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Article

An Empirical Study on GenAI Pedagogical Adoption among Indian Management Faculty

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Abstract: Generative Artificial Intelligence (GenAI) is transforming management education through AI-driven pedagogical innovations. However, faculty adoption in developing nations like India is still uneven. There is a dearth of empirical studies that examines the effect of demographic and institutional factors on faculty usage of GenAI. This study explores the effect of demographic and institutional factors on GenAI adoption among Indian management faculty. Using a descriptive and empirical design survey data were collected from 156 faculty members across government, deemed and autonomous management institutes. Chi-square analyses were done to examine the associations between GenAI usage with gender, educational qualification, work experience, institutional affiliation, and geographic location. The findings reveal distinct trends. Educational qualification, institutional location, and affiliation significantly influence GenAI use in assessment automation, tutoring support and student-engagement. Gender differences are significant in data-intensive tasks, whereas there is no difference in creative and low-stake uses. Interestingly, adoption cannot be determined by work experience challenging the assumption that senior faculty are more resistant to technological change. The findings indicate that digital infrastructure or structural readiness are important factors that influence successful adoption.

Keywords: GenAI adoption, Management education, Faculty readiness, Institutional factors, Pedagogical innovation.

INTRODUCTION

In recent times, Generative Artificial Intelligence (GenAI) has transitioned from an experimental educational technology to an accepted teaching and learning tool. International business schools are using GenAI tools in their pedagogy for experiential learning. AI-generated simulations and dynamic case-based learning materials are redefining the way learning is conceived and delivered. GenAI tools are extensively being used for content curation, case generation, scenario-based simulation and personalised feedback (Bahroun, 2025). Faculty are leveraging GenAI to improve student engagement, assessment quality, and classroom innovation. In management education AI tools help create context-specific business problems to analyse the critical thinking and analytical problem-solving skills of students (Chiu,2024). However, the effectiveness of such tools depends greatly on the willingness and readiness of faculty to adopt them. Thus, one of the most critical factors for GenAI integration is faculty adoption.

Accreditation organizations are stressing the importance of innovative teaching methods and the use of new technologies. Also, the management students look for exposure to real-world industry scenarios and current market data that will equip them to solve industry challenges when they join the work force. They also value localised content and constructive feedback that makes learning relevant to their needs. GenAI can provide these elements by generating realistic simulations, current case studies, and personalized feedback, making management education more engaging, practical, and meaningful for students (Jose et al., 2025).

Individual characteristics such as comfort level with technology, usefulness and trust in AI results may have an impact on AI adoption. In developing nations like India , where business schools differ in terms of resources, digital readiness, and training, institutional policy and technological infrastructure could be important. Faculty demographics, such as gender, educational background, teaching experience, institutional affiliation, and geographic location, could impact the adoption of GenAI. The digital divide between well-funded autonomous business schools and resource-constrained institutions, as well as between metro and non-metro campuses, may lead to uneven adoption of GenAI.

While AI has gained in popularity in management education there are very few studies that have explored the influence of demographic and institutional factors on GenAI adoption among faculty member of Indian management school. Most of the existing research has focused on student perception, technological availability and institutional preparedness. There is a gap in research that investigates the influence of human-level determinants on the use of AI-assisted pedagogy. The current study addresses this gap by exploring how demographic factors affect adoption of GenAI generated pedagogy among management faculty in India. This will help institutions design better faculty training, create effective policies, and ensure equitable adoption of AI-enabled teaching across diverse academic contexts.

Literature Review

The review summarises the latest research on GenAI in higher education, faculty preparedness, demographic factors and institutional facilitators for adoption. It highlights gaps in Indian empirical studies. Over the last ten years AI in education has changed from exploratory tools to analytics-driven GenAI learning systems. (Zawacki-Richter et al., 2019). GenAI supports assessment automation, content generation, tutoring and student engagement. So it has become essential in modern education (Sadiq & Khanna, 2023). Also research findings reveal that AI can improve learning outcomes through automated iterative feedback, personalized tutoring, and assessments. Nevertheless, pedagogical integration differs across institutions and demographic. GenAI is seen as a driving force for relevant content creation, adaptive assessment, and personalized learning. Studies show that GenAI tools augment higher-order thinking by assisting in the creation of efficient scenario-based simulations and through iterative feedback (Li & Chen, 2024). In pedagogy, GenAI offers cognitive apprenticeship models wherein learners are given structured, contextually aware instruction. Studies reveal that learning analytics and intelligent tutoring systems improve retention and learning effectiveness (Holmes et al., 2022). Based on student's capability and profile AI-driven learning platforms generate differential instruction as per each learner's unique profile (Chen et al., 2020). However, researchers emphasise against over-reliance and highlight the need for AI literacy and ethical use (Martinez, 2023).

Faculty preparedness and competence are strong determinants for adoption. Also, self-efficacy, ease of use and training influence adoption (Farhan & Abdullah, 2021). Digital literacy, workload, age and institutional standards influence adoption intention (Raman & Don, 2022). Faculty members engaged in ongoing research show higher adoption tendencies most likely because of experimental culture. On the other hand senior faculty cite lack of trust, academic integrity and lack of professional development as barriers (Kumar & Singh, 2022). Perceived usefulness, complexity, institutional type and ranking moderate adoption intention. The adoption is determined by institutional factors including incentive structures, policy frameworks, digital infrastructure, and leadership support. Universities that have established ethical standards and centralized AI strategies exhibit more seamless GenAI deployment (O'Donnell, 2023). AI tools are more confidently adopted by universities with robust data governance frameworks (Li & Jung, 2021). Compliance-driven cultures impede innovation while collaborative cultures speed up experimentation. Notably, the relationship between institutional readiness and actual technological adoption is mediated by organizational trust and collective teacher efficacy (Martínez & Sahu, 2023).

Despite the increasing popularity of GenAI in pedagogy, India-specific studies are still scarce and dispersed. Most Indian studies focus on LMS adoption and not on GenAI tools. Most of the research relies on descriptive analysis and there is a dearth of empirical research that focus on other statistical techniques. There is limited research that explores the influence of faculty demographics and institutional factors on adoption.

Objectives of the Study

1. To analyse the association between gender and the use of GenAI tools in pedagogy among management faculty.

2. To examine the association between educational qualification and the use of GenAI tools in pedagogy.
3. To study whether work experience is associated with differences in the adoption of AI for teaching.
4. To determine whether the type of institute affiliation is associated with the use of AI in teaching and learning.
5. To assess the association between geographical location and the use of AI tools in pedagogy.

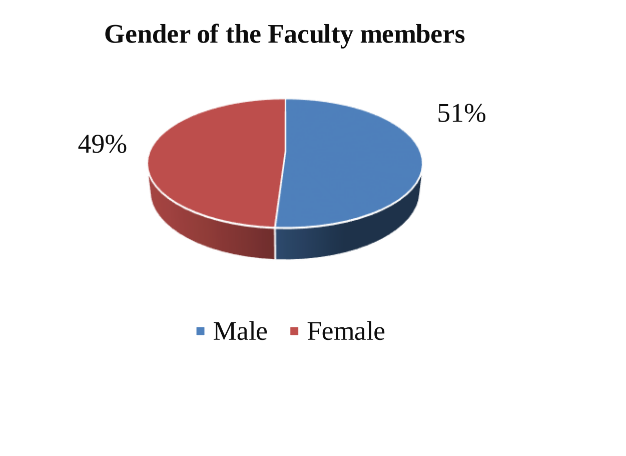
This study adopts a descriptive and empirical research design to examine demographic and institutional determinants influencing the adoption of GenAI tools in pedagogy among management faculty in India. The methodology provides an overview of usage patterns. It also includes statistical tests for associations that align with the research objectives. A purposive stratified sampling approach was used. Data was collected through structured online questionnaire. The survey included 156 faculty members from different government, deemed and autonomous business schools across India. The instrument includes demographic details, institutional information and validated items on AI tool used in tasks like assessment automation, content generation, tutoring support and student engagement. Analysis was conducted using SPSS. Descriptive statistics were used to summarize faculty characteristics and AI usage patterns. Chi-square tests were applied to assess relationships between AI usage with gender, qualification, experience, affiliation type, and location. The methodology provides an overview of usage patterns.

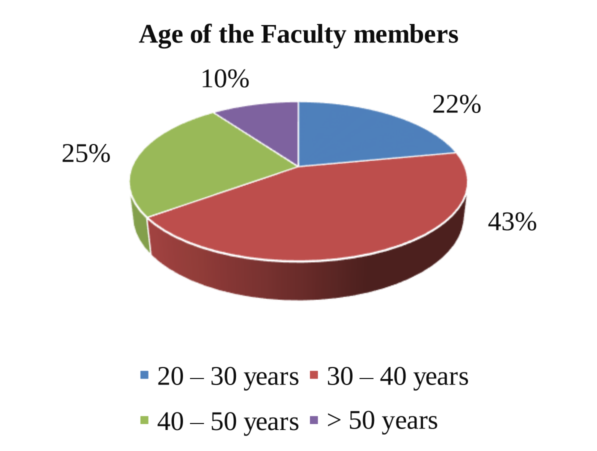
Hypothesis

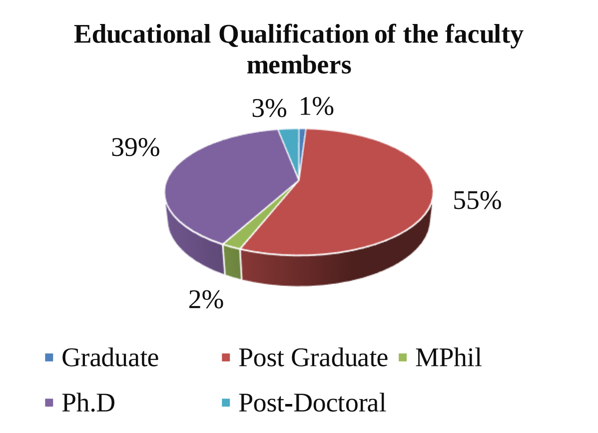
H1: There is no significant association between **gender** and GenAI use in pedagogy.
H2: There is no significant association between **educational qualification** and GenAI use in pedagogy.
H3: There is no significant association between **work experience** and GenAI use in pedagogy.
H4: There is no significant association between **institutional affiliation** and GenAI use in pedagogy.
H5: There is no significant association between **geographical location** and GenAI use in pedagogy.

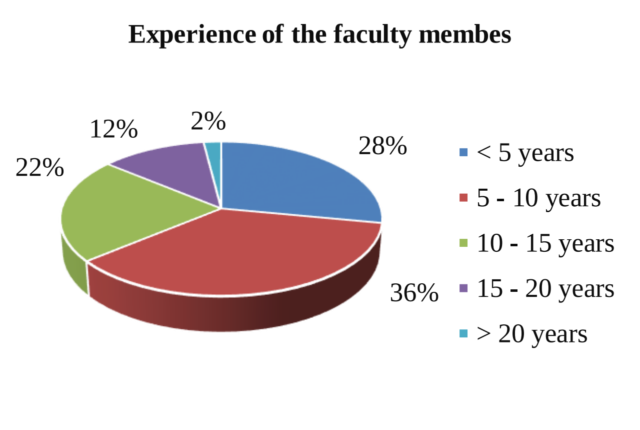
Analysis and Interpretation

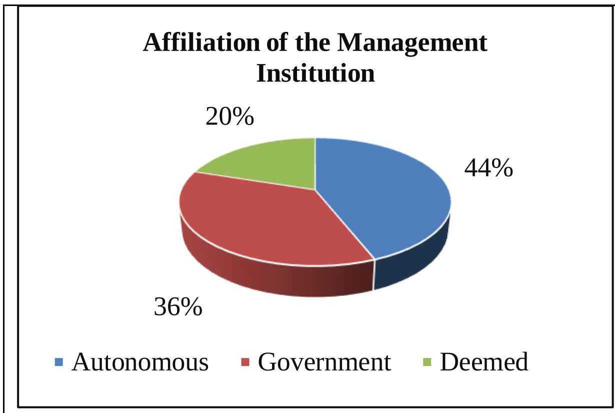
DEMOGRAPHIC DETAILS











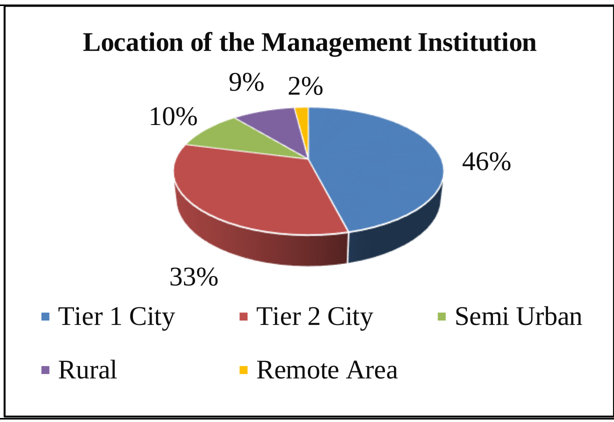


Table 1 Chi Square - Association between gender and use of GenAI among faculty

Faculty Response to use of GenAI	Chi Square Value	Degree of Freedom	p-value	Result
Assessment automation	6.876[a]	2	.033	Dependent
Content generation	.391[a]	2	.824	Independent
Tutoring support	3.362[a]	2	.187	Independent
Student engagement	8.954[a]	2	.012	Dependent
a. significance value is 0.05				

The chi-square analysis examining the association between faculty gender and adoption of GenAI tools yields 2 degrees of freedom. The GenAI usage factors like assessment automation ($\square^{2}$ = 6.876) and using AI for student engagement ($\square^{2}$ = 8.954) are dependent on gender of faculty members, as their respective p-value is less than 0.05 at 95% confidence level. The chi square for all the other factors is less than critical value and their respective p-value is greater than 0.05 at 95% confidence level. Thus, there is no association between gender of faculty and the use of GenAI for content creation or tutoring support.

Table 2 Chi Square - Association between Educational Qualification and use of GenAI among faculty

Faculty Response to use of GenAI	Chi Square Value	Degree of Freedom	p-value	Result
Assessment automation	24.720[a]	8	.002	Dependent
Content generation	13.033[a]	8	.112	Independent
Tutoring support	15.879[a]	8	.045	Dependent
Student engagement	22.007[a]	8	.005	Dependent
a. significance value is 0.05				

The chi-square test examining the association between faculty educational qualifications and their use of GenAI tools shows 8 degrees of freedom. The results indicate that assessment automation (χ^2 = 24.720), student engagement (χ^2 = 22.007), and tutoring support (χ^2 = 15.879) are significantly associated with educational qualification, as each has a p-value below 0.05 at the 95% confidence level. For all other GenAI usage factors, the chi-square values are below the critical value, and their p-values exceed 0.05, indicating no significant association with educational qualification.

Table 3 Chi Square - Association between work experience and use of GenAI among faculty

Faculty Response to use of GenAI	Chi Square Value	Degree of Freedom	p-value	Result
Assessment automation	8.897[a]	8	.351	Independent
Content generation	6.218[a]	8	.623	Independent
Tutoring support	6.889[a]	8	.549	Independent
Student engagement	11.390[a]	8	.181	Independent
a. significance value is 0.05				

The chi-square test examining the association between faculty work experience and use of GenAI shows 8 degrees of freedom. The results indicate that all GenAI usage tasks are independent of work experience, as the chi-square values for all factors are below the critical value, and their p-values are greater than 0.05 at the 95% confidence level.

Table 4 Chi Square - Association between affiliation and use of GenAI among faculty

Faculty Response to use of GenAI	Chi Square Value	Degree of Freedom	p-value	Result
Assessment automation	83.603[a]	4	.000	Dependent
Content generation	4.667[a]	4	.323	Independent
Tutoring support	22.987[a]	4	.000	Dependent
Student engagement	26.147[a]	4	.000	Dependent
a. significance value is 0.05				

The chi-square test examining the association between the type of institution and faculty use of AI tools shows 4 degrees of freedom. The results indicate that assessment automation (χ^2 = 83.603), student engagement (χ^2 = 26.147) and tutoring support (χ^2 = 22.987) are significantly associated with institutional affiliation as its p-value is below 0.05 at the 95% confidence level. For content generation AI usage factors, the chi-square values are below the critical value, and their p-values exceed 0.05, indicating no significant association with institutional affiliation.

Table 5 Chi Square - Association between location and use of GenAI among faculty

Faculty Response to Indicated tasks of ICT Usage factors	Chi Square Value	Degree of Freedom	p-value	Result
Assessment automation	21.385[a]	8	.005	Dependent
Content generation	9.178[a]	8	.337	Independent
Tutoring support	20.464[a]	8	.009	Dependent
Student engagement	39.260[a]	8	.000	Dependent
a. significance value is 0.05				

The chi-square test examining the association between the institution's location and faculty use of GenAI tools shows 8 degrees of freedom. The results indicate that assessment automation (χ^2 = 21.385), student engagement (χ^2 = 39.260) and tutoring support (χ^2 = 20.464) are significantly associated with institutional location, as their p-values are below 0.05 at the 95% confidence level. For content generation the chi-square values is below the critical value, and the p-values exceed 0.05, indicating no significant association with institutional location.

DISCUSSION

The results show a distinct pattern of GenAI adoption among Indian management faculty, influenced more by institutional and contextual factors than by personal traits like experience. The significant gender-based differences in assessment automation and student-engagement suggest that male and female faculty may differ in their comfort with data-driven teaching tasks. This is consistent with the findings of Raman and Don (2022), who pointed out that digital self-efficacy differs among demographic subgroups. However, the lack of gender disparities in content generation and tutoring support suggest that lower-stakes, creativity-oriented GenAI tasks have already become democratised across faculty groups. Educational qualification is an important differentiator in the case of assessment automation, tutoring support, and student engagement. Faculty members with doctoral or research-intensive backgrounds may be more likely to experiment with AI-based formative feedback systems. This supports the claim that academics who conduct research frequently have greater digital agility and methodological confidence. On the other hand, work experience has no significant effect challenging the assumptions that senior faculty resist innovation. This implies that neither age nor tenure affect resistance to use of GenAI adoption. Institutional characteristics of affiliation type and geographic location have a significant impact on GenAI adoption. There are persistent digital disparities between metro and non-metro campuses usage of GenAI. This indicates that infrastructure readiness is a prerequisite for effective GenAI adoption. Similarly, the association between institutional affiliation and assessment automation suggests that government, deemed and autonomous B-schools differ in their GenAI readiness, in terms of technology, policies, and institutional support.

CONCLUSION

This study empirically examines how demographic and institutional factors influence adoption of GenAI among Indian management faculty. The findings show that GenAI usage varies across faculty groups and is not same. Factors such as geographic location, institutional affiliation and educational background all influence adoption. Interestingly for data-heavy tasks there are noticeable gender differences. However, work experience has no influence on adoption. This suggests that senior faculty are open to adopting GenAI. The impact of location and affiliation point to some policy-level and infrastructure inequalities among Indian business schools. These results highlight that preparedness and not only individual willingness determine the success of GenAI integration. There is need for structured GenAI usage with focus on enhancing infrastructure, having clear AI-use policies and training. It is important that all institutes have access to GenAI so that location and affiliation do not limit the extent of pedagogical innovation. The results also suggest that faculty development programs should have competency-based, separate training. Training should be on scenario-based practicals rather than on tool demonstrations since there are adoption gaps in student engagement and assessment automation. The findings highlight the importance of AI literacy and institutes should create an environment that encourages experimentation. Using GenAI for assessments and feedback can help standardize adoption across different faculty groups.

Future research could include longitudinal studies to track the changes in adoption of GenAI. It would also be interesting to explore the effect of institutional policy and incentive schemes as mediating variables. Comparing the use of GenAI across different disciplines and its impact on student outcomes can be valuable. Qualitative or mixed-method studies might reveal barriers and faculty beliefs that affect adoption.

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