International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Impact of AI-Powered Personalized Learning Systems on Student Engagement and Academic Achievement: A Regional Empirical Study of Kozhikode District

Dhanya M C

Assistant Professor, National College of Arts and Science, Puliyavu, Nadapuram

Abstract

This study examines how undergraduate students at University of Calicut-affiliated colleges in Kozhikode district use AI-powered personalized learning tools, and how that use relates to their engagement and self-reported academic performance. A structured questionnaire and follow-up interviews were administered to 150 undergraduate students across Arts, Science, and Commerce streams. A large majority of respondents reported using AI tools — chatbot assistants such as ChatGPT, writing aids such as Grammarly, and platforms such as Khan Academy — as study aids (94.0% agreement) and as substitutes for immediate tutoring support (95.0% agreement). AI engagement was positively associated with continuous assessment performance ($r = .74$, $p < .001$), though this association is interpreted here as correlational rather than causal, given the likelihood that academically motivated students self-select into heavier AI use. Despite this enthusiasm, 80.0% of respondents rejected the idea that AI could substitute for a human instructor, citing mentorship, ethical guidance, and personal attention as functions AI does not provide. The findings support a human-in-the-loop model of AI integration for Kerala's higher education institutions, consistent with India's National Education Policy 2020.

Keywords: artificial intelligence, personalized learning, student engagement, higher education, Kozhikode, human-centered AI

1. Introduction

Undergraduate teaching in India still relies largely on a single pace and a single curriculum for an entire classroom, an arrangement that fits some students far better than others. Students differ in prior preparation, in how quickly they absorb new material, and in how they study outside class, and a uniform lecture schedule cannot adjust to any of this. The result, documented repeatedly in the technology-enhanced learning literature, is uneven engagement and uneven outcomes (Bergdahl et al., 2020; Dunn & Kennedy, 2019).

Artificial intelligence tools — conversational assistants such as ChatGPT and Claude, writing-support tools such as Grammarly, and structured platforms such as Khan Academy — offer students a way to get individualized help outside the classroom: instant explanations, practice questions, and feedback calibrated to what they already know (Molenaar, 2021; Zhai et al., 2021). India's National Education Policy 2020 explicitly encourages this kind of technology-enabled, adaptive learning as a way of closing

gaps and building self-directed study habits (National Council of Educational Research and Training [NCERT], 2020).

Most published research on this shift, however, either evaluates the technology in the abstract or surveys adoption at a national scale (Sharma et al., 2024), leaving little evidence about how specific regional student populations actually use these tools. Kozhikode district, with its high literacy rate and expanding digital access, offers a useful setting to look more closely. Anecdotal conversations with faculty at colleges affiliated with the University of Calicut suggest that students already move fluidly between conversational assistants for conceptual doubts, grammar-checking tools for assignment writing, and structured practice platforms for exam preparation, often without any formal institutional guidance on how these tools should be used. This study asks three questions: how do undergraduate students at colleges affiliated with the University of Calicut in Kozhikode district perceive AI-based study tools; is there a measurable association between AI engagement and continuous assessment performance; and where do students themselves draw the line between AI assistance and human teaching?

2. Literature Review

2.1 Technology-Enhanced Learning and Personalization

Digital tools have long been part of higher education, but their role has shifted from static computer-assisted instruction toward adaptive, data-driven systems. Early work cautioned that installing digital tools does not by itself improve outcomes; benefits depend on how well the tool is embedded in teaching practice and how ready students are to use it (Shohel & Kirkwood, 2012). Dunn and Kennedy (2019), studying undergraduates, found that motivation and engagement mediate the relationship between technology use and achievement — technology helps mainly by increasing engagement, not through any automatic property of the tool. Bergdahl et al. (2020) add that students' existing digital skills and self-regulation strongly predict whether they engage with or disengage from a given platform, a point relevant to interpreting engagement data from any single sample.

Personalization is AI's specific contribution to this picture. Walkington and Bernacki (2020) note that the term has been applied inconsistently across studies, from simple difficulty adjustment to deeper content tailoring, and argue that personalization sustains engagement only when tied to genuine motivational needs. Rienties et al. (2020) distinguish AI-driven automated content delivery from learning analytics, which instead turns learner data into information a human instructor can act on; most classroom AI tools now combine both functions. Molenaar (2021) describes a spectrum of hybrid human-AI systems in which routine decisions — sequencing practice items, timing feedback — shift to algorithms while pedagogical judgment stays with the teacher, a pattern Zhai et al. (2021), reviewing AI-in-education studies published between 2010 and 2020, associate most strongly with feedback and adaptive-pathway tools rather than with more experimental applications such as affective computing. Most recently, du Plooy et al. (2024), synthesizing higher-education studies, report that adaptive algorithms increase engagement and comprehension, with gains that vary by discipline and by how well an institution implements the technology — a caveat worth keeping in mind when comparing Arts, Science, and Commerce students below.

2.2 AI Adoption in Indian and Kerala Higher Education

NEP 2020 provides the policy backdrop for AI adoption in Indian higher education (NCERT, 2020). Sharma et al. (2024), surveying students, faculty, and administrators across Indian institutions, found that perceived usefulness and institutional support predict adoption, and that students consistently outpace

faculty and administration in actually using AI tools. Kerala's comparatively strong public investment in digital classroom infrastructure suggests that, in a district like Kozhikode, the binding constraint on AI use is less likely to be internet access than the absence of institutional policy, faculty training, and vetted, curriculum-relevant tools — the same gap Sharma et al. (2024) identify nationally.

2.3 The Limits of AI: A Theoretical Synthesis

Two established frameworks jointly explain why students might embrace AI for some functions and reject it for others. The Technology Acceptance Model treats perceived usefulness and ease of use as the primary drivers of adoption (Sharma et al., 2024), which accounts for high approval of AI as a study aid. Self-Determination Theory frames engagement around three needs — autonomy, competence, and relatedness (Walkington & Bernacki, 2020). AI tools plausibly support autonomy (self-paced study) and competence (immediate, low-stakes feedback), but not relatedness, which depends on genuine human contact. Renz and Vladova (2021) and Rienties et al. (2020) make the same point from a design perspective, arguing that AI should be built to extend teacher capacity rather than substitute for the ethical reasoning and mentorship that relatedness requires. This synthesis — usefulness driving adoption, relatedness bounding it — anticipates the central pattern in the findings reported below, and no published study has tested it against district-level data from Kerala.

3. Methodology

3.1 Design and Sample

This study used a cross-sectional, mixed-methods design combining a structured survey with follow-up interviews, collected concurrently and integrated at interpretation. Because the design is cross-sectional, it can identify association but not causal direction between AI use and academic performance — a constraint that shapes how the correlational results in Section 4 are read.

A stratified random sample of 150 undergraduate students was drawn from Arts, Science, and Commerce streams at colleges affiliated with the University of Calicut in Kozhikode district, stratified by gender, stream, and year of study. Colleges were selected across government, aided, and self-financing institutions in and around Kozhikode city to avoid skewing the sample toward one institutional type. Table 1 summarizes the achieved sample: close to gender-balanced (54.7% female), spread across streams (36.7% Science and Technology, 30.0% Arts, 33.3% Commerce) and years, with 48.0% of respondents reporting daily AI use and a further 34.0% reporting use three to four times weekly. This skew toward already AI-engaged students is a relevant scope condition, since it means the sample likely overrepresents the more digitally confident segment of the undergraduate population.

Demographic Category	Sub-Classification	n	%
Gender	Male / Female	68 / 82	45.3 / 54.7
Academic Stream	Science & Tech / Arts / Commerce	55 / 45 / 50	36.7 / 30.0 / 33.3
Year of Study	1st / 2nd / 3rd Year	42 / 58 / 50	28.0 / 38.7 / 33.3
AI Usage Frequency	Daily / 3–4× Week / Occasional	72 / 51 / 27	48.0 / 34.0 / 18.0
Total	Undergraduate Students	N = 150	100.0

Table 1. Sample composition (N = 150).

3.2 Instruments and Procedure

A five-point Likert questionnaire (1 = Strongly Disagree to 5 = Strongly Agree) measured four dimensions — perceived importance of AI, AI as self-study support, AI as virtual tutor, and perceived feasibility of AI replacing instructors — with item wording drawn from established technology-acceptance and personalized-learning constructs (Walkington & Bernacki, 2020) and piloted before full administration. Cronbach's alpha for the full instrument was .88. A subsample of volunteers completed semi-structured interviews (20–30 minutes, English or Malayalam) probing which specific tools they used, for what purposes, and how they viewed AI relative to faculty support. Interviews were transcribed, coded inductively, and grouped into themes, with a second reviewer checking coding on a subset of transcripts. A composite AI-engagement score — combining self-reported usage frequency, self-study time, and item responses on the self-study and tutor dimensions — was correlated with continuous assessment scores using Pearson's r. Because both the engagement measure and the assessment scores rely on self-report and institutional records collected at a single time point, the resulting coefficient should be read as evidence of association: students who are already strong performers, or already highly self-directed, may simply be more likely to adopt AI tools, which would produce the same correlation without any causal contribution from AI use itself. Informed consent was obtained from all participants, data were anonymized before analysis, and institutional permission was secured for access to academic records.

4. Findings

Table 2 summarizes response distributions across the four survey dimensions.

Dimension	Strongly Agree	Agree	Disagree	Strongly Disagree
1. Importance of AI in Learning	82.0% (123)	12.0% (18)	4.0% (6)	2.0% (3)
2. AI as Self-Study Alternative	68.0% (102)	18.0% (27)	10.0% (15)	4.0% (6)
3. AI as Virtual Tutor	84.0% (126)	11.0% (17)	3.0% (4)	2.0% (2)
4. Feasibility of AI Replacing Teachers	8.0% (12)	12.0% (18)	28.0% (42)	52.0% (78)

Table 2. Response distribution across four dimensions (N = 150).

Ninety-four percent of respondents (Strongly Agree plus Agree) endorsed AI as a study aid; 86.0% viewed it as useful for autonomous self-learning; and 95.0% found AI tools helpful for immediate clarification of doubts. By contrast, 80.0% disagreed that AI could replace a human instructor. Science and Technology students reported the highest daily AI use, consistent with problem-set-heavy subjects where instant worked feedback is especially useful; Arts students more often described AI as useful for organizing notes and summarizing readings rather than for concept-level tutoring.

4.1 Association Between AI Engagement and Assessment Performance

The composite AI-engagement score correlated positively with continuous assessment scores, $r = .74$, $p < .001$. This is consistent with international evidence linking AI-supported study to stronger academic outcomes (du Plooy et al., 2024; Zalte, 2023), but the design here cannot separate two competing explanations: that AI engagement improves performance, or that stronger, more self-directed students simply use AI more — a form of selection bias consistent with Bergdahl et al.'s (2020) finding that pre-

existing digital skills and self-regulation predict engagement with any learning technology. Table 3 reports the same academic and study-behaviour indicators as self-reported perceived impact rather than as measured pre/post gains, since no baseline was independently verified and all figures rely on retrospective recall.

Indicator	Self-Reported Prior Level	Self-Reported Current Level	Perceived Change
Continuous assessment performance	62.4%	68.9%	Modest perceived increase
Weekly self-study time	4.2 hrs	5.9 hrs	Modest perceived increase
Classroom participation (1–10)	5.1	6.4	Slight perceived increase
Assignment on-time completion	71.0%	79.6%	Modest perceived increase
Perceived concept retention	58.5%	67.2%	Modest perceived increase

Table 3. Self-reported perceived change in study behaviour and performance associated with AI use (retrospective recall; not an experimental pre/post measure).

4.2 Interview Findings

Three patterns recurred across interviews. First, students described AI tools — most often ChatGPT, alongside Grammarly for writing tasks and, among a smaller group, Khan Academy for structured practice — as valuable chiefly for low-stakes clarification outside class hours. Several participants indicated that asking a chatbot a basic question felt less exposing than asking a professor or classmate, which several linked to a greater willingness to seek help at all. Second, students in the Commerce stream more often reported using AI for organizing study schedules and condensing long reading material than for conceptual tutoring, suggesting the survey's "self-study" category covers a wider range of actual practice than a single item can capture. A recurring qualification among second- and third-year Science students was that AI explanations were most useful as a first pass — enough to attempt a problem set — but that they still brought unresolved questions to faculty during lab or tutorial hours, indicating that AI use and faculty consultation functioned as sequential rather than competing steps in their study process. Third, and most consistently, students distinguished between tasks they trusted AI to handle — practice problems, quick explanations, grammar correction — and functions they associated exclusively with faculty: recognizing when a student was struggling, offering career guidance, and providing encouragement during stressful periods. This distinction, raised independently by students across all three streams, underlies the 80.0% rejection of AI-as-replacement reported in Table 2 and suggests that students' skepticism is grounded in specific expectations of mentorship rather than general unfamiliarity with the technology.

5. Discussion

These findings describe a fairly consistent division of labour that Kozhikode district undergraduates have drawn for themselves: AI tools handle routine, on-demand academic support, while faculty retain responsibility for judgment, mentorship, and ethical guidance. The high approval of AI as a virtual tutor (95.0%) is consistent with Molenaar's (2021) account of hybrid human-AI systems and with Zhai et al.'s (2021) observation that engagement gains cluster around feedback-oriented tools rather than more experimental applications. The theoretical synthesis proposed in Section 2.3 helps explain why: AI's strength in supporting autonomy and competence maps onto the functions students embrace, while its absence of relatedness maps onto the functions they withhold.

The positive association between AI engagement and continuous assessment scores ($r = .74$, $p < .001$) should not be read as evidence that AI use causes better performance. Selection effects are a plausible alternative explanation: students with stronger existing study habits or higher baseline motivation may simply be more likely to adopt AI tools consistently, which would generate the same correlation independent of any effect of the tools themselves. Distinguishing these explanations would require a longitudinal or quasi-experimental design that this study does not provide. The self-reported perceived-impact figures in Table 3 reinforce this caution: they describe how students perceive their own study behaviour has shifted, not a verified measure of what AI contributed.

The clearest finding, and the one least open to this kind of alternative explanation, is the boundary students draw around mentorship. This corroborates the human-centered AI position argued by Renz and Vladova (2021) and the functional limits described by Rienties et al. (2020), and echoes Sharma et al.'s (2024) observation that Indian students' enthusiasm for AI regularly outpaces institutional readiness to formally support it. For colleges in Kerala, the practical implication is that AI adoption should be planned around this boundary rather than around either resisting the technology or expanding it into functions — mentorship, ethical guidance, personal encouragement — that students themselves say they still want from a human instructor.

Discipline-level variation within the sample points to a further implication for course design. Science and Technology students' heavier reliance on AI for problem-solving practice suggests these departments could gain the most from formally integrating AI-generated diagnostic data into tutorial planning, while Arts departments, where AI use skewed toward organizational and summarization tasks, may benefit more from guidance on using these tools to support close reading and argument construction rather than as a substitute for it. Treating AI integration as a single, uniform policy across streams risks underserving both groups.

6. Conclusion and Recommendations

Undergraduate students in Kozhikode district report substantial reliance on AI tools for self-study and tutoring support, and this engagement is associated — though not demonstrably causally — with stronger self-reported academic outcomes. At the same time, students consistently reject the idea of AI replacing human instructors, anchoring that rejection in specific expectations of mentorship and personal attention. Colleges seeking to act on these findings might reasonably prioritize equitable access to vetted AI platforms, structured faculty training in interpreting AI-generated diagnostic data, clear institutional policy on data privacy and academic integrity in AI use, and course designs that explicitly preserve time for mentorship alongside AI-supported self-study. Because this study is cross-sectional and confined to one district, longitudinal and multi-district replications would help establish whether the association reported

here reflects a genuine effect of AI engagement or primarily reflects the study habits of students who were already inclined to use these tools.

References

1. Shohel, M. M. C., & Kirkwood, A. (2012). Using technology for enhancing teaching and learning in higher education: Challenges and consequences. Learning, Media and Technology, 37(4), 414–428. https://doi.org/10.1080/17439884.2012.670326
2. Dunn, T. J., & Kennedy, M. (2019). Technology enhanced learning in higher education: Motivations, engagement and academic achievement. Computers & Education, 137, 104–113. https://doi.org/10.1016/j.compedu.2019.04.004
3. Bergdahl, N., Nouri, J., & Fors, U. (2020). Disengagement, engagement and digital skills in technology-enhanced learning. Education and Information Technologies, 25(2), 957–983. https://doi.org/10.1007/s10639-019-09998-w
4. National Council of Educational Research and Training. (2020). National Education Policy 2020. Ministry of Education, Government of India.
5. Rienties, B., Simonsen, H. K., Herodotou, C., & Levy, J. (2020). Defining the boundaries between artificial intelligence in education, computer-supported collaborative learning, educational data mining, and learning analytics. Frontiers in Education, 5, Article 128. https://doi.org/10.3389/feduc.2020.00128
6. Walkington, C., & Bernacki, M. L. (2020). Appraising research on personalized learning: Definitions, theoretical alignment, advancements, and future directions. Journal of Research on Technology in Education, 52(3), 235–252. https://doi.org/10.1080/15391523.2020.1747757
7. Molenaar, I. (2021). Personalisation of learning: Towards hybrid human-AI learning technologies. In OECD, Digital education outlook 2021: Pushing the frontiers with artificial intelligence, blockchain and robots (pp. 57–77). OECD Publishing.
8. Renz, A., & Vladova, G. (2021). Reinvigorating the discourse on human-centered artificial intelligence in educational technologies. Technology Innovation Management Review, 11(5), 5–16.
9. Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., Liu, J.-B., Yuan, J., & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. Complexity, 2021, Article 8812542. https://doi.org/10.1155/2021/8812542
10. Zalte, S. M. (2023). Revolutionizing education: Leveraging AI-ML technologies to enhance teaching and learning outcomes. European Chemical Bulletin, 12(12), 679–688.
11. du Plooy, E., Casteleijn, D., & Franzsen, D. (2024). Personalized adaptive learning in higher education: A scoping review of key characteristics and impact on academic performance and engagement. Heliyon, 10(21), Article e39630. https://doi.org/10.1016/j.heliyon.2024.e39630
12. Sharma, S., Singh, G., & Sharma, C. S. (2024). Artificial intelligence in Indian higher education institutions: A quantitative study on adoption and perceptions. International Journal of System Assurance Engineering and Management. https://doi.org/10.1007/s13198-023-02193-8
13. Swargiary, K. (2024). The impact of AI-driven personalized learning and intelligent tutoring systems on student engagement and academic achievement: Ethical implications and the digital divide. SSRN. https://ssrn.com/abstract=4897241