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The Study of Digital Transformation, Artificial Intelligence and Their Implications for Future Research

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Abstract: *Digital transformation changes the conditions under which organizations produce and use knowledge. Artificial intelligence adds new ways to search, predict, generate, and evaluate information. Yet greater use of these tools does not establish that research becomes more reliable or more original. This paper develops a critical narrative review and descriptive secondary-data analysis to examine that distinction. Selected publications on organizational change, AI-assisted work, scientific discovery, and governance provide the conceptual foundation. Published statistics from Stanford's AI Index and Eurostat illustrate changes in adoption between 2023 and 2025. The two series are analysed separately because their populations and measurement procedures differ. The evidence indicates expanding use, but adoption statistics cannot demonstrate causal improvements in research quality. An original conceptual framework links digital foundations and AI capabilities with changes in research practice, conditioned by human expertise, institutional arrangements, and governance. Four propositions translate the framework into questions for future testing. The proposed agenda prioritizes reproducibility, task-specific evaluation, skill development, equitable participation, and preservation of intellectual diversity. The paper concludes that future research should evaluate the complete knowledge-production process, including verification and correction costs, rather than treating faster output as sufficient evidence of progress. No primary survey, experiment, or model validation is claimed. The contribution is an integrated account of how organizations can study AI-enabled transformation while maintaining the evidentiary standards needed for credible knowledge.*

Keywords: digital transformation; artificial intelligence; future research; research quality; organizational capabilities; responsible AI

I. INTRODUCTION

Digital systems can make research easier while changing which questions and evidence receive attention. With AI, evaluation extends beyond efficiency to decision making, verification, and the ability to challenge automated outputs.

Digital transformation scholarship distinguishes changes in information format, operational processes, and organizational arrangements [1]. Research on AI-assisted scientific discovery identifies opportunities across the research process [4]. Connecting these perspectives requires a clear boundary between a tool's capability and the validity of the knowledge produced with it.

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This paper examines how transformation and AI interact, what adoption indicators establish, and how future studies could evaluate research quality. It connects technical resources, human judgment, and institutional practice through a review, descriptive graphs, and an untested framework.

II. LITERATURE REVIEW

2.1 Transformation as organizational change

Verhoef and colleagues distinguish digitization, digitalization, and digital transformation, connecting the latter with changes in business models, capabilities, and organizational structures [1]. Nadkarni and Prügl emphasize technological and actor-related dimensions [2]. Hanelt and colleagues place transformation within an organizational-change perspective [3]. Together, these accounts support examining how technology is incorporated into work rather than simply recording whether it is available.

For research organizations, converting paper records into searchable files differs from revising how evidence is selected or decisions are authorized. A laboratory could adopt an AI assistant while retaining its existing approval process. Another organization could reorganize responsibilities around automated recommendations. These are analytically different changes. Table 1 specifies the distinctions used in this paper.

Table 1. Working distinctions for studying digitally enabled research

Construct	Unit examined	Observable change	Inference to avoid
Digitization	Information record	Conversion into usable digital form	Digital access equals new knowledge
Digitalization	Workflow	Changes in coordination or processing	Faster processing establishes validity
Digital transformation	Organization	Changes in roles, strategy, or value creation	A tool pilot establishes transformation
AI capability	Defined task	Specified prediction or generation performance	Benchmark success generalizes to all research

Source: Original analytical synthesis informed by [1–4]. The distinctions are working definitions, not measured scales.

2.2 Assistance, productivity, and understanding

Wang and colleagues review AI applications across scientific discovery, including hypothesis development and interpretation of complex data [4]. Noy and Zhang demonstrate productivity benefits in an experiment involving professional writing tasks [5]. The latter evaluates defined tasks; it does not establish an effect on scientific validity, research originality, or every occupation.

Messeri and Crockett warn that AI adoption can encourage misplaced confidence in understanding and narrow the range of questions or approaches pursued [6]. This makes task performance and knowledge quality separate evaluation problems. An accurate prediction may be useful without supplying a complete explanation. A fluent manuscript may still require its claims and references to be checked.

The review separates adoption, capability, use, and outcome. Keeping these constructs distinct helps identify whether change follows from technology, the workflow, or user expertise.

III. RESEARCH METHODOLOGY

3.1 Design and source selection

The study combines a critical narrative review with descriptive analysis of published aggregate statistics. Targeted web searches were conducted on 14 October 2026. Search terms combined digital transformation, organizational change,

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artificial intelligence, scientific discovery, research productivity, and governance with review, experiment, adoption, and future research. Bibliographic details were checked against publisher, author-institution, or official agency records. Selection prioritized peer-reviewed work relevant to the conceptual relationships, experimental evidence with a defined task, and official reports with identifiable data coverage. Foundational transformation reviews are paired with more recent AI research and 2025–2026 adoption reports. This is a purposive, non-exhaustive review. No registered protocol, complete screening log, duplicate screening, or formal risk-of-bias score is claimed. These boundaries limit coverage and permit selection bias.

3.2 Secondary indicators and comparability

The first series contains the share of survey respondents reporting organizational AI use for 2023, 2024, and 2025, as summarized by the Stanford AI Index [7, 8]. It is a survey-based indicator, not an estimate that every organization worldwide has adopted AI. The second series concerns covered EU enterprises with at least ten employees or self-employed persons [9]. Sector coverage and questionnaire definitions are part of that indicator.

Eurostat values follow its December 2025 release, including 8.1% for 2023. The 2025 questionnaire added a category for generating images, video, and audio [9]. Changes therefore require caution about measurement scope. No missing value was interpolated.

3.3 Analysis and presentation

Values were transcribed into a small source ledger and checked against the figures and Table 2. Changes are expressed in percentage points, calculated by subtracting percentages. The two populations are not pooled. No confidence interval, significance test, causal coefficient, or forecast is calculated because the material does not support those analyses. Lines connect observed years only.

The review organizes evidence by its unit of analysis and permitted inference. Original tables clarify constructs and measurement boundaries. Original charts visualize attributed secondary figures. The conceptual framework and propositions are interpretive contributions, not statistically validated results.

IV. DESCRIPTIVE EVIDENCE AND DISCUSSION

4.1 Organizational adoption in survey reports

The AI Index summaries report organizational AI use at 55% in 2023, 78% in 2024, and 88% in 2025 [7, 8]. Figure 1 displays those published values. The observed increases are 23 and 10 percentage points respectively. This arithmetic describes reported diffusion; it does not identify why adoption changed.

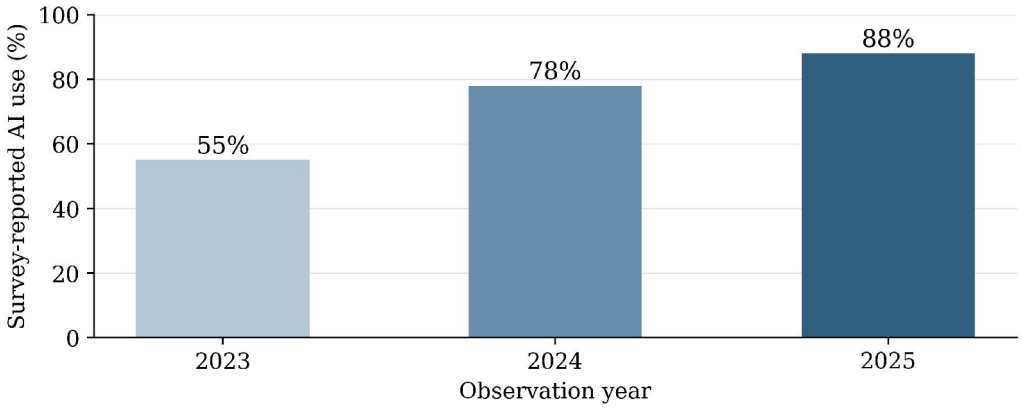


Figure 1. Survey-reported organizational AI use, 2023–2025

Source: Original chart from Stanford AI Index summaries [7, 8]. Values refer to survey respondents' organizations, not a population census.

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Use is a starting point for investigation. It does not show how deeply AI is incorporated into decisions, whether employees use it consistently, or whether its outputs are dependable. Repeated surveys may also differ in participation and reporting. The chart should therefore guide questions about implementation rather than serve as proof that research performance improved.

4.2 Why adoption is an incomplete outcome

An institution could count a single trial of an AI tool as use. Another could rely on it for a recurring analytical task. A research design should distinguish these levels through observable workflow records and clearly defined frequency measures. It should also record the system version and the role given to its output.

This paper proposes examining verification effort alongside production effort. A reduction in drafting time may be offset by reference checks, correction, or reanalysis. The relevant outcome is the time required to produce a defensible result. That outcome must be measured directly; it cannot be derived from the adoption percentages.

4.3 Enterprise use in the European Union

Eurostat's December 2025 release reports covered enterprise AI use of 8.1% in 2023, 13.5% in 2024, and 20.0% in 2025 [9]. Figure 2 presents the series from that release. The increases are 5.4 and 6.5 percentage points. Questionnaire expansion in 2025 limits a strict like-for-like interpretation.

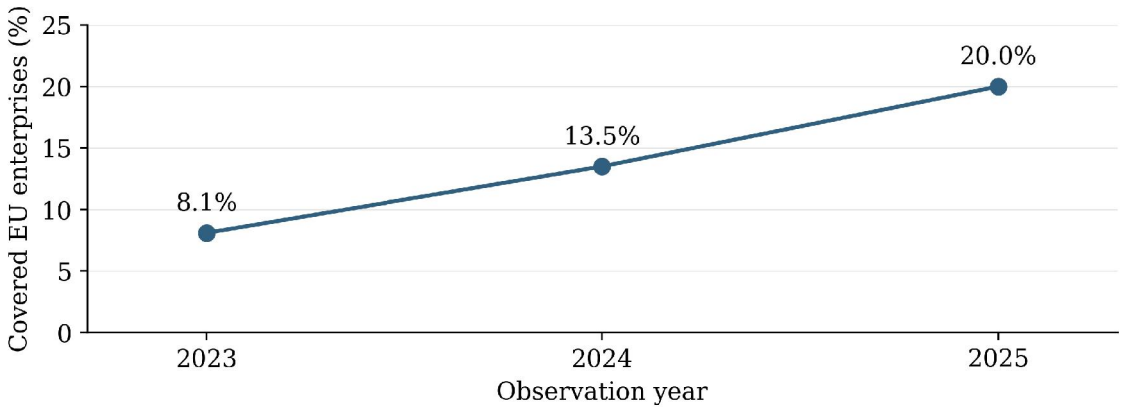


Figure 2. AI use among covered EU enterprises, 2023–2025

Source: Original graph from Eurostat's December 2025 release [9]. Covered sectors and enterprises with at least ten workers. AI categories expanded in 2025.

Table 2. Values used in the charts and their measurement boundaries

Year	AI use reported for surveyed organizations (%)	Covered EU enterprises using AI (%)
2023	55 [7]	8.1 [9]
2024	78 [7]	13.5 [9]
2025	88 [8]	20.0 [9]

Sources: [7–9]. Different populations and measurement systems; values are not directly comparable. Percentage-point changes are author calculations.

Both series indicate wider reported use within their own coverage. Their different levels cannot be interpreted as a geographical performance gap. Nor do enterprise statistics measure adoption by universities or individual researchers. Future studies should define the population first and investigate outcomes separately from adoption.

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V. CONCEPTUAL FRAMEWORK

5.1 From digital foundations to credible knowledge

The proposed framework treats digital foundations and AI capability as complementary inputs. Foundations include accessible data, compatible systems, and clear responsibilities. AI capability concerns a specified task. Together, these inputs may change the research workflow through human–AI interaction. Human expertise and governance condition whether that change supports credible knowledge. Figure 3 represents these proposed relationships; none is estimated from the adoption data.

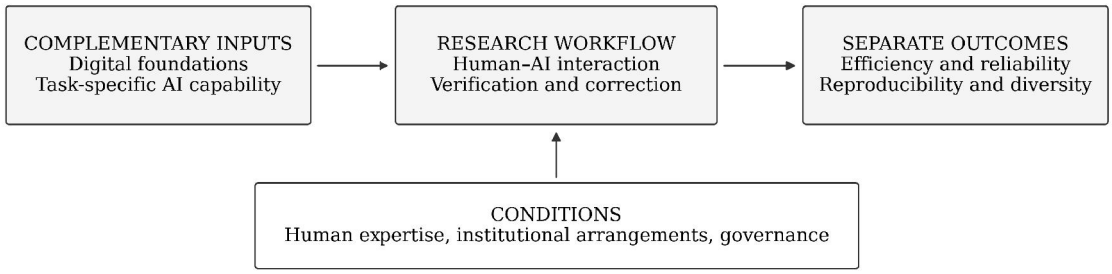


Figure 3. Proposed framework for studying AI-enabled research transformation

Source: Original conceptual graph. Arrows are untested relationships; no causal effect or statistical estimate is asserted.

5.2 Propositions for empirical investigation

Proposition 1: The association between AI capability and research quality depends on the quality of the digital foundations supporting its use. Testing requires separate measures of data readiness, integration, and the performance of the defined AI task.

Proposition 2: Human expertise conditions the relationship between AI assistance and research outcomes. Studies should assess whether users can identify errors, explain decisions, and complete comparable tasks when assistance is unavailable.

Proposition 3: Governance affects whether changes in workflow produce reliable and reproducible results. Tests should examine documented verification, correction, and responsibility rather than the existence of a policy alone.

Proposition 4: Greater efficiency can coexist with reduced diversity of research questions or methods. Studies should evaluate both the value of completed work and the range of alternatives considered. These propositions organize future inquiry; they are not confirmed hypotheses.

VI. IMPLICATIONS FOR FUTURE RESEARCH

6.1 Evaluate complete tasks

Researchers should identify the task before choosing an evaluation metric. Search assistance can be assessed through relevant evidence retrieved and evidence missed. Coding assistance requires examination of executable behavior and analytical assumptions. Writing assistance needs evaluation of factual accuracy, argument quality, and citation validity. A single satisfaction score cannot establish all of these outcomes.

Comparative studies should use equivalent task conditions and record the verification performed after the initial output. Appropriate randomization may support causal inference where access can be assigned ethically. When randomization is not feasible, baseline differences and simultaneous workflow changes need explicit analysis. Results should remain limited to the evaluated task and setting.

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6.2 Study reproducibility and system change

An AI-enabled workflow has several moving parts. Model versions, prompts, retrieval sources, preprocessing, and human decisions can affect the result. Future research should preserve these elements wherever consent, licensing, and security permit. A later researcher needs enough information to reconstruct the analytical procedure and identify where discretion entered.

Reproducibility also requires specifying its meaning. Repeating a procedure is different from obtaining an identical generated response or confirming a conclusion on new data. Researchers should report which form was tested. If a provider changes a system, comparisons across time should investigate whether the intervention remained equivalent.

6.3 Examine skill development and intellectual diversity

Longitudinal studies could follow how repeated AI assistance changes learning and independent judgment. A useful design would assess performance with and without assistance, the ability to explain reasoning, and transfer to unfamiliar problems. It should avoid inferring skill gain merely because participants complete more work.

Research portfolios deserve similar attention. Teams could compare the questions, sources, and methods considered before and after adoption. The purpose would be to test whether assistance widens inquiry or channels it towards familiar patterns. Such evaluation would operationalize the concern about restricted understanding raised in the literature [6]. Diversity should be defined carefully; a longer list of outputs is not necessarily a broader range of ideas.

6.4 Establish meaningful time horizons

Immediate convenience and sustained benefit may diverge. Evaluations should include follow-up, correction work, and maintenance. A pilot that works with intensive support may not scale under routine staffing. Studying that transition would help explain why a tool-level advantage sometimes fails to become an institutional improvement.

VII. GOVERNANCE AND MULTIDISCIPLINARY PRACTICE

7.1 Assign responsibility across the workflow

The NIST AI Risk Management Framework organizes voluntary risk-management activity around governance, contextual mapping, measurement, and management [10]. Applied to research, this suggests that evaluation belongs before deployment and throughout use. It does not guarantee that a particular system is safe. Institutions still need evidence for their intended application.

This paper proposes a named responsibility for each consequential decision. One role should authorize access to sensitive material. Another should review the analytical output, while the researcher remains responsible for the claim presented. When responsibilities overlap, the process should make that overlap visible. Automatic processing does not remove the need for an accountable decision.

7.2 Keep disciplinary expertise in the evaluation

Computer science can assess task performance and technical uncertainty. Domain specialists can evaluate whether a claim makes sense within the field. Research-methods expertise can examine identification, measurement, and sampling. Organizational studies can explain changes in work and authority. Their shared question is whether the process produces knowledge that withstands scrutiny.

A practical evaluation could give an interdisciplinary team the same output and ask it to identify different classes of error. Disagreement would be recorded and resolved through a stated procedure. Such a design would test whether collaboration detects errors that a single disciplinary review misses. It is a proposed study, not an outcome demonstrated here.

7.3 Address access and representational limits

UNESCO guidance emphasizes human capacity and a human-centred approach to generative AI in education and research [11]. Bender and colleagues identify risks related to language-model development and deployment, including the relationship between training material, representation, and apparent fluency [12]. These concerns motivate evaluation with the languages and users for whom a system is intended.

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Indian studies could compare performance across English, Hindi, and regional-language tasks, subject to adequate design and resources. Institutional access, training, and licensing costs could also affect participation. These are questions for investigation, not findings about Indian institutions. Claims of universal benefit should await evidence beyond a narrow development sample.

7.4 Preserve evidence and document corrections

Teams should record accepted outputs, rejected suggestions, and corrections that materially affect a result. This record would help distinguish the contribution of the tool from that of the researcher. Disclosure should follow the receiving journal's current policy. Neither text fluency nor an automated detector can substitute for a transparent account of how the work was produced.

VIII. DISCUSSION AND LIMITATIONS

8.1 Adoption creates questions rather than answers

The conceptual and descriptive analyses point to different levels of change. Published adoption indicators show that AI use is becoming more widespread in the populations covered. Transformation research asks whether the organization of work changes. Research-quality evaluation asks whether the resulting claims are reliable. Moving from one level to another requires additional evidence.

The main analytical contribution is to join these levels without collapsing them. Digital foundations may enable a task, but task completion does not establish validity. Human review may identify mistakes, but its effectiveness depends on time, expertise, and authority. Governance may define a process, but its operation must be observed. Future research should examine these connections directly.

8.2 Boundaries of the evidence

The review is selective and cannot claim comprehensive coverage. Publicly accessible material and the chosen search terms shaped source selection. The adoption series use different populations and definitions, so their levels cannot be pooled. Changes in survey participation or questionnaire scope may influence the reported trends. No uncertainty estimates were constructed from aggregate percentages.

The paper also draws on research conducted at different levels, from professional writing tasks to organizational change and scientific practice. These findings are not interchangeable. The framework has not been validated, and the charts do not test its propositions. New system versions and institutional arrangements may further limit the duration of a finding's applicability.

IX. CONCLUSION

Digital transformation and artificial intelligence can alter how research is organized and performed. Their implications extend to the questions selected, the evidence examined, and the responsibilities assigned. The published adoption data establish growing reported use within specified populations. They do not establish that research has become more accurate or more original.

This paper provides an integrated conceptual framework and four propositions for future testing. It calls for evaluation of complete workflows, including verification, correction, independent skill, and intellectual diversity. The central priority is credible knowledge. Research should measure whether that priority is served, rather than assuming that increased output or wider adoption is sufficient evidence of progress.

Data availability

All numerical observations are published aggregates identified in Table 2 and the cited sources. No primary dataset was generated. The figures are original visualizations of those observations or of the proposed framework.

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