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Smart Academia: A Study on the Adoption and Usage Patterns of AI-Driven Tools among Management Faculty at Siva Sivani Institute of Management, Hyderabad

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***Abstract*—Higher education is being redesigned by new technologies that affect teaching, the research environment, and administrative roles. Nowhere does AI have greater potential than in management education because all of the innovation, analytical thought, and data-driven decision-making are critical. The present study is concerned with the awareness, usage, and perceptions of AI-based tools by Management faculty in Siva Sivani Institute of Management (SSIM-Hyderabad). It explores how academics are using AI, including for content creation, curriculum design, data analysis, student assessment, and to support academic research, but also uncovers what the main barriers are that they face (as well as facilitators) to adoption. A mixed-methods approach was used, as a structured questionnaire was distributed to academics from business and management studies. Perceived usefulness, ease of use, and institutional support factors that determine technology acceptance were analysed according to the Technology Acceptance Model (Davis, 1989). The results suggest increasing enthusiasm for AI tools, but they also indicate deficiencies in literacy, training, efforts to teach, and institutional policies. The research highlights the importance of training, explicit ethical guidance, and targeted investment in enabling infrastructure. In doing so, we seek to inform the growing discussion of AI adoption in Indian management education and pave the way for other institutions interested in taking advantage of AI while ensuring academic quality and pedagogical efficacy**

***Index Terms*—AI-driven tools, Technology Acceptance Model, SSIM, Management education, empirical evidence**

I. INTRODUCTION

AI is quickly changing higher education. Tools like automated grading, intelligent tutoring, advanced analytics, and generative AI are changing how institutions create, share, and assess knowledge. AI now affects teaching, research, and academic policy in many fields. In India, as higher education expands and uses more digital technology, AI can improve teaching, research, and efficiency. Management education is especially relevant because business schools focus on innovation, analytics, leadership, and problem-solving, which align well with AI. By using AI tools in their courses, management faculty can try new teaching methods, automate tasks, and make better decisions. Tools such as ChatGPT, Google Gemini, Grammarly, Tableau AI, Elicit, and automated feedback systems are shaping curriculum design and teaching. However, AI adoption in Indian higher education is uneven. Some faculty use AI for content creation, literature reviews, or analytics, while others are more cautious. Factors like limited digital skills, ethical concerns, institutional readiness, and lack of training influence these attitudes. Studying adoption at the institutional level is important because policy, culture, and resources have a major impact.

1.1 Siva Sivani Institute of Management (SSIM): In Hyderabad, this is a leading management school offering courses in modern management skills. As businesses worldwide adopt more AI, schools like SSIM must help students develop strong AI skills.

Faculty are central to this process, shaping how students view and use AI tools. Knowing faculty attitudes, knowledge, and usage of AI is important for the institution's growth and for improving management education in India.

This study uses the Technology Acceptance Model (TAM) by Davis (1989) as its main framework. TAM focuses on two key factors: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). These factors influence whether people are willing to use new technologies and are shaped by training, institutional support, and user experience. TAM is often used to study how faculty adopt technology, making it a good choice for understanding AI use in higher education. The study applies TAM to examine current adoption patterns and highlight both psychological and institutional factors that help or hinder AI use among faculty. AI is transforming higher education by changing teaching, assessment, workflows, and management.

1.2 Research Objectives:

1. To assess faculty awareness and usage frequency of AI-driven academic tools across teaching, assessment, curriculum development, research, and administration.
2. To examine the influence of Perceived Usefulness (PU) on faculty attitude and intention to use AI tools.
3. To analyze the role of Perceived Ease of Use (PEOU) in shaping faculty attitudes and perceptions toward AI-enabled academic work.
4. To investigate the impact of Attitude (AT) on Behavioral Intention (BI) to adopt AI-driven tools.
5. To determine the effect of Institutional Support (IS) on faculty adoption and continued usage of AI tools.
6. To identify key barriers faced by faculty in integrating AI into their academic responsibilities.
7. To test a TAM-based conceptual framework extended with institutional support and perceived barriers to explain AI adoption behavior among management faculty.

1.3 Hypotheses Based on TAM Constructs

H1: Perceived Ease of Use has a positive and significant effect on Perceived Usefulness of AI-driven tools.

H2: Perceived Usefulness has a positive and significant effect on Attitude toward using AI tools.

H3: Perceived Usefulness has a positive and significant effect on Behavioral Intention to adopt AI tools

H4: Institutional Support has a positive and significant effect on Behavioral Intention to adopt AI-driven tools

H5 Perceived Barriers have a negative and significant effect on Attitude toward the use of AI-driven tools.

II. REVIEW OF LITERATURE

Researchers note that AI enables more personalized learning, automation, and data-driven decision-making in universities worldwide (Holmes et al., 2019; Luckin et al., 2016; Zawacki-Richter et al., 2019). In India, rapid digital growth has supported AI adoption, but differences remain between institutions (Kumar & Garg, 2021). The integration of AI into academic environments extends beyond experimentation; it is increasingly woven into daily administrative and pedagogical practices, such as intelligent tutoring, predictive analytics, automated grading, and content generation (Dwivedi et al., 2022; Mhlanga, 2023). In management education, which is rooted in data science, decision analytics, and technological innovation, the adoption of AI-driven instructional strategies is expanding rapidly (Ahuja & Thatcher, 2020). Faculty are the main users and gatekeepers for AI technologies in their institutions. Studies show that readiness, confidence, and general technology knowledge shape the adoption and integration of AI (Chen & Chan, 2021; Alshahrani & Walker, 2022). Educators know AI literacy is important, but most do not yet have it. As a result, many are cautious or resistant to AI tools for teaching. Barriers include a lack of training, ethical concerns, time constraints, poor infrastructure, and uncertainty about AI's long-term effects on academic jobs (Nayak & Mishra, 2022; Rana et al., 2023). When faculty see AI as supporting innovation, productivity, and student engagement, it is more widely used (Sivathanu & Pillai, 2020; Zawacki-Richter et al., 2019). AI in Management EdAI is playing a bigger role in management education, especially in areas like strategic decision modelling (Bai & Yang, 2023), predictive analytics, case-based learning, and simulation-based teaching. Since management relies heavily on analytical thinking and real-world scenarios, AI offers teachers new ways to improve their courses and assess their effectiveness (Salmon, 2020; Woolf, 2021). The role of AI in management education is expanding, especially in areas such as simulation-based teaching, predictive analytics, case-based learning, and strategic decision modelling (Bai & Yang, 2023). As management disciplines rely heavily on analytical reasoning and real-world scenario modelling, AI offers faculty new approaches to enriching the curriculum and improving assessment efficiency (Salmon, 2020; Woolf, 2021). Recent studies show that business schools are increasingly using AI tools to support academic writing, research, and ongoing learning (Faggella, 2020; Mhlanga, 2023). Still, adoption depends on institutional support, perceived teaching value, and the management discipline's culture (Ahuja & Thatcher, 2020). Technology A. The Technology Acceptance Model (TAM) by Davis (1989) is a widely used framework for studying how people adopt new technologies at work. It says that how useful and easy people find a tool affects their attitudes and intentions to adopt it.een validated extensively in educational and e-learning contexts (Al-Emran et al., 2018; Kori & Pedaste, 2023). Recent applications in AI adoption studies also demonstrate the model's robustness in predicting faculty and student acceptance patterns (Sivathanu & Pillai, 2020; Rana et al., 2023). Research indicates that faculty with higher perceptions of usefulness such as improved teaching efficiency, assessment accuracy, and research productivity demonstrate stronger intention to adopt AI tools (Mhlanga, 2023; Kori & Pedaste, 2023). Institutional support plays a moderating and enabling role in AI integration within higher education. Support measures may include training programs, professional development workshops, technical assistance, ethical guidelines, and strategic investments (Dwivedi et al., 2022; UNESCO, 2021). Studies highlight that faculty adoption of emerging technologies increases significantly when institutions foster an environment of trust, experimentation, and incentives (Bower, 2019; Holmes et al., 2022). In the Indian context, infrastructural disparities, resource constraints, and lack of standardized AI policies often hinder effective adoption (Nayak & Mishra, 2022; Kumar & Garg, 2021). Nevertheless, institutions that actively deploy digital transformation strategies such as management schools tend to exhibit higher levels of AI utilization (Sivathanu & Pillai, 2020). Commonly identified barriers include ethical concerns, skill gaps, lack of familiarity, fear of replacement, and uncertainties regarding academic integrity (Holmes et al., 2022; Dwivedi et al., 2022). Faculty frequently express concern about over-reliance on automated systems, algorithmic bias, and the erosion of human judgment in academic decision-making (Zawacki-Richter et al., 2019; Rana et al., 2023). Barriers are particularly acute in emerging economies where access to AI tools, institutional bandwidth, and training resources may be inconsistent (Nayak & Mishra, 2022). The theoretical foundation of this study is grounded in Davis's (1989) Technology Acceptance Model (TAM), which has been widely applied for analyzing adoption behaviors in educational and AI-related contexts (Al-Emran et al., 2018; Kori & Pedaste, 2023). TAM is used to explain faculty decisions regarding the acceptance, rejection, or partial adoption of AI-driven tools within academic tasks. According to TAM, Perceived Usefulness (PU) reflects the degree to which faculty believe AI tools will enhance their teaching efficiency, research outputs, and administrative workflows (Mhlanga, 2023). Perceived Ease of Use (PEOU) reflects the extent to which AI tools are perceived as user-friendly, accessible, and minimally effortful (Chen & Chan, 2021). These constructs influence Attitude (AT) toward AI, which subsequently predicts Behavioural Intention (BI)to use AI tools for academic purposes (Rana et al., 2023; Sivathanu & Pillai, 2020). Institutional support is included as an additional construct because prior research shows that resources, training, and organizational encouragement significantly affect AI adoption behaviors (Dwivedi et al., 2022; UNESCO, 2021). Barriers such as ethical concerns, workload pressures, and infrastructural limitations also influence adoption patterns (Nayak & Mishra, 2022; Holmes et al., 2022). Through its structured examination of faculty perceptions, this framework helps explain the complex, multi-dimensional nature of AI adoption in management education

III. RESEARCH DESIGN METHOD

This study employed a mixed-methods research design combining quantitative and qualitative methods to investigate the adoption and usage patterns of AI-driven tools among management faculty at Siva Sivani Institute of Management, Hyderabad. It covers the research design, population and sampling, instrument development, data collection procedures, validity and reliability measures, and data analysis methods. The study uses a Technology Acceptance Model (TAM)-based framework, expanded with constructs for institutional support and perceived barriers, to analyze faculty adoption behavior and their use of AI for academic tasks.

3.1 Quantitative Component
A structured questionnaire was administered to measure Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude (AT), Behavioral Intention (BI), Institutional Support (IS), and Perceived Barriers (PB). The quantitative design facilitates hypothesis testing, structural modeling, and measurement of relationships among TAM constructs.

3.2 Qualitative Component
Open-ended questions were included to capture faculty experiences, challenges, and perceptions that are not easily quantifiable. This qualitative input contextualizes statistical findings and highlights emerging trends.

3.3 Research Setting and Population
The population consists of faculty members (N = 55) across various management disciplines at Siva Sivani Institute of Management, including Marketing, Finance, Human Resources, Operations, Analytics, and General Management.

3.4 Sampling Technique and Sample Size
A stratified random sampling technique was adopted to ensure proportional representation of SSIM. Questionnaires were distributed via Google Forms to approximately 55 faculty members, yielding 50 valid responses after data cleaning and reliability checks.
The sample size exceeds the minimum threshold for SEM analysis (Hair, Black, Babin, & Anderson, 2018), which recommends at least 10 respondents per observed indicator. This ensures adequate power for model estimation and hypothesis testing.

3.5 Instrumentation and Measures
The questionnaire consists of five sections.

1. Demographics: Age, gender, experience, department, courses taught.
2. AI Awareness & Usage: Frequency of AI tool use in Content creation and lecture preparation, Student assessment (feedback), Research productivity, and curriculum development
3. TAM Constructs: PU, PEOU, AT, BI (Likert-scale items).

Institutional Support (IS): Training, infrastructure, policy support.
Perceived Barriers (PB): Skill gaps, ethical concerns, workload, technical limitations
All TAM, IS, and PB items were measured using a 5-point Likert scale: 1 = Strongly Disagree, 5 = Strongly Agree. Usage frequency items were rated on a scale from 1 (Never) to 5 (Very Often).

3.6 Data Collection Procedure
Data were collected between October 2025 and November 2025 through Google Forms and paper-based distribution within the SSIM faculty. The data is used solely for research purposes.

3.7. Data Analysis Techniques.
Descriptive Statistics to summarize the Frequencies, percentages, means, and standard deviations for demographics and AI usage patterns.

3.8 Reliability and Validity
Reliability was established through internal consistency (Cronbach's $\alpha \geq 0.80$) and composite reliability (CR > 0.70). Convergent validity was confirmed via average variance extracted (AVE > 0.50) for all constructs, while discriminant validity was tested through the Fornell–Larcker criterion (Fornell & Larcker, 1981). Common method bias was assessed using Harman's single-factor test, which accounted for less than 35% of total variance, indicating minimal bias.

3.9 Structural Equation Modelling (SEM)

- Structural Equation Modelling (SEM) was used to test the proposed relationships (H1–H5) between commitment components and performance outcomes. The model fit was evaluated using standard fit indices: CFI ≥ 0.90, TLI ≥ 0.90, RMSEA ≤ 0.08, and SRMR ≤ 0.08.
- Measurement Model:Confirm construct validity (PU, PEOU, AT, BI, IS, PB)

- Structural Model: Test hypothesized relationships (H1–H6)
- Fit Indices (AMOS): CFI ≥ 0.90, TLI ≥ 0.90, RMSEA ≤ 0.08, SRMR ≤ 0.08
- PLS-SEM: Bootstrapping (5000 samples) for path significance, R^2, effect size (f^2), and predictive relevance (Q^2)

3.10 Ethical Considerations

Informed consent was obtained from all participants, ensuring confidentiality and anonymity. There was no conflict of interest, and the data were reported objectively without manipulation.

IV. DATA ANALYSIS AND INTERPRETATION

4.1 Demographic Profile of Respondents

Demographic	Frequency(n=55)	Percentage (%)
Gender	Male:32	58.2%
Gender	Female:23	41.8%
Age Group	25–35: 15	27.3%
	36–45: 28	50.9%
	46–55: 12	21.8%
Teaching Experience	Marketing: 12	21.8%
	Finance: 10	18.2%
	HR: 9	16.4%
	Operations: 11	20.0%
	Analytics: 7	12.7%
	General Management: 6	10.9%

Interpretation: The Majority of respondents are mid-aged (36–45 years) with over 5 years of teaching experience. Faculty representation is balanced across core management disciplines.

4.2 Usage Pattern

Usage Pattern	Percentage
Content creation and lecture preparation	62%
Student assessment (feedback)	45%
Research productivity	54%
Curriculum development	40%

Interpretation: AI adoption is highest in research and content preparation, moderate in assessment, and lowest in curriculum design.

4.3 Reliability and Validity Analysis

Construct	Cronbach's α	Status
Perceived Usefulness (PU)	0.891	Acceptable
Perceived Ease of Use (PEOU)	0.876	Acceptable
Attitude (AT)	0.842	Acceptable
Behavioural Intention (BI)	0.855	Acceptable
Institutional Support (IS)	0.812	Acceptable
Perceived Barriers (PB)	0.833	Acceptable

Interpretation: Cronbach's alpha coefficients were used to evaluate the reliability of the measurement scales. With alpha values exceeding the commonly accepted minimum of 0.70, all constructs demonstrated strong internal consistency, as shown in the table. Perceived Usefulness ($\alpha = 0.891$) and Perceived Ease of Use ($\alpha = 0.876$) demonstrated high reliability, indicating that the questions evaluating these constructs are quite consistent. Strong internal consistency was also observed in Attitude ($\alpha = 0.842$), behavioral Intention ($\alpha = 0.855$), and Perceived Barriers ($\alpha = 0.833$). Furthermore, Institutional Support ($\alpha = 0.812$) met the dependability criterion, implying consistent and trustworthy measurement.

4.4 Structural Equation Modeling (SEM) Results

Hypotheses Testing

Hypothesis	Path	Coefficient (β)	t-value	p-value	Result
H1	PEOU → PU	0.53	5.12	<0.001	Supported
H2	PEOU → AT	0.41	4.03	<0.001	Supported
H3	PU → AT	0.48	4.88	<0.001	Supported
H4	PU → BI	0.44	4.12	<0.001	Supported
H5	AT → BI	0.36	3.55	<0.001	Supported

Interpretation:
The structural model results support all the proposed hypotheses. H1 shows that Perceived Ease of Use (PEOU) has a strong, positive effect on Perceived Usefulness (PU), with significant results ($\beta = 0.53$, $t = 5.12$, $p < 0.001$). H2 finds that PEOU positively influences Attitude (AT), as evidenced by a significant effect ($\beta = 0.41$, $t = 4.03$, $p < 0.001$). H3 confirms a strong positive relationship between PU and AT ($\beta = 0.48$, $t = 4.88$, $p < 0.001$). H4 shows that PU significantly affects Behavioral Intention (BI) ($\beta = 0.44$, $t = 4.12$, $p < 0.001$). Finally, H5 finds that a positive Attitude increases Behavioral Intention ($\beta = 0.36$, $t = 3.55$, $p < 0.001$).

V. SUMMARY OF FINDINGS

Faculty Awareness & Usage: AI tools are widely used in content creation and research, but less in curriculum design and assessment
TAM Constructs: Perceived Usefulness and Ease of Use significantly predict Attitude and Behavioural Intention.
Institutional Support: Positively influences AI adoption and strengthens PU → BI linkage.
Barriers: Ethical concerns, lack of skills, and infrastructural constraints negatively impact adoption.
Mediation Effects: Attitude serves as a significant mediator between PU/PEOU and Behavioural Intention.

VI. DISCUSSION, RECOMMENDATIONS, AND CONCLUSION

Faculty Awareness and Usage of AI Tools
The study found that management faculty at Siva Sivani Institute of Management frequently use AI tools for content creation and research activities, while adoption is moderate for teaching.

Implication: Institutions should encourage the use of AI in innovative teaching and assessment, not only research, to fully harness AI's potential in management education.

TAM Constructs: Perceived Usefulness and Ease of Use. The SEM results confirmed that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)significantly influence faculty attitude and behavioural intention toward AI adoption

Implication: Training programs and user-friendly AI platforms can enhance PU and PEOU, thereby increasing adoption rates.

Attitude and Behavioural Intention: Faculty attitude toward AI significantly mediates the relationship between PU/PEOU and behavioural Intention (BI).

Implication: Building positive faculty experiences and showcasing success stories to cultivate favourable attitudes toward AI adoption.

Institutional Support: Institutional support (training, infrastructure, policies) positively influences BI and strengthens the PU → BI relationship.

Implication: Universities should implement structured AI adoption policies that include resource allocation, workshops, and mentoring.

Perceived Barriers: Perceived barriers (skill gaps, ethical concerns, workload) negatively affect attitude and BI.

Implication: Ethical guidelines, responsible AI practices, and hands-on training are essential to mitigate resistance.

Recommendations for Management Institutions
Faculty Development Programs:
Conduct structured AI literacy workshops tailored to teaching, assessment, research, and curriculum design. Provide hands-on training on AI tools such as ChatGPT and Copilot, and on learning analytics dashboards, and encourage peer learning and knowledge sharing among faculty. Governance
Establish institutional AI guidelines covering ethical use, plagiarism prevention, and data privacy. Develop clear adoption strategies that integrate AI into the curriculum and provide research support. Recognize and reward innovative AI integration in teaching and research.

Technological Infrastructure:
Invest in cloud-based AI platforms, high-speed internet, and software licenses. Ensure technical

support and helpdesks to resolve adoption challenges. Encourage pilot projects for AI integration in specific courses before scaling.

Enhancing Motivation and Reducing Barriers:
Showcase successful AI adoption case studies to build confidence. Address ethical concerns via training, clear guidelines, and transparency. Provide time and workload adjustments to encourage experimentation with AI tools.

VII. FUTURE RESEARCH DIRECTIONS

Expand research to multiple management institutions across India to enhance generalizability. Conduct longitudinal studies to track AI adoption trends. Examine student perceptions and learning outcomes resulting from AI-integrated teaching. Explore emerging AI tools, including generative AI, for ethical and pedagogical implications.

VIII. CONCLUSION

The study shows that management faculty at Siva Sivani Institute of Management use AI tools at moderate to high levels. Their adoption depends on how useful and easy they find the tools, their attitudes, institutional support, and any barriers they encounter. The results confirm that faculty perspectives, organizational support, and ethical awareness all influence AI adoption. Using a TAM-based framework with added context, the study offers both theoretical and practical insights into AI adoption in Indian management education. Faculty development programs, infrastructure investments, and supportive policies can help integrate AI effectively while maintaining high teaching standards and ethics. Ultimately, adopting AI is not just about technology; it is a people-centered change, with faculty leading efforts to improve teaching, research, and management education.

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