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The Future of Research with AI: A Study of Innovation, Efficiency and Responsible Use

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Abstract: *Artificial intelligence (AI) has moved within a single decade from a specialised computational method to a general-purpose research instrument that now touches almost every stage of the scholarly lifecycle, from problem formulation and literature synthesis to experimentation, analysis, writing and peer review. This paper asks three connected questions: where AI produces genuine innovation in research rather than incremental automation; where it delivers measurable efficiency; and what conditions of responsible use must hold for those gains to be epistemically and ethically legitimate. The study adopts a structured narrative review of peer-reviewed literature, policy instruments and editorial guidance published between 2016 and 2026, and synthesises the evidence through thematic coding into a conceptual model. We find that innovation gains cluster in domains where AI compresses very large combinatorial search spaces—protein structure prediction, molecular and materials screening, and simulation surrogates—while efficiency gains are widest in language-intensive and data-curation work, where they are also most weakly audited. The dominant risks are epistemic rather than merely procedural: fabricated citations, homogenisation of research questions, and an illusion of explanatory depth in which fluent output is mistaken for understanding. We argue that disclosure statements alone are an insufficient governance response, and propose the Innovation–Efficiency–Responsibility (IER) framework, comprising three pillars, twelve operational levers and a five-level institutional maturity scale. Implications are drawn for universities, funders, publishers and policymakers, with particular attention to resource-constrained institutions in India and comparable settings.*

Keywords: artificial intelligence; generative AI; large language models; research productivity; research integrity; responsible AI; research policy; scholarly publishing; higher education.

I. INTRODUCTION

The relationship between research and its instruments has always been reciprocal: the microscope did not merely accelerate biology, it made cell theory thinkable. Artificial intelligence is now widely argued to occupy a comparable position. The transformer architecture [1] and the family of large-scale pretrained models that followed [2], [31] produced systems that generalise across tasks they were never explicitly trained for, and this generality is precisely what has carried AI out of computer science departments and into laboratories, clinics, archives and management schools.

Three developments explain the speed of this diffusion. First, capability crossed a practical threshold in scientific domains: AlphaFold's protein structure predictions reached experimentally useful accuracy [3], deep models identified structurally novel antibiotic candidates from screening libraries far larger than any wet-lab campaign could traverse [4], and reviews now describe AI as a general infrastructure for discovery across the natural and social sciences [5]. Second,

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the interface collapsed: conversational access removed the requirement that a researcher be able to program in order to use a model, which is why adoption in 2023–2026 has been fastest not in machine learning but in writing, translation, coding assistance and literature triage. Third, institutional incentives amplified both: publication pressure, grant competition and the sheer volume of the literature make any credible time-saving technology difficult to decline.

The consequences are contested. Surveys of active researchers report enthusiasm about faster computation and processing alongside substantive anxiety about opacity, error propagation and dependence on tools owned by a small number of firms [7]. A more fundamental critique holds that widespread AI adoption may narrow rather than widen the space of questions science asks, producing monocultures of method and an illusion of understanding in which the apparent explanatory completeness of a model output substitutes for genuine comprehension [8], [9]. Meanwhile the integrity apparatus of scholarly publishing has been forced into rapid improvisation: journals now prohibit AI systems as authors while requiring disclosure of their use [11]–[13], and empirical estimates suggest that a non-trivial and rising fraction of published abstracts already carries lexical signatures of model-assisted writing [15], [16].

What is missing from this literature is integration. Studies of AI-enabled discovery rarely engage with integrity scholarship; integrity scholarship rarely quantifies the productivity gains that make the technology attractive; and both are largely silent on the institutional conditions of universities outside well-funded research systems, where compute, licences and training are constrained but publication pressure is not. This paper addresses that gap. Its contributions are fourfold:

1) A structured synthesis of the 2016–2026 evidence base on AI in research, organised by lifecycle stage rather than by technique, so that innovation and efficiency claims can be assessed against the risks specific to each stage.
2) A distinction between three mechanisms of innovation—search-space compression, representational transfer and workflow agency—that clarifies why AI has transformed some disciplines and merely accelerated others.
3) The Innovation–Efficiency–Responsibility (IER) framework, which links each claimed benefit to a verification obligation and an auditable indicator.
4) A five-level maturity scale and a set of implementable recommendations for institutions, funders and publishers, with specific reference to Indian regulatory and policy instruments [25]–[28].

Section II reviews the relevant literature. Section III sets out the methodology. Sections IV and V examine innovation and efficiency respectively. Section VI analyses risk and responsible use. Section VII presents the framework, Section VIII discusses implications, and Sections IX and X state limitations and conclusions.

II. BACKGROUND AND RELATED WORK

A. From statistical tools to general-purpose models

AI in research was for decades a domain-specific affair: classifiers for genomics, computer vision for astronomy, natural language processing for corpus linguistics. Each application required bespoke feature engineering and a specialist team. The attention mechanism [1] and the subsequent demonstration that scale alone confers broad few-shot competence [31] changed the economics of that arrangement. Foundation models are trained once at great expense and adapted cheaply to many downstream tasks, which shifts the unit of analysis from the algorithm to the model-as-infrastructure and introduces the dependency, homogenisation and accountability problems that Bommasani et al. catalogue [2].

B. AI as an engine of discovery

The strongest evidence for transformative rather than incremental impact comes from domains with well-defined objective functions and intractably large candidate spaces. AlphaFold reduced a decades-old structural biology bottleneck to a routine computational query [3]; graph neural networks surfaced antibiotic candidates whose structures were unlike those of known drug classes [4]; and comparable results are reported in materials discovery, catalysis and weather modelling [5]. Krenn et al. distinguish AI as a computational microscope, as a source of artificial muses generating candidate hypotheses, and as a prospective agent of understanding, arguing that only the first two are presently established [6]. More recently, agentic systems that plan and execute experimental sequences—coupling language models to synthesis planners, databases and laboratory hardware—have demonstrated end-to-end autonomous chemical work [18], [19], and prototype systems have attempted the full pipeline from idea to manuscript [20].

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C. AI in the scholarly workflow

A parallel literature examines AI applied not to nature but to the research process itself: retrieval and screening for systematic reviews, translation and language editing for authors writing in a second language, code generation for analysis pipelines, and triage support in peer review [17]. Controlled evaluation here is thinner than enthusiasm would suggest. A large study of research ideation found that language-model-generated proposals were rated as more novel than those of expert researchers but weaker on feasibility, illustrating how easily novelty and value diverge [21]. Hallucination remains the characteristic failure mode: fluent, well-formed and confidently wrong output, including fabricated references [32].

D. Integrity, ethics and governance

Editorial and ethical bodies converged rapidly on a minimal position: AI systems cannot be authors because they cannot take responsibility, and their use must be declared [11]–[13]. Scholarly analyses of these rules note their limits—disclosure is unverifiable, thresholds for "use" are undefined, and detection tools are unreliable enough to generate false accusations [14]. Broader critiques address training-data bias and the exclusionary effects of models trained predominantly on English-language, Global North corpora [10], the environmental cost of large-scale training [35], and the concentration of research capability in the hands of a few well-resourced actors [2], [9]. At the policy layer, UNESCO's ethics recommendation [22], the OECD principles [24], the EU AI Act [23] and the NIST risk management framework [29] supply governance vocabulary; in India, the national AI strategy [25], the IndiaAI Mission [26], the Digital Personal Data Protection Act [27] and the ICMR guidelines for AI in biomedical research [28] together define the operating constraints for most academic users.

E. Research gap

These four literatures rarely cite one another. The result is a discourse in which benefits and harms are asserted at different levels of abstraction and cannot be traded off. This paper responds by mapping both onto a common lifecycle and binding each claimed benefit to a verification obligation.

III. RESEARCH METHODOLOGY

A. Design

The study is a structured narrative review combined with conceptual framework synthesis. A narrative rather than fully systematic design was chosen because the object of study spans heterogeneous evidence types—empirical benchmarks, disciplinary case studies, opinion surveys, editorial policy and statutory instruments—that cannot be pooled into a single effect measure. The review protocol was nevertheless made explicit so that the selection is reproducible in intent.

B. Sources and search strategy

Literature was drawn from Scopus, Web of Science, PubMed, the ACM Digital Library, IEEE Xplore, arXiv and Google Scholar, covering January 2016 to March 2026. Search strings combined technology terms ("artificial intelligence", "machine learning", "large language model", "generative AI", "foundation model") with research-process terms ("scientific discovery", "literature review", "peer review", "research productivity", "research integrity", "authorship", "research ethics"). Grey literature was included where it is authoritative for governance questions: publisher and editorial policies, national strategies, statutes and intergovernmental recommendations.

C. Inclusion and exclusion criteria

- Included: peer-reviewed studies reporting AI application to a research task with an outcome measure; disciplinary reviews of AI-enabled discovery; surveys of researcher attitudes and practice; conceptual and ethical analyses of AI in scholarship; and binding or widely adopted policy instruments.
- Excluded: purely technical papers on model architecture with no research-process implication; vendor marketing material; and commentary without argumentative or empirical contribution.

D. Analysis

Selected sources were coded thematically in two passes. The first pass assigned each source to one or more stages of a nine-stage research lifecycle (problem formulation through archiving). The second pass coded the claim type as innovation, efficiency, or risk, and recorded the strength of the supporting evidence as demonstrated, reported or asserted. Codes were then aggregated to produce the lifecycle mapping in Table I. Framework construction followed an

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iterative approach: candidate pillars were derived inductively from recurring code clusters, cross-checked against the control families of established governance instruments [22]–[24], [29], and refined until every risk code in the corpus mapped to at least one operational lever.

E. Methodological transparency

No human participants, patient data or personally identifiable information were involved, and no institutional review was therefore required. The review synthesises published evidence only; it does not report primary experimental or survey data, and the framework is offered as a conceptual contribution awaiting empirical validation. Consistent with the disclosure norms this paper advocates, the authors note that generative AI tools were used for language editing and reference formatting; all substantive claims, source selection, interpretation and the framework itself are the authors' own, and every cited source was verified against its original record.

IV. AI AND INNOVATION IN RESEARCH

Innovation is used here in a strict sense: a change that makes previously unanswerable questions answerable, as distinct from answering existing questions faster. Three mechanisms account for most documented cases.

A. Compression of combinatorial search spaces

The clearest transformations occur where the space of candidate answers is astronomically large, an evaluation function exists, and exhaustive search is impossible. Protein folding [3] and antibiotic discovery [4] are canonical: in both, a learned surrogate replaces an expensive oracle and reduces years of laboratory or simulation effort to hours of inference. The same pattern recurs in materials screening, retrosynthesis and physics simulation [5]. The critical precondition is a verifiable ground truth against which the surrogate can be trained and audited—which is exactly what most humanities, management and clinical-judgement questions lack, and why the transformation has been uneven across disciplines.

B. Representational transfer across domains

Foundation models encode structure learned in one domain in forms reusable in another, allowing methods developed for language to be applied to molecules, code, medical images or administrative text [2]. For interdisciplinary work this lowers the entry cost of borrowing a technique from an unfamiliar field. It also introduces a subtler hazard: a representation adequate for prediction may embed assumptions invalid in the borrowing domain, and its opacity makes that invalidity hard to detect.

C. Workflow agency and self-driving laboratories

The newest mechanism is agentic: systems that decompose a goal, select tools, execute actions and revise plans. Demonstrations include autonomous planning and execution of chemical syntheses [18] and language models augmented with domain toolchains that outperform unaided models on chemistry tasks [19]. Prototype pipelines have generated research ideas, run experiments and drafted manuscripts with minimal supervision [20]. These results are genuinely novel in kind, but present evaluations are narrow, and where automation extends to the writing and reviewing of the scientific record it engages integrity questions that Section VI takes up directly.

D. Democratisation and its asymmetry

Conversational access has widened participation: a researcher without programming training can now perform analyses that recently required a collaborator, and non-native English speakers can compete more evenly for space in Anglophone journals [14]. This is a real equity gain and, for institutions of the kind represented by the present authors, arguably the most consequential one. It is nonetheless asymmetric. Frontier capability depends on compute and licences concentrated among a few firms, and evidence on ideation suggests AI raises apparent novelty while depressing feasibility [21]—meaning wider access to generation does not by itself widen access to good judgement. Democratised generation without democratised verification capacity risks increasing volume faster than knowledge.

V. EFFICIENCY ACROSS THE RESEARCH LIFECYCLE

Efficiency claims are best assessed stage by stage, because both the magnitude of the gain and the nature of the exposure vary sharply across the lifecycle. Table I maps the nine stages of the coding scheme against representative capabilities, the reported efficiency effect and the principal risk introduced at that stage.

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TABLE I. AI CAPABILITIES, EFFICIENCY GAINS AND PRINCIPAL RISKS ACROSS THE RESEARCH LIFECYCLE

Research stage	Representative AI capability	Reported efficiency effect	Principal risk introduced
Problem formulation and ideation	Prompted hypothesis generation; gap detection across corpora	Faster generation of candidate questions; broader initial framing	Higher apparent novelty with weaker feasibility; convergence on similar questions
Literature search and synthesis	Semantic retrieval; automated screening; extraction into evidence tables	Largest single time saving reported; screening reduced from weeks to days	Fabricated or misattributed citations; silent omission of non-indexed and non-English work
Study and experiment design	Design-space exploration; power and sample simulation; protocol drafting	Moderate; faster iteration over design alternatives	Optimisation for statistical tractability rather than substantive relevance
Data collection and curation	Entity extraction; de-duplication; annotation; format harmonisation	High; annotation and cleaning costs substantially reduced	Propagated labelling error; privacy exposure when data leave institutional control
Analysis and modelling	Code generation; automated model selection; surrogate models	High for routine analysis; transformative where surrogates replace simulation	Unverified code and silent statistical error; overfitting; opaque model choice
Interpretation and theory building	Explanation generation; contrastive reasoning over results	Low to moderate; fluency exceeds reliability	Illusion of explanatory depth; plausible narrative fitted to noise
Writing and translation	Drafting, editing, structural revision, language equalisation	High and near-universal in reported practice	Undisclosed authorship contribution; stylistic homogenisation of the literature
Peer review and editorial screening	Triage; consistency and statistical checking; reviewer matching	Moderate; useful for detectable formal defects	Confidentiality breach when manuscripts are pasted into external services; delegated judgement
Archiving and reproducibility	Metadata generation; provenance capture; FAIR alignment	Moderate; improves discoverability at low cost	Non-reproducible outputs where model version and prompts are unrecorded

Two patterns in Table I deserve emphasis. First, the gains are largest and the verification weakest in exactly the same places—literature synthesis and writing. Both are language tasks at which current models excel superficially, and both are stages where errors are hard to detect precisely because the output reads well. Second, efficiency at one stage can create cost at another: a review completed in days but seeded with fabricated references imposes a larger downstream correction burden than the time it saved. Estimates that a growing share of published abstracts bears markers of model-assisted writing [15], [16] should therefore be read not as a scandal in itself but as an indicator that the verification layer has not scaled with the generation layer.

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VI. RISK AND THE CONDITIONS OF RESPONSIBLE USE

A. Epistemic risk

The most serious risks are epistemic. Hallucination is well documented [32], but its research-specific danger is that fabricated citations are format-correct and therefore pass casual inspection while corrupting the citation graph on which subsequent work depends. Beyond fabrication lie two structural effects. Monoculture arises when many researchers use the same few models, whose training data and defaults nudge them toward similar framings, similar methods and similar literatures, narrowing collective exploration even as individual productivity rises [8], [9]. The illusion of explanatory depth arises when a fluent output is mistaken for comprehension: the researcher can reproduce the explanation but cannot interrogate it, and the ordinary error-correcting friction of not-yet-understanding is bypassed [8].

B. Integrity, authorship and accountability

The prohibition on AI authorship rests on accountability: authorship entails answerability for the content, which no current system can bear [11]–[13]. The harder question is the boundary of legitimate assistance. Language editing is uncontroversial; generating the argument is not; and the wide middle ground—structural revision, drafting from the authors' own outline, summarising sources the authors have read—has no settled norm [14]. Because detection is unreliable, enforcement built on detection will produce both undetected violations and false accusations that fall disproportionately on non-native English writers. Governance must therefore rest on documented process rather than on post-hoc classification of text.

C. Bias, equity and epistemic representation

Models trained predominantly on English-language, high-income-country corpora underrepresent other languages, regional literatures and research traditions [10]. In practice this means AI-assisted reviews systematically under-retrieve regional scholarship, and AI-assisted framing tends to reproduce dominant paradigms. For Indian institutions this is a substantive methodological concern, not only an ethical one: a literature review of an Indian public-health or management question conducted through a global model will silently privilege sources indexed in Western databases.

D. Privacy, confidentiality and data protection

Submitting unpublished manuscripts, interview transcripts, clinical records or participant data to a third-party service may transfer personal data outside institutional control. Under India's Digital Personal Data Protection Act [27], such processing engages consent and purpose-limitation obligations, and the ICMR guidelines impose additional requirements for biomedical research [28]. Peer review deserves separate mention: a manuscript under review is confidential, and pasting it into a commercial model is a breach independent of whether the resulting review is any good.

E. Reproducibility, sustainability and concentration

An AI-assisted result is reproducible only if the model version, parameters and prompts are recorded; proprietary models are deprecated and updated without notice, so an unlogged pipeline may be irreproducible within months. Training and inference at scale carry material energy and water costs [35]. And the concentration of frontier capability among a small number of firms creates a dependency in which the direction of scientific tooling is set by commercial roadmaps rather than research priorities [2], [9].

VII. THE INNOVATION–EFFICIENCY–RESPONSIBILITY (IER) FRAMEWORK

The framework rests on a single design rule: every claimed benefit must be paired with a verification obligation and an observable indicator. Innovation and efficiency are treated as objectives to be pursued; responsibility is treated not as a constraint on them but as the condition under which their outputs count as knowledge. Table II sets out the three pillars and their operational levers.

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TABLE II. PILLARS, LEVERS AND INDICATORS OF THE IER FRAMEWORK

Pillar	Objective	Operational levers	Illustrative indicators
Innovation	Direct AI at questions that were previously unanswerable rather than merely slow	L1 Target search-space problems with verifiable ground truth; L2 Fund method transfer across disciplines; L3 Maintain methodological diversity by mandating non-AI comparison arms; L4 Support agentic tooling with human checkpoints at hypothesis and interpretation	Share of AI-assisted projects addressing previously infeasible questions; diversity of methods and research questions within a unit
Efficiency	Convert time savings into research quality rather than output volume	L5 Deploy AI first at high-gain, low-risk stages (curation, formatting, retrieval support); L6 Require human verification at every stage where output enters the record; L7 Standardise reusable prompt and pipeline templates; L8 Reinvest saved time in replication and verification	Verified-output ratio; correction and retraction rate; replication activity per unit of output
Responsibility	Ensure AI-assisted findings are accountable, reproducible and equitable	L9 Provenance logging of model, version, prompts and date; L10 Differentiated disclosure by contribution type, not blanket declaration; L11 Data-protection triage before any external submission; L12 Equity and capacity measures including regional-source supplementation and researcher training	Proportion of outputs with complete provenance logs; disclosure completeness; data-protection incidents; training coverage

Four features distinguish this from existing checklists. First, it is stage-differentiated: obligations attach to lifecycle stages rather than to the technology in general, which avoids both blanket prohibition and blanket permission. Second, disclosure is differentiated by contribution type—language editing, analysis, drafting and ideation carry different accountability weights and should be declared separately, since an undifferentiated statement that "AI was used" conveys almost nothing to a reader. Third, provenance logging replaces detection as the primary control, shifting the evidentiary burden from unreliable classifiers to documented process. Fourth, methodological diversity is treated as a governable quantity, with non-AI comparison arms as the practical instrument for resisting monoculture.

Because institutions differ widely in capacity, the framework is accompanied by the maturity scale in Table III. The scale is diagnostic rather than aspirational in the abstract: Level 2 is a realistic near-term target for most teaching-intensive institutions, and Level 4 presupposes infrastructure that few possess.

TABLE III. INSTITUTIONAL MATURITY SCALE FOR RESPONSIBLE AI USE IN RESEARCH

Level	Descriptor	Characteristic practice
L0 — Unmanaged	Ad hoc individual use	No policy, no disclosure, no training; use is invisible to the institution and risk is borne entirely by individuals
L1 — Declared	Disclosure only	A policy exists and use is declared in outputs, but declarations are undifferentiated and unverified
L2 — Verified	Human verification embedded	Mandatory verification of AI-assisted citations, code and data; differentiated disclosure; basic researcher training in place

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Level	Descriptor	Characteristic practice
L3 — Governed	Provenance and data controls	Provenance logs archived with outputs; data-protection triage before external submission; approved-tool register; ethics-committee guidance aligned with national instruments
L4 — Generative	Capability-building and diversity management	Institutional compute or licensing provision; methodological-diversity monitoring; reinvestment of efficiency gains into replication; contribution to open models and regional corpora

VIII. DISCUSSION AND RECOMMENDATIONS

The synthesis supports a position that is neither celebratory nor restrictive. AI has demonstrably changed what is knowable in domains that meet specific structural conditions, and it has demonstrably reduced effort across most of the research lifecycle. What it has not yet done is generate a commensurate verification capacity, and it is that asymmetry—not the technology as such—that produces the risks catalogued in Section VI. The practical implication is that the marginal institutional investment should go to verification, provenance and training rather than to further generation capacity.

A. For universities and research institutions

- Adopt a stage-differentiated AI policy that specifies permitted, permitted-with-disclosure and prohibited uses for each lifecycle stage, rather than a single blanket rule.
- Make provenance logging a submission requirement: model, version, date, prompts or prompt classes, and the human verification performed. This is low-cost and immediately raises reproducibility.
- Prohibit submission of confidential material—manuscripts under review, participant data, unpublished theses—to non-approved external services, and maintain an approved-tool register with data-processing terms reviewed against national data-protection law [27].
- Treat AI literacy as core research-methods training, covering hallucination, verification technique, bias in retrieval, prompt documentation and disclosure norms; supervisors need this before students do.

B. For funders and policymakers

- Fund verification and replication explicitly, on the reasoning that cheaper generation raises the social value of confirmation.
- Support shared regional infrastructure—compute access, institutional licensing consortia, and Indian-language and regional-literature corpora—so that democratisation does not stop at consumption of foreign models. The IndiaAI Mission [26] and the national AI strategy [25] provide an existing policy vehicle for this.
- Align institutional guidance with the emerging governance stack [22]–[24], [29] to avoid divergent local rules that raise compliance cost without raising standards.

C. For publishers and editors

- Replace undifferentiated disclosure with a structured contribution statement covering language, analysis, drafting and ideation separately, and require it at submission rather than at acceptance.
- Do not act on detector output alone; the false-positive burden falls on non-native English authors [14]. Require documented process instead.
- State an explicit policy on AI in peer review, addressing confidentiality directly, and provide reviewers with a compliant institutional option if triage assistance is permitted.

D. For individual researchers

Three habits carry most of the benefit. Verify every AI-supplied factual claim, citation and line of code against a primary source before it enters a draft. Log what was used, when and how, at the time of use rather than retrospectively. And preserve at least one stage of every project—typically interpretation—as deliberately unassisted, both as a check on the illusion of understanding and as maintenance of the judgement that makes the rest of the work defensible.

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IX. LIMITATIONS

This study is a conceptual synthesis and inherits the limitations of that design. It reports no primary empirical data, so the IER framework and maturity scale are proposals awaiting validation rather than tested instruments. The review, though protocol-guided, is narrative rather than systematic and involves interpretive judgement in coding. Coverage is skewed toward English-language and indexed sources, reproducing at a smaller scale the very representation bias the paper identifies. Finally, the evidence base is unusually volatile: capability claims from 2024–2026 may date quickly, and conclusions drawn about specific systems should be read as conclusions about a moving class of technology.

X. CONCLUSION AND FUTURE WORK

AI is best understood as a genuine but conditional expansion of research capacity. Its innovation record is strongest where large combinatorial search spaces meet verifiable ground truth, and weakest where interpretation and judgement dominate. Its efficiency record is broad, largest in language-intensive and data-curation work, and most weakly audited in exactly those places. Its principal risks are epistemic—fabrication, monoculture, and the substitution of fluency for understanding—and they are not adequately addressed by disclosure statements alone. The IER framework proposed here responds by pairing each benefit with a verification obligation and an auditable indicator, and by offering a maturity scale that lets institutions of very different means identify a realistic next step rather than an unreachable ideal.

Three lines of future work follow directly. First, empirical validation of the framework through multi-institution case studies, including measurement of the verified-output ratio and its relationship to correction rates. Second, longitudinal measurement of methodological diversity, to test whether the predicted monoculture effect is observable in citation and method distributions. Third, comparative study of adoption in resource-constrained research systems, where the equity gains of AI are largest and the governance capacity to secure them is smallest—a combination that makes such settings the most informative test of whether responsible use can scale.

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