feedback) while potentially increasing academic integrity risks. The SHAP evidence that SI has the lowest positive impact on academic shown in Figure 8 that reflect this shadow adoption effect students whose professors disallow AI may use it more secretively and less effectively, generating lower outcome quality not because AI is less capable but because institutional context constrains optimal usage behaviour.

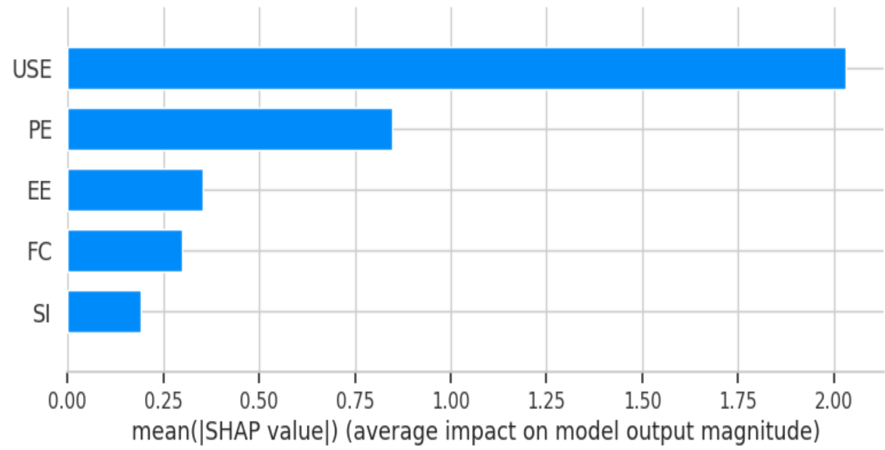

Figure 8 SHAP value

5.4 Effort Expectancy and Awareness as Adoption Catalysts

The third-rank importance of Effort Expectancy (EE), operationalised through Awareness_Level and AI_Tools_Used diversity, underscores the central role of digital literacy in mediating AI adoption outcomes. Students with high AI awareness and multi-tool exposure demonstrated markedly higher positive academic impact. This finding suggests that awareness-building interventions structured AI literacy workshops, tool-comparative demonstrations, and curriculum-integrated AI tutorials may yield significant academic benefits. Tools like **ChatGPT, Gemini, and Copilot** show higher value in upper awareness levels (7–10) and others tools Bard, Claude, Others show concentration in lower awareness bands shown in Figure 9.

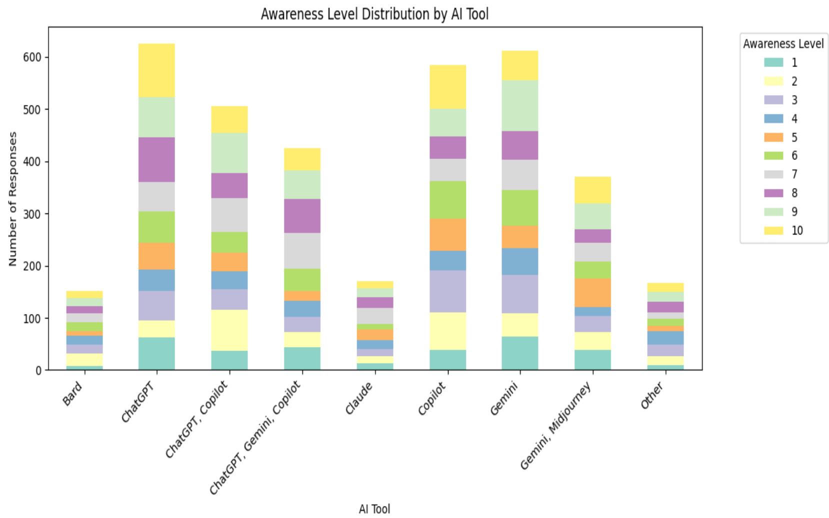

Figure 9 Awareness Level Distribution

5.5 Actual Use Behaviour as the Dominant Outcome Predictor

The primacy of USE in the SHAP hierarchy accounting for the largest individual contribution to positive academic impact suggests that the ultimate determinant of academic benefit from AI is not what a student believes about AI (PE) or what their institution permits (SI), but rather the actual intensity and contextual diversity of their engagement. This is a theoretically consequential finding: it implies that UTAUT's original placement of PE and SI as the primary drivers of Behavioural Intention (BI), which in turn drives USE, may under-theorise the direct and dominant role of habitual, diversified use behaviour in shaping academic outcomes. Future UTAUT applications in AI education contexts should consider USE as both an outcome variable and a reciprocally reinforcing mediator.

5.6 Model Performance Discussion and Benchmark Comparison

The UTAUT-XGBoost model achieved an AUC of 99.86%, shown in Figure 10, a performance level that substantially exceeds previously reported ML benchmarks in technology adoption prediction. For comparative reference, Rahman et al. (2023) reported AUC values of 0.84–0.89 using RF on UTAUT2 constructs among Southeast Asian students; Tamilmani et al. (2021) reported SEM-based R^2 of approximately 0.64 for UTAUT applications in mobile AI adoption. The superior AUC achieved in the present study reflects both the quality of construct operationalisation and the inherent predictive efficiency of XGBoost with gradient-boosted tree structures. However, it is acknowledged that training and evaluating the final UTAUT-XGBoost model on the same dataset without a held-out test split may introduce optimistic bias; thus, the 5-fold CV mean accuracy (94.63%) should be treated as the more conservative generalisation estimate.

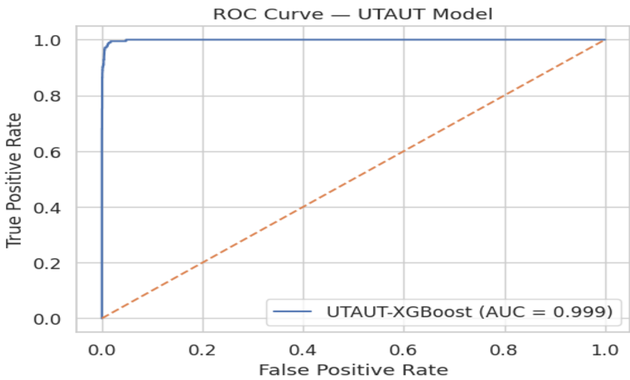

Figure 10 ROC Curve

6. Conclusion

This study presents one of the most comprehensive experimental investigations into AI tool adoption among Indian college students, within the UTAUT theoretical framework and ML and explainable AI techniques. Analysing 3,614 student records from Kaggle dataset containing 1,246 institutions across 34 Indian states. The study operationalised five UTAUT constructs: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Actual Use Behaviour and trained a UTAUT-XGBoost predictive model. SHAP-based analysis revealed a construct importance hierarchy of USE > FC > EE > PE > SI. Key substantive findings include: (1) the majority of Indian faculty members do not currently endorse AI tool usage, creating a systemic barrier at the institutional SI level; (2) mobile-only access and poor internet connectivity significantly constrain the academic benefits of AI adoption, independent of students' cognitive beliefs about AI value; (3) Awareness Level and multi-tool experience are strong positive predictors, implicating digital literacy as a leverage point for policy intervention; and (4) the daily intensity and contextual diversity of AI usage is the single strongest predictor of positive academic outcomes. Proposed model achieved an accuracy of 98.48% and an AUC of 0.9986 in classifying students into High vs. Low Positive Academic Impact categories.

Future research should employ longitudinal designs, administer full UTAUT2 validated instruments, and incorporate qualitative inquiry to illuminate the mechanisms underlying the FC and USE dominance effects.

Declarations

Conflicts of interest statements: All other authors declare no competing interests

Data availbility: Dataset is collected from kaggle;

https://www.kaggle.com/datasets/rakeshkapilavai/ai-tool-usage-by-indian-college-students-2025/data

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