

Beyond access: AI literacy, instructional design and perceived autonomous learning among students in Indian higher education

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Abstract

Universities are rapidly adopting artificial intelligence, yet access to AI tools does not guarantee that students experience greater ownership of their learning. This study examines how three learner side factors, AI literacy, AI readiness and perceived value of AI tools, and one pedagogy side factor, AI enhanced instructional design, relate to perceived autonomous learning outcomes. Drawing on the Technology Acceptance Model and Self Determination Theory, we conducted a cross sectional online survey of students in Indian higher education who had used AI supported tools for academic purposes in the previous six months. After data cleaning, 516 valid responses were analysed. The measurement model showed strong reliability and convergent validity, and discriminant validity was supported (all HTMT values below 0.85). A simultaneous multiple regression explained 46.7 percent of the variance in perceived autonomous learning outcomes ($F(4, 511) = 111.887, p < .001$). All four factors were positively associated with the outcome, with AI literacy the strongest ($\beta = .336$), followed by AI enhanced instructional design ($\beta = .178$), perceived value of AI tools ($\beta = .147$) and AI readiness ($\beta = .120$). Because the data are self reported, cross sectional and drawn from a nonprobability sample, the results indicate associations among perceptions, not causal effects or objective learning gains. The findings suggest that institutions should pair AI adoption with systematic AI literacy development and thoughtful instructional design, treating student agency rather than tool availability as the goal.

Keywords: AI Literacy, AI Readiness, Instructional Design, Perceived Autonomous Learning, Student Autonomy, Technology Acceptance Model, Self Determination Theory, Generative AI, Higher Education, India

JEL Classification: I21, I23, I28

1. Introduction

Artificial intelligence (AI) is becoming embedded in higher education through adaptive learning systems, intelligent tutoring platforms, automated feedback, learning analytics and AI-supported content design (Ng et al., 2021; Lee & Moore, 2024; Raman et al., 2026). These developments have encouraged universities across very different national systems to reconsider how technology can support teaching, learning and assessment. The momentum is global, but its consequences are uneven, because access to AI tools and improvement in learning are too often treated as if they were the same thing. A student may have access to a generative AI assistant and still gain little, while another may use the same tool to clarify concepts, rehearse skills and direct their own study. The educational value of AI therefore depends not on availability alone, but on how students understand, accept and experience these tools within academic settings.

The stakes of getting this right are considerable. Proponents argue that AI can personalise instruction, widen access to high-quality support and free educators to concentrate on higher-order guidance (Raman et al., 2026). Critics counter that the same tools can erode independent thinking, normalise uncritical reliance on machine output and entrench the advantages of students who already possess strong digital and academic skills (UNESCO, 2021; Lee & Moore, 2024). Between these positions lies an empirical question that institutions cannot settle by counting tools or licences: under what conditions does AI-supported learning correspond to students experiencing more, rather than less, ownership of their own learning? The Indian case sharpens these issues. The system enrolls tens of millions of students across a heterogeneous mix of public and private institutions, with wide variation in infrastructure, faculty preparedness and students' prior digital exposure. National policy has actively encouraged technology-enabled and blended learning, and AI tools have diffused quickly through both formal course provision and students' independent study. This combination of scale, heterogeneity and rapid, policy-backed adoption makes India a revealing site for studying how AI-related factors relate to learning experiences, and one whose dynamics are echoed in many middle-income and rapidly digitalising systems worldwide.

India offers an instructive setting for examining this question, and one whose lessons travel. It operates one of the world's largest and most diverse higher education systems within a policy environment that actively promotes digital and technology-enabled learning under the National Education Policy 2020 (Ministry of Education, 2020). Conditions of rapid adoption, uneven digital access and strong policy ambition are not unique to India; they characterise many education systems now integrating AI at scale. Evidence from this context thus contributes to an international debate while addressing a region that remains underrepresented in the AI-in-education literature. This study focuses on four AI-related factors and deliberately separates student capacity from pedagogical provision. AI literacy refers to students' ability to understand, use and critically evaluate AI tools in academic contexts (Long & Magerko, 2020; Ng et al., 2021). AI readiness reflects students' preparedness, confidence and willingness to engage with AI-supported learning

(Rahman et al., 2025; Pasupuleti et al., 2026). Perceived value of AI tools captures the extent to which students regard AI as useful for academic work, a position aligned with the Technology Acceptance Model (Davis, 1989; Acosta-Enriquez et al., 2024). These three are learner-side factors. AI-enhanced instructional design, by contrast, is a pedagogy-side factor, describing how AI-supported content, adaptive pathways and personalised resources are built into course delivery (Monib et al., 2025; Raman et al., 2026). The outcome variable, perceived autonomous learning outcomes, captures students' self-reported sense of learning responsibility, independent learning, knowledge improvement and academic confidence, a framing grounded in Self-Determination Theory (Ryan & Deci, 2000). The study does not claim to measure objective achievement, grades or institutional performance; it examines the perceived learning experience in AI-supported settings. The contribution is threefold. First, the study provides empirical evidence from a large and underrepresented context whose adoption dynamics resonate internationally. Second, it distinguishes learner-side factors from pedagogy-side design, avoiding the common tendency to treat AI integration as a single, undifferentiated construct. Third, it offers a cautious, perception-based account of how these factors relate to perceived autonomous learning outcomes, while explicitly acknowledging the risks that accompany AI use. The study is guided by one question: which AI-related learner and pedagogical factors are significantly associated with perceived autonomous learning outcomes among students in higher education?

2. Theoretical Background and Hypothesis Development

The study draws on two complementary theories. The Technology Acceptance Model (TAM) explains why students engage with AI tools, holding that use is shaped mainly by perceived usefulness and ease of use (Davis, 1989; Venkatesh et al., 2003). In higher education, this implies that students are more likely to adopt AI-supported tools when they understand them, feel ready to use them and perceive a clear academic benefit (Acosta-Enriquez et al., 2024). TAM therefore informs the learner-side factors in this model, AI literacy, AI readiness and perceived value, each of which concerns a student's relationship to the technology. Acceptance alone, however, does not explain whether students experience greater learning responsibility, confidence or independence. Self-Determination Theory (SDT) supplies that link, identifying autonomy, competence and self-directed motivation as conditions for meaningful learning (Ryan & Deci, 2000; Cullen & Oppenheimer, 2024). SDT informs the outcome side of the model: AI-supported learning is valuable to the extent that it helps students regulate their study, monitor progress and develop confidence in their own ability. The two theories are not competing but sequential, with TAM accounting for engagement and SDT for the autonomous learning experience that engagement may support.

The pairing also clarifies why the four factors should relate to perceived autonomy rather than to mere usage. TAM was developed to predict adoption, and on its own it says little about the quality of the learning that follows acceptance. Self-Determination Theory addresses precisely that gap

by specifying the psychological conditions, competence and a sense of volition, under which engagement becomes self-directed. Read together, the two frameworks imply a sequence in which understanding, readiness and perceived value dispose students to engage with AI, while well-designed AI-supported environments help translate that engagement into a stronger sense of ownership over learning. The cross-sectional design cannot test this sequence as a temporal process, but it can establish whether the factors the frameworks identify are empirically associated with the autonomous learning experience they jointly predict.

This framing also requires a critical posture. AI in higher education raises well-documented concerns, including inaccurate or misleading feedback, algorithmic bias, threats to academic integrity, privacy risks, digital inequality and the danger that students become dependent on automated outputs rather than developing their own judgement (UNESCO, 2021; Lee & Moore, 2024). These tensions are especially salient in resource-diverse systems where students differ in digital access and prior exposure. The present study does not assume that AI improves learning; it tests whether distinct learner-side and pedagogy-side factors are associated with perceived autonomy and interprets any associations against this backdrop of risk.

These risks are not incidental to the questions examined here. If students lean on AI feedback that is fluent but occasionally inaccurate, perceived autonomy may rise even where genuine understanding does not; if access to capable tools is unequally distributed, AI may widen rather than close attainment gaps; and if assessment practices do not adapt, dependence on automated output can erode the academic integrity that autonomous learning presupposes (UNESCO, 2021; Lee & Moore, 2024). The constructs examined here are therefore best understood as necessary but not sufficient conditions for beneficial AI use, and the associations reported below should be read with these tensions in view. Existing empirical work has tended to concentrate either on technology acceptance, explaining whether students adopt AI tools, or on broad claims about AI-enabled transformation. Less attention has been given to how distinct learner-side and pedagogy-side factors relate to perceived autonomy once they are modelled together, and less still in large, rapidly digitising systems beyond North America and Europe. By estimating the unique association of each factor within a single model, and by separating what students bring to AI from how institutions deploy it, this study addresses both gaps. Prior empirical studies offer partial support for these expectations, but rarely in combination. Research on AI literacy has linked students' understanding of AI to more confident and discerning use (Long & Magerko, 2020; Ng et al., 2021); studies grounded in technology acceptance have tied perceived usefulness and readiness to adoption intentions (Davis, 1989; Acosta-Enriquez et al., 2024; Rahman et al., 2025); and instructional-design research has connected AI-supported personalisation to engagement and perceived gains (Monib et al., 2025; Raman et al., 2026). These literatures have largely developed in parallel, however, each examining a single factor or mechanism, and most have been situated in North American, European or East Asian settings. The combined, comparative question, how learner-side capacities and pedagogy-side design relate to perceived autonomy when modelled

together in a large, rapidly digitalising system, remains substantially open. AI literacy denotes students' capacity to understand, use, evaluate and critically engage with AI systems in academic contexts (Long & Magerko, 2020; Ng et al., 2021). Students with stronger AI literacy can select appropriate tools, interpret AI-generated output, recognise its limitations and use AI as a support for, rather than a replacement of, their own effort. Such students are better placed to use AI purposefully for independent study, practice and academic decision-making, which should be reflected in stronger perceived autonomy. Based on this we propose following hypothesis.

H1. AI literacy is positively associated with perceived autonomous learning outcomes.

AI readiness reflects students' willingness, preparedness and confidence to engage with AI-supported tools. Access does not guarantee meaningful use; students may reach AI platforms yet lack the confidence or preparedness to use them well. Studies of AI adoption indicate that readiness and technology preparedness shape engagement and willingness to incorporate AI into academic work (Rahman et al., 2025; Pasupuleti et al., 2026). Students who feel ready are more likely to experiment with AI resources, seek personalised support and take responsibility for their learning. Therefore:

H2. AI readiness is positively associated with perceived autonomous learning outcomes.

Perceived value of AI tools captures the extent to which students believe AI resources are useful and beneficial for academic purposes, a construct closely linked to perceived usefulness in TAM (Davis, 1989; Venkatesh et al., 2003). When students perceive clear academic value, they are more likely to integrate AI into learning routines for tasks such as summarising, feedback, self-paced study and conceptual clarification, and to report stronger autonomous learning experiences. Accordingly, we propose following hypothesis.

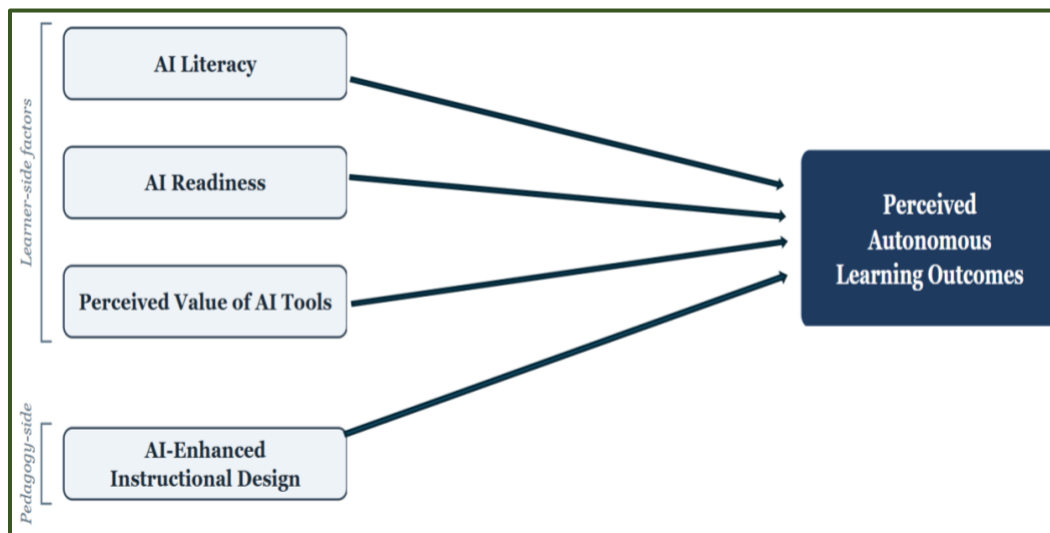
H3. Perceived value of AI tools is positively associated with perceived autonomous learning outcomes.

AI-enhanced instructional design refers to the use of AI-supported content, adaptive learning pathways, personalised resources and intelligent tutoring features within course delivery. Unlike the three learner-side factors, it is a pedagogy-side factor, reflecting how educators and institutions structure AI-supported learning rather than what students bring to it (Monib et al., 2025; Raman et al., 2026). Effective design can support autonomy by enabling students to revisit difficult content, progress at an appropriate pace and access resources matched to their needs. Accordingly, we propose following hypothesis.

H4. AI-enhanced instructional design is positively associated with perceived autonomous learning outcomes.

Based on the above discussion we intend to test the following framework (Refer Figure 1).

Figure 1. Hypothesised Framework



Source: Authors own work

3. Methodology

3.1 Design and Participants

The study adopted a quantitative, cross-sectional survey design to examine associations between AI-related learner and pedagogical factors and perceived autonomous learning outcomes among students in Indian higher education. A cross-sectional design was appropriate because the aim was to capture student perceptions of AI-supported learning at a particular point in time. Because the data are cross-sectional and self-reported, the study makes no claim to causal effects or to objective learning improvement. The target population comprised students enrolled in Indian higher education institutions who had prior exposure to AI-supported learning. Respondents were eligible if they had used AI-supported tools, platforms, assessment systems or learning resources for academic purposes during the previous six months; this criterion was confirmed through a screening question at the start of the survey. Data were collected through a structured online questionnaire distributed via academic networks across institutions located in India. Of approximately 1200 students reached, 524 questionnaires were returned, corresponding to a response rate of about 43.67%. Participation was voluntary, no personally identifiable information was collected, and respondents were informed that the data would be used only for academic research.

3.2 Measures

All constructs were measured with multi-item scales on a five-point Likert format ranging from 1 (strongly disagree) to 5 (strongly agree). AI literacy items were adapted from Long and Magerko (2020) and Ng et al. (2021). AI readiness items were adapted from AI-adoption and technology-

readiness work in higher education (Rahman et al., 2025; Pasupuleti et al., 2026). Perceived value of AI tools was measured with items aligned to the Technology Acceptance Model (Davis, 1989; Venkatesh et al., 2003; Acosta-Enriquez et al., 2024). AI-enhanced instructional design was measured with items informed by AI-supported instructional-design literature (Monib et al., 2025; Raman et al., 2026). Perceived autonomous learning outcomes was treated as a single, multifaceted construct capturing self-reported learning responsibility, progress monitoring, independent learning, knowledge improvement, skill development and academic confidence, drawing on Self-Determination Theory and prior work on student autonomy (Ryan & Deci, 2000; Cullen & Oppenheimer, 2024). The full item set is available from the authors on request. An additional block measuring AI-enabled assessment and feedback was examined during instrument validation but was not retained in the final model, as it did not achieve adequate discriminant validity from the outcome measure; the four factors above were therefore carried forward for hypothesis testing. Each scale was adapted to the AI-in-education context through minor wording changes suited to higher-education respondents, and the instrument was reviewed by subject experts for clarity and content relevance before administration. Items were kept deliberately concise and non-technical to reduce response burden and limit misinterpretation across a linguistically diverse respondent pool. A short pilot was used to confirm that items were understood as intended before full administration. Purposive sampling was appropriate because the research question concerned students with genuine exposure to AI-supported learning rather than the general student population; respondents without such exposure could not meaningfully report on the constructs of interest.

3.3 Data Screening and Analysis

The dataset contained 524 responses. Four cases were removed for out-of-range Likert values arising from data-entry error, and four exact duplicate response records, identical across all items and demographic fields, were removed. No case was removed for complete straight lining, as none was present. The final cleaned sample comprised 516 valid responses. Negatively worded AI readiness items were reverse-coded before construct scores were computed. Internal consistency was examined using Cronbach's alpha and composite reliability (CR), with values above 0.70 considered acceptable (Hair et al., 2019). Convergent validity was assessed using standardised factor loadings and average variance extracted (AVE), with AVE above 0.50 indicating acceptable convergent validity. Discriminant validity was examined using the Heterotrait Monotrait (HTMT) ratio, with values below 0.85 taken as conservative evidence of distinctiveness (Henseler et al., 2015). Common method bias was assessed using Harman's single-factor diagnostic and a full-collinearity check (Podsakoff et al., 2003; Kock, 2015). Multicollinearity was assessed through variance inflation factors (VIF), with values below 5 considered acceptable. The four hypotheses were tested using multiple regression with all predictors entered simultaneously, so that each association is estimated controlling for the others and reflects a unique contribution rather than shared variance.

4. Results

Analysis was conducted on the 516 cleaned responses. The sample comprised 287 male (55.62 per cent) and 229 female (44.38 per cent) respondents. Most were aged 18-22 (42.25 per cent) or 23-27 (35.66 per cent). Undergraduates made up 45.16 per cent of the sample, postgraduates 37.40 per cent and doctoral students 17.44 per cent. Public institutions accounted for 56.98 per cent of responses and private institutions for 43.02 per cent (Table 1).

Table 1. Demographic profile of respondents (n = 516)

Variable	Category	Frequency	Percentage (%)
Gender	Male	287	55.62
	Female	229	44.38
Age	18-22	218	42.25
	23-27	184	35.66
	28-32	90	17.44
	33 and above	24	4.65
Programme	Undergraduate	233	45.16
	Postgraduate	193	37.40
	Doctoral	90	17.44
Institution type	Public	294	56.98
	Private	222	43.02

Source: Authors own work

The measurement model showed acceptable reliability and convergent validity (Table 2). Cronbach's alpha ranged from 0.874 to 0.961 and composite reliability from 0.909 to 0.967, both comfortably above the 0.70 threshold. Standardised loadings of retained items ranged from 0.782 to 0.916, and AVE ranged from 0.667 to 0.799, all exceeding 0.50. These results support the internal consistency and convergent validity of the retained constructs. Taken together, the measurement results indicate that the four predictors and the outcome function as reliable and empirically distinguishable constructs, providing a sound basis for the regression that follows.

Table 2. Reliability and Convergent Validity

Construct	Mean	SD	Alpha	CR	AVE
AI Literacy	3.780	0.892	0.929	0.947	0.780
AI Readiness	3.489	1.005	0.937	0.952	0.799
Perceived Value of AI Tools	3.590	0.899	0.874	0.909	0.667
AI-Enhanced Instructional Design	3.516	0.841	0.917	0.938	0.752
Perceived Autonomous Learning Outcomes	3.773	0.960	0.961	0.967	0.744

Note. CR = composite reliability; AVE = average variance extracted.

Source: Authors own work

Discriminant validity was supported. As shown in Table 3, all HTMT values fell below the conservative 0.85 threshold, ranging from 0.539 to 0.820; the highest, between AI literacy and AI readiness (0.820), remained within the acceptable range. Bivariate correlations among constructs were positive and significant, with perceived autonomous learning outcomes correlating most strongly with AI literacy ($r = 0.643$) and least with perceived value ($r = 0.503$). The moderate correlations among predictors justified estimating their unique associations through simultaneous regression.

Table 3. Correlations (below diagonal) and HTMT ratios (above diagonal)

Construct	AIL	AIR	PVAI	AIID	PALO
AIL	—	0.820	0.593	0.815	0.678
AIR	0.766	—	0.690	0.734	0.621
PVAI	0.543	0.631	—	0.600	0.539
AIID	0.754	0.681	0.544	—	0.631
PALO	0.643	0.592	0.503	0.593	—

Note. AIL = AI literacy; AIR = AI readiness; PVAI = perceived value of AI tools; AIID = AI-enhanced instructional design; PALO = perceived autonomous learning outcomes. Below-diagonal values are Pearson correlations (all $p < 0.01$); above-diagonal values are HTMT ratios.

Source: Authors own work

Because all variables were collected from the same respondents through one questionnaire, common method bias was examined. Harman's single-factor diagnostic indicated that the first unrotated factor accounted for 52.88 per cent of the variance, slightly above the 50 per cent guideline, so common method bias cannot be wholly excluded. A full-collinearity check provided complementary reassurance: all predictor VIF values lay between 1.731 and 3.200, below the 3.3 criterion associated with method-bias concern (Kock, 2015) and well below the conventional 5.0 threshold for multicollinearity. The findings are nonetheless interpreted cautiously as associations among perceptions rather than as causal effects. The regression model was significant, $F(4, 511) = 111.887$, $p < 0.001$, explaining 46.69 per cent of the variance in perceived autonomous learning outcomes (adjusted R-squared = 0.463). All four predictors were positively and significantly associated with the outcome (Table 4). AI literacy showed the strongest standardised association (beta = 0.336), followed by AI-enhanced instructional design (beta = 0.178), perceived value of AI tools (beta = 0.147) and AI readiness (beta = 0.120). Hypotheses H1 to H4 were therefore supported. The relative ordering of the standardised coefficients is itself informative: the two factors most directly concerned with students' own understanding and with the design of their learning, AI literacy and instructional design, carried more weight than readiness or perceived value, a pattern consistent with the view that capability and provision matter more than general disposition. The variance explained, close to half, is substantial for cross-sectional perception data and points to practical as well as statistical relevance.

Table 4. Simultaneous multiple regression predicting perceived autonomous learning outcomes

Predictor	B	SE	Beta	t	VIF	Result
AI Literacy	0.362	0.062	0.336	5.821	3.200	Supported
AI Readiness	0.115	0.053	0.120	2.165	2.954	Supported
Perceived Value of AI Tools	0.157	0.045	0.147	3.470	1.731	Supported

AI-Enhanced Instructional Design	0.203	0.059	0.178	3.457	2.535	Supported
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Note. R-squared = 0.467; adjusted R-squared = 0.463; $F(4, 511) = 111.887, p < 0.001$. AI readiness $p = 0.031$; all other predictors $p < 0.01$.

Source: Authors own work

5. Discussion and Implications

The findings indicate that students who reported stronger AI literacy, greater AI readiness, higher perceived value of AI tools and richer AI-enhanced instructional design also reported stronger perceived autonomous learning outcomes. Because all four predictors were entered simultaneously, each association holds while controlling for the others, which addresses the risk that shared variance among correlated predictors would inflate apparent effects. The pattern is consistent with the integrated theoretical frame: acceptance-related factors drawn from TAM and a design factor are each associated with the autonomous learning experience that SDT places at the centre of meaningful learning. AI literacy was the strongest predictor, and this is the result with the clearest practical message. It suggests that students' capacity to understand and critically use AI may matter more to their perceived learning experience than the mere presence of tools. For higher education internationally, the implication is direct: AI adoption should be accompanied by systematic AI literacy development, including responsible use, critical evaluation of AI output and awareness of limitations. Treating literacy as an afterthought risks widening rather than narrowing gaps between students who can harness AI and those who cannot. AI-enhanced instructional design was the second strongest association, supporting the view that AI is most useful when embedded in learning design rather than bolted on as a technical novelty. Thoughtful design may help students revisit difficult material, access personalised resources and progress at a suitable pace. This should not be read as evidence that AI-based design improves objective achievement; it indicates that students who experienced stronger design also perceived stronger autonomy and learning gains. Perceived value showed a similar, smaller association, consistent with TAM's emphasis on perceived usefulness as a condition for meaningful engagement (Davis, 1989). Institutions can strengthen perceived value through orientation, discipline-specific use cases and clear, ethical-use guidance. AI readiness had the smallest, though still significant, association, suggesting that willingness and preparedness matter but are not sufficient alone; readiness needs to be supported by literacy, value clarity and sound instructional integration. Institutions should not assume that digitally active students are ready for AI-supported learning without structured exposure and support.

The relative weakness of AI readiness deserves comment. Readiness is often assumed to be the gateway to productive AI use, yet once literacy, perceived value and design were accounted for,



its independent association was the smallest of the four. One reading is that readiness is necessary but largely subsumed by the more specific capability that AI literacy represents: feeling prepared matters little if a student cannot critically interpret what an AI tool returns. A second is that, among respondents already using AI, variation in readiness is compressed, leaving literacy and design to do more of the explanatory work. Either way, the finding cautions against equating general comfort with technology with the capacity to learn well through it. Theoretically, the results illustrate the value of combining an acceptance lens with a motivational one rather than relying on either alone. A pure acceptance account would predict that perceived value should dominate, yet here it was among the weaker factors; a purely motivational account would underplay design, yet instructional design emerged as the second strongest correlate. The pattern fits an integrated reading in which what students understand and how their learning is structured jointly shape the autonomous experience, and it suggests that future models of AI in education should treat learner capability and pedagogical provision as distinct, co-acting levers rather than collapsing them into a single notion of AI integration.

Theoretically, the study combines TAM and SDT without treating AI adoption as an automatic educational benefit, and it separates learner-side factors from pedagogy-side design. This distinction matters because student capacity and institutional provision are related but not interchangeable, and conflating them obscures where intervention is most needed. Empirically, the study contributes evidence from a large, policy-active system that is underrepresented in the literature but whose conditions, rapid adoption alongside uneven access, are shared widely across global higher education. At the same time, the boundary conditions matter. These associations emerged in one national setting and among students already using AI for academic work, so they should not be read as universal. What travels is less a fixed set of coefficients than an analytical lesson: that learner capacity and pedagogical design are separable levers, and that literacy appears the more powerful of the two. For practice and policy, four priorities follow, and they are framed cautiously in light of the design. First, AI literacy should be embedded across curricula rather than treated as an optional technical skill. Second, students need explicit guidance on productive, ethical and critical AI use, including the risks of inaccurate feedback, bias, privacy and over-dependence noted earlier. Third, AI-supported instructional design should be aligned with intended learning outcomes rather than driven by novelty. Fourth, institutions should treat student agency, not tool count, as the central goal of AI-supported learning. These implications concern the design of learning environments; the study does not evaluate interventions or system-level strategies, and stronger policy claims would require evidence the present design cannot provide.

A cautionary reading is warranted alongside these implications. Because the strongest association ran through AI literacy, the very capability that helps students use AI productively is also what equips them to question inaccurate output, recognise bias and act with integrity. Where that capability is unevenly distributed, AI-supported learning may advantage students who are already well prepared and disadvantage those who are not, reproducing rather than reducing existing

inequalities. The perception of greater autonomy, moreover, is not the same as deeper learning; a student who feels more in control while leaning on automated answers may be experiencing confidence without competence. These possibilities cannot be tested with the present cross-sectional, self-report data, but they bear directly on how institutions should act. Investment in AI literacy, ethical-use guidance and equitable access is therefore better treated not as an optional supplement to AI adoption but as a precondition for it, if the gains observed here are to be realised broadly rather than narrowly.

6. Conclusion

Using cleaned survey data from 516 students in Indian higher education, this study found that AI literacy, AI readiness, perceived value of AI tools and AI-enhanced instructional design were each positively associated with perceived autonomous learning outcomes, with AI literacy the strongest predictor. The study separates learner capacity from pedagogical provision and offers a deliberately cautious, perception-based account whose lessons extend beyond its national setting. Its central message for global higher education is simple: the value of AI-supported learning should be judged not by the number of tools introduced but by whether students are prepared, informed and supported to use AI in ways that strengthen autonomy and academic confidence. The task is not merely to make higher education more AI-enabled, but to make AI-supported education more learner-centred, ethical and pedagogically meaningful. The broader contribution is a reframing of the policy question: the pertinent issue for institutions is no longer whether to adopt AI, but how to ensure that adoption is matched by the literacy, design and equitable access that allow students to benefit from it.

6.1 Limitations and Future Research

Several limitations qualify these findings. First, the cross-sectional design permits only statements of association, not causal inference; the results show that AI-related factors co-occur with perceived autonomy, not that they produce it. Second, the outcome is a perceived, self-reported measure rather than objective academic performance; future work should pair survey responses with grades, learning analytics, completion data or performance-based tasks. Third, all data came from a single source at one time, so common method bias cannot be wholly excluded despite the diagnostics reported. Fourth, the sampling was non-probabilistic, which limits generalisability beyond the respondent group and counsels against treating the findings as representative of Indian or global higher education as a whole. Finally, AI-enabled assessment and feedback was not retained because it lacked discriminant validity from the outcome; future research should redesign this construct with items that clearly separate the experience of feedback from the perception of learning gain. Longitudinal and experimental designs, and cross-national comparison, would help establish whether AI literacy development, instructional design or structured training produce measurable change in autonomy and outcomes over time.

Two further caveats apply. The merged outcome construct, although reliable and well-validated, combines facets of autonomy and perceived gain that some frameworks would keep separate; replication with instruments designed to distinguish them would test the robustness of the present account. In addition, perceptions gathered during a period of rapid AI diffusion may shift as tools mature and as institutional norms around their use settle, so the associations reported here should be revisited as the technology and its governance evolve.

Ethics Statement

The study used voluntary and anonymous survey responses. Participants were informed of the academic purpose of the research and could withdraw before submitting the questionnaire, and no personally identifiable information was collected. Ethical approval was granted by MIT School of Distance Education, institutional review board, approval reference MITSDE 2025-26/3, dated 18 November 2025.

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