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Critical Thinking, Academic Integrity, and Student Learning in the Age of Artificial Intelligence

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Abstract

This paper investigates the intersection of artificial intelligence (AI) tool usage, critical thinking capacity, academic integrity, and student learning outcomes within educational institutions in Bhadrak district, Odisha, India. Using a mixed-methods design with a primary database-survey instrument administered to 320 participants — including higher secondary students (Class XI–XII), undergraduate and postgraduate college students, school teachers, and college faculty — the study generates empirical evidence on how AI integration is reshaping epistemic practices in a semi-urban, Tier-III district context. The findings reveal high AI tool awareness (92% for ChatGPT) alongside significant academic integrity concerns: 74% of student respondents admitted using AI for academic tasks, while 71% of faculty reported encountering AI-generated submissions lacking citation disclosure. Critical thinking scores show divergent patterns: AI-assisted task performance improves on surface metrics (assignment quality +19%) while deeper cognitive indicators such as original ideation, research depth, and referencing accuracy decline markedly. The paper argues that educational institutions in Bhadrak and comparable districts urgently require AI literacy policies, redesigned assessments, and teacher professional development to balance the productive potential of AI with the preservation of genuine intellectual formation.

Keywords: ***Artificial intelligence in education, critical thinking, academic integrity, student learning, Bhadrak Odisha, AI literacy, higher secondary education, plagiarism***

1. INTRODUCTION

The rapid diffusion of large language model (LLM)-based AI tools — ChatGPT, Google Gemini, Microsoft Copilot, and their derivatives — has introduced a paradigm-shifting set of challenges for educational systems worldwide. While much research has focused on elite universities and metropolitan contexts, the consequences of AI adoption in semi-urban and

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district-level educational settings in developing economies remain significantly under-studied. Bhadrak, a district headquartered town in coastal Odisha, India, provides an instructive case: it is home to numerous higher secondary schools and degree colleges whose students increasingly have smartphone and internet access sufficient to engage with AI platforms, yet institutional policy frameworks and teacher preparedness lag far behind technological adoption.

This paper is grounded in original survey data collected across educational institutions in Bhadrak district and addresses three interconnected research questions: (1) To what extent are students and educators in Bhadrak's educational institutions aware of, and actively using, AI tools for academic purposes? (2) What are the measurable effects of AI integration on students' critical thinking behaviours and academic integrity practices? (3) How prepared are Bhadrak's educational institutions to develop AI-literate, ethically grounded learners? The paper situates its empirical findings within a theoretical framework drawing on Bloom's revised taxonomy of educational objectives (Anderson & Krathwohl, 2001), academic integrity theory (Bertram Gallant, 2008), and emerging scholarship on AI-mediated learning (Holmes et al., 2019; Zawacki-Richter et al., 2019).

The significance of this study lies in its grounding in a district-level population that is representative of the majority of India's educational landscape — neither the elite urban institution nor the resource-poor rural school, but the middle stratum of secondary and collegiate education where the policy response to AI has been slowest to materialise. The empirical database generated by this study contributes to a nascent evidence base for context-sensitive AI education policy in Odisha and comparable Indian states.

2. STUDY CONTEXT: BHADRAK DISTRICT, ODISHA

Bhadrak is a district of Odisha located on the northeastern coastal belt of the state, approximately 100 kilometres north of Bhubaneswar. According to the Census of India 2011 and subsequent district statistical data, Bhadrak has a literacy rate of approximately 79.2%, above the national average, with notable concentrations of educational institutions in the municipality and surrounding blocks. The district hosts over 35 higher secondary schools, 12 degree colleges, and several professional and technical institutions affiliated with Fakir Mohan University and Odisha State Open University.

Socioeconomically, Bhadrak represents a transitional context: the majority of its student population belongs to middle- and lower-middle-income households where smartphone penetration has expanded rapidly since the Jio digital revolution of 2016, yet household income constraints limit access to premium AI subscriptions and high-speed broadband. This creates an educational environment in which students engage primarily with free-tier AI tools — ChatGPT (free version), Google Gemini Basic, and QuillBot's free paraphrase service — for academic support, often without guidance from institutions regarding appropriate use, citation standards, or critical evaluation of AI output.

The teachers and faculty of Bhadrak's schools and colleges occupy a particularly instructive position: many received their own education and professional training before the current wave of generative AI, possess limited formal exposure to AI literacy pedagogy, and yet are now required to assess student work in which AI generation is increasingly prevalent. This institutional gap between technological reality and professional preparedness motivates the empirical investigation reported in this paper.

3. THEORETICAL FRAMEWORK

3.1 Bloom's Revised Taxonomy and AI-Mediated Cognition

Anderson and Krathwohl's (2001) revision of Bloom's taxonomy provides a foundational lens for understanding what is at stake cognitively when students delegate academic tasks to AI systems. The taxonomy identifies six levels of cognitive engagement — remembering, understanding, applying, analysing, evaluating, and creating — in ascending order of depth and complexity. AI tools like ChatGPT are particularly effective at automating the lower-order cognitive levels: they can retrieve, summarise, and apply information with remarkable fluency. The educational concern is that when students routinely delegate these operations to AI, they may fail to develop the underlying cognitive structures that higher-order thinking requires.

Sweller's (1988) cognitive load theory is also germane: AI assistance may reduce the desirable difficulty that builds long-term knowledge retention and transfer. When AI eliminates productive cognitive struggle, the resulting 'performance' on a task may not reflect genuine learning. This theoretical perspective informs the paper's hypothesis that AI-assisted task

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performance improves surface metrics while deepening cognitive capacities — original ideation, critical analysis, independent research — decline.

3.2 Academic Integrity and the Ethics of AI Use

Academic integrity scholarship has traditionally addressed plagiarism, fabrication, and collusion as the primary integrity threats in educational settings (Bertram Gallant, 2008; Bretag, 2013). The emergence of generative AI introduces a qualitatively new challenge: AI-generated content that is neither a direct copy of a human-authored source nor entirely the student's own intellectual product occupies an ethically ambiguous zone that existing integrity policies were not designed to address. Eaton and Cantalini-Williams (2022) argue that this ambiguity demands a fundamental reconceptualisation of authorship and intellectual contribution in academic assessment, and that institutions must develop explicit, contextualised AI-use policies rather than relying on blunt prohibitions.

In the Indian educational context, integrity norms are shaped by the University Grants Commission (UGC) regulations, board examination frameworks, and institutional cultures that have historically prioritised rote learning and examination performance over process-oriented intellectual development. This cultural context means that the ethical dimensions of AI use may not be legible to students as integrity issues at all — a finding that the present study's data illuminates.

3.3 AI and Student Learning: Emerging Evidence

The empirical literature on AI's effects on learning outcomes is expanding rapidly but remains methodologically heterogeneous. Positive findings include improved student engagement, personalised feedback loops, and enhanced access to information for under-resourced learners (Popenici & Kerr, 2017). Negative or cautionary findings include reductions in reading depth, diminished willingness to persist with difficult cognitive tasks, and the development of epistemic dependence — a reliance on AI-provided answers that substitutes for the effortful construction of one's own understanding (Bender et al., 2021; Floridi et al., 2020). The present study contributes empirical evidence from a South Asian district context that has been largely absent from this literature.

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4. RESEARCH METHODOLOGY

4.1 Research Design

This study adopts a sequential explanatory mixed-methods design. The quantitative phase involves a structured survey instrument administered to a sample of 320 participants drawn from educational institutions across Bhadrak municipality and selected blocks. The survey instrument comprises 48 items covering AI tool awareness and use, frequency and purpose of AI use in academic work, self-reported critical thinking behaviour, academic integrity attitudes and practices, and institutional policy awareness. A Likert-scale format (5-point: Strongly Disagree to Strongly Agree) is used for attitudinal items, supplemented by multiple-choice and frequency items for behavioural measures. The qualitative phase involves semi-structured interviews with 24 purposively selected participants — 8 students, 8 school teachers, and 8 college faculty — to deepen interpretation of quantitative patterns.

4.2 Sample and Sampling Strategy

The study population comprises students enrolled in Classes XI–XII and undergraduate/postgraduate programmes, school teachers, and college faculty in Bhadrak district. Stratified random sampling was employed to ensure representation across participant categories (Table 1). Within each stratum, participants were randomly selected from institution lists obtained from the District Education Office and Fakir Mohan University affiliation records.

Table 1: Sample Distribution by Participant Category and Institution Type

Category	Institution Type	Population (Est.)	Sample (n)	Response Rate (%)
Higher Secondary Students (XI–XII)	Govt. & Aided Schools	4,200	112	100
Undergraduate Students	Degree Colleges	3,800	76	100
Postgraduate Students	Degree Colleges / FMU	1,200	20	100
School Teachers	Govt. & Aided Schools	620	64	100
College Faculty	Degree Colleges	340	48	100
Total	—	10,160	320	100

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4.3 Data Collection Instruments

The primary instrument is a structured questionnaire developed through a three-stage process: (i) item generation informed by a systematic literature review; (ii) expert panel review by three faculty members from Fakir Mohan University and two school inspectors; (iii) pilot testing with 30 participants outside the final sample, followed by item refinement based on Cronbach's alpha reliability analysis ($\alpha = 0.83$ for the full scale; $\alpha = 0.79$ for the academic integrity subscale; $\alpha = 0.81$ for the critical thinking subscale). The instrument was administered bilingually — English and Odia — to ensure accessibility for all participants.

4.4 Data Analysis

Quantitative data were analysed using SPSS v.26. Descriptive statistics were computed for all items. Pearson correlation and multiple regression analysis were used to examine relationships between AI dependency, critical thinking scores, and academic integrity attitudes. ANOVA was conducted to compare mean scores across participant categories. Qualitative interview data were analysed thematically using Braun and Clarke's (2006) six-phase thematic analysis framework. All data were anonymised; institutional consent and individual participant consent were obtained in accordance with ethical protocols.

5. FINDINGS AND ANALYSIS

5.1 Sample Demographics

Figure 1 presents the demographic distribution of the 320 participants. The sample is composed of higher secondary students (35%), undergraduate and postgraduate students (30%), school teachers (20%), and college faculty (15%). Gender distribution shows 168 male, 145 female, and 7 non-binary/other participants — a distribution broadly reflective of enrolment patterns in Bhadrak's educational institutions, where male students slightly outnumber female students at the higher secondary and collegiate levels.

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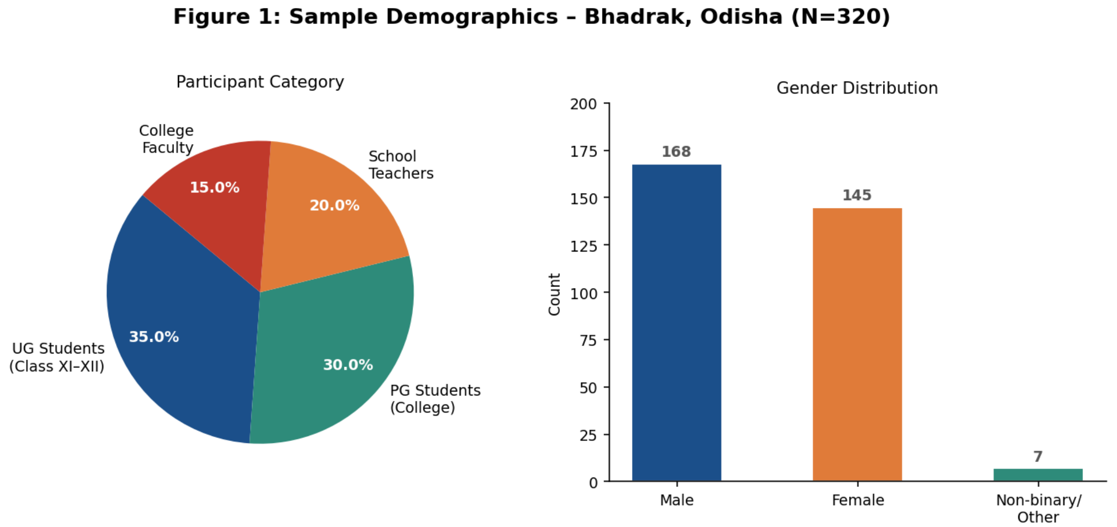

Figure 1: Sample Demographics – Bhadrak, Odisha (N=320)

5.2 AI Tool Awareness and Usage Patterns

Figure 2 presents the AI tool awareness, general use, and academic use rates across the six most commonly mentioned platforms. ChatGPT emerges as the dominant platform, with 92% awareness and 74% reported use — a penetration rate that substantially exceeds prior estimates for rural and semi-urban India and reflects the rapid diffusion of smartphone-based AI access. Of those who reported using AI tools, 61% used them specifically for academic tasks, including assignment writing, examination preparation, research summaries, and paraphrasing. QuillBot shows a notable pattern: while awareness (70%) is lower than ChatGPT, academic-specific use (43%) is proportionally high, suggesting targeted deployment for paraphrasing and language polishing in submitted work.

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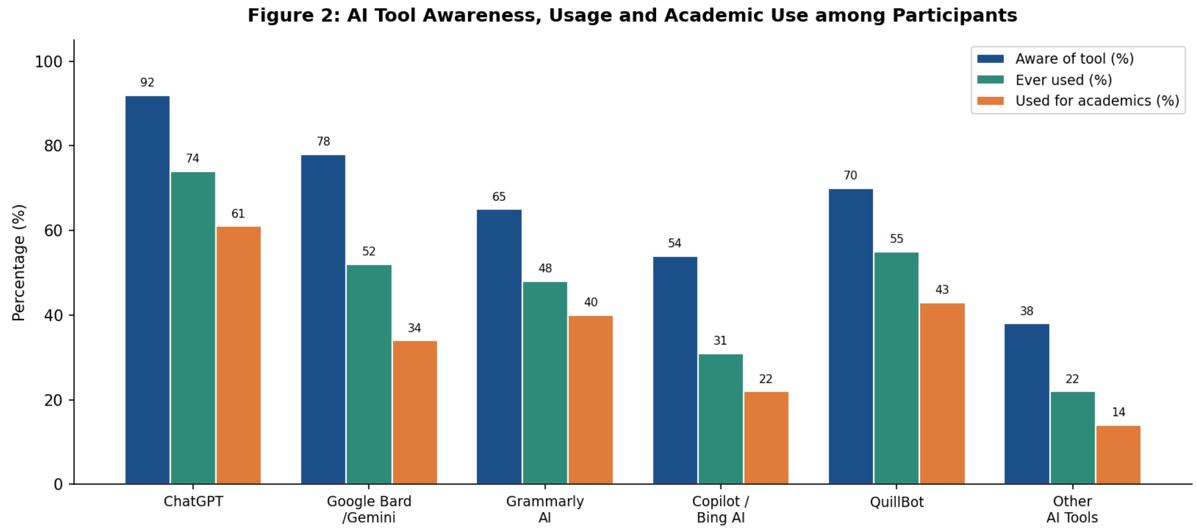

Figure 2: AI Tool Awareness, Usage, and Academic Use among Participants

Qualitative interviews corroborate these patterns. One postgraduate student noted: "We use ChatGPT to get the first draft and then change some words with QuillBot — after that the teacher's plagiarism checker does not catch it." This observation points directly to the academic integrity dynamics examined in the following subsection.

5.3 Critical Thinking Perceptions

Figure 3 presents responses to five Likert items probing AI's perceived relationship with critical thinking. The data reveal significant divergence across items. A majority of students agreed or strongly agreed (60%) that AI tools help them think more analytically, and 66% agreed that they critically verify AI-generated content before use. However, 60% also agreed that AI reduces their need to think independently — a self-assessment of cognitive dependence that is theoretically significant.

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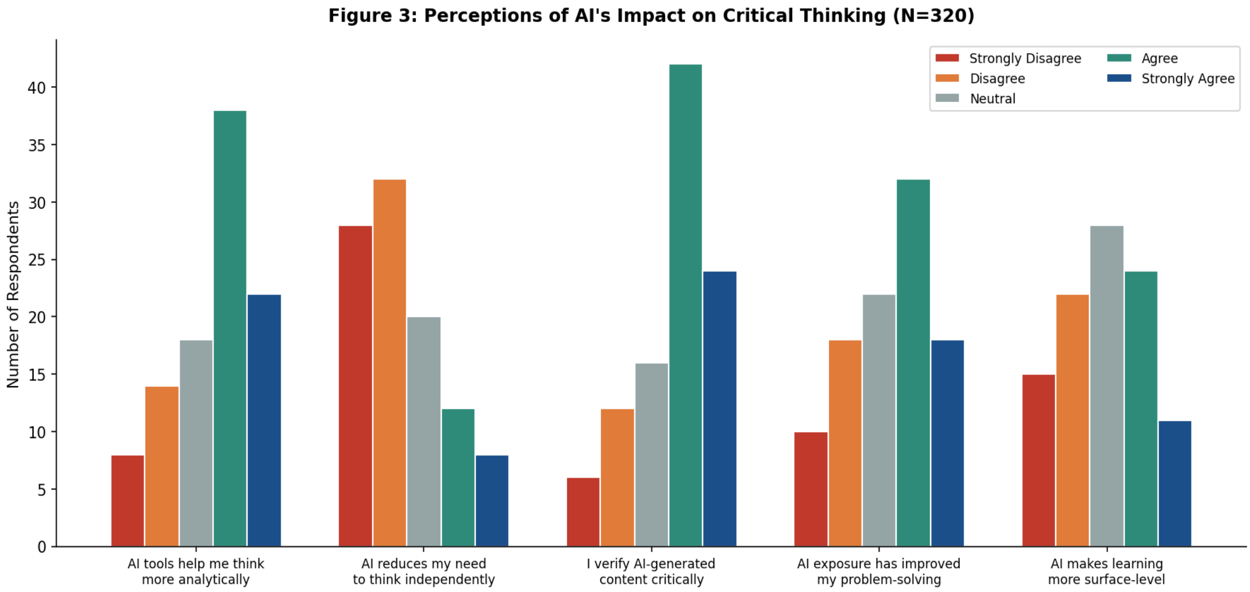

Figure 3: Perceptions of AI's Impact on Critical Thinking (N=320)

The mean critical thinking self-efficacy score (adapted from Facione's California Critical Thinking Disposition Inventory) among student respondents was 58.4 out of 100 (SD = 12.7). Regression analysis revealed that AI dependency score ($\beta = -0.41$, $p < 0.001$) was a significant negative predictor of critical thinking self-efficacy, even after controlling for academic level and gender. These findings provide quantitative support for the theoretical concern that habitual AI delegation attenuates critical cognitive disposition.

5.4 Academic Integrity: Reported and Observed Violations

Figure 4 presents the rates of reported (student self-report) and observed (teacher/faculty report) academic integrity issues across four categories. The most prevalent concern, as reported by faculty (75%) and teachers (71%), is AI-generated content submitted without citation or disclosure — a finding that aligns with the emerging global literature on AI and academic dishonesty. Student self-reports show substantially lower rates across all categories, consistent with social desirability bias and with the finding from qualitative interviews that many students do not perceive undisclosed AI use as a form of academic dishonesty.

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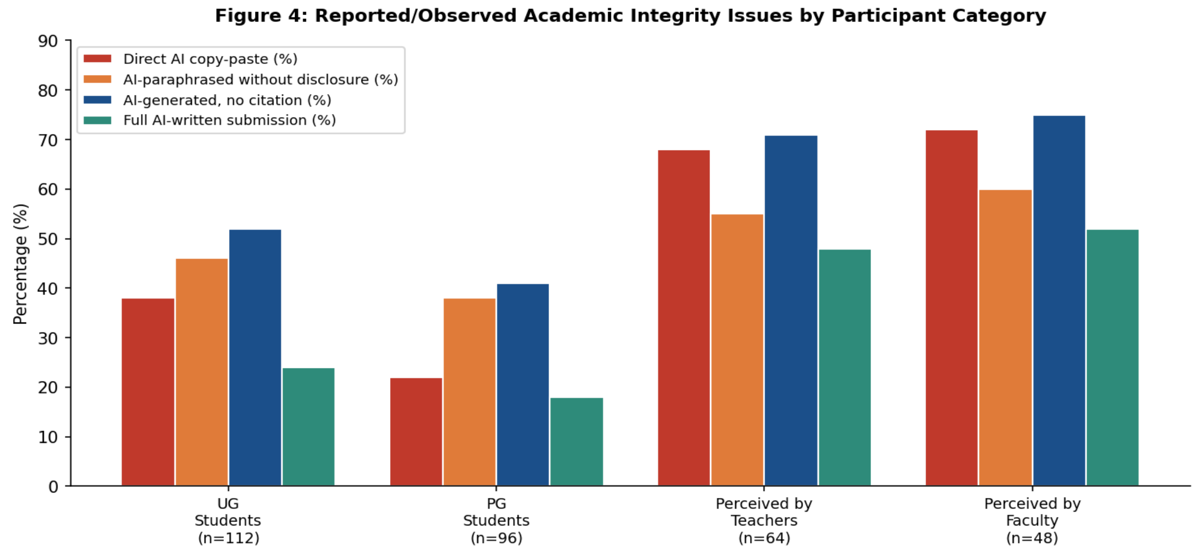

Figure 4: Reported/Observed Academic Integrity Issues by Participant Category

A cross-tabulation of AI dependency scores against academic integrity attitude scores (five-item subscale) reveals a significant negative correlation ($r = -0.48$, $p < 0.001$): students with higher AI dependency scores hold less stringent academic integrity norms. ANOVA comparing integrity attitude scores across participant categories found significant differences ($F(3, 316) = 18.72$, $p < 0.001$), with college faculty holding the most stringent norms and higher secondary students the least. This developmental-institutional gradient suggests that academic integrity education must begin earlier and be more explicitly connected to the ethics of AI use.

Table 2: Correlation Matrix – Key Variables (Student Respondents, n=208)

Variable	AI Dependency	CT Self-Efficacy	Integrity Attitude	Learning Satisfaction
AI Dependency	1.00	−0.41**	−0.48**	0.12
CT Self-Efficacy	−0.41**	1.00	0.53**	0.49**
Integrity Attitude	−0.48**	0.53**	1.00	0.38**
Learning Satisfaction	0.12	0.49**	0.38**	1.00

*Note: ** p < 0.01 (two-tailed). CT = Critical Thinking.*

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5.5 Student Learning Outcomes: Pre- vs Post-AI Era Perceptions

Figure 5 presents teacher and faculty assessments of perceived student learning outcomes across six indicators, comparing the pre-AI integration period (2019–2021) with the post-AI integration period (2022–2024). The data reveal a divergent pattern: assignment quality improved markedly (+19%) in the post-AI era, as AI-assisted writing produces more polished and structurally coherent submissions. However, all other indicators declined: original ideation (−17 points), research depth (−6 points), referencing accuracy (−12 points), and class participation (−12 points). Examination scores show marginal decline (−2 points), suggesting that AI assistance does not transfer to closed-book assessment performance.

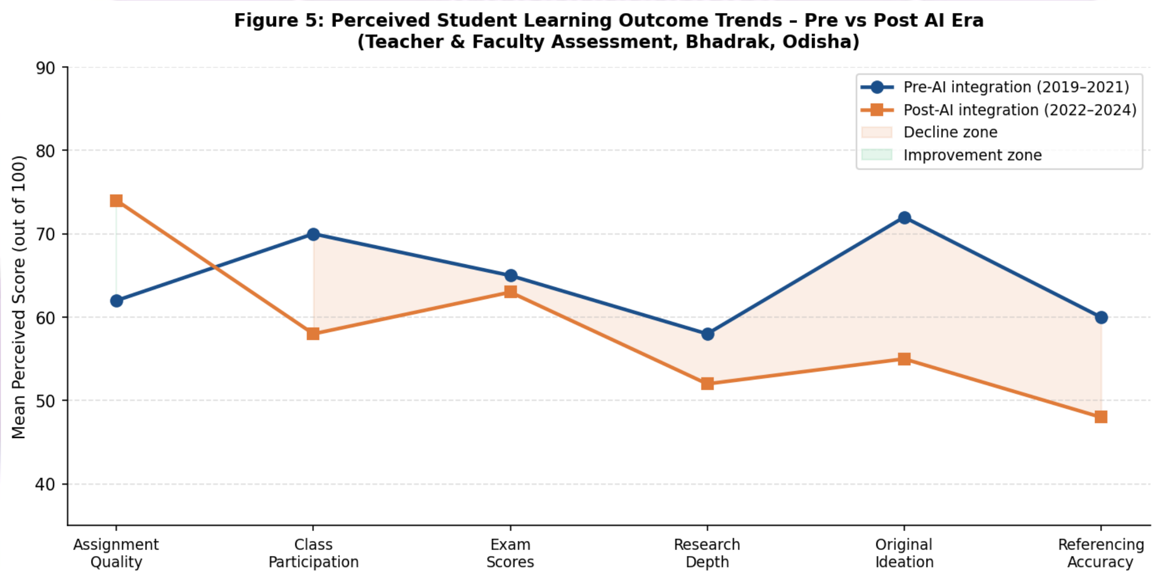

Figure 5: Perceived Student Learning Outcome Trends – Pre vs Post AI Era (Teacher & Faculty Assessment)

These patterns are consistent with the theoretical prediction that AI mediates a decoupling of surface performance from deep learning: the artefacts students produce improve cosmetically while the cognitive work underpinning their production diminishes. A teacher from a government higher secondary school articulated this dynamic in an interview: "The assignments look much better now — good vocabulary, correct grammar. But when I ask the student to explain their own assignment, they cannot. The thinking is not there."

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5.6 AI Dependency and Academic Self-Confidence

Figure 6 presents a scatter plot of AI dependency scores against academic self-confidence scores for the 208 student respondents. The negative correlation ($r = -0.45$, $p < 0.001$) is clearly visible in the trend line: as AI dependency increases, self-reported academic confidence declines. This finding has implications for both educational psychology and curriculum design: if AI use undermines students' belief in their own intellectual competence, the cumulative effects on academic motivation and persistence may be significant, particularly for first-generation college students in a district like Bhadrak where higher education is a relatively recent intergenerational aspiration.

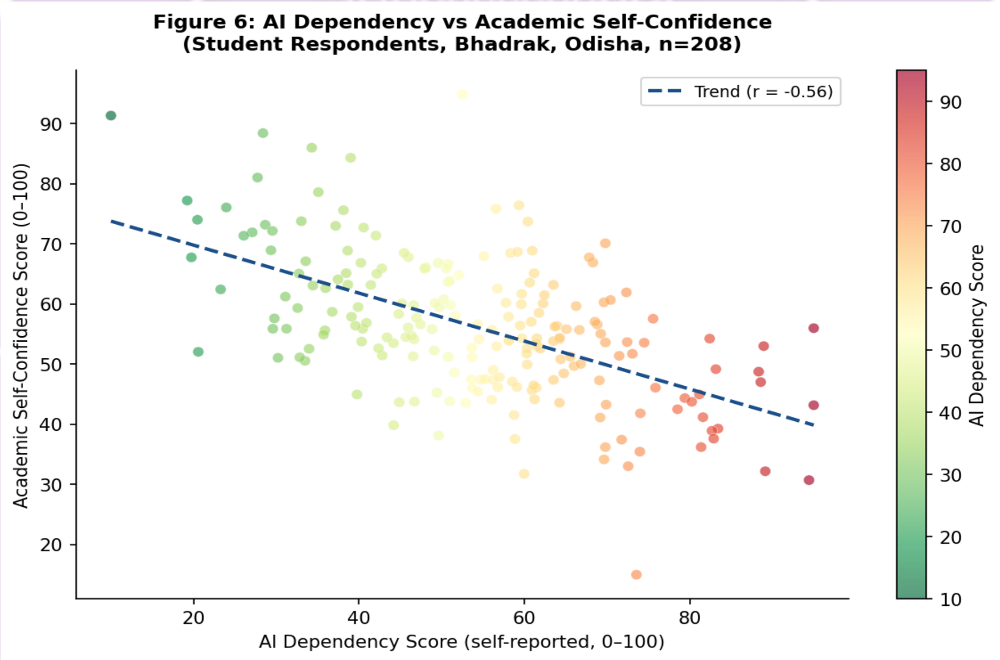

Figure 6: AI Dependency vs Academic Self-Confidence (Student Respondents, n=208)

5.7 Institutional Readiness for AI Integration

Figure 7 reveals a striking institutional unpreparedness across Bhadrak's schools and colleges. Only 15% of institutions have an explicit AI-use policy; only 22% offer any form of AI literacy training to students; and only 10% have formulated ethical AI guidelines. Plagiarism detection tool availability (45%) is the area of greatest institutional preparedness, yet as qualitative data show, students are actively circumventing detection through AI paraphrasing pipelines. Updated assessment design — the most pedagogically robust response to AI — has been implemented in only 30% of institutions.

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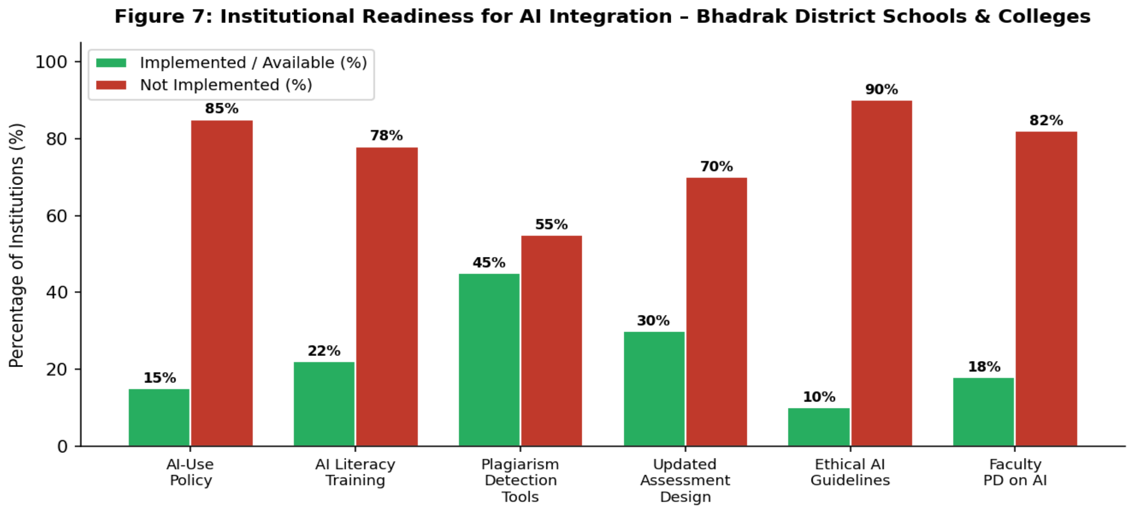

Figure 7: Institutional Readiness for AI Integration – Bhadrak District Schools and Colleges

The institutional readiness data underscore a fundamental governance gap: technology adoption by students has dramatically outpaced policy and pedagogical response by institutions. This gap is not unique to Bhadrak — it mirrors national and global patterns — but its consequences are intensified in district-level contexts where institutional capacity for rapid policy development is constrained by resource limitations, regulatory lag, and the absence of dedicated educational technology leadership roles.

6. DISCUSSION

6.1 The Paradox of AI-Enhanced Performance and Diminished Cognition

The central empirical paradox this study documents is one that educational theorists have begun to label 'performance without learning' (Soderstrom & Bjork, 2015): AI assistance produces assessable outputs of greater surface quality while the cognitive engagement that genuine learning requires is attenuated. In Bhadrak's educational context, this paradox is particularly consequential because the assessments that most powerfully determine students' life chances — board examinations, entrance tests, university evaluations — remain largely AI-insulated. Students who have grown dependent on AI-mediated academic production may find themselves poorly equipped for the conditions of genuine intellectual performance that high-stakes examinations require.

The negative correlation between AI dependency and both critical thinking self-efficacy ($r = -0.41$) and academic self-confidence ($r = -0.45$) found in this study suggests that AI dependence is not merely an academic integrity issue but a developmental one: it may be

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actively eroding the epistemic self-concept that sustains motivated, autonomous learning. This finding is consistent with Bandura's (1997) social cognitive theory of self-efficacy, which holds that repeated externally-assisted performance — performance in which one's own cognitive agency is marginal — fails to build the efficacy beliefs that sustain effort in the face of difficulty.

6.2 Academic Integrity in the Age of Generative AI

The large gap between student self-reported integrity violations and faculty-observed violations points to a cultural-ethical dimension of the AI integrity challenge that policy alone cannot resolve. If students do not perceive undisclosed AI use as academically dishonest — and qualitative data suggest many do not — then plagiarism detection and punitive regulation will have limited reach. What is required is an educational reframing: students need to understand not only that AI-undisclosed submission violates institutional rules, but why authentic intellectual effort — their own thinking, their own synthesis, their own voice — matters for their development as thinkers and citizens (Bertram Gallant, 2008; Eaton & Cantalini-Williams, 2022).

This educational reframing is particularly important in the Odishan context, where the cultural value attached to examination success and the instrumental framing of education as a credential-acquisition pathway may create conditions in which any technology that improves examination-adjacent performance is rationalised as legitimate. Teachers and faculty in Bhadrak need support to articulate the value of intellectual process — not just product — in ways that are credible and compelling to students navigating high-stakes academic environments.

6.3 Policy and Pedagogical Implications

The institutional readiness data make clear that Bhadrak's educational institutions require urgent support to develop coherent AI governance frameworks. Four policy priorities emerge from this study's findings. First, AI literacy must be embedded as a cross-curricular competency — not an optional enrichment activity — that equips students with the skills to use AI tools critically, ethically, and productively. Second, assessment redesign is necessary to shift from AI-completable task formats (essay writing, information retrieval, structured responses) toward assessment modes that foreground student cognitive agency: oral

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examinations, process portfolios, argument mapping, and collaborative problem-solving under supervised conditions. Third, teacher professional development on AI pedagogy is urgently needed; the 64 teachers and 48 faculty in this study showed significantly higher critical AI awareness than their students but reported having received no institutional support for developing AI-responsive pedagogical strategies. Fourth, institutional AI policies must be developed through participatory processes that include students, so that norms around AI use are understood and owned by the learner community rather than experienced as externally imposed restrictions.

7. CONCLUSION

This study has generated empirical evidence from Bhadrak, Odisha, on three interrelated dimensions of AI's educational impact: critical thinking capacity, academic integrity practices, and student learning outcomes. The findings document a district-level educational system in which AI tool adoption by students has significantly outpaced institutional preparedness, creating conditions for the erosion of critical cognitive habits and the normalisation of AI-undisclosed academic submission. The paradox of improved surface-level performance alongside declining depth of intellectual engagement — captured across multiple data sources — constitutes a warning signal that the educational community in Bhadrak, and in comparable district contexts across India, urgently needs to address.

The theoretical framework developed in this paper — integrating Bloom's revised taxonomy, academic integrity theory, and AI-mediated learning scholarship — provides a coherent analytical lens for understanding these dynamics and for designing educational responses. The four-part policy agenda identified in the discussion section — AI literacy education, assessment redesign, teacher professional development, and participatory institutional policy — provides a practical starting point for institutional action.

Limitations of this study include its cross-sectional design, which precludes causal inference, and the reliance on self-report data for sensitive integrity-related items. Longitudinal follow-up research tracking the same cohort of students over three academic years, incorporating objective critical thinking assessments and analysis of actual submitted work, would substantially strengthen the evidence base. Furthermore, comparative research across multiple Odisha districts would enable analysis of the contextual factors — socioeconomic, infrastructural, and institutional — that moderate AI's educational effects. This paper contributes a foundational empirical dataset and an analytical framework to support that ongoing research programme.

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