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Article

Managing Academic Integrity and Character Formation in AI-Enabled Education: A NEP 2020–Aligned Framework

Rajbala Gauttam[1], Dipika Jain[2], Vibhor Sharma[3], Nikita[4], Khusboo Gauttam[5], Nitin Jain[6]

[1]Department of Business Economics, Dr. Bhim Rao Ambedkar Vollege. University of Delhi. Rajbala.gauttam@bramb.du.ac.in
[2]Department of Computer Science Engineering & Technology, Amity School of Engineering & Technology (ASET), Amity University, Noida, Uttar Pradesh, India
dipikajain12.24@gmail.com
[3]Department of Information Technology, Maharaja Agrasen Institute of Technology, Delhi. vibhorsharma@mait.ac.in
[4]Department of Computer Science and Engineering (AI&ML), Greater Noida Institute of Technology, Greater Noida, India. Nikita.verma0@gmail.com
[5]Department of Psychology, Dr. Bhim Rao Ambedkar College University of Delhi, India. Kgauttam@psychology.du.ac.in
[6]School of Computer Science and Engineering, Bennett University, Greater Noida, India. garg.nitin007@gmail.com
*Corresponding author – Nitin Jain (garg.nitin007@gmail.com)

Abstract: The broad adoption and adoption of generative AI (GenAI) in higher education is reshaping how education is delivered, assessed, and experienced, and is posing novel challenges for academic integrity, IP rights, and character development in university education. Within this study, a structured integrative literature review (ILR) has been conducted according to the PRISMA framework with the support of a primary literature comprising 36 empirical, conceptual, review, and policy texts on AI in HE, along with 15 foundational methodological and theoretical texts. A hybrid inductive–deductive thematic-synthesis approach is used to identify the recurring integrity risks, pedagogical responses and governance mechanisms, and inner-development requirements, followed by mapping the evidence with the four research questions and corresponding principles of India's National Education Policy (NEP) 2020. The synthesis indicates that responsible AI-enabled higher education requires coordinated attention to responsible AI use, assessment redesign, AI literacy, ethical and inner development, institutional governance, and continuous monitoring. These findings are synthesized in the six dimensions of the proposed Samanvaya Framework which are interconnected and involve individual development, pedagogical transformation and institutional governance. The framework is evidence-informed and policy-aligned, with NEP 2020 serving as the current policy-mapping case; cross-jurisdictional transferability and empirical effectiveness require further validation.
Keywords: Generative artificial intelligence, academic integrity, higher education, character formation, AI literacy, assessment redesign, institutional governance, NEP 2020, thematic synthesis, Samanvaya Framework

1. INTRODUCTION

A. Background: AI-Enabled Transformation of Higher Education

The increasing presence of artificial intelligence (AI) in higher education involves the use of generative systems that are able to generate text, code, explanations, summaries, images and other academic content. AI tools like ChatGPT have become widely adopted, enabling new possibilities for how students and faculty collaborate in the classroom, for learning, for evaluation, and for academic tasks. These technologies may enable personalisation and customisation, immediate feedback, producing of content, brainstorming, language support, and access to learning materials, and can help to alleviate some of the routine tasks involved in teaching and administration. The learning value of generative AI goes beyond being just another digital learning tool, transforming how knowledge is created,


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shared, assessed, and credited in educational settings. This shift helps to propel a new era of possibilities and institutional challenges (Chan & Hu, 2023; Lim et al., 2023; Williams, 2024). In contrast to a traditional education technology, which is more of a conduit for access to information or the mechanisms by which information is delivered to students, generative AI can generate outputs that closely mirror work done independently. The lines can thus become blurred between assistance and substitution. A student can use AI to explain a concept, enhance language, brainstorm or provide formative feedback, but it can also be used to write lengthy sections of an assignment without them engaging in intellectual work. Such doubt does not only have a negative impact on the academic integrity procedures, but also on the notion of originality, authorship, learning and the evidence value of traditional assessment. (Cotton et al., 2024; Draxler et al., 2024; Kofinas et al., 2025; Sharma, 2026)

B. Academic-Integrity and Educational Challenges

With the advent of generative AI, longstanding worries about academic honesty are getting worse, and new questions are being created. The use of AI-generated information without proper acknowledgment, suggestions of possible AI-assisted content, lack of author identity, content plagiarism, and reliance on AI output can have a detrimental impact on the connection between the original writing and the learner's own ideas and contributions. Plagiarism, in this case, is not the problem. Disclosed use without identifiable source may raise institutional expectations about authorship, intellectual ownership and accurate representation of academic work, even if generated text is not distinguishable from the source text. (Eke, 2023; Gruenhagen et al., 2024; Bittle & El-Gayar, 2025; Ying, 2026) These concerns are coupled to constraints in traditional assessment and response to detection. Reliable assessments to document the reasoning, drafting, decision making, and learning processes to which they are linked may be somewhat limited in assessments that largely involve the assessment of polished final works. Simultaneously, AI-detection tools can't, on their own,prove if a specific student is using AI in a proper or improper way or within the requirements of the institution. A blanket ban, or detection, response alone might address the apparent impact of the use of AI without taking into account the underlying pedagogical context that gives rise to healthy or unhelpful deployments of AI. (Kizilcec et al., 2024; Revell et al., 2024; Xia et al., 2024; Ahangama, 2026) The challenge is thus not just prevention of misconduct, but an even more wide-ranging one. It is also the responsibility of higher education institutions to maintain the possibility of students engaging in critical thinking, creativity, independent thinking, consideration, and independent intellectual property, as well as the understanding that AI will continue to be an integral piece of the education puzzle. This involves analysing assessment practices, the learning potential, faculty readiness, institutional governance and moral aspects of AI supported academic work. (Peters & Angelov, 2025; Kangwa et al., 2025)

C. Beyond Compliance: Character and Human Development

Academic Integrity is a behavioral decision as well as rules of the institution. Policies can outline what is and isn't acceptable in relation to AI, and monitoring mechanisms can detect potential breaches, but these do not fully account for why people are able to comply with, challenge, or go beyond the expectations of the institution. The ability to use AI responsibly also relies on character attributes like self-regulation, ethical awareness, responsibility, reflection, honesty and understanding of the impact of academic decisions. (Rest, 1986; Bandura et al., 1996; Ryan & Deci, 2000; Schön, 1983) This internal dimension is more relevant when the activities supported by AI are not clearly observable. Students who understand the distinction between legitimate AI assistance and substitution of intellectual effort are more likely to engage with AI in ways consistent with institutional expectations and learning goals. Conversely, AI may undermine learning when it is used primarily to avoid substantive intellectual engagement. Likewise, teachers need to understand not just the technicalities of AI tools but also to be able to decide when they help to enhance learning and when they detract from it. The responsibility for character formation and inner development is thus a complementary way of looking at outer governance. The goal is to look at observable dimensions of education – self-awareness, self-control, ethical discernment, responsibility, reflective learning, compassion and integrity – that could help with responsible behaviors, rather than considering spirituality or character as quantifiable alternative to institutional controls. This view is in line with the 'big picture' of school education that

holds that success in school is related to moral growth, self-discipline, human values and responsible social involvement. (Holmes et al., 2022; Mouta et al., 2024)

D. Institutional and Policy Context

This implies a need for coordination at individual, pedagogical, and institutional levels for effective integration of AI. A new AI literacy is needed that involves critical assessment of AI-generated outputs, identification of limitations and manufactured information, responsible disclosure and sensible usage. Faculty need to be prepared to restructure the assessment process, set guidelines for the use of AI, and assess the learning process, not just the results. Accountable use, privacy, accountability, stakeholder accountability, monitoring and ongoing policy development need to be covered by governance mechanisms in institutions. (Chan, 2023; Mack & Byanjankar, 2025; Thaldar et al., 2025; Qian, 2026; Crompton et al., 2026) It is a multi-dimensional need which has gained specific pertinence in the background of India's National Education Policy (NEP) 2020. The policy focuses on issues of holistic growth, critical and creative thinking, ethics, experiential learning, digital literacy, self-discipline, human values, and good citizenship. These principles offer a more foundational level of understanding about how education can be used to reflect on AI as a learning, values, institutional, and human development concern, rather than just a technology-management one. The challenge is thus to keep the AI practices emerging in tandem with these educational goals without making NEP 2020 a checklist of policy requirements. Government of India (GoI), Ministry of Education (MoE), 2020; Miao et al., 2024)

E. Research Gap

There is ample though limited evidence from existing scholarship in all these areas. Studies on generative AI have explored issues of academic integrity, authorship, plagiarism, AI-generated information, and the ineffectiveness of AI detection. There is an enquiry body of work around the redesign of assessments, authentic learning, AI literacy, critical thinking, and faculty preparedness, among other topics. Additional research and policy statements focus on institutional AI governance, privacy, accountability, and responsible use of AI. An additional perspective on internal qualities related to responsible academic behaviour comes from literature around character education, ethical reasoning, self-regulation and reflective learning. (Zawacki-Richter et al., 2019; Ng et al., 2021; Chaudhry & Kazim, 2022; Ahsan et al., 2022) Such strands, however, tend to be dealt with in isolation from one another and as intervention areas. Assessment design can be assessed without the need to consider academic integrity, and the governance of academic integrity is possible without outcomes for AI literacy and without focus on character formation, and character formation can be peripheral to discussions on generative AI. There is a lack of synthesis relating to how external factors like policy, measurement, training and monitoring can work alongside internal attributes like ethical sensibility, self-control, accountability and introspection. Also, there is scant research on how to translate this integrated evidence base into a framework explicitly linking educational principles of the NEP 2020. (Dieterle et al., 2022; Salhab & Aboushi, 2025; Hackl et al., 2026) This gap is thus a motivation for the present review. Instead of simply describing the potential dangers of generative AI, this research delves into how the documented dangers, pedagogical reactions and governance frameworks, and developmental needs can be integrated into a cohesive institutional framework. The review then moves from identifying challenges to educational and institutional responses, and lastly to aligning the requirements in a NEP 2020-based framework. The novelty is not, however, in proposing AI literacy, assessment reform, governance, monitoring and value education as stand-alone interventions, but in embedding these mechanisms within an internal developmental quality system in an institutional framework that is compatible with the NEP 2020. While NEP 2020 applies as a national-policy in the present study, the Samanvaya architecture is designed with a policy-mappable, not policy-exclusive approach. That evidence-to-policy mapping process can, in principle, be repeated against other national or institutional policy contexts; this transferability will need to be cross-juridically validated in the future.

F. Research Questions

The review addresses four research questions:

1. **RQ1:** What integrity, ethical, and learning challenges arise from AI use in higher education?
2. **RQ2:** Which pedagogical and assessment practices support originality, critical thinking, self-regulation, and character formation?
3. **RQ3:** Which governance and technology-management mechanisms support responsible institutional AI adoption?
4. **RQ4:** How can these requirements be aligned with NEP 2020 within an integrated framework?

These questions establish a progression from problem identification to pedagogical and institutional response and, finally, to policy-aligned integration. The corresponding methodology and evidence-mapping procedure are described in Section II.

G. Contributions

This research has five related contributions. First, it offers a structured integrative synthesis of 36 primary sources ranging from empirical, conceptual, review and policy evidence related to AI tools in academic integrity and character formation. Second, it presents an evidence-mapping method laying the groundwork for a discussion of common patterns across academic honesty, pedagogy, AI literacy, governance, and inner development. Third, it integrates these evidence-derived themes into the six-dimensional Samanvaya Framework and maps them to relevant NEP 2020 principles. Fourth, it operationalizes the framework through dimensions, stakeholder roles, illustrative actions, indicators, and intended outcomes for institutional implementation. Fifth, it formulates conceptual propositions that can guide subsequent empirical testing of the framework and its proposed relationships. It does not present itself as an empirically proven intervention but rather as a synthesis of the findings from the literature and the policy goals. It aims to offer a unified framework within which higher education institutions can think about responsible use of AI, transformation of assessment, ethics, institutional governance, and constant evaluation in the context of education, and in a shared language.

2. RESEARCH METHODOLOGY

A. Review Design

This study employs a PRISMA 2020-informed integrative literature review combining structured evidence identification, critical appraisal, and thematic synthesis. The integrative design was selected to accommodate heterogeneous empirical, conceptual, review, policy, and institutional evidence relevant to AI-enabled higher education (Page et al., 2021). An integrative review was chosen due to the wide range of evidence bases, education, technology, ethics, governance and policy, as well as the different types of studies and sources. A more narrow focus on intervention studies would exclude policy documents, institutional guidance, and conceptual work integral to this growing body of work. This integrative approach allows synthesis of these types of evidence in a common thematic framework. Because this research is not interested in estimating the common intervention effect, a statistical meta-analysis is not performed. The underlying studies vary too much in their study design, sample size and outcome measurements to be combined in a single effect estimate, and so would be inappropriate in this instance to force them into pooling and misrepresent the heterogeneity which the review is designed to present. To identify the challenges and pedagogical responses as well as ethical demands and institutional mechanisms that will shape the proposed framework, thematic synthesis is employed instead. This option preserves the "context sensitivity" of the review at the same time as it gives a structured and comparable account of the literature across sources. The review procedure was engineered to answer the four research questions that are outlined in Section I.F. The search blocks, extraction fields, thematic synthesis and evidence-mapping approach ensure traceability between the research questions and the evidence streams.

B. Search Strategy and Eligibility Criteria

The review window was defined from January 2020 through July 2026. The year 2020 was selected because it corresponds with the introduction of NEP 2020 and captures the period during which AI-enabled education and generative AI became increasingly prominent in higher education. Restricting the search to this window keeps the review focused on the period in which both the policy instrument and the technology under examination were active, while foundational pre-2020 sources were used only for theoretical or methodological grounding and were not counted as included review studies unless they met the review protocol.

The primary databases were multidisciplinary (Scopus), technical (IEEE Xplore and Web of Science), and education (ERIC). As a supplementary coverage check to determine if any important literature or terminology was omitted with the database approach, Google Scholar and backward and forward citation searching were used, but did not generate a separately enumerated record set. Official policy and institutional documents were also consulted as far as they were directly relevant to governance or NEP 2020 interpretation. Documents that fulfilled the eligibility criteria and were listed in Supplementary Table 1A were considered as primary-corpus documents while documents used only for contextual interpretation were not counted as included review studies. The PRISMA flow includes the screening process that was consolidated from the database, and the source-level mapping identifies the policy and institutional evidence included.

Table I reports the database-specific Boolean strategies, search fields, and temporal and language limits used to retrieve the evidence base.

TABLE I. DATABASE-SPECIFIC SEARCH STRATEGIES

Database	Search strategy	Fields searched	Date range	Language
Scopus	TITLE-ABS-KEY(("generative AI" OR ChatGPT OR "artificial intelligence") AND ("higher education" OR universit*) AND ("academic integrity" OR plagiarism OR authorship OR misconduct))	Title, abstract, keywords	Jan. 2020–July 2026	English
Web of Science	TS=(("generative AI" OR ChatGPT OR "artificial intelligence") AND ("higher education" OR universit*) AND ("academic integrity" OR plagiarism OR authorship OR misconduct))	Topic	Jan. 2020–July 2026	English
IEEE Xplore	("generative AI" OR ChatGPT OR "artificial intelligence") AND ("higher education" OR university) AND ("academic integrity" OR plagiarism OR authorship OR misconduct)	Metadata/full-text search fields available in database	Jan. 2020–July 2026	English
ERIC	("generative AI" OR ChatGPT OR "artificial intelligence") AND ("higher education" OR university) AND ("academic integrity" OR plagiarism OR authorship OR misconduct)	ERIC search fields	Jan. 2020–July 2026	English

The principal database retrieval used a unified Boolean core anchored in generative AI, higher education, and academic-integrity terminology. This strategy was directly responsive to RQ1, while RQ2-RQ4 concepts such as assessment redesign, AI literacy, governance, ethics, and inner development were captured during eligibility screening, evidence extraction, backward/forward citation tracking, and consideration of eligible policy or institutional

sources. Because the core database string emphasized integrity terminology, literature expressed primarily through assessment, governance, or inner-development vocabulary may have been under-retrieved; this is treated as a search-scope limitation rather than evidence that those areas are intrinsically less developed.

Database-specific field tags, truncation symbols, phrase-search rules, and Boolean syntax were adapted for each database. Searches were conducted across titles, abstracts, and keywords. Backward and forward citation tracking was used as a supplementary coverage-check procedure to identify whether important concepts or terminology had been missed by the database strategy; it did not generate a separately added record set in the PRISMA screening flow. Citation tracking was included because a keyword-based search alone can miss relevant sources that use different terminology for closely related concepts, and tracing the reference lists of clearly relevant sources and subsequent citations provided an additional check on the recall and conceptual coverage of the search strategy.

Formal policy and institutional documents were retained within the 36-source primary corpus only when they satisfied the review's relevance criteria for RQ3 or RQ4. Documents used solely for contextual interpretation were not counted as included review studies. Accordingly, the NEP 2020, UNESCO, Russell Group, and TEQSA sources listed in Supplementary Table 1A are treated as primary-corpus evidence, whereas the 15 foundational methodological standards and classical theoretical models are kept outside the primary corpus.

A source was included when it:

- contained a meaningful AI, generative-AI, or AI-enabled education component;
- addressed higher education or had direct institutional relevance to higher education; and
- contributed evidence related to academic integrity, assessment, originality, critical thinking, AI literacy, governance, value education, character formation, or inner development.

A source was excluded when it:

- was unrelated to education;
- reported technical AI development without educational implications;
- focused exclusively on school education without transferable higher-education relevance;
- duplicated another record;
- was unavailable in English; or
- lacked usable empirical, conceptual, review, policy, or institutional evidence.

These criteria were set to admit the widest range of relevant evidence types while still excluding material with no bearing on the review's higher-education focus. The exclusion of purely technical AI-development literature and the exclusion of school-level material without transferable relevance were both included because these are the two categories most likely to appear in database results while contributing little to the specific questions the review addresses.

C. Pilot Screening and Study Selection

The study-selection process included the following stages: Identification, Duplicate removal, Title and abstract screening, Full-text assessment, and Final inclusion, all of which were guided by PRISMA. A pilot set of 50 records was selected from a range of databases and search blocks and assessed independently by two reviewers prior to formal screening. Relevant, irrelevant and borderline records were included in the set to calibrate eligibility decisions. The screening guidance was clarified and differences discussed prior to formal screening, which minimised the inconsistent interpretation of borderline cases. After calibration, both reviewers separately screened the titles, abstracts and possibly eligible full texts. Records that were rated as eligible or uncertain by either rater were advanced to full-text assessment to ensure recall. Any disagreements were discussed and, when needed, adjudicated by a third reviewer.

One exclusion reason was reported for each full-text exclusion. A PRISMA 2020 flow diagram (Fig. 1) summarizes the study-selection process. A total of 1,864 records were identified through database searching. Of the 1,318 records that were title and abstract screened, 1,122 records were excluded. 196 reports were sought for full text, of which six reports were not retrieved. Of the remaining 190 full-text reports, 154 were excluded based on the pre-defined criteria. A final primary corpus of 36 sources was used in the integrative synthesis, with an additional 15 sources kept separately as methodological and theoretical foundations.

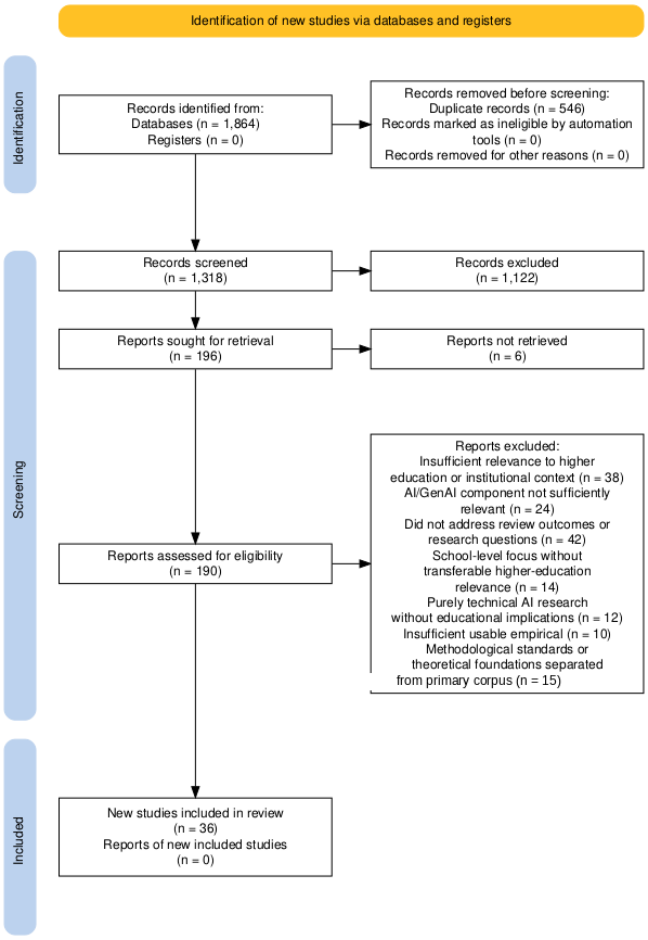


Fig. 1. PRISMA 2020 flow diagram

D. Data Extraction and Critical Appraisal

A set Bibliographic information, evidence type, context, design, AI application, integrity concern, learning or assessment outcome, institutional implication, technology-management requirement, NEP 2020 relevance, inner-development construct, and reported limitation were recorded on a standardized extraction form. Fixed fields facilitated comparison between evidence types and traceability to the thematic synthesis. The form was tested on 5-10 diverse sources and adjusted prior to full extraction. The review architecture consists of 51 documents in total, with a primary evidence corpus of 36 documents aligned with the Samanvaya dimensions and a foundational grounding corpus of 15 documents of known methodological standards and theoretical models.

The main evidence collection was divided into three streams of analysis:

1. Empirical evidence, which is used to identify observed behaviours, perceptions, risks, interventions and educational outcomes;

2. Conceptual and review evidence, which is used to find definitions, theoretical relationships, and recurring arguments; and

3. Policy and institutional evidence, to identify governance expectations, implementation mechanisms and NEP 2020 alignment.

This three-stream structure reflects the different kinds of claim that each evidence type can support. Empirical sources speak most directly to what is happening in practice; conceptual and review sources speak to how the field defines and relates its central constructs; and policy and institutional sources speak to what is formally expected of institutions. Keeping these streams distinct during extraction, while still allowing them to be brought together during thematic synthesis, was intended to prevent conceptual claims from being read as empirical findings, or institutional expectations from being read as evidence of actual practice.

Critical appraisal was evidence-type specific rather than based on a single review-specific numerical score. Empirical qualitative, quantitative, and mixed-methods studies were appraised using the Mixed Methods Appraisal Tool (MMAT 2018); SANRA was used exclusively for genuine narrative reviews; systematic reviews were appraised using AMSTAR 2; for scoping reviews, AMSTAR 2 criteria were used as a structured appraisal lens and interpreted cautiously because AMSTAR 2 was not developed specifically for scoping-review methodology; conceptual or textual evidence was assessed using the JBI textual-evidence checklist; and policy or institutional grey literature was appraised using AACODS (Hong et al., 2018; Baethge et al., 2019; McArthur et al., 2025; Tyndall, 2010). Any dual-tool or asterisked entries indicate sources evaluated across multiple evidence dimensions.

Because these instruments differ in purpose, criteria, and scale, their outputs were not converted into a common 0–12 score. Appraisal was reported as a tool-specific profile of strengths and limitations by evidence type and was used to inform interpretive weight rather than as an automatic exclusion threshold. This avoided false numerical equivalence between empirical studies, narrative reviews, conceptual papers, and institutional or policy documents. Supplementary Table 1A therefore identifies the appraisal tool applied to each source, while Table III summarizes evidence-type-level appraisal profiles.

Critical appraisal was conducted using the evidence-type-specific procedures described above, with interpretive differences resolved through comparison against the predefined appraisal criteria.

E. Thematic Synthesis and Evidence Mapping

The extracted evidence was analyzed using a hybrid inductive-deductive thematic-synthesis process. Inductive coding and theme development were informed by established thematic-analysis procedures (Braun & Clarke, 2021; Byrne, 2022), but the review does not claim to implement reflexive thematic analysis in full. Findings were coded, grouped into descriptive categories, and developed into higher-order analytical themes before subsequent mapping to the research questions and relevant NEP 2020 principles. This sequencing allowed themes to emerge from the reviewed evidence before policy interpretation.

First, findings were coded inductively for recurring concerns, practices, and institutional responses, including unauthorized AI assistance, authorship ambiguity, fabricated information, assessment vulnerability, AI literacy, faculty preparedness, privacy, policy, and monitoring. Related codes were then grouped into descriptive categories; for example, disclosure and accountability contributed to academic-integrity themes, while oral defence, reflective writing, contextual problem-solving, and process documentation contributed to assessment redesign. Categories were refined through constant comparison across evidence types, retaining convergent, contradictory, and context-dependent findings. Finally, higher-order themes were mapped to the four research questions and relevant NEP 2020 principles, including holistic development, critical and creative thinking, ethical reasoning, digital literacy, self-discipline, human values, and institutional accountability.

To strengthen analytical traceability, an evidence-mapping procedure was applied after thematic synthesis. Each source was mapped by principal research question, thematic category, corresponding Samanvaya dimension,

evidence type, and critical-appraisal assessment. This preserved distinctions among empirical findings, conceptual or review arguments, and policy or institutional recommendations. The mapping documented the provenance, distribution, and coverage of evidence contributing to or mapped onto each framework dimension; it was not intended to constitute independent empirical validation of the framework. The results of this mapping are reported in Section III, with the resulting framework developed in Section IV.

The coding process maintained a source-level pathway from extracted evidence to initial code, descriptive category, higher-order theme, and final framework dimension, while retaining discrepant and context-dependent findings. This structure supports traceability between individual sources, evidence-derived themes, research questions, NEP 2020 principles, and the final Samanvaya dimensions.

F. Ethical and Inner-Development Lens

The ethical and inner-development lens is a reflection on dispositions that augment institutional regulation for responsible usage of AI. Academic integrity is as much a matter of rules and detection as well as self-regulation, ethical judgment, responsibility, reflection, and truthful conduct. This point of view is brought in, because constructs related to it appear in both character education and moral development, and reflective-learning literature. The lens is operationalized in eight observable educational dimensions; self-awareness, self-control, ethical discernment, human-AI balance, responsibility, reflective self-learning, compassion, and integrity. Their selection is not a spiritual, unprovable entity, but rather it is secured by theory. Rest's Four-Component Model is related to moral sensitivity, moral judgment, moral motivation, and moral implementation; Bandura puts forward the concepts of moral disengagement to study how responsibility and self-sanctions can be selectively suspended; self-determination theory helps to understand internalization and self-regulation; character-education scholarship emphasizes moral reflection, responsibility, and acting character; and reflective-practice theory was developed to discuss reflective self-learning (Rest, 1986; Bandura et al., 1996; Ryan & Deci, 2000; Schön, 1983; Mouta et al., 2024). These are the areas covered and are to be considered as indicators of observable educational behaviours in relation to an academic use of AI and not as indicators of personal spirituality.

TABLE II. CODING FRAMEWORK FOR ETHICAL AND INNER-DEVELOPMENT DIMENSIONS

Dimension	Observable relevance to AI-enabled academic conduct
Self-awareness	Identifies when AI assistance has replaced rather than supported personal understanding.
Self-control	Resists unauthorized or shortcut-based AI use despite its availability.
Ethical discernment	Distinguishes legitimate assistance from substitution of intellectual effort.
Human–AI balance	Uses AI support while retaining independent judgment, verification, and accountability.
Responsibility	Verifies outputs and truthfully discloses material AI assistance.
Reflective self-learning	Explains how AI use affected personal reasoning, learning, or decision-making.
Compassion	Considers bias, accessibility, equity, and consequences for other people.
Integrity	Ensures reported AI use is consistent with actual academic practice.

The English language analytical categories have parallels in the Indian educational thinking like Asmita-Bodha, Atma-Sanyam, Viveka, Kartavya-Bodha, Swadhyaya, Karuna and Nishtha. The Sanskrit terms are merely used as context and to illustrate the behavior, which then recodes the Sanskrit term into the behaviour; the behavioural definitions of the Sanskrit terms by the English, and the cited psychological and educational theories provide the analytical work in coding. A dimension is only documented when it has a meaningful relation to AI-related education, academic integrity, assessment, learner responsibility or institution practice during coding. This limitation is to stop the lens being used in general discussion of character or values which are not directly related to the content of the

review. The synthesis does not compute a composite spirituality score, but rather provides information on the number, context and nature of the sources for every dimension. Reporting the pattern of coverage across the sources prevents the implication of any precision that is not inherent in the information, and maintains the qualitative, thematic nature of the coverage. The lens does not seek to measure individual spirituality, but it aims to explore how inner-development qualities can contribute to proper AI use, intellectual property, ethical choice-making, and character building. The construct at the individual level is called human–AI balance and is defined as maintaining human judgment, verification, and responsibility with the use of AI assistance. Samanvaya is open to the larger system level mechanism to mobilize individual development, pedagogical transformation and institutional governance. The two concepts are related, each having its own analytical aspects.

G. Reliability and Methodological Limitations

Reliability was enhanced with pilot calibration, dual independent screening, pre-established eligibility criteria, documented exclusion rationales, pilot testing of extraction and evidence-type specific appraisal and constancy of comparison across evidence types. Inconsistencies in screening decisions were resolved with independent decisions and through consensus of the reviewers. Differences of interpretation were discussed and resolved in the process of extraction, coding and/or appraisal by comparing the various interpretations with the predetermined review criteria and the research questions. The review therefore, sought to reinforce the consistency in the identification, screening, extraction, appraisal, and synthesis, by structured procedural safeguards. However, screening, appraisal, and thematic coding rely on the judgment of the researcher. The dimensions indicated as inner-development are not mutually exclusive and can be understood differently in various cultural and disciplinary contexts, as well as with differing terminology. Two reviewers can code the same segment under different constructs which are contiguous, especially when there is some overlap in responsibility with integrity or ethical discernment. Therefore, explicit behavioural definitions, a coding audit trail that remains, and reporting of discrepancies between codes is crucial in making an interpretative decision transparent. The results of the appraisal should not be pooled together into a single number of value regardless of the tool.

Limitations include English-language restriction, database-coverage differences, reduced reproducibility of Google Scholar searches, publication bias, heterogeneous evidence types, and rapid changes in AI tools and terminology. These factors may omit relevant regional material and reduce the currency of earlier studies in the review window, particularly in a fast-moving technological domain.

Subsequent validation will assess the framework's conceptual clarity, stakeholder relevance, implementation feasibility, and institutional applicability through expert review, stakeholder surveys, cross-institutional comparison, and pilot implementation. These validation activities are treated as a distinct phase of work that lies outside the scope of the present review, but they are noted here because the framework presented in Section IV is offered as evidence-informed and policy-aligned rather than as empirically validated, and the limitations documented in this subsection define what such validation would need to address.

Protocol transparency was addressed through the documentation of the review design, research questions, eligibility criteria, search strategy, screening procedures, data-extraction fields, critical-appraisal approach, and thematic-synthesis process within the manuscript. The review was not prospectively registered, and no preregistered protocol was available. The full database-specific search strategies, screening criteria, coding procedures, and appraisal approach are reported to provide transparency regarding the development and conduct of the review. A PRISMA 2020 flow diagram and checklist accompany the review to support transparent reporting of the identification, screening, eligibility, and inclusion processes (Page et al., 2021).

3. REVIEW FINDINGS AND EVIDENCE SYNTHESIS

A. Evidence Profile and Distribution

The evidence-mapping analysis provides an overall characterization of the evidence contributing to and mapped onto the proposed Samanvaya Framework. As summarized in Table III, the reviewed literature is distributed across all six framework dimensions, but the degree of coverage is not uniform. The evidence is more concentrated in areas directly concerned with the management of AI-related academic risks, particularly responsible generative-AI use, AI literacy and stakeholder preparedness, assessment redesign, and institutional governance. In comparison, ethical, value-based, and inner-development education receives comparatively less attention, indicating a less developed evidence base for the internal dimensions of responsible AI-enabled academic conduct.

TABLE III. EVIDENCE DISTRIBUTION ACROSS THE SAMANVAYA FRAMEWORK DIMENSIONS

Samanvaya Dimension	No. of Sources	Empirical	Review/Conceptual	Policy/Institutional	Appraisal profile (tool-specific)
Responsible Use of Generative AI	29	12	10	7	MMAT: generally adequate methodological reporting; SANRA/JBI: coherent synthesis and argumentation; AACODS: authority and applicability evident
AI Literacy & Stakeholder Preparedness	25	10	9	6	MMAT: generally adequate study design/reporting; SANRA/JBI: clear conceptual treatment; AACODS: relevant institutional/policy grounding
Assessment Redesign & Original Thinking	27	13	10	4	MMAT: comparatively stronger empirical evidence; SANRA/JBI: consistent assessment-focused synthesis; AACODS: limited but relevant policy evidence
Ethical, Value-Based & Inner-Development Education	16	4	8	4	MMAT: limited empirical coverage; SANRA/JBI: greater reliance on conceptual/theoretical evidence; AACODS: supportive policy context
Institutional AI Governance	26	7	8	11	MMAT: mixed empirical coverage; JBI/SANRA: coherent governance interpretation; AACODS: substantial policy/institutional representation
Academic-Integrity Monitoring & Continuous Evaluation	22	9	8	5	MMAT: mixed empirical evidence; SANRA/JBI: variable methodological/argumentative depth; AACODS: relevant governance and assurance evidence

* Note: Sources may contribute to more than one framework dimension. Therefore, the total number of dimension-level mappings exceeds the final corpus of 36 included sources. Dimension-level source counts indicate

breadth of coverage within the included corpus and should not be interpreted as effect sizes, comparative quality scores, or quantitative estimates of relative importance.

The evidence base is methodologically diverse. Empirical studies offer first-hand accounts of observed practices, perceptions, risks, and educational outcomes; review studies and conceptual studies give wider interpretations of new issues and possible responses. Policy and institutional sources provide evidence relating to governance expectations, implementation conditions, privacy, accountability, and responsible institutional adoption. This heterogeneity supports the integrative review design and suggests that there is no one evidence stream which could support the four research questions sufficiently. Findings from critical-appraisal were not collapsed across evidence types, but rather interpreted within evidence type. As such, in Table III, appraisal profiles for each of the tools are reported, alongside source distribution, so that methodological strengths and weaknesses can support the synthesis process, but do not let the data suggest any numeric equivalence between MMAT, SANRA, JBI or AACODS. The same applies to the counts of research questions: the individual counts for research questions are non-exclusive, as a source can address more than one question; the number of research questions cannot be added up to calculate the total number of sources included in the sample.

B. Findings for RQ1: Integrity, Ethical, and Learning Challenges

According to the review, the problems involving generative AI in a higher education context go past traditional notions of academic dishonesty. In the main body of evidence, the 16 relevant sources included empirical studies, systematic or scoping reviews, conceptual analyses, and institutional or policy-oriented evidence. Common problems stem from unauthorized support, unclear authorship, fabricated data, reliance on AI-generated content, risk of assessments being compromised, and the general issue of academic honesty and learning (Eke, 2023; Draxler et al., 2024; Gruenhagen et al., 2024; Bittle & El-Gayar, 2025; Ying, 2026). Concurrently, the evidence was not exclusively risk-oriented; as students gain benefits when generative AI is used, purposefully, transparently, and in areas where students feel it can support them (Chan & Hu, 2023; Kangwa et al., 2025). The difference in these figures suggests that it is not the use of AI that is the problem, but its context.

C. Findings for RQ2: Pedagogical and Assessment Responses

AI literacy and assessment redesign are pedagogical responses identified in the synthesis. For RQ2, 19 primary-corpus empirical, review, conceptual, and policy-oriented sources were found relevant. Foundational learning and moral-development theories were used for interpretive grounding and are not included in this RQ count. In the literature, AI literacy is correlated with the ability to assess created outputs, identify false or skewed information, check sources, comprehend privacy considerations, and properly acknowledge the use of AI and ICTs. Responses are focused on assessment, using authentic activities and tasks that are meaningful, contextual, and focused on oral defence, reflective writing, process documentation, iterative submission, and critical evaluation of AI outputs. These practices combine to move the focus from surface products and finished work to thinking, reasoning, and reflection that is visible. Faculty preparedness is identified as an enabling condition since the faculty has to create an appropriate framework for the use of AI, redesign tasks and evaluate learning processes besides just relying on detection or final output assessment (Xia et al., 2024; Kofinas et al., 2025; Peters & Angelov, 2025; Ahangama, 2026). But the evidence also reveals that the responses are by no means easily implementable across the board. Redesigning assessments and building AI literacy among faculty can be a burden on their time and require institutional support, and inconsistent access to AI knowledge and resources can hinder its campus-wide adoption among learners in different disciplines and stakeholder groups (Kangwa et al., 2025; Hackl et al., 2026). This limitation supports the conclusion that pedagogical adaptation cannot be separated from faculty preparedness and institutional support. But the refashioning of assessments is not always protective. The results of the reviewed evidence indicates that authentic assessments can still be susceptible to substantial GenAI support, and markers may not be able to tell the difference between AI-supported and independently created writing. Rather than being used as an AI-proof tool, authenticity ought to be paired with process evidence, with some sort of oral or performative component, and explicit expectations of using AI (Kofinas et al., 2025; Xia et al., 2024).

D. Findings for RQ3: Governance and Technology-Management Requirements

The synthesis highlights the need for institutional governance to set a clear course and expectations for the responsible use of AI, disclosure, privacy, accountability, role of stakeholders, and monitoring. RQ3 was explored in 14 informatively relevant empirical, conceptual, policy, and institutional sources. The cited literature suggests that governance should not be considered a one-off compliance exercise in one office, but stretched across the academic leadership, faculty, technology and information-security (IT/IS) roles, quality-assurance (QA) units, and students (Chan, 2023; Mack & Byanjankar, 2025; Tan et al., 2025; Thaldar et al., 2025; Qian, 2026; Crompton et al., 2026). Meanwhile, governance must be flexible between subject and in the context of technology as different forms of AI application can be required for each learning goal measured. Therefore, continuous review becomes a key factor: policies, training, assessment practices, and monitoring procedures must be revised periodically as in the case of the evolution of institutional experience and new developments in the field of AI. Further evidence shows a conflict between policy to ensure consistency across all institutions and a need for flexibility in how the disciplines and assessments are implemented. The institutional guidelines aim to foster shared norms on disclosure, accountability and responsible AI use while stakeholders might have varying needs for AI in their respective disciplines, evaluation goals, or access to technology. This divergence supports the rationale for a common core of institutional governance principles combined with context-sensitive implementation across disciplines and assessment settings.

E. Findings for RQ4: NEP 2020 Alignment and Integrated Requirements

The synthesis shows that educational, ethical, and governance requirements identified in RQ1-RQ3 can be mapped to relevant NEP 2020 principles. RQ4 was answered with 12 relevant sources including policy, institutional, conceptual and review oriented sources, with the NEP 2020 being the primary policy base for the mapping. Digital literacy was mapped to critical and responsible AI use; critical and creative thinking to authentic and process-oriented assessment; ethical reasoning, human values, and value-based conduct to responsibility, integrity, reflection, and self-regulation; and institutional accountability to governance, privacy, stakeholder responsibility, and continuous review (Government of India, Ministry of Education, 2020; Miao & Holmes, 2023; Miao et al., 2024; Chan, 2023; TEQSA, 2023). Holistic development is the foundation for linking intellectual, ethical, reflective and behavioural aspects. Not all evidence-derived themes mapped cleanly to a single NEP 2020 principle. The themes that were related to authorship ambiguity, AI-output verification, privacy, procurement and technological monitoring were handled as interpretative cross-mapping as they reflect contemporary institutional challenges which are not explicitly articulated as discrete AI categories within NEP 2020. These relationships, therefore, were seen in terms of wider concepts of Digital Literacy, ethical responsibility, institutional accountability and holistic development, rather than as prescription policies in their own right. This mapping does not establish the NEP 2020 as a pre-designed coding framework, but takes a policy perspective to align themes based on evidence. This interpretive alignment is summarized in Table IV and provides the policy-mapping layer of the Samanvaya Framework. The policy comparison also shows differences in emphasis across frameworks. While there is international consensus on the principles of responsible, human-centred, and transparent use of AI, the focus differs amongst these: UNESCO prioritises human-centred ethics and capacity building, while the principles of the Russell Group focus on literacy, adaptation of AI in assessment, and institutional review, and TEQSA focuses more on assessment reform and integrity assurance. It is important to note that, in view of the NEP 2020 mapping, the interpretation must be context-specific (Miao & Holmes, 2023; Russell Group, 2023; TEQSA, 2023; Miao et al., 2024) and not a policy consensus in general.

Across the four RQs, the synthesis also retained tensions rather than forcing consensus: GenAI can create integrity risks while supporting learning when use is transparent and purposeful (RQ1); authentic assessment can increase process visibility yet remain vulnerable to substantial GenAI assistance unless paired with oral or process evidence (RQ2); institution-wide governance benefits from common disclosure and accountability standards while disciplines require contextual flexibility (RQ3); and international frameworks converge on responsible, human-centred AI use but differ in emphasis, making NEP 2020 alignment interpretive and context-specific (RQ4). These discrepant patterns support coordinated rather than single-mechanism institutional responses.

TABLE IV. INTERPRETIVE NEP 2020–TO–SAMANVAYA MAPPING

NEP 2020 principle	Evidence-derived requirement	Samanvaya dimension	NEP 2020 paragraph(s)
Digital literacy and technology-enabled learning	Critical evaluation and responsible AI use	AI literacy and stakeholder preparedness	Para. 4.23; Paras. 23.5-23.8
Critical and creative thinking	Authentic and process-oriented assessment	Assessment redesign and original thinking	Paras. 11.2-11.3
Ethical reasoning and human values	Responsibility, integrity, reflection, and ethical judgment	Ethical, value-based, and inner-development education	Para. 11.8
Responsible/value-based conduct	Self-regulation and responsible AI use	Ethical, value-based, and inner-development education	Para. 11.8
Institutional accountability	Policy, privacy, stakeholder responsibility, and review	Institutional AI governance and monitoring	Para. 18.8; Paras. 19.2-19.3
Holistic development	Integration of learning, ethics, responsibility, and governance	Cross-layer Samanvaya integration	Paras. 11.3-11.4; Para. 12.3

The NEP 2020 mappings in Table IV are anchored to the specific policy paragraphs shown rather than inferred from the policy as a whole; the mappings remain interpretive because NEP 2020 does not explicitly address generative-AI academic-integrity practices (Government of India, Ministry of Education, 2020).

F. Cross-Cutting Evidence Gap

The results suggest overall a significant disparity between the current evidence bases, with the literature being more robust in tackling external means of managing AI (acceptable use policies, AI literacy, assessment reform, institutional governance) than the internal means of its development (self-regulation, ethical judgments, reflective learning, character development). This imbalance is an important finding of the review and it lends itself as the background to integrate both external institutional mechanisms and internal developmental qualities within the Samanvaya Framework. (Holmes et al., 2022; Mouta et al., 2024; Kangwa et al., 2025; Hackl et al., 2026)

These findings establish the evidential basis for the Samanvaya Framework developed in Section IV.

4. PROPOSED NEP 2020–ALIGNED SAMANVAYA FRAMEWORK

A. Evidence-to-Framework Mapping

The evidence-base findings were mapped against the four research questions and relevant NEP 2020 principles to identify recurring relationships among AI-related challenges, educational responses, ethical requirements, and institutional mechanisms. Rather than treating the six dimensions as independent concepts, the mapping examined themes that consistently co-occurred across empirical, conceptual, review, policy, and institutional evidence.

The synthesis generated the following six higher-level dimensions: (1) responsible use of generative AI, related to academic integrity, authorship, disclosure, verification, and unauthorized assistance; (2) AI literacy and stakeholder preparedness, related to critical evaluation, awareness of the limitations of and biases in generative AI, privacy, and faculty preparedness; (3) assessment redesign and original thinking, related to redesigning assessment, reflection based, authentic, and contextual assessments, and limitations of conventional assessment; (4) ethical, value-based and inner-development education, related to responsible use, self-regulation, ethical discernment, reflection, and integrity;

(5) institutional AI governance, related to policy, privacy, accountability, stakeholder responsibilities, and risk management; (6) academic-integrity monitoring and continuous evaluation, related to assessment verification, limitations in assessment, faculty review, and adaptive improvement. The dimensions were subsequently mapped against relevant NEP 2020 principles, including holistic development, critical and creative thinking, ethical reasoning, digital literacy, experiential learning, self-discipline, human values, and institutional accountability. This policy mapping provides interpretive alignment rather than empirical validation. The resulting analytical pathway is:

Evidence-derived themes → Research questions → NEP 2020 principles → Six Samanvaya dimensions.

Thus, the six dimensions represent evidence-informed higher-order synthesis categories developed through the hybrid inductive–deductive process rather than categories imposed as fixed structures at the initial coding stage. They integrate fragmented responses to AI-enabled higher education into a coherent institutional structure, which is developed through the framework architecture presented in Section IV.B. The evidence-to-framework mapping establishes analytical traceability and coverage; it does not constitute independent empirical validation of the framework.

B. Framework Architecture

The Samanvaya Framework is organized as an input–process–outcome system operating across three interdependent levels.

1) Framework Inputs

The framework considers five principal inputs:

- educational opportunities created by AI;
- academic-integrity and learning-related risks;
- institutional readiness and technological capacity;
- stakeholder needs and responsibilities; and
- educational and ethical principles reflected in NEP 2020.

Inputs vary across institutions, disciplines, learner populations, and technological environments. The framework is therefore an adaptable institutional architecture rather than a uniform compliance checklist; implementation of the six dimensions should reflect institutional readiness, capacity, and context.

2) Operating Levels

The six framework dimensions operate across three levels:

- Individual and inner development: self-awareness, self-control, ethical discernment, responsibility, reflective learning, compassion, and integrity.
- Pedagogical transformation: AI literacy, authentic assessment, critical thinking, creativity, reflective learning, and intellectual ownership.
- Institutional governance: policy development, stakeholder coordination, privacy, accountability, risk management, monitoring, and continuous improvement.

The three levels are interdependent: individual responsibility requires supportive policy, governance depends on suitable assessment design and stakeholder preparedness, and assessment reform is more effective when institutional expectations are clear. They therefore function as complementary levels rather than alternative intervention points.

3) Intended Outcomes

The framework seeks to support:

- greater transparency in AI-assisted academic work;
- stronger intellectual ownership;
- improved critical and reflective thinking;
- responsible institutional AI adoption;
- greater consistency in academic-integrity practices; and
- increased attention to ethical and character development.

Monitoring and evaluation create a feedback loop through which policies, training programmes, and assessment practices can be periodically reviewed and adapted. This feedback loop is what distinguishes the framework from a static compliance document: the sixth dimension, academic-integrity monitoring and continuous evaluation, is designed to feed back into the other five dimensions, so that policy, literacy training, and assessment design can be revised as institutional experience and AI technology both continue to change. Figure 2 summarizes the input-process-outcome architecture of the Samanvaya Framework and its continuous feedback relationship.

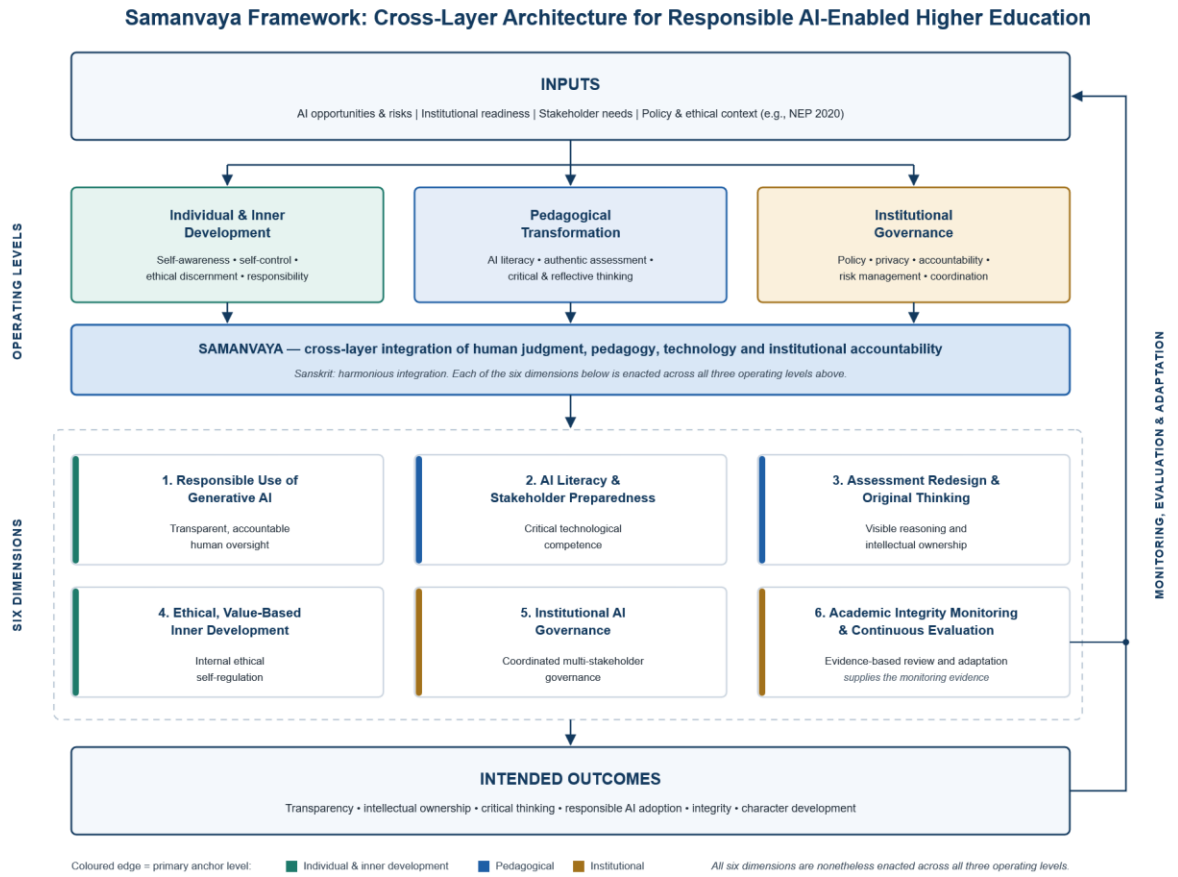


Fig. 2. Samanvaya Framework architecture integrating inputs, operating levels, six dimensions, intended outcomes, and continuous monitoring feedback.

C. Framework Dimensions

1) Responsible Use of Generative AI

The dimension focuses on people's uncertainty about acceptable, limited and prohibited use of AI. Its core mechanism is transparent and accountable human oversight. This requires clear distinctions between AI use that supports learning and AI use that substitutes for intellectual effort. Brainstorming, language support, concept clarification, formative feedback, etc., are permitted practices, whereas graded tasks that call for independent thinking are restricted and content generated by AI cannot be presented as original, references or data can be fabricated, or AI tools used in exams without authorization are prohibited. There is thus a context- and learning-outcome dependent distinction. Students and professors should inform others when they are using meaningful AI support, check any responses they receive for accuracy, detect errors or biases, and acknowledge and take responsibility for the responses. The use of AI is judged on its ethics, verified and disclosed for accountability, and consistent between reported and actual use for integrity. The desired result is to achieve more authorship, better ownership of academic work and a responsible human–AI collaboration.

2) AI Literacy and Stakeholder Preparedness

This dimension addresses gaps in understanding AI capabilities, limitations, and institutional implications. Its core mechanism is reflective awareness and critical technological competence. Students should be prepared to formulate appropriate prompts, verify sources, identify fabricated or biased outputs, understand privacy implications, and critically evaluate AI-generated information. The faculty development needs include pedagogy with AI support, assessment strategy redesign, verification, and policy interpretation; and for administrators, infrastructure, security, accessibility, governance, and institutional risk. The different responsibilities of these stakeholders are represented in these stakeholder profiles (Ng et al., 2021; Salhab & Aboushi, 2025; Hackl et al., 2026). Self-awareness helps users identify what they don't know and what areas they may be relying on AI. Both reflective self-learning and ethical discernment help to analyze the impact of produced content on the understanding of the learner and to check the ethical use of it. The goal is for students to become informed users of AI, applying its capabilities with judgement, caution and an understanding of educational purpose.

3) Assessment Redesign and Original Thinking

This dimension reflects the lack of criticality in the use of standard AI-based, generic and unsupervised assessment approaches. The centerpiece of its mechanism is the demonstration of reasoning, process and intellectual ownership. This dimension can be realized at the institutional level by means of oral defence, real problem solving, contextual case analysis, reflective commentary, iterative submission, process documentation, classroom based activities, and project based learning. AI can also be integrated directly into assessment, where the student is required to analyze generated responses, pinpoint errors and/or biases, and compare the reasoning process of humans with AI, or even to record evidence of how AI contributed to their work. This final approach sees AI as a means to be assessed, rather than excluded from assessment—it moves the demand for the assessment away from the generation of a final answer and toward judgment of the AI-generated work product. Self-control is demonstrated through a discipline of not taking the "shortcut," through reflective learning (writing the reasoning process), and through integrity (showing an honest personal effort). Anti-cheating strategies should not be the only measures used in redesigning assessment, but should also be complemented by making reasoning, creativity, reflection, and individual contribution visible. This pedagogical emphasis responds directly to RQ2 and is a way of minimising reliance on polished final products as evidence of learning (Cotton et al., 2024; Xia et al., 2024; Kizilcec et al., 2024; Peters & Angelov, 2025; Sharma, 2026). The desired result is an increased level of originality, critical thinking, and decreased reliance on the generation of final answers.

4) Ethical, Value-Based, and Inner-Development Education

This dimension is critical to the shortcomings of academic-integrity systems that are rule- and detection- and punishment-centered. It is based on intrinsic moral management and moral education that emphasizes values. Curricula can include AI-related ethical dilemmas, reflective journals, bias analysis, value-based case studies, social-impact conversations, and professional-responsibility activities within the institutions. It should be encouraged to discuss with students how their AI use will be used for real learning, respecting intellectual work, affecting others

fairly and in accordance with academic responsibility. These four questions are not meant to be an abstract declaration of values unlinked to a specific situation of the use of AI, but rather a pragmatic question a student can pose when he/she uses AI in a specific instance. The dimension focuses on observable characteristics such as self-awareness, self-control, ethical understanding, empathy, accountability, learning from reflection and honesty. The above-mentioned qualities have contextual parallels in India in the concepts of Atmabodha, Viveka, Kartavya-Bodha, Karuna and Nishtha and the English words are the major operative categories in the Indian educational context. The desired goal is to encourage another shift from compliance to responsibility, that is, from imposed to internalized accountability. This dimension works with governance and monitoring: external constraints help prevent misbehaviour; internalised judgement helps promote responsible behaviour in situations which policies and detection systems might not entirely foresee.

5) Institutional AI Governance

This dimension is related to the lack of coherence and fragmented institutional response to AI. It has its core in coordinated multistakeholder governance. The following aspects should be incorporated into the institutional AI policy: Acceptable use, Disclosure, Privacy, Data protection, Intellectual ownership, Procurement, Student rights, Faculty responsibilities, Student grievance redressal, Policy review. Additionally, there should be the flexibility to adapt to disciplinary differences since how to use AI should be tailored to the learning outcome and/or the professional context, not just one blanket policy. An interdisciplinary governance body can consist of academic leaders, faculty, learning technologists, information-security experts, ethics advisors, students and quality-assurance staff. Focus should be on clearly defined roles for responsibility, consistent application of policy for integrity, and the balancing of innovation and accountability at system level of integration. (Mack & Byanjankar, 2025; Tan et al., 2025; Thaldar et al., 2025; Qian, 2026) The goal is for AI to be used by institutions in a coordinated, context-responsive and responsible manner.

6) Monitoring and Continuous Evaluation

This dimension addresses the limitations of static policies in a rapidly evolving technological environment. Its core mechanism is evidence-based institutional learning and adaptation.

Institutions may monitor:

- student awareness of AI-use policies;
- AI-disclosure practices;
- faculty preparedness;
- adoption of redesigned assessments;
- academic-integrity case patterns;
- stakeholder perceptions; and
- evidence of critical thinking and intellectual ownership.

AI-detection tools should not be treated as the sole basis for disciplinary decisions because their outputs may be inaccurate or contextually misleading. Monitoring should combine technological indicators with human review, student explanation, assessment evidence, and procedural fairness. This qualification follows directly from the limitations documented in the empirical literature reviewed under RQ1, in which detection-tool outputs are treated as one input among several rather than as conclusive evidence, since relying on a single automated indicator risks both false accusations and missed instances of misuse. (Cotton et al., 2024; Revell et al., 2024)

At the institutional level, self-awareness is reflected in recognizing policy, training, and implementation gaps. Responsibility requires transparent review, corrective action, and accountability for identified shortcomings.

The intended outcome is an adaptive governance system capable of responding to changes in AI technologies, stakeholder practices, and educational risks.

D. Harmonious Integration as the Central Mechanism

Harmonious integration, or Samanvaya, is the cross-layer mechanism connecting the six dimensions. At the individual level, it balances AI assistance with human judgment and responsibility; at the pedagogical level, it connects technological support with authentic, reflective, and experiential learning; and at the institutional level, it balances innovation with privacy, equity, accountability, and risk management.

Samanvaya is not a seventh dimension but the integrating mechanism that links the six dimensions across individual, pedagogical, and institutional levels. Its purpose is to prevent policy, assessment reform, literacy training, governance, and monitoring from operating as disconnected initiatives and instead align them within a coherent institutional response.

E. Operationalization and Evaluation Indicators

TABLE V. OPERATIONALIZATION OF THE SAMANVAYA FRAMEWORK

Dimension	**Mechanism / illustrative action**	**Stakeholders**	**Illustrative indicator**	**Intended outcome**
Responsible AI use	Transparency through AI-use and disclosure guidelines	Students, faculty, academic offices	Appropriate AI-use disclosure	Ownership and integrity
AI literacy	Training, faculty development, and critical verification	Students, faculty, administrators	Participation and demonstrated AI literacy	Informed AI use
Assessment redesign	Oral, reflective, authentic, and process-based assessment	Faculty and examination units	Proportion of redesigned assessments	Originality and critical thinking
Ethical and inner development	Ethical cases, reflection, and responsibility-based activities	Students, faculty, curriculum committees	Evidence of reflective ethical judgment	Character development
Institutional governance	AI policy, oversight, privacy, and risk-management controls	Leadership, IT, faculty, quality units	Policy clarity and stakeholder compliance	Responsible institutional adoption
Monitoring and evaluation	Reviews, audits, surveys, and outcome analysis	Governance and quality-assurance units	Trends in incidents, preparedness, and outcomes	Continuous improvement

The table maps out the literature-derived themes and translates them into institutional mechanisms, illustrative actions, responsible stakeholders, indicators, and intended outcomes. The indicators are of an indicative nature and should be tailored to the institutional context, discipline and implementation capacity. The table shows all four elements for each dimension; an indicator without a named stakeholder responsible for monitoring it, or a mechanism without a corresponding outcome, would not be translated to institutional practice, and therefore, the table reflects all four elements per dimension, which can in principle be read independently by the office responsible for that dimension.

F. Conceptual Propositions

The framework proposes the following for further empirical investigation:

P1: It is expected that there is a positive relationship between higher AI-policy clarity and stakeholder AI-literacy and more transparent disclosure of AI-use and less ambiguity about academic authorship.

P2: It is expected that the increased use of assessments that require students to explain, reflect, apply in context, and justify orally will be correlated with higher intellectual ownership and lower uncritical dependence on generative AI.

P3: Responsible AI-use outcomes are likely to be stronger in institutions with more developed responsibility, self-regulation, ethical understanding and integrity in institutional governance mechanisms.

P4: Institutions that have more robust system-level Samanvaya - coordinated integration of technological capability, human judgment, pedagogy and institutional accountability - are expected to show more coherent and adaptive AI adoption than institutions that are predominantly using restrictive or technology-centred approaches.

P5: There is expected to be a positive correlation between the frequency of evidence-based monitoring and feedback and the speed of adaptation of policy, training and assessment practices to changes in AI technologies, integrity risks and stakeholder needs.

These propositions represent the framework in the form of relationships that can be operationalized and tested in further expert, stakeholder and institutional studies. They are not findings but rather propositions, since the present review does not produce primary data for testing the propositions.

5. DISCUSSION

A. From Fragmented Interventions to Integrated Governance

Across the four research questions, the synthesis indicates that the challenges associated with generative AI extend beyond conventional academic misconduct and involve interconnected concerns related to authorship, fabricated information, dependence on generated content, assessment vulnerability, AI literacy, privacy, governance, and ethical responsibility. Taken together, these findings indicate that detection or prohibition alone is insufficient; effective responses require simultaneous attention to learner behaviour, assessment design, stakeholder preparedness, institutional governance, and ethical development.

A central implication of the synthesis is that existing responses to AI-enabled academic-integrity challenges are frequently distributed across separate intervention areas. AI-use policies may define acceptable behaviour, faculty-development programmes may address AI literacy, assessment reforms may reduce vulnerability to generated submissions, and integrity mechanisms may focus on monitoring or detection. Character and value education introduces another dimension concerned with responsibility, self-regulation, and ethical decision-making. Each intervention addresses a legitimate aspect of the problem, but their effectiveness may be constrained when they operate independently.

The Samanvaya Framework takes up this fragmentation and views these mechanisms as interdependent aspects of one institutional system. AI literacy can help to enhance the ability to use and assess AI tools responsibly, but part of that will be shaped by whether assessment practices encourage students to demonstrate reasoning and take intellectual ownership. In the same way, institutional policies can help to establish clear expectations, and policy can be influential where students have the capacity and motivation to manage their own use of AI. Possible issues may be detected through monitoring, but monitoring may not facilitate assessment redesign and efforts with curriculum education, if no effort is made. The framework thus moves away from piecemeal actions to a coordinated governance approach. Its three operating levels (individual and inner development, pedagogical transformation and institutional governance) are not mutually exclusive rather they are designed to work synergistically. It is an integrated structure which is consistent with the framework architecture presented in Section IV.B.

B. External Controls and Internal Development

The distinction between external mechanism of control and internal mechanism of responsible conduct is an important contribution of the review. External expectations and mechanisms for accountability are defined by institutional rules and procedures of assessment, disclosure and monitoring. It is important to note that, beyond their ability to identify ethical limits, students must also possess the capacity to self-manage and self-regulate their use of AI, as well as the ability to assess whether the use of AI has enhanced their own learning or replaced it. The ethical and inner-development lens of the second section, II.F offers a means of integrating these aspects without using them to replace the institutionally established forms of governance. Self-awareness, self-control, ethical discernment, responsibility, reflective learning, compassion and integrity have been identified as observable educational characteristics which can supplement external control. The focus of the synthesis is not on the direct influence of the synthesis on AI-related misconduct, but on internal development as a theoretically and educationally relevant component that requires further study in relation to institutional and pedagogical mechanisms. This difference also serves as the foundation of the idea of harmonious integration (Samanvaya). The intent is not to substitute rules for values or technology for judgment. Rather, it is important to strike a balance between setting clear expectations and enabling people to apply those expectations appropriately relative to the context in which they are being used.

C. Implications for NEP 2020

The framework also outlines how to connect with the overarching principles of NEP 2020 with the specific challenges that generative AI poses. The convergence of intellectual, ethical, reflective and behavioural aspects is indicative of holistic development. Assessment practices encourage critical and creative thinking by focusing on reasoning and innovative thinking in addition to product. Relationships between ethical thought, self-control and human values are associated with responsible application of AI, disclosure, and personal responsibility. Beyond the technical aspects of being digitally literate, students are taught how to critically evaluate information produced by AI tools and understand the associated limitations. Experiential and reflective learning are especially relevant when AI, otherwise, decreases the need for independent thinking to accomplish academic activities. The governance aspect that coordinates policies, commitments of stakeholders, privacy protection, monitoring and continuous improvement is a dimension of institutional accountability. In this sense, NEP 2020 is not being used as simply a policy reference context; the principles of this provide an interpretation to link the use of technology to wider education goals.

D. Implications for Higher-Education Institutions

The framework suggests moving students from mere instructions on the use or misuse of AI to learning to be literate with AI, to disclose data that may be used for AI training, to verify information, to self-regulate, and to gain ownership of intellectual products. Students must know how to differentiate between aid and substitution of their own work, and know their accountability for the accuracy and integrity of work completed with the aid of AI. These insights highlight the need for faculty to adopt an AI-responsive teaching and learning approach, focusing on the redesign of their teaching and assessment methods. Faculty need to be adequately informed to counsel students on the types of forms of AI usage and to create assessments that show students how they've reasoned and learned, as well as to grade student work without solely using automated detection. This may then be complemented by alternative assessment methods such as reflective writing, contextual tasks, oral defence, process documentation and others. The framework identifies the issues of coordinating governance to tackle acceptable use, privacy, accountability, responsibilities of stakeholders, technological capacity, and institutional readiness as important considerations for administrators. The quality-assurance and academic-integrity functions can help by monitoring, conducting regular audits, reviewing the evidence and providing feedback on policies, training, and assessments that can be adapted to change as institutional practices and experiences with AI grow.

E. Theoretical Contribution

The study's theoretical contribution lies in integrating domains that are often examined separately: technology management, academic integrity, AI-enabled pedagogy, higher-education governance, and character formation. The framework treats these not as isolated aspects of AI adoption but as interacting elements of an institutional architecture.

Samanvaya therefore functions not only as a six-theme categorization but also as an integrating mechanism. The framework suggests that responsible human-centric education becomes a reality through coordinating the dispositions of individuals, pedagogical approaches, and institutional constructs. This offers a framework for discussing the relationship between external governance and internal development, and how they can impact responsible academic conduct. Importantly, the novelty does not lie in treating AI literacy, assessment reform, academic-integrity policy, value education, governance, or monitoring as individually novel; it lies in specifying how these functions interact within a coordinated institutional design. In practice, these functions are likely to be distributed across institutional units, and Samanvaya provides the common logic by which they can respond in mutually reinforcing ways. (Bittle & El-Gayar, 2025; Kangwa et al., 2025; Hackl et al., 2026) A second theoretical contribution is the explicit linkage between external institutional mechanisms and internal developmental qualities. The framework therefore connects its institutional dimensions with observable qualities such as self-awareness, self-control, ethical discernment, responsibility, compassion, reflective learning, and integrity.

F. Comparison with Existing Frameworks and Policy Transferability

Samanvaya is designed to be used in addition to existing guidance. The UNESCO guidance of 2023 focuses on human-centred, ethical, safe, equitable and policy awareness of using GenAI, while the Russell Group's principles focus on AI literacy, adaptation of assessment, academic integrity, equitable access to AI, collaboration and regular policy review (Miao & Holmes, 2023; Russell Group, 2023); UNESCO's 2024 AI Competency Framework for Students focuses on a human-centred mindset, ethics, AI techniques and applications, and system design (Miao et al., 2024); TEQSA's guidance on assessment reform focuses on redesigning assessment to ensure integrity with GenAI opportunities (TEQSA, 2023). Table VI compares these approaches to the area covered by Samanvaya.

TABLE VI. COMPARATIVE POSITIONING OF SAMANVAYA AGAINST SELECTED INTERNATIONAL GUIDANCE AND FRAMEWORKS

Framework / guidance	Responsible use & AI literacy	Assessment redesign	Governance & monitoring	Inner development & cross-layer integration
UNESCO GenAI guidance (2023)	Explicit emphasis	Partial coverage	Explicit emphasis	Not a primary focus
Russell Group principles (2023)	Explicit emphasis	Explicit emphasis	Explicit emphasis	Not a primary focus
UNESCO AI Competency Framework (2024)	Explicit emphasis	Not a primary focus	Not a primary focus	Partial coverage
TEQSA Assessment Reform (2023)	Partial coverage	Explicit emphasis	Partial coverage	Not a primary focus
Samanvaya Framework	Explicit emphasis	Explicit emphasis	Explicit emphasis	Explicit emphasis

The comparison indicates that Samanvaya's contribution is integrative rather than substitutive; the qualities related to responsible use, AI literacy, assessment, governance, monitoring, and observable inner development are combined in one cross-layer architecture. The scope of each comparison document as stated in their respective coverage is what is used to render coverage judgments in Table VI — not quality rankings. The Samanvaya architecture is therefore understood as policy-mappable: NEP 2020 is the current demonstration case and further studies are encouraged to repeat the mapping process with other countries before the architecture can be generalized across nations.

G. Practical and Policy Contribution

On the practical side, the framework can provide a blueprint or framework for institutional development of AI policies, reform of assessment systems, AI-literacy programmes, planning for governance, and ongoing assessment. Its size enables it to be used to determine if the institution's focus is directed towards compliance and detection, or learning, intellectual ownership and ethical development, as well as their preparedness for stakeholders. The framework helps to understand the challenges arising from AI in education in the context of NEP 2020 and not as a purely technological problem. Meanwhile, the framework should not be understood as an entitlement to institutional intervention which has been proven. It currently plays a role in organizing and integrating evidence into an actionable conceptual structure that can be tested and improved. It is not anti-AI or permissive by default; rather, the position calls for pedagogical, governance, ethical, and developmental safeguards that go with the use of AI-enabled innovation in higher education.

H. Limitations and Future Research

The proposed framework is subject to a number of limitations that should be taken into account in interpreting the framework. First, the framework has not yet undergone primary empirical or expert-consensus validation and the relationships shown in its conceptual propositions should thus not be considered as causal effects. Second, a wide diversity of sources provides evidence, including evidence from empirical studies, review, conceptual studies, policy and institutional. This diversity is meaningful to the integrative design but does not allow for easy comparison of evidence types. Third, generative-AI technologies and institutional responses evolve rapidly, so findings and policy requirements may change over time. Fourth, the framework is developed within the NEP 2020 policy context and requires evaluation across different national, institutional, disciplinary, and cultural settings. Lastly, a number of dimensions, especially inner development, ethical sensibility and character formation, would need careful specification prior to an empirical evaluation of their linkages with AI-associated academic disciplines. A next validation phase should begin with a multi-round Delphi study involving experts in higher education, academic integrity, institutional governance, educational technology, artificial intelligence, and policy. The consensus criteria must be established beforehand and if the level of consensus is not reached, the dimensions of the framework, indicators or propositions should be adjusted or deleted (Jünger et al., 2017). Exploring the relevance, feasibility, contextual adaptability, proposed indicators, and the relationships between dimensions in the framework can be done through subsequent stakeholder surveys, cross-institutional comparisons, pilot implementation studies, and longitudinal evaluations. This would allow the evidence-informed framework to be refined through structured expert and stakeholder review before institutionalized use.

The framework should be evaluated across higher-education institutions and stakeholder groups through mixed-method and longitudinal studies. Empirical studies should test the proposed relationships among AI literacy, assessment redesign, governance, inner development, and academic-integrity outcomes and determine whether they are supported in practice. Such work can refine the proposed indicators, establish context-specific standards, and estimate the added value of integrated implementation. Samanvaya should therefore be regarded as a starting architecture for empirical research and institutional experimentation, not as a universal or final model.

6. CONCLUSION

The review, which used an integrative synthesis of 36 primary evidence sources, found that there is an imbalance between comparatively well-developed external governance mechanisms and less developed evidence on inner development. Generative AI offers educational opportunities and poses new questions about integrity, evaluation, intellectual property, and institutional management. The synthesis reveals that prevention, prohibition and policy is not enough; responsible AI-enabled higher education needs coordinated action on responsible AI usage, stakeholder readiness, assessment redesign, ethical and value-based development, institutional governance and ongoing monitoring. These requirements are embedded in the six dimensions of the Samanvaya Framework at the individual, pedagogical and institutional levels. NEP 2020 is not used as a policy-mapping case per se, and the mapping logic can be transferred, though it needs to be validated across jurisdictions. The framework is evidence informed and policy aligned but not yet tried in practice. Future research should assess its dimensions, indicators, and

propositions across institutions and stakeholder groups through expert-consensus, mixed-method, and longitudinal designs to explore the possibility of integrated implementation strengthening academic integrity, originality, responsible use of AI, critical thinking, and character development.

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53. Supplementary Table 1A: Primary Evidence Corpus and Analytical Mapping
54. (Key: D1 = Responsible AI Use; D2 = AI Literacy; D3 = Assessment Redesign; D4 = Ethical/Inner Development; D5 = Institutional Governance; D6 = Monitoring & Evaluation)
55. Supplementary Table 1B: Foundational Methodological and Theoretical References