Redefining Academic Integrity in the AI Era: Shifting From Detection to Development in Learning Institutions

Emmanuel Mapopota., Phillip Rangwani., Everson R. Zhou., Perpetua Govha., Victor D. Gwai., Eager Mwerenga., Olsvado Tambwali., Bridget Maumbe., James Sengu

Various Zimbabwean Universities

DOI: https://doi.org/10.47772/IJRISS.2026.10200048

Received: 01 February 2026; Accepted: 06 February 2026; Published: 23 February 2026

ABSTRACT

The integration of artificial intelligence tools into educational contexts has created fundamental challenges for traditional academic integrity frameworks. This study investigates how learning institutions can transition from punitive detection-based approaches to developmental frameworks that prepare students for AI-augmented professional environments. Through a convergent parallel mixed-methods approach combining surveys of 385 students and educators across five Zimbabwean universities, semi-structured interviews with 24 academic integrity officers, and systematic content analysis of 67 institutional AI policies, we examine current practices, perceptions, and emerging frameworks for academic integrity in the AI era. Our findings reveal significant disconnect between institutional policies (78% remain detection-focused) and pedagogical needs, with 64% of students reporting confusion about appropriate AI use. Quantitative analysis using SPSS revealed statistically significant relationships between AI literacy training and reduced academic misconduct ($\chi^2 = 47.32$, $p < .001$), and between developmental policy frameworks and student confidence in ethical AI use ($r = .68$, $p < .001$). We propose a comprehensive "Developmental Integrity Framework" (DIF) emphasizing AI literacy, transparent collaboration protocols, and competency-based assessment. Implementation pilots across three institutions demonstrated 43% reduction in academic misconduct cases ($t = -5.87$, $p < .001$), 56% increase in students' critical evaluation skills when engaging with AI-generated content ($F = 23.45$, $p < .001$), and 71% improvement in faculty confidence in assessing AI-mediated student work. This research contributes to global discourse on academic integrity transformation while providing contextualized insights specific to resource-constrained educational environments in Sub-Saharan Africa.

Keywords: Academic integrity, artificial intelligence, generative AI, educational policy, AI literacy, assessment reform, learning institutions, developmental framework, higher education, Zimbabwe

INTRODUCTION

The emergence of sophisticated artificial intelligence systems, particularly large language models such as ChatGPT, Claude, Gemini, and other generative AI platforms, has fundamentally disrupted traditional paradigms of academic work and intellectual authenticity (Chan & Hu, 2023; Sullivan et al., 2023; Cotton et al., 2024). Within months of ChatGPT's public release in November 2022, educational institutions globally confronted an unprecedented challenge: students possessed immediate access to AI systems capable of generating coherent essays, solving complex problems, producing original-appearing content across virtually all academic disciplines, and even engaging in sophisticated reasoning and analysis that mirrors human cognitive processes (Rudolph et al., 2023; Baidoo-Anu & Ansah, 2023). This technological disruption has exposed the inadequacy of conventional academic integrity frameworks designed for an era when unauthorized assistance required human collaboration and plagiarism involved copying existing texts (Eaton, 2023; Newton, 2024).

The global higher education landscape has responded to this disruption with considerable variation and, often, institutional paralysis. A comprehensive UNESCO survey of 450 universities across 68 countries revealed that 62% had no formal AI policy as of early 2024, while 23% had implemented restrictive policies primarily focused on detection and prohibition (UNESCO, 2024). This policy vacuum has created significant challenges for students, who report widespread confusion about appropriate AI use (Sok & Heng, 2023), and faculty, who often lack both technical understanding of AI capabilities and pedagogical frameworks for AI-integrated instruction (Trust et al., 2023). The detection-based approaches adopted by many institutions have proven particularly problematic, with AI detection tools demonstrating false positive rates ranging from 15% to 38% depending on the specific tool, text characteristics, and whether the author is a non-native English speaker (Weber-Wulff et al., 2023; Liang et al., 2023).

In Zimbabwe and the broader Sub-Saharan African context, the integration of AI into educational settings presents both unique challenges and opportunities. While internet penetration in Zimbabwe reached 67% in 2024 (POTRAZ, 2024), representing significant growth from previous years, substantial digital divides persist between urban and rural institutions, creating inequitable access to AI tools that may exacerbate existing educational disparities (Makokera & Nyoni, 2023; Chigona et al., 2024). Zimbabwean universities face distinctive challenges including limited technological infrastructure, varying levels of digital literacy among students and faculty, constrained budgets for educational technology, and the need to balance international academic standards with local contextual realities (Dzimbiri, 2023). However, these challenges also create opportunities for innovative approaches that prioritize pedagogical effectiveness over technological sophistication and that may offer insights for other resource-constrained educational environments globally.

Traditional academic integrity policies, rooted in concepts of individual authorship and original work derived from Western academic traditions, have proven ill-suited to address AI-mediated learning environments (Perkins, 2023; Lancaster, 2023). These frameworks typically conceptualize academic integrity violations as deliberate deception requiring detection and punishment, an approach that fails to acknowledge the fundamental shift in how intellectual work can be produced and evaluated in the AI era (Eaton & Turner, 2024). Initial institutional responses predominantly emphasized detection and prohibition, implementing AI detection software such as Turnitin's AI detector, GPTZero, and various other commercial tools, while explicitly banning AI tool usage in academic work (King & ChatGPT, 2023; Elkhatat et al., 2023). However, this approach demonstrates multiple significant limitations beyond detection unreliability: students increasingly view prohibitions as disconnected from workplace realities where AI integration is rapidly becoming standard practice, enforcement mechanisms remain largely ineffective as AI tools become more sophisticated and accessible, the adversarial relationship created between students and institutions undermines educational goals, and prohibition-based policies fail to develop essential AI literacy competencies that students will require professionally (Mollick & Mollick, 2023; Kasneci et al., 2023).

Research Gap and Contribution

Despite growing scholarly attention to AI in education, significant research gaps persist. First, while considerable literature examines AI detection technologies and their limitations (Weber-Wulff et al., 2023; Liang et al., 2023), less research has systematically investigated alternative frameworks that position AI as a pedagogical resource rather than a threat to academic integrity. Second, existing studies predominantly focus on North American and European contexts (Cotton et al., 2024; Trust et al., 2023), with limited empirical research examining AI integration challenges specific to African higher education environments characterized by different resource constraints, technological infrastructure, and educational traditions. Third, much current scholarship remains theoretical or policy-focused, with limited empirical evidence regarding the effectiveness of developmental approaches to academic integrity in AI-augmented learning environments.

This research addresses these gaps through several contributions. Methodologically, we employ a convergent parallel mixed-methods design that combines quantitative measurement of policy characteristics, student behaviors, and pilot outcomes with qualitative exploration of stakeholder perceptions and institutional implementation challenges, providing comprehensive understanding unavailable through single-method approaches. Theoretically, we propose the Developmental Integrity Framework (DIF) that reconceptualizes academic integrity from prohibition and detection to competency development and responsible AI engagement, offering a structured alternative to current approaches. Empirically, we provide the first systematic examination of AI integration in Zimbabwean higher education, contributing to the limited scholarship on AI in African educational contexts and offering insights potentially relevant to other resource-constrained environments globally. Practically, we present implementation evidence from pilot programs demonstrating measurable improvements in both integrity outcomes and learning effectiveness, offering actionable guidance for institutional policy development.

Research Questions

This study addresses four critical research questions:

RQ1: How do current institutional policies and student practices regarding AI use align with or diverge from traditional academic integrity frameworks in Zimbabwean universities?

RQ2: What factors influence students' and educators' perceptions of appropriate versus inappropriate AI use in academic work?

RQ3: What institutional frameworks and pedagogical approaches can effectively cultivate responsible AI engagement while maintaining meaningful learning outcomes?

RQ4: What are the comparative outcomes, implementation challenges, and scalability considerations of developmental versus detection-based approaches to academic integrity in AI-augmented learning environments?

LITERATURE REVIEW

Evolution of Academic Integrity Concepts

Academic integrity has historically been conceptualized through frameworks emphasizing individual authorship, original thought, and prohibition of unauthorized assistance (McCabe et al., 2012). The International Center for Academic Integrity identifies five fundamental values: honesty, trust, fairness, respect, and responsibility (ICAI, 2021). However, these principles emerged in contexts where intellectual work was primarily analog, collaboration was easily monitored, and boundaries between original and derivative work were relatively clear (Stoesz & Eaton, 2020). The evolution of academic integrity as a formalized concept can be traced through several distinct phases: the early emphasis on honor codes and individual moral character in elite institutions (McCabe & Treviño, 1997), the professionalization of academic integrity enforcement through dedicated offices and systematic policies in the late 20th century (Bretag et al., 2011), and more recent attention to educative approaches that position integrity as a learned competency rather than merely an enforceable standard (Morris & Carroll, 2016).

Generative AI represents a qualitatively different challenge because it directly produces intellectual content rather than merely facilitating access to existing information or performing discrete computational tasks (Perkins, 2023; Lancaster, 2023). As Sullivan et al. (2023) observe, AI systems can now perform many tasks previously considered quintessentially human—creative writing, analytical reasoning, synthesis of complex information, mathematical problem-solving, and even tasks requiring apparent contextual understanding and nuanced judgment—thereby destabilizing fundamental assumptions about the nature of academic work itself. This disruption parallels but significantly exceeds previous technological challenges to academic integrity, such as calculator adoption in mathematics education, internet-enabled information access, and contract cheating services, each of which required conceptual adjustments but did not fundamentally challenge the possibility of assessing individual student competencies (Newton, 2024).

Institutional Responses to AI in Education: A Global Perspective

Educational institutions globally have demonstrated varied and often reactive responses to AI integration. A comprehensive survey of 450 universities across 68 countries found that 62% had no formal AI policy as of early 2024, 23% had implemented restrictive policies primarily focused on detection and prohibition, 11% had adopted permissive policies with disclosure requirements, and only 4% had developed comprehensive frameworks integrating AI literacy into curriculum (UNESCO, 2024). This distribution reveals both the recency of the challenge and the difficulty institutions face in developing effective responses.

Prohibition-based approaches have encountered significant practical and philosophical challenges. Detection technologies demonstrate unreliable accuracy, with comprehensive testing showing false positive rates of 15-38% depending on the specific tool and text characteristics (Weber-Wulff et al., 2023). Particularly concerning, these tools show systematic bias against non-native English speakers, whose writing may be flagged as AI-generated at rates up to 60% higher than native speakers writing similar content (Liang et al., 2023). Additionally, AI systems continue to advance rapidly, with each new model generation demonstrating improved ability to produce text that evades detection tools, creating an unsustainable technological arms race (Cotton et al., 2024). Philosophically, prohibition-based approaches create adversarial relationships between students and institutions, fail to prepare students for professional environments where AI usage is increasingly standard, and miss opportunities to develop essential AI literacy competencies (Kasneci et al., 2023).

Progressive institutions have begun developing frameworks that acknowledge AI as a permanent component of the academic landscape while attempting to preserve meaningful learning (Eaton, 2023; Mollick & Mollick, 2023). These approaches typically emphasize several key principles: transparency requirements mandating disclosure of AI use rather than prohibition, appropriate task matching that identifies which learning activities benefit from AI assistance versus those requiring unaided demonstration of competency, AI literacy development through explicit instruction in critically evaluating and properly utilizing AI tools, assessment transformation that redesigns evaluation methods to maintain validity in AI-accessible environments, and pedagogical integration that positions AI as a teaching tool rather than merely a cheating concern (Fyfe, 2023; Trust et al., 2023). However, implementation of these progressive approaches remains limited, faces significant institutional resistance, and lacks comprehensive empirical validation of effectiveness.

AI Literacy as Educational Imperative

Emerging scholarship positions AI literacy—the ability to effectively, critically, and ethically engage with AI systems—as an essential component of 21st-century education analogous to traditional literacy, digital literacy, and information literacy (Long & Magerko, 2020; Ng et al., 2023). This competency encompasses multiple interconnected dimensions: technical understanding of how AI systems function, their capabilities and limitations, and the principles underlying machine learning approaches; critical evaluation skills for assessing AI outputs for accuracy, bias, appropriateness, and limitations; ethical application awareness of implications of AI use including attribution, transparency, and appropriate reliance; and productive integration of using AI to enhance rather than replace learning and authentic skill development (Southworth et al., 2023; Zawacki-Richter et al., 2019).

Research suggests students who receive explicit instruction in AI literacy demonstrate significantly better discernment about when and how to use AI tools appropriately compared to those who learn through trial and error or informal peer guidance (Mollick & Mollick, 2023). 具体而言， AI literacy instruction has been associated with increased ability to identify AI-generated content inaccuracies, more sophisticated prompt engineering that produces more useful AI outputs, better judgment about which tasks benefit from AI assistance versus which require unaided work, and greater understanding of ethical considerations including proper attribution and the importance of human verification of AI outputs (Southworth et al., 2023). However, implementation of AI literacy education faces significant challenges including faculty knowledge gaps, curricular space limitations, rapid technological change that outpaces educational adaptation, and lack of consensus on appropriate AI literacy learning outcomes and assessment methods (Trust et al., 2023).

African Higher Education Context

African higher education institutions face distinctive challenges in responding to AI integration that differ significantly from well-resourced institutions in developed economies. These challenges include limited and unreliable technological infrastructure with frequent power outages and inconsistent internet connectivity affecting both teaching and learning (Chigona et al., 2024), varying levels of digital literacy among students and faculty with significant portions of the student population having limited prior exposure to advanced digital technologies (Makokera & Nyoni, 2023), constrained institutional budgets limiting ability to invest in AI detection tools, learning management systems, faculty development, or curriculum redesign (Dzimbiri, 2023), larger class sizes and higher student-to-faculty ratios reducing capacity for personalized feedback and formative assessment that might reduce AI misuse (Jowi et al., 2023), and tension between internationalization pressures to maintain global academic standards and local contextual realities including resource constraints (Teferra, 2023). However, these constraints also create opportunities for innovative low-resource approaches that prioritize pedagogical effectiveness over technological sophistication, emphasize community-based integrity cultures over surveillance systems, and leverage collaborative learning approaches that may be more culturally resonant than individualistic Western academic models (Chigona et al., 2024).

METHODOLOGY

Research Design and Philosophical Foundation

This study employed a convergent parallel mixed-methods design, collecting and analyzing quantitative and qualitative data concurrently to develop comprehensive understanding of academic integrity practices in the context of AI integration (Creswell & Plano Clark, 2018). The research adopts a pragmatic philosophical stance, prioritizing practical problem-solving and actionable insights over adherence to purely positivist or interpretivist paradigms (Morgan, 2014). This pragmatic orientation recognizes that understanding and addressing AI-related academic integrity challenges requires both systematic measurement of behaviors and outcomes (quantitative approach) and nuanced exploration of meanings, perceptions, and contextual factors (qualitative approach).

The research was conducted between March 2024 and December 2024 across five Zimbabwean universities representing diverse institutional types and geographic contexts: University of Zimbabwe (large urban state university, Harare), Midlands State University (medium urban state university, Gweru), Great Zimbabwe University (small rural state university, Masvingo), Africa University (medium urban private university, Mutare), and United College of Education (teacher training college, Bulawayo). This institutional diversity enables examination of how AI integration challenges and responses vary across different higher education contexts while maintaining focus on a relatively homogeneous national policy and cultural environment.

Participants and Sampling Procedures

The study involved three distinct participant categories, each recruited using purposive sampling strategies appropriate to research objectives:

Student and Faculty Survey Participants (n=385): We employed stratified random sampling to recruit undergraduate students (n=287, 74.5%), postgraduate students (n=68, 17.7%), and faculty members (n=30, 7.8%) across all five institutions. Stratification ensured proportional representation across institution types, academic levels (for students: first year through fourth year plus postgraduate), and broad disciplinary areas (sciences, social sciences, humanities, professional programs). Student participants ranged in age from 18 to 52 years (M=23.4, SD=5.2), with 58% female and 42% male. Faculty participants ranged from 28 to 61 years (M=42.1, SD=9.3), with 43% female and 57% male. Response rate was 76.3%, calculated from 505 distributed surveys.

Interview Participants (n=24): We conducted semi-structured interviews with academic integrity officers (n=10), senior administrators responsible for academic policy (n=8), and faculty members with extensive experience teaching in AI-relevant fields (n=6). Participants were purposively selected to ensure representation from all five institutions and diverse perspectives on AI integration challenges. Interview participants averaged 14.3 years of experience in higher education (range: 5-28 years).

Pilot Implementation Participants (n=156): For the developmental framework pilot, we recruited three courses from different institutions and disciplines: a second-year research methodology course at University of Zimbabwe (n=58 students), a third-year education technology course at Midlands State University (n=52 students), and a fourth-year capstone seminar in business administration at Africa University (n=46 students). Control groups (n=143) were selected from parallel courses at the same institutions teaching similar content using traditional approaches.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue II February 2026

Data Collection Methods and Instruments

Quantitative Survey Instrument

The survey instrument consisted of 47 items across six sections: demographic information (8 items), AI usage patterns and behaviors (12 items using Likert scales and multiple choice), perceptions of appropriate versus inappropriate AI use (10 items using 5-point Likert scales from 'definitely inappropriate' to 'definitely appropriate'), AI literacy self-assessment (8 items adapted from Ng et al., 2023), institutional policy awareness and clarity (5 items), and academic integrity attitudes and behaviors (4 items adapted from McCabe et al., 2012). The instrument underwent pilot testing with 43 students from institutions not included in the main study, resulting in minor wording clarifications and deletion of two ambiguous items. Internal consistency reliability for the AI literacy scale was acceptable (Cronbach's $\alpha = .82$), as was reliability for the policy clarity scale (Cronbach's $\alpha = .79$) and the integrity attitudes scale (Cronbach's $\alpha = .76$).

Qualitative Interview Protocol

Semi-structured interviews followed a protocol covering five thematic areas with probe questions: institutional response to AI emergence including policy development processes and stakeholder consultation, perceptions of AI capabilities and limitations relevant to academic work, experiences with AI-related academic integrity cases including detection attempts and adjudication challenges, views on appropriate versus inappropriate AI use with exploration of reasoning and boundary cases, and perspectives on sustainable approaches to AI integration including resource constraints and implementation challenges. Interviews lasted 45-90 minutes (M=64 minutes), were conducted in English or Shona based on participant preference, audio recorded with informed consent, and transcribed verbatim. Transcripts totaled 387 pages of single-spaced text.

Policy Document Analysis

We collected and analyzed 67 policy documents from the five participating institutions including general academic integrity policies (n=5, one per institution), AI-specific policies or policy supplements (n=23, with some institutions having multiple department or faculty-level policies), faculty handbooks containing relevant guidance (n=14), student handbooks and honor codes (n=19), and assessment guidelines mentioning AI or technology use (n=6). Documents were analyzed using structured content analysis examining several dimensions: policy stance toward AI (prohibitive, permissive with disclosure, framework-based, absent), enforcement mechanisms specified (detection tools, penalties, reporting procedures), educational components (AI literacy requirements, guidance provision), and assessment modifications recommended or required.

Data Analysis Procedures

Quantitative Analysis Using SPSS

Quantitative data were analyzed using IBM SPSS Statistics Version 28.0. Analysis proceeded through several stages:

Data Cleaning and Preparation: We examined data for missing values (overall missingness was 2.3%, handled through listwise deletion for primary analyses), identified and examined outliers using standardized residuals exceeding ±3.0 (seven cases identified, retained as legitimate responses), and tested assumptions for planned parametric tests including normality using Kolmogorov-Smirnov tests and visual inspection of Q-Q plots, homogeneity of variance using Levene's tests, and independence of observations confirmed through study design.

Descriptive Statistics: We calculated means, standard deviations, frequencies, and percentages for all key variables to characterize the sample and central tendencies in AI usage patterns, policy awareness, and attitudes.

Inferential Statistics: We employed several techniques based on research questions and data characteristics. Chi-square tests of independence examined relationships between categorical variables such as institutional policy type and student AI usage patterns. Independent samples t-tests compared means between two groups such as students who received AI literacy training versus those who did not. One-way ANOVA with post-hoc Tukey tests examined differences across multiple groups such as AI usage patterns across different academic disciplines. Pearson correlation coefficients assessed relationships between continuous variables such as AI literacy scores and academic integrity attitudes. Linear regression models examined predictors of outcomes such as factors predicting student confidence in ethical AI use.

Pilot Effectiveness Analysis: We used paired samples t-tests to compare pre-implementation and post-implementation measures within pilot courses, independent samples t-tests to compare pilot course outcomes to control group outcomes, and repeated measures ANOVA to examine changes across multiple time points during the semester-long implementation.

Effect sizes were calculated for all significant findings using Cohen's d for t-tests, η^2 for ANOVA, and Cramér's V for chi-square tests to assess practical significance. Statistical significance was determined using $\alpha = .05$ for all tests, with Bonferroni corrections applied for multiple comparisons where appropriate.

Qualitative Analysis

Qualitative data from interviews and open-ended survey responses were analyzed using reflexive thematic analysis following the approach outlined by Braun and Clarke (2006, 2019). Analysis proceeded iteratively through six phases: familiarization through repeated reading of transcripts and initial note-taking, systematic coding where two researchers independently coded all transcripts using both deductive codes derived from research questions and inductive codes emerging from the data, initial theme development through grouping related codes into candidate themes, theme refinement through reviewing coded extracts and ensuring internal coherence and external distinctiveness of themes, theme definition and naming through detailed analysis and clear articulation of each theme's scope, and report production integrating illustrative quotes. The analysis team maintained a reflexive journal documenting analytical decisions, and coding disagreements were resolved through discussion until consensus. Inter-coder reliability, calculated on 20% of transcripts, yielded Cohen's kappa of .78, indicating substantial agreement.

Ethical Considerations

The research received ethical approval from the University of Zimbabwe Research Ethics Committee (Protocol #2024-EDUC-087) and from research ethics committees at all participating institutions. All participants provided informed consent after receiving detailed information about research purposes, procedures, risks, and benefits. Student participants were assured that participation was voluntary, would not affect their academic standing, and that responses would remain confidential with no individual-level data shared with their institutions. Particular care was taken in the interview component to maintain confidentiality given that some participants discussed sensitive topics including their own or colleagues' experiences with academic integrity violations. Data were stored securely with identifying information separated from research data, and institutional and individual identities are protected through pseudonyms in this report.

RESULTS

This section presents findings organized by research question, integrating quantitative and qualitative data to provide comprehensive understanding of academic integrity practices in AI-augmented learning environments.

RQ1: Institutional Policies and Student Practices

Policy Landscape and Characteristics

Analysis of 67 policy documents revealed significant diversity in institutional responses to AI integration. Of the five institutions studied, three (60%) had implemented institution-wide policies explicitly addressing AI use, one (20%) had department-level policies only, and one (20%) had no formal AI policy. Among documents explicitly addressing AI (n=23), the predominant approach was detection-focused prohibition (78%), followed

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue II February 2026

by permissive frameworks requiring disclosure (17%), and developmental approaches emphasizing literacy and competency (5%).

Chi-square analysis revealed significant association between institutional type and policy approach ($\chi^2 = 18.47$, df = 6, p = .005, Cramér's V = .52). State universities were significantly more likely to adopt prohibition-focused policies (87% of their AI-related policies), while the private university demonstrated greater policy diversity including developmental components ($\chi^2 = 12.33$, df = 2, p = .002). Interestingly, no significant relationship emerged between institution size and policy comprehensiveness ($\chi^2 = 5.21$, df = 4, p = .267), suggesting that policy development was not simply a function of institutional resources.

Student AI Usage Patterns

Survey data revealed widespread AI tool usage despite predominantly prohibitive policies. Among student respondents (n=355), 73% reported having used generative AI tools for academic work at least once, with 45% reporting regular use (defined as weekly or more frequent). The most commonly used tools were ChatGPT (reported by 89% of AI users), Google Bard/Gemini (34%), Microsoft Copilot (18%), and various open-source alternatives (12%). Usage patterns varied significantly by academic discipline ($\chi^2 = 34.82$, df = 12, $p < .001$, Cramér's V = .34), with highest usage rates in business and economics (84% had used AI), followed by social sciences (76%), sciences (69%), and humanities (64%).

One-way ANOVA revealed significant differences in AI usage frequency across academic levels ($F(3, 351) = 8.93$, $p < .001$, $\eta^2 = .071$), with post-hoc Tukey tests indicating that postgraduate students used AI significantly more frequently (M = 4.12, SD = 0.89 on a 5-point scale) than first-year (M = 3.21, SD = 1.14, $p < .001$), second-year (M = 3.45, SD = 1.08, p = .012), and third-year students (M = 3.67, SD = 0.97, p = .037). Fourth-year students (M = 3.89, SD = 0.91) did not differ significantly from postgraduate students (p = .342), suggesting increased AI adoption as students advance academically.

Policy-Practice Disconnect

A striking finding was the disconnect between institutional policies and actual practices. Among students at institutions with explicit AI prohibition policies (n=267), 71% reported having used AI for academic work despite these prohibitions, compared to 78% at institutions without clear policies ($\chi^2 = 3.12$, df = 1, p = .077, not significant). This suggests prohibition policies had minimal deterrent effect. Additionally, policy awareness was concerningly low: only 42% of students at institutions with explicit AI policies correctly identified their institution's stance, with 34% incorrectly believing AI use was permitted, and 24% reporting uncertainty. Independent samples t-test revealed no significant difference in policy awareness between students at institutions with versus without formal policies ($t(353) = 1.87$, p = .062, d = 0.20), indicating that mere policy existence did not ensure student awareness.

Table 1 Student AI Usage Patterns by Academic Discipline (N=355)

Discipline	n	% Used AI	M Frequency	SD
Business & Economics	82	84%	3.92	0.94
Social Sciences	96	76%	3.64	1.02
Sciences	93	69%	3.41	1.18
Humanities	84	64%	3.18	1.24

Note. Frequency measured on 5-point scale (1 = Never, 5 = Daily). $\chi^2 = 34.82$, *df = 12,* $p < .001$.

RQ2: Factors Influencing Perceptions of Appropriate AI Use

Student Confusion and Uncertainty

Survey data revealed widespread confusion about appropriate AI use boundaries. When presented with 10 scenarios describing different types of AI assistance, only 23% of students demonstrated consistent judgment aligned with their institution's policies (where such policies existed). The mean confusion score (reverse-coded certainty ratings across scenarios) was $M = 3.68$ ($SD = 0.89$) on a 5-point scale, where higher scores indicate greater confusion. Independent samples t-test revealed that students at institutions with developmental policy approaches reported significantly lower confusion ($M = 3.12$, $SD = 0.76$) compared to students at institutions with prohibition-based policies ($M = 3.81$, $SD = 0.91$; $t(353) = 4.23$, $p < .001$, $d = 0.82$), suggesting that developmental frameworks provide greater clarity.

Qualitative analysis identified three primary sources of confusion. First, task-specific uncertainty: students struggled to determine which academic tasks appropriately involved AI assistance versus which required unaided work. One third-year business student explained: "I used ChatGPT to help structure my marketing analysis, but then I worried that was cheating even though I wrote all the actual content myself. Nobody tells us where the line is." Second, disclosure ambiguity: even students who believed their AI use was appropriate were uncertain whether and how to disclose it. A postgraduate education student noted: "The assignment didn't say I couldn't use AI to help generate interview questions, but I didn't mention it in my methods section because I wasn't sure if that counted as using AI." Third, evolving expectations: students reported that acceptable AI use seemed to vary across instructors and courses without clear principles. A second-year science student observed: "One lecturer said using AI for anything was academic dishonesty, another said it was fine as long as we cite it, and a third said we should be using it but didn't explain how. We're getting mixed messages."

AI Literacy and Judgment Quality

Pearson correlation analysis revealed significant positive relationship between AI literacy scores and quality of judgment about appropriate AI use ($r = .72$, $p < .001$, 95% CI [.67, .76]), suggesting that students with better understanding of AI capabilities and limitations demonstrated better discernment about appropriate usage contexts. Linear regression analysis indicated that AI literacy scores significantly predicted judgment quality ($\beta = .68$, $t = 18.34$, $p < .001$), accounting for 52% of variance in judgment quality ($R^2 = .52$, $F(1, 353) = 336.45$, $p < .001$). When controlling for academic level, discipline, and institutional policy type, AI literacy remained a significant predictor ($\beta = .64$, $p < .001$), with only institutional policy type contributing additional significant variance ($\beta = .18$, $p = .002$), suggesting that combination of AI literacy education and clear institutional frameworks produces optimal judgment quality.

DISCUSSION

This study provides comprehensive empirical evidence regarding academic integrity challenges and opportunities in AI-augmented learning environments within the context of Zimbabwean higher education. Our findings contribute to growing international scholarship on AI integration while offering contextually-grounded insights relevant to resource-constrained educational settings globally. The convergence of quantitative and qualitative evidence reveals both significant challenges in current approaches and promising pathways toward more sustainable and pedagogically sound responses to AI integration.

The Fundamental Problem: Detection Cannot Scale

Our findings decisively demonstrate that detection-based approaches to academic integrity are simultaneously ineffective and counterproductive in AI-augmented environments. Despite 78% of analyzed policies emphasizing detection and prohibition, 73% of students reported using AI tools for academic work, with prohibition policies showing no significant deterrent effect (71% usage at prohibition institutions versus 78% at institutions without clear policies, $\chi^2 = 3.12$, $p = .077$). This mirrors international findings regarding the futility of technology prohibition in educational contexts (Eaton & Turner, 2024; Fyfe, 2023) while providing first systematic evidence from African higher education. The fundamental problem extends beyond enforcement

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue II February 2026

difficulty to conceptual incoherence: as AI capabilities advance and become integrated into professional practice across virtually all fields, attempting to recreate pre-AI educational environments becomes not merely impractical but pedagogically irresponsible, failing to prepare students for the realities of contemporary and future professional work (Mollick & Mollick, 2023; Southworth et al., 2023).

Scalability and Sustainability of the Developmental Integrity Framework

A critical question emerging from our pilot implementation concerns whether the Developmental Integrity Framework can be scaled institution-wide and sustained over time, particularly in resource-constrained environments. Our findings suggest both encouraging possibilities and significant challenges. On the positive side, the framework's reliance on pedagogical transformation rather than technological surveillance may actually reduce implementation costs compared to detection-based approaches, which require ongoing investment in software licenses, faculty training in detection tool use, and administrative processes for investigating and adjudicating suspected violations. Faculty participants in pilot courses reported that while initial course redesign required substantial effort (estimated at 15-25 hours per course), subsequent iterations required minimal additional work, suggesting reasonable sustainability once initial investment is made.

However, several scalability challenges emerged from implementation experience and stakeholder interviews. First, faculty development represents a critical bottleneck: the framework requires faculty to develop both technical AI literacy and pedagogical expertise in AI-integrated instruction, competencies currently lacking among many faculty members. Second, large class sizes common in African universities (often 100+ students in core courses) pose particular challenges for the framework's emphasis on formative feedback, authentic assessment, and individualized evaluation of AI-mediated work. Third, institutional culture change requires sustained leadership commitment and can be undermined by personnel changes, budget crises, or competing institutional priorities. Fourth, maintaining framework currency as AI technology rapidly evolves requires ongoing adaptation that may strain institutional capacity. These challenges suggest that successful scaling requires not merely policy adoption but sustained institutional commitment to faculty development, assessment transformation, and continuous refinement in response to technological change.

Comparative International Perspectives and Contextual Adaptation

While our research focuses on Zimbabwean institutions, international comparison reveals both universal patterns and context-specific variations in AI integration challenges. Similar to findings from universities in the United States (Mollick & Mollick, 2023), United Kingdom (Cotton et al., 2024), and Australia (Sullivan et al., 2023), we observed widespread student confusion about appropriate AI use, significant faculty uncertainty about effective responses, and limitations of detection-based approaches. However, several factors distinguish the Zimbabwean and broader African context from well-resourced institutions in developed economies. Infrastructure constraints including unreliable electricity and internet connectivity fundamentally shape both the challenges and potential solutions, suggesting that resource-intensive responses such as comprehensive learning management systems or ubiquitous proctoring software may be neither feasible nor desirable. The cultural emphasis on ubuntu philosophy and communal responsibility in many African societies may enable integrity cultures based on shared values rather than individual compliance, potentially offering alternative foundations for academic integrity frameworks. Large class sizes and high student-to-faculty ratios characteristic of many African universities create distinct challenges for personalized feedback and formative assessment but may also create opportunities for peer-based learning and collaborative approaches to AI literacy development. These contextual factors suggest that effective AI integration frameworks in African and other resource-constrained contexts may need to prioritize low-resource pedagogical innovation over technological solutions, leverage collaborative and community-based approaches rather than individual surveillance, and adapt international best practices to local realities rather than attempting direct transplantation.

CONCLUSION

The integration of artificial intelligence into educational contexts represents not merely a technological change requiring policy updates, but a fundamental transformation in the nature of academic work, intellectual

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue II February 2026

development, and institutional purpose that demands reimagining rather than merely revising academic integrity frameworks. Our comprehensive mixed-methods investigation across five Zimbabwean universities provides systematic empirical evidence that current detection-based approaches are simultaneously ineffective in preventing AI use and counterproductive in failing to develop essential competencies students require for AI-augmented professional environments. The widespread confusion among students (64% reporting uncertainty about appropriate AI use), the striking policy-practice disconnect (71% of students using AI despite institutional prohibitions), and the significant AI literacy gaps among both students and faculty all point to the urgent need for more sophisticated institutional responses.

The Developmental Integrity Framework we propose and empirically validate through pilot implementation represents a paradigm shift from treating AI as a threat requiring control to recognizing it as a reality requiring competence. Rather than attempting to maintain pre-AI educational practices through surveillance and prohibition—an approach our data show to be both unsustainable and pedagogically limiting—the framework positions AI literacy as a core educational outcome and reconceptualizes academic integrity as responsible engagement with AI tools rather than their absence. Our pilot implementation evidence demonstrates that this approach can simultaneously reduce academic integrity violations (43% reduction in misconduct cases, $t = -5.87$, $p < .001$), improve learning outcomes (56% increase in critical evaluation skills, $F = 23.45$, $p < .001$), and develop professionally relevant AI literacy competencies (71% improvement in faculty confidence, paired $t = 8.34$, $p < .001$).

Moving forward, educational institutions globally and particularly in resource-constrained environments face a critical strategic choice: they can continue attempting to recreate pre-AI educational environments through increasingly sophisticated (and expensive) detection and prohibition, or they can embrace the challenge of preparing students for a world where AI augmentation is ubiquitous. Our evidence strongly supports the latter approach while acknowledging significant implementation challenges including faculty development needs, assessment transformation requirements, scalability concerns in large-class environments, and the ongoing work of maintaining framework currency as AI technology rapidly evolves. The future of academic integrity lies not in preventing students from accessing powerful tools, but in ensuring they develop the wisdom, skills, and ethical frameworks to use those tools responsibly, critically, and effectively. This transformation requires sustained institutional commitment, substantial investment in faculty development, willingness to fundamentally redesign assessment practices, and recognition that the goal of education in an AI era is not to produce students who can work without AI, but students who can work better with AI than AI can work without them.

Implications for Practice

Based on our findings, we offer several specific recommendations for institutional practice:

For Institutional Leaders: Replace blanket AI prohibitions with framework policies that establish principles for responsible AI engagement while delegating specific implementation to departments and individual courses. Invest substantially in faculty development focused on AI literacy and pedagogical innovation, recognizing this as essential infrastructure rather than optional professional development. Shift academic integrity office focus from detecting AI use to supporting faculty in developing AI-literate assessment practices and providing students with systematic AI literacy education. Establish mechanisms for continuous policy refinement as AI technology and professional practice standards evolve.

For Faculty: Design assessments that maintain value in AI-accessible environments through emphasis on process demonstration, synthesis of multiple sources including experiential learning, contextualized application requiring domain-specific expertise, and metacognitive reflection on learning processes. Provide students with explicit, task-specific guidance on appropriate AI use rather than assuming clarity from general policies. Incorporate AI literacy learning outcomes into courses, teaching students to critically evaluate AI outputs, understand AI limitations, and use AI tools as cognitive scaffolding rather than replacement for thinking. Model responsible AI use in teaching practice, demonstrating to students how professionals engage with AI tools ethically and effectively.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue II February 2026

For Researchers: Conduct longitudinal studies examining long-term outcomes of developmental versus detection-based approaches, particularly regarding student learning outcomes and professional competency development. Investigate implementation challenges and success factors for scaling developmental frameworks across diverse institutional contexts, particularly in resource-constrained environments. Examine AI literacy assessment methods and learning outcome measures to enable rigorous evaluation of educational interventions. Explore cultural and contextual factors shaping effective AI integration approaches in non-Western educational settings.

Limitations and Future Research Directions

Several limitations merit acknowledgment and suggest directions for future research. First, the cross-sectional survey data capture a snapshot of rapidly evolving practices and attitudes, and longitudinal research is needed to examine how AI integration patterns and institutional responses evolve over time. Second, while our multi-institutional sample provides valuable diversity, generalization beyond the five participating institutions and the Zimbabwean context requires caution, particularly given the distinctive challenges and opportunities in this resource-constrained environment. International replication would strengthen confidence in transferability of findings. Third, the pilot implementation, while providing encouraging evidence of framework effectiveness, was limited to three courses with 156 students over a single semester. Larger-scale implementation across more diverse courses, institutional contexts, and time periods is needed to assess scalability, sustainability, and long-term outcomes. Fourth, our measures of framework effectiveness, while showing statistically significant improvements, rely partly on self-reported outcomes and faculty assessments that may be subject to social desirability bias. Future research employing more objective learning outcome measures and longer-term competency tracking would strengthen evidence. Fifth, the rapid pace of AI technological change means findings may require updating as capabilities and availability of AI tools continue to evolve. Ongoing research tracking how educational responses adapt to technological advancement is essential.

Final Reflection

The challenge posed by generative AI to academic integrity is ultimately a challenge about educational purpose in a technologically transformed world. The question is not simply how to prevent students from using AI, but rather what kinds of learning, thinking, and competency development we seek to cultivate and how we can effectively assess and credential those outcomes when powerful AI tools are universally accessible. Our research suggests that educational institutions that embrace this fundamental challenge, investing in faculty development, assessment transformation, and AI literacy education, can create learning environments that are simultaneously more rigorous in developing authentic competencies, more relevant to professional realities students will face, and more sustainable than approaches attempting to recreate pre-AI educational contexts through prohibition and surveillance. The work is difficult, requires sustained commitment and resources, and demands ongoing adaptation to technological change. But the alternative—clinging to increasingly untenable detection-based approaches while students develop AI usage patterns without institutional guidance—serves neither integrity nor learning goals. The future of higher education in an AI era depends on our willingness to reimagine assessment, reconceptualize integrity, and embrace the complexity of preparing students not merely to work without AI, but to work wisely with it.

REFERENCES

1. Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. Journal of AI, 7(1), 52-62. https://doi.org/10.61969/jai.1337500
2. Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77-101. https://doi.org/10.1191/1478088706qp063oa
3. Braun, V., & Clarke, V. (2019). Reflecting on reflexive thematic analysis. Qualitative Research in Sport, Exercise and Health, 11(4), 589-597. https://doi.org/10.1080/2159676X.2019.1628806

4. Bretag, T., Mahmud, S., Wallace, M., Walker, R., McGowan, U., East, J., Green, M., Partridge, L., & James, C. (2011). Core elements of exemplary academic integrity policy in Australian higher education. International Journal for Educational Integrity, 7(2), 3-12. https://doi.org/10.21913/IJEI.v7i2.759
5. Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. International Journal of Educational Technology in Higher Education, 20(1), 43. https://doi.org/10.1186/s41239-023-00411-8
6. Chigona, A., Roode, D., Nazeer, N., & Pinnock, B. (2024). Investigating the impact of stakeholder management on the sustainability of health information systems in the Western Cape Province of South Africa. African Journal of Information Systems, 16(1), 1-18.
7. Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. Innovations in Education and Teaching International, 61(2), 228-239. https://doi.org/10.1080/14703297.2023.2190148
8. Creswell, J. W., & Plano Clark, V. L. (2018). Designing and conducting mixed methods research (3rd ed.). SAGE Publications.
9. Dzimbiri, L. B. (2023). The role of ICT infrastructure in enhancing e-learning in higher education institutions in Malawi. International Journal of Education and Development using ICT, 19(2), 45-61.
10. Eaton, S. E. (2023). Beyond contract cheating: Toward a theory of academic integrity in the age of artificial intelligence. Frontiers in Education, 8, 1291425. https://doi.org/10.3389/feduc.2023.1291425
11. Eaton, S. E., & Turner, K. L. (2024). Exploring academic integrity in the age of artificial intelligence. International Journal for Educational Integrity, 20(1), 2. https://doi.org/10.1007/s40979-024-00144-1
12. Elkhatat, A. M., Elsaid, K., & Almeer, S. (2023). Evaluating the efficacy of AI content detection tools in differentiating between human and AI-generated text. International Journal for Educational Integrity, 19(1), 17. https://doi.org/10.1007/s40979-023-00140-5
13. Fyfe, P. (2023). How to cheat on your final paper: Assigning AI for student writing. AI & Society, 38(4), 1395-1405. https://doi.org/10.1007/s00146-022-01397-z
14. International Center for Academic Integrity. (2021). The fundamental values of academic integrity (3rd ed.). https://academicintegrity.org/resources/fundamental-values
15. Jowi, J. O., Obamba, M., & Sehoole, C. (2023). Quality assurance and the internationalization of African higher education. Higher Education Policy, 36(2), 234-252. https://doi.org/10.1057/s41307-022-00278-3
16. Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274. https://doi.org/10.1016/j.lindif.2023.102274
17. King, M. R., & ChatGPT. (2023). A conversation on artificial intelligence, chatbots, and plagiarism in higher education. Cellular and Molecular Bioengineering, 16(1), 1-2. https://doi.org/10.1007/s12195-022-00754-8
18. Lancaster, T. (2023). Artificial intelligence, contract cheating, and next-generation academic integrity threats. International Journal for Educational Integrity, 19(1), 12. https://doi.org/10.1007/s40979-023-00135-2
19. Liang, W., Yuksekgonul, M., Mao, Y., Wu, E., & Zou, J. (2023). GPT detectors are biased against non-native English writers. Patterns, 4(7), 100779. https://doi.org/10.1016/j.patter.2023.100779
20. Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (pp. 1-16). ACM. https://doi.org/10.1145/3313831.3376727
21. Makokera, C., & Nyoni, J. (2023). Bridging the digital divide in Zimbabwe: Challenges and prospects for educational technology adoption. International Journal of Education and Development using ICT, 19(1), 78-94.
22. McCabe, D. L., & Treviño, L. K. (1997). Individual and contextual influences on academic dishonesty: A multicampus investigation. Research in Higher Education, 38(3), 379-396. https://doi.org/10.1023/A:1024954224675
23. McCabe, D. L., Butterfield, K. D., & Treviño, L. K. (2012). Cheating in college: Why students do it and what educators can do about it. Johns Hopkins University Press.

24. Mollick, E. R., & Mollick, L. (2023). Assigning AI: Seven approaches for students, with prompts. The Wharton School Research Paper. https://doi.org/10.2139/ssrn.4475995
25. Morgan, D. L. (2014). Pragmatism as a paradigm for social research. Qualitative Inquiry, 20(8), 1045-1053. https://doi.org/10.1177/1077800413513733
26. Morris, E. J., & Carroll, J. (2016). Developing a sustainable holistic institutional approach: Dealing with realities 'on the ground' when implementing an academic integrity policy. In T. Bretag (Ed.), Handbook of academic integrity (pp. 449-462). Springer. https://doi.org/10.1007/978-981-287-098-8_22
27. Newton, P. M. (2024). How common is commercial contract cheating in higher education and is it increasing? A systematic review. Frontiers in Education, 9, 1165842. https://doi.org/10.3389/feduc.2024.1165842
28. Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2023). Conceptualizing AI literacy: An exploratory review. Computers and Education: Artificial Intelligence, 2, 100041. https://doi.org/10.1016/j.caeai.2021.100041
29. Perkins, M. (2023). Academic integrity considerations of AI large language models in the post-pandemic era: ChatGPT and beyond. Journal of University Teaching & Learning Practice, 20(2), 07. https://doi.org/10.53761/1.20.02.07
30. Postal and Telecommunications Regulatory Authority of Zimbabwe. (2024). Abridged postal and telecommunications sector performance report: Fourth quarter 2024. https://www.potraz.gov.zw
31. Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education? Journal of Applied Learning and Teaching, 6(1), 342-363. https://doi.org/10.37074/jalt.2023.6.1.9
32. Sok, S., & Heng, K. (2023). ChatGPT for education and research: A review of benefits and risks. Cambodia Journal of Educational Research, 3(1), 110-121.
33. Southworth, J., Migliaccio, K., Glover, J., Reed, D., McCarty, C., Brendemuhl, J., & Thomas, A. (2023). Developing a model for AI across the curriculum: Transforming the higher education landscape via innovation in AI literacy. Computers and Education: Artificial Intelligence, 4, 100127. https://doi.org/10.1016/j.caeai.2023.100127
34. Stoesz, B. M., & Eaton, S. E. (2020). Academic integrity policies of publicly funded universities in Western Canada. Educational Policy, 36(6), 1387-1409. https://doi.org/10.1177/0895904820983032
35. Sullivan, M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. Journal of Applied Learning and Teaching, 6(1), 31-40. https://doi.org/10.37074/jalt.2023.6.1.17
36. Teferra, D. (2023). The anatomy of African universities: Governance, leadership, and academic culture. African Books Collective.
37. Trust, T., Whalen, J., & Mouza, C. (2023). Editorial: ChatGPT: Challenges, opportunities, and implications for teacher education. Contemporary Issues in Technology and Teacher Education, 23(1), 1-23.
38. UNESCO. (2024). Global education monitoring report 2024: Artificial intelligence and education. UNESCO Publishing. https://doi.org/10.54676/AXQB4440
39. Weber-Wulff, D., Anohina-Naumeca, A., Bjelobaba, S., Foltýnek, T., Guerrero-Dib, J., Popoola, O., Šigut, P., & Waddington, L. (2023). Testing of detection tools for AI-generated text. International Journal for Educational Integrity, 19(1), 26. https://doi.org/10.1007/s40979-023-00146-z
40. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? International Journal of Educational Technology in Higher Education, 16(1), 39. https://doi.org/10.1186/s41239-019-0171-0

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue II February 2026

Supplementary Materials

Detailed Statistical Analyses and Additional Tables

Redefining Academic Integrity in the AI Era: Shifting from Detection to Development in Learning Institutions

Emmanuel Mapopota et al.

Variable	M	SD	Min	Max
AI Usage Frequency	3.64	1.08	1.00	5.00
AI Literacy Score	2.87	0.76	1.13	4.88
Policy Clarity Score	2.34	0.93	1.00	5.00
Judgment Quality Score	3.21	0.87	1.20	5.00
Confusion Score	3.68	0.89	1.40	5.00
Academic Integrity Attitudes	4.12	0.72	1.75	5.00

Note. All scales measured on 5-point Likert scales. Higher scores on AI Literacy, Judgment Quality, and Academic Integrity Attitudes indicate more positive outcomes. Higher Confusion Scores indicate greater confusion (reverse-coded certainty ratings).

Table S2 Chi-Square Analysis: Institutional Policy Type and Student AI Usage Patterns

Policy Type	Never Used	Occasional	Regular	Total
Prohibition	77 (29%)	70 (26%)	120 (45%)	267
Permissive/Disclosure	14 (24%)	18 (31%)	26 (45%)	58
No Formal Policy	13 (22%)	16 (27%)	31 (52%)	60

Note. $\chi^2 = 3.12$, $df = 4$, $p = .537$ *(not significant). Percentages in parentheses represent row percentages. Despite prohibition policies, 71% of students at prohibition institutions reported using AI (occasional + regular users).*

Table S3 One-Way ANOVA: AI Usage Frequency Across Academic Levels

Academic Level	n	M	SD	95% CI
First Year	89	3.21	1.14	[2.97, 3.45]
Second Year	92	3.45	1.08	[3.23, 3.67]
Third Year	86	3.67	0.97	[3.46, 3.88]
Fourth Year	78	3.89	0.91	[3.68, 4.10]
Postgraduate	68	4.12	0.89	[3.90, 4.34]

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue II February 2026

ANOVA Results:

$F(4, 351) = 8.93$, $p < .001$, $\eta^2 = .071$ (medium effect size). Post-hoc Tukey comparisons revealed that postgraduate students used AI significantly more frequently than first-year ($p < .001$, $d = 0.91$), second-year ($p = .012$, $d = 0.68$), and third-year students ($p = .037$, $d = 0.49$). Fourth-year students did not differ significantly from postgraduate students ($p = .342$).

Table S6 Pilot Implementation Outcomes: Pre-Post Comparisons (N=156)

Measure	**Pre M (SD)**	**Post M (SD)**	**t**	**p**	**d**
AI Literacy Score	2.76 (0.82)	4.21 (0.64)	15.34	<.001	1.96
Critical Evaluation Skills	2.98 (0.91)	4.21 (0.73)	11.87	<.001	1.48
Judgment Quality	3.14 (0.88)	4.32 (0.71)	10.23	<.001	1.47
Policy Clarity	2.43 (0.96)	4.47 (0.68)	18.76	<.001	2.43
Confidence in Ethical Use	2.67 (1.02)	4.38 (0.74)	14.21	<.001	1.95

Note. All measures on 5-point scales. Paired samples t-tests, df = 155. All effect sizes (Cohen's d) indicate large effects ($d > 0.80$). Percentage improvements: AI Literacy +53%, Critical Evaluation Skills +41%, Judgment Quality +38%, Policy Clarity +84%, Confidence +64%.

Table S7 Comparison of Pilot and Control Groups at Semester End

Outcome Measure	**Pilot M (SD)**	**Control M (SD)**	**t**	**p**	**d**
Misconduct Incidents	0.08 (0.27)	0.23 (0.43)	-3.47	<.001	0.43
Course Performance (GPA)	3.68 (0.51)	3.42 (0.58)	3.28	.001	0.48
AI Literacy	4.21 (0.64)	2.81 (0.79)	13.87	<.001	1.94
Critical Thinking Skills	4.21 (0.73)	3.54 (0.82)	6.12	<.001	0.88

Note. Pilot n=156, Control n=143. Independent samples t-tests. Misconduct incidents measured as rate per student over semester. All other measures on 5-point scales. The pilot group showed 65% reduction in misconduct incidents compared to control (effect size $d = 0.43$). Faculty confidence in assessing AI-mediated work increased 71% in pilot courses (data not shown in table).

Additional Statistical Notes

All statistical analyses were conducted using IBM SPSS Statistics Version 28.0. Assumptions for parametric tests were verified prior to analysis. Normality was assessed using Kolmogorov-Smirnov tests and visual inspection of Q-Q plots; all key variables demonstrated acceptable normality ($p > .05$ on K-S tests or minor deviations within acceptable limits). Homogeneity of variance was tested using Levene's test for independent samples comparisons and Mauchly's test of sphericity for repeated measures analyses. Where assumptions were violated, appropriate corrections (Welch's correction for heterogeneous variances, Greenhouse-Geisser correction for sphericity violations) were applied. Missing data patterns were examined and found to be missing completely at random (Little's MCAR test: $\chi^2 = 127.43$, df = 134, $p = .634$), justifying listwise deletion for primary analyses. Effect sizes are reported using established conventions: Cohen's d for t-tests (small = 0.20, medium = 0.50, large = 0.80), η^2 for ANOVA (small = 0.01, medium = 0.06, large = 0.14), and Cramér's V for chi-square (varies by df).

Developmental Integrity Framework

Implementation Guide for Higher Education Institutions

A Practical Framework for Academic Integrity in the AI Era

Based on empirical research from Zimbabwean universities demonstrating 43% reduction in academic misconduct and 56% improvement in critical evaluation skills

Executive Summary

The Developmental Integrity Framework (DIF) represents a paradigm shift in how educational institutions respond to artificial intelligence integration. Rather than attempting to detect and prohibit AI use an approach our research shows to be both ineffective and counterproductiveDIF reconceptualizes academic integrity as a developmental competency focused on responsible AI engagement.

This implementation guide provides practical, evidence-based guidance for institutions seeking to adopt DIF. It is specifically designed for resource-constrained environments but principles apply broadly across institutional contexts. The guide draws from pilot implementation across three institutions involving 156 students and 12 faculty members, demonstrating measurable improvements in both integrity outcomes and learning effectiveness.

Key Framework Principles

1. AI literacy as core educational outcome: Students must develop technical understanding, critical evaluation skills, and ethical judgment regarding AI use.

2. Transparency over prohibition: Clear disclosure requirements and guidance rather than blanket bans.

3. Assessment transformation: Redesign evaluation to maintain validity in AI-accessible environments.

4. Competency-based approach: Focus on what students can do with AI rather than preventing AI use.

Implementation Phases

Successful DIF implementation requires systematic progression through four phases. Institutions should anticipate 6-12 months for full implementation, with early positive outcomes visible within the first semester.

Phase 1: Foundation Building (Months 1-2)

Leadership Commitment

Secure commitment from senior leadership including Vice-Chancellor/President, Provost/Academic Vice-President, and Deans. DIF implementation requires sustained institutional support and cannot succeed as merely departmental initiative. Leadership must publicly endorse the framework, allocate necessary resources, and commit to multi-year implementation timeline.

Stakeholder Engagement

Form implementation committee representing diverse stakeholders: faculty from multiple disciplines, academic integrity officers, students, IT professionals, and library staff. Committee responsibilities include adapting framework to institutional context, developing policies and guidelines, coordinating faculty development, and monitoring implementation progress.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue II February 2026

Current State Assessment

Conduct systematic assessment of current situation including policy audit (review all academic integrity policies for AI-relevance), student survey (assess current AI usage patterns, confusion levels, and literacy needs), faculty survey (evaluate AI literacy, pedagogical concerns, and development needs), and technology audit (assess existing infrastructure and tools available). This baseline data will enable measurement of implementation effectiveness.

Phase 2: Policy and Curriculum Development (Months 2-4)

Framework Policy Development

Develop institutional framework policy establishing core principles rather than specific rules. Policy should articulate values (transparency, competency development, responsible engagement), define AI literacy learning outcomes, establish disclosure requirements, provide assessment guidelines, and delegate implementation details to departments and courses. Avoid prohibition-based language; instead emphasize guidance and development.

AI Literacy Curriculum Design

Develop AI literacy curriculum including foundational module (2-3 hours) covering how AI systems work, capabilities and limitations, common AI tools and applications, and ethical considerations. This should be delivered to all incoming students during orientation or first semester. Discipline-specific modules (1-2 hours each) should address AI applications and integrity considerations specific to different fields. Advanced modules for upper-level students should cover sophisticated AI literacy topics including bias detection, prompt engineering, and professional AI integration.

Faculty Development Program

Design comprehensive faculty development program including AI literacy workshops (technical understanding and hands-on experience with AI tools), pedagogical workshops (assessment redesign, AI-integrated instruction, policy implementation), discipline-specific sessions (contextualizing AI integration for different fields), and ongoing support mechanisms (peer learning communities, consultation services, resource repositories). Our research shows faculty confidence increases 71% with structured development programs.

Phase 3: Pilot Implementation (Months 4-8)

Begin with pilot implementation in 3-5 courses before full-scale rollout. Pilot courses should represent diverse disciplines, academic levels, and class sizes to test framework adaptability.

Pilot Course Selection Criteria

• Enthusiastic faculty willing to invest significant redesign effort

• Courses with significant writing or analytical components where AI integration is relevant

• Mix of course levels (introductory, intermediate, advanced) to test scalability

• Varied class sizes to assess effectiveness across different teaching contexts

Pilot Course Components

Explicit AI literacy instruction:

Dedicate 2-3 class sessions to AI literacy covering how relevant AI tools work, their strengths and limitations in the course context, appropriate versus inappropriate use for course activities, how to critically evaluate AI outputs, and proper attribution and disclosure practices. Include hands-on activities where students use AI tools under guidance to develop practical competency.

Clear task-specific guidance:

For every assignment, provide explicit guidance on AI use including whether AI tools may be used, if so which tasks AI can assist with and which must be done independently, how to disclose AI use, and what constitutes inappropriate AI reliance. Avoid ambiguity; students report that unclear expectations are primary source of confusion.

Transformed assessments:

Redesign major assessments to maintain validity in AI-accessible environments. Effective approaches include process portfolios requiring documentation of thinking process, synthesis assignments requiring integration of experiential learning with research, contextualized applications requiring domain-specific expertise, metacognitive components requiring reflection on learning and AI use, and multi-stage projects with formative feedback at each stage.

Data Collection and Monitoring

Collect systematic data throughout pilot including pre-post surveys of student AI literacy and attitudes, academic integrity incident tracking, student performance outcomes, faculty experience and time investment logs, and qualitative feedback from students and faculty. This evidence will inform full-scale implementation and demonstrate effectiveness to stakeholders.

Phase 4: Full Implementation and Continuous Improvement (Months 8+)

After successful pilot demonstration, proceed with institutional scaling while maintaining support structures and continuous refinement processes.

Staged Rollout Strategy

Implement framework across institution in stages rather than all at once. Recommended sequence: Semester 1 - all first-year courses and required general education courses (establishes common AI literacy foundation); Semester 2 - add second and third-year courses in core majors; Semester 3 - extend to advanced courses and electives; Semester 4 - complete implementation including specialized programs. Staged approach allows support resources to scale with implementation and enables learning from early adopters to inform later implementation.

Practical Implementation Tools

Sample Assignment Language

Template 1: AI Permitted with Disclosure

"For this assignment, you may use AI tools to assist with brainstorming, outlining, and initial draft generation. However, all final analysis, argument development, and writing must be your own work. You must disclose any AI use in a brief statement (1-2 paragraphs) explaining which AI tools you used, for which tasks, and how you verified and refined the AI outputs. This statement should be included as an appendix to your submission. Undisclosed AI use or submitting AI-generated content as your own work constitutes academic misconduct."

Template 2: AI Not Permitted

"This assignment assesses your ability to [specific learning outcome]. To demonstrate this competency authentically, you may not use AI tools for any aspect of this assignment. This restriction is pedagogically necessary because [explanation of why independent work is required]. Use of AI tools for this assignment, even

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue II February 2026

with disclosure, will be treated as academic misconduct. If you have questions about appropriate resources or need support completing the assignment, please consult with me during office hours."

Assessment Design Examples

Example 1: Process Portfolio Assignment

Rather than traditional research paper, require students to submit portfolio documenting their research and writing process including initial topic exploration notes, annotated bibliography with critical evaluation of sources, outline with explanation of organizational choices, rough draft with instructor feedback incorporated, final draft, and reflection on learning process including any AI tool use. This approach makes authentic student work visible and develops metacognitive skills while accepting that students may use AI for certain process elements.

Example 2: Contextualized Application Project

Require students to apply course concepts to specific local context requiring direct observation, data collection, or stakeholder engagement. For instance, in business course, analyze local company's marketing strategy through interviews with managers and customers rather than purely desk research. For education course, design lesson plan based on observation of specific classroom and student needs. This approach requires domain knowledge and contextual understanding that AI cannot provide, maintaining assessment validity while acknowledging AI can assist with certain components.

Resource Requirements and Budget Considerations

DIF implementation requires investment but potentially costs less than detection-based approaches requiring expensive software licenses and extensive investigation processes. Key resource needs include:

Personnel Time

• Implementation coordinator: 0.5 FTE for first year, 0.25 FTE ongoing

• Faculty development facilitator: 0.25 FTE ongoing

• Faculty course redesign time: Approximately 20 hours per course initial redesign, 5 hours per semester ongoing adjustment

Technology and Materials

Framework implementation does not require expensive technology purchases. Most AI tools students will use are freely available. Recommended investments include learning management system with assignment submission and feedback capabilities (most institutions already have this), video recording equipment for creating AI literacy instructional materials, and digital repository for sharing resources and exemplars across faculty. Budget $2,000-5,000 for initial development, minimal ongoing costs.

Common Implementation Challenges and Solutions

Faculty resistance: Some faculty members resistant to change, prefer prohibition-based approaches, or fear that framework legitimizes cheating.	Share pilot data demonstrating effectiveness. Provide extensive faculty development and peer support. Allow voluntary early adoption rather than mandating immediate change. Frame as supporting faculty goals rather than imposing external agenda.
Large class sizes: Personalized feedback and formative assessment difficult with 100+	Employ peer review and collaborative learning approaches. Use AI literacy instruction in large group format with smaller discussion sections. Design assessments requiring process

student classes common in resource-constrained environments.	documentation that provides formative feedback without requiring individual instructor review of every element.
Rapid AI evolution: AI capabilities change faster than policies and curricula can be updated, potentially rendering framework obsolete.	Focus framework on principles rather than specific technologies. Establish regular review cycles (annually minimum). Build faculty learning communities that share emerging practices and challenges. Position continuous adaptation as framework feature rather than bug.
Unequal AI access: Digital divide means some students have better access to AI tools than others, potentially creating new inequities.	Provide institutional access to AI tools through computer labs or library resources. Design assignments acknowledging access constraints. Focus AI literacy instruction on free tools with offline capabilities where possible. Monitor and address emerging equity concerns.

Success Indicators and Evaluation

Monitor implementation effectiveness through multiple indicators across different timeframes:

Short-term indicators (Within First Semester)

• Reduction in student confusion about AI use policies (target: 50% reduction in confusion scores)

• Increase in AI literacy scores (target: 40-50% improvement from baseline)

• Faculty confidence in managing AI in courses (target: 60-70% increase)

• Student engagement with framework resources (participation rates in AI literacy sessions)

Medium-term indicators (Within First Year)

• Reduction in academic misconduct cases (target: 40-50% reduction)

• Improvement in critical thinking and evaluation skills (assessed through assignments)

• Faculty adoption of transformed assessment practices (percentage of courses implementing framework principles)

• Stakeholder satisfaction (surveys of students, faculty, administrators)

Long-term indicators (Beyond First Year)

• Sustained improvements in learning outcomes

• Graduate and employer feedback on AI competencies

• Institutional culture shift toward development-focused academic integrity

• Framework sustainability and continuous improvement evidence

Conclusion

The Developmental Integrity Framework represents more than a policy change—it reflects fundamental reconceptualization of academic integrity in an AI-augmented world. Implementation requires sustained commitment, significant faculty development investment, and willingness to fundamentally transform assessment practices. However, our research demonstrates that institutions making this investment can simultaneously reduce academic integrity violations, improve learning outcomes, and develop professionally relevant AI literacy competencies.

This guide provides roadmap for implementation, but successful adoption requires adaptation to local context, continuous refinement based on experience, and sustained institutional commitment. The alternative—attempting to maintain pre-AI educational practices through detection and prohibition—is both unsustainable and pedagogically limiting. The future of academic integrity lies in preparing students not to work without AI, but to work wisely with it.

Document Structure

This comprehensive document contains three integrated parts:

- • Part I: Main Research Manuscript
- • Part II: Supplementary Materials (Detailed SPSS Statistical Analyses)
- • Part III: Implementation Guide (Practical Framework Application)

Part I: Main Manuscript

Part Ii: Supplementary Materials

Detailed Statistical Analyses and Additional Tables

Part Iii: Implementation Guide

Practical Framework for Institutional Adoption

Redefining Academic Integrity in the AI Era: Shifting from Detection to Development in Learning Institutions

Emmanuel Mapopota[1], Phil Rangwani[2], Everson R. Zhou[3], Perpetua Govha[4],

Victor D. Gwai[5], Eager Mwerenga[6], Olsvado Tambwali[7], Bridget Maumbe[8] James Sengu[9]

[1]*Department of Educational Psychology, University of Zimbabwe*

[2]*Faculty of Education, Great Zimbabwe University*

[3]*Centre for Academic Integrity, Midlands State University*

[4]-[8]*Various Affiliated Institutions*