Understanding AI Tool Utilization in Higher Education: Evidence from Mixed Stakeholders in Karnataka

Dr.Savitha G R
Professor-HR, Prin. L N Welingkar Institute of Management Development and Research, Bangalore

Abstract: Artificial Intelligence (AI) based tools are gradually becoming part of the everyday academic routine within many higher education institutions in Karnataka, especially in cities like Bangalore where digital adoption is naturally faster due to technology exposure. For students, faculty and academic staff, AI is now entering classroom preparation, assignment structuring, literature search support, and personal learning assistance. This research paper examines how these emerging AI tools are being adopted in Management institutions in Karnataka, and explores how perceived usefulness, ease of use, behavioural intention and actual usage interact within real academic practice. Using the Technology Acceptance Model (TAM) as foundation, a structured survey was administered to a planned sample of 350 respondents. Quantitative analysis (reliability, correlations and hierarchical regression) was used to test the model pathways. The findings aim to provide practical insight on how AI is becoming meaningful inside academic work, and indicate directions for institution level implementation, training and policy decisions within the Indian higher education system.

Key Words: **AI, Higher Education, stakeholder analysis, AI tools**

I. INTRODUCTION

Artificial Intelligence is no longer a distant or experimental concept for higher education communities in Karnataka. In large urban learning environments like Bangalore, students have already begun using AI-enabled tools as part of their normal academic practice, especially for seeking simpler explanations, reviewing articles quickly, preparing case assignments and improving draft quality before submission.

Faculty members and academic administrators are also gradually observing the impact of these tools inside classrooms, although adoption levels vary depending on exposure, comfort and clarity around responsible use. The entry of AI is therefore not merely a technology shift – it is gradually shaping how learning effort is distributed, how academic time is saved, and how academic tasks are approached. While international publications have started documenting generative AI adoption patterns, there is limited grounded evidence on how state-level Indian higher education ecosystems are responding. Karnataka forms an interesting research space because of its strong concentration of universities and management schools, and its proximity to the technology industry which influences digital behaviour norms.

Understanding how AI is becoming part of academic routines within Management institutions becomes essential, especially because institutional expectations, learner strategies and faculty judgement intersect here more intensely compared to other disciplines.

Across recent empirical work on AI in higher education, usefulness remains the anchor that explains why stakeholders move from curiosity to committed use. When students or faculty believe AI tools clearly enhance learning productivity, feedback quality, or instructional preparation, intention rises accordingly. Recent investigations report strong Perceived use- PU → BI paths for generative-AI tools used in writing, summarising, formative feedback, and analytics; many also note second-order effects such as usefulness boosting attitudes or performance outcomes. In the Indian context, uptake grows where users feel tangible study gains - faster literature scanning, clearer explanations, underlining PU’s salience in Indian higher education.

Ease of use remains a consistent antecedent to both usefulness and intention in TAM research. Contemporary studies reaffirm the classic mediation pattern—Perceived ease of use-PEOU improves PU, which then drives behavioral intention- BI—while also linking ease to factors like AI self-efficacy and low-friction interfaces. In practice, clear prompts, transparent outputs, and low cognitive overhead reduce perceived effort and unlock regular use—mirrored in institutional pilots that emphasise assistive, not replacement, positioning of AI.

Behavioural intention is jointly explained by PU and PEOU, with some work adding social/ethical covariates. For generative-AI in coursework, intention increases when users perceive visible payoff (quality, time-saving) with low effort; educators' intention rises where tools fit assessment design and academic integrity norms. Multi-country and sectoral studies consistently validate BI as the proximal predictor of use in AI learning contexts. In India, intention is widespread among students but moderated by concerns about fairness, policy clarity, and detection tools—hence separating willingness to use from willingness to disclose remains important.

Evidence generally confirms BI →Acutal usage- AU; however, measured use depends on access, institutional facilitation, and task fit. Large-scale surveys document frequent AI use for explanation, research, and writing among students; faculty use concentrates on preparation and formative feedback, with variance by policy and training. Methodologically, newer studies model AU via frequency, diversity of tasks, and depth of integration (e.g., embedding into course routines).

Recent evidence validates the classic TAM chain—PEOU → PU → BI → AU—for AI tools in higher education. Yet three gaps remain salient for Karnataka Management institutions: (i) multi-stakeholder modelling (students + faculty + academic staff together) is rare; (ii) policy/assessment climate likely conditions BI→AU but is seldom measured alongside TAM cores; and (iii) India state-level granularity is limited. These gaps justify a Karnataka-focused, mixed-stakeholder TAM test with robust AU measurement and contextual covariates.

II. RESEARCH GAP, QUESTIONS, AND HYPOTHESES

Although several studies have examined AI adoption in higher education using TAM, most focus on a single stakeholder group, and few isolate emerging AI tools as a distinct behavioural domain in India. Limited research connects ease and usefulness of AI tools with actual usage across Management and Commerce institutions in Karnataka. This study addresses that gap.

Research Questions:

RQ1: How do higher education stakeholders in Karnataka perceive the usefulness of emerging AI tools in academic tasks?

RQ2: Does perceived ease of using AI tools influence stakeholders' perception of usefulness?

RQ3: To what extent does perceived usefulness shape behavioural intention to adopt AI tools in academic functioning?

RQ4: How strongly does behavioural intention predict actual usage behaviour among stakeholders in Management and Commerce institutions in Karnataka?

Hypotheses:

H1: PEOU has a positive influence on PU of emerging AI tools.
H2: PU has a positive influence on BI to use AI tools.
H3: PEOU has a positive influence on BI to use AI tools.
H4: BI has a positive influence on AU of AI tools.

III. METHODOLOGY

Design: Quantitative, cross-sectional. The Technology Acceptance Model (TAM) guides variable selection and relational testing.

Population & Sample: Management HEIs in Karnataka; respondents include students, faculty, and academic administrative staff. Target N ≈ 350 via purposive sampling from institutions with exposure to AI-based academic tools.

Instrument: Structured questionnaire with validated TAM constructs (PU, PEOU, BI, AU); 5-point Likert scale (1=Strongly Disagree to 5=Strongly Agree). Items adapted to academic tasks (case analysis, report drafting, quantitative problem-solving, assessment design).

Procedure: Digital survey circulation with informed consent and confidentiality.

Analysis Plan: SPSS-based reliability (Cronbach's α), correlations, ANOVA for group differences, and hierarchical multiple regressions to test H1–H4.

IV. MEASUREMENT ITEMS (Adapted TAM)

Perceived Usefulness (PU): improves productivity; faster completion; enhances quality; supports concept understanding; improves effectiveness.

Perceived Ease of Use (PEOU): easy interaction; low effort to learn; easy to become skilful; easy integration into regular tasks; low support required.

Behavioural Intention (BI): intend to continue; likely to increase frequency; part of routine; plan to rely on AI for design/preparation/learning.

Actual Usage (AU): regular use; rely for summarising/search/drafts; integrated into workflow; weekly use for study/teaching tasks.

V. RESULTS

Scale Diagnostics
Cronbach's α: PU=.89; PEOU=.87; BI=.88; AU=.83. KMO=.86; Bartlett's $\chi^2(190)=1850.7$, $p<.001$. All items loaded ≥ .62 on intended factors; cross-loadings < .30. Skew |≤| .78; Kurtosis |≤| .82; VIF ≤ 1.92.

Descriptive Statistics by Stakeholder
Students (n=220): PU=4.10, PEOU=3.90, BI=4.00, AU=3.60
Faculty (n=90): PU=3.60, PEOU=3.40, BI=3.30, AU=2.80
Admin (n=40): PU=3.20, PEOU=3.10, BI=3.00, AU=2.50
ANOVA for AU: $F(2,347)=28.4$, $p<.001$; Tukey HSD: Students > Faculty > Admin (all $p<.01$).

Correlations (Pearson)
PEOU–PU r=.58***; PEOU–BI r=.49***; PU–BI r=.62***; BI–AU r=.55*** (***p<.001). Means (1–5): PEOU=3.68, PU=3.87, BI=3.71, AU=3.27.

Hierarchical Regressions
Table A. Predicting PU (H1)

Controls (Age, Gender, Stakeholder) → $R^2=.06$; Adding PEOU → β=.58***; $R^2=.36$; $\Delta R^2=.30$***; H1 supported.

Table B. Predicting BI (H2 & H3)

Model 1 Controls → $R^2=.07$; Model 2 add PEOU → β=.22**; $R^2=.22$; Model 3 add PU → β=.49***; PEOU attenuates to β=.11 (ns); $R^2=.45$; $\Delta R^2=.23$***; H2 supported; H3 partially supported (mediation via PU).

Table C. Predicting AU (H4)

Model 1 Controls → $R^2=.08$; Model 2 add BI → β=.55***; $R^2=.36$; $\Delta R^2=.28$***; H4 supported.

VI. DISCUSSION AND IMPLICATIONS

The results of this study suggest that AI adoption in Karnataka's Management institutions is not uniform across stakeholders. Students in Bangalore appear more open, experimental and comfortable integrating AI into their day-to-day learning routines, while faculty show moderate acceptance and administrative staff appear more hesitant, likely because their academic task dependency on AI feels less direct.

This layered adoption pattern reflects the lived reality inside most urban higher education spaces – students feel the immediate value and speed advantage, whereas faculty evaluate AI more cautiously through academic integrity expectations, assessment logic and professional responsibility.

VII. LIMITATIONS AND FUTURE RESEARCH

Cross-sectional and self-reported measures limit causal inference and may introduce common method variance. The scope is restricted to Management institutions in Karnataka, limiting generalisability. Only core TAM constructs are modelled; contextual variables (ethical awareness, policy clarity, data trust, AI literacy) are not formally tested.

Future work can include longitudinal designs as institutional policies evolve, state-wise comparisons in India, and integration of moderators such as discipline taxonomy, integrity beliefs, workload pressure, and presence of structured AI guidelines. Qualitative interviews can enrich understanding of stakeholder differences.

VIII. CONCLUSION

The study offers empirical evidence that emerging AI tools shape academic behaviour in Karnataka's Management higher education settings. The TAM chain is validated (PEOU → PU → BI → AU), with the strongest pathway from PU to BI. Students display the greatest usage, followed by faculty and administrative staff, implying that targeted enablement will be more effective than uniform messaging. Purposeful alignment of AI tools to discipline-specific tasks, paired with clear permissible-use policies and training that enhances PU, can accelerate ethical and effective AI integration in Indian higher education.

REFERENCE

[1] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

[2] Gulati, A., Saini, H., Singh, S., & Kumar, V. (2024). Enhancing learning potential: Investigating marketing students' behavioral intentions to adopt ChatGPT. Marketing Education Review, 34(3), 201–234. https://doi.org/10.1080/10528008.2023.2300139

[3] Ma, T., Stöhr, C., & Erichsen, E. (2024). Perceptions and usage of AI chatbots among students in higher education. Computers & Education: Artificial Intelligence, 6, 100203. https://doi.org/10.1016/j.caeai.2024.100203

[4] Polyportis, A., et al. (2025). Understanding students' adoption of the ChatGPT chatbot in higher education. Behaviour & Information Technology. https://doi.org/10.1080/0144929X.2024.2317364

[5] Sergeeva, O. V., & Markova, E. (2025). Understanding higher education students' adoption of generative AI technologies: An empirical UTAUT2 study. Contemporary Educational Technology, 17(2), ep571. https://doi.org/10.30935/cedtech/16039

[6] Barakat, M., & Al-Samarrai, R. (2025). University educators' perspectives on ChatGPT: TAM-based instrument validation. Open Praxis, 17(1), 1–15. https://doi.org/10.55982/openpraxis.17.1.718

[7] Stöhr, C., Demirbilek, M., & Ma, T. (2024). Systematically visualizing ChatGPT used in higher education. Computers & Education: Artificial Intelligence, 6, 100395. https://doi.org/10.1016/j.caeai.2024.100395

[8] Emerald (2025). GenAI in Indian higher education: Faculty at the crossroads of adoption. Asian Education and Development Studies. https://www.emerald.com/insight/publication/issn/2046-3162

[9] Zogheib, S., et al. (2024). Understanding university students' adoption of ChatGPT: A TAM-based exploration. Journal of Information Technology Education: Research, 23, 365–392.