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A Global Systematic Review of Artificial Intelligence and Research Productivity in Higher Education

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Systematic Review

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Abstract

Background

Artificial intelligence (AI), including generative AI and large language models (LLMs), is increasingly used throughout university research. However, faster completion of individual tasks does not necessarily indicate sustained gains in research productivity.

Objective

To synthesize global evidence published from 2017 to 2025 on how AI affects research productivity in higher education.

Methods

Following Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidance, Scopus was searched and 212 records were identified. Database filters retained 65 records; 40 full texts were assessed, and 18 studies were included in a qualitative thematic synthesis.

Results

Six application clusters emerged: literature discovery and synthesis; idea generation and research design; data management and analysis; academic writing and language support; collaboration and workflow automation; and dissemination, peer review, and research administration. Evidence consistently indicated perceived or task-level efficiency gains, but direct measures of publication output, research quality, novelty, impact, and long-term productivity were rare.

Conclusion

AI is currently supported more strongly as a research-efficiency technology than as a proven driver of sustainable research productivity. Benefits depend on researcher capability, institutional governance, data quality, and human verification.

Plain-language summary

Artificial intelligence tools are now used by university researchers to search literature, develop ideas, analyze data, improve writing, coordinate projects, and communicate findings. This review examined global research published between 2017 and 2025 to determine whether these tools improve research productivity. A Scopus search identified 212 records; after filtering and screening, 18 studies were

synthesized. The evidence shows consistent benefits for specific tasks, especially information retrieval, summarization, coding, drafting, and language support. However, few studies measured whether these time savings produced more publications, better-quality research, greater originality, stronger reproducibility, or lasting scholarly impact. The review therefore concludes that AI is currently better established as a tool for research efficiency than as a proven source of sustained productivity. Universities should combine responsible access with practical training, clear rules for privacy and disclosure, and careful human verification of AI-assisted work.

1. Introduction

Artificial intelligence (AI) has moved from a specialized computational resource to a general-purpose layer within academic work. Universities now encounter AI in search and recommendation systems, automated transcription, machine translation, statistical modelling, qualitative coding, laboratory automation, writing assistance, research administration, and generative systems capable of producing text, code, images, and synthetic data. Earlier research on AI in higher education concentrated largely on teaching, learning analytics, prediction, assessment, and institutional administration (Chen et al., 2020; Ouyang et al., 2022; Zawacki-Richter et al., 2019). The public release and rapid diffusion of generative AI after 2022 broadened the focus. Researchers began using conversational systems across the full research cycle, from identifying a topic and generating search terms to drafting manuscripts and preparing public-facing summaries (Khalifa & Albadawy, 2024; Ray, 2023). This shift has created a practical and theoretical question for universities: does AI merely accelerate isolated research tasks, or does it improve research productivity in a meaningful and sustainable sense?

The distinction between efficiency and productivity is particularly important in the current evidence base. Experimental research outside the university sector shows that generative AI can reduce completion time and improve the average quality of certain writing tasks (Noy & Zhang, 2023). Studies of researchers and doctoral writers similarly report faster drafting, language support, and more iterative human–AI interaction (Andersen et al., 2025; Nguyen et al., 2024). However, a time saving on a bounded task does not automatically establish an increase in long-term scholarly productivity. Time saved may be reinvested in deeper analysis, additional projects, or mentoring, but it may also be absorbed by verification work, prompt refinement, institutional compliance, or increased expectations. Moreover, productivity effects can vary by discipline, language, career stage, infrastructure, and the sensitivity of the data being handled.

Although research on artificial intelligence (AI) in higher education is expanding, evidence focused specifically on research productivity remains fragmented (Bond et al., 2024; Crompton & Burke, 2023; Khalifa & Albadawy, 2024). This systematic review covers 2017–2025 and asks how AI applications affect research work, which productivity dimensions are reported or measured, which conditions enable or constrain gains, and what evidence is still required. It contributes six application clusters and distinguishes task-level efficiency from sustained scholarly productivity.

1.1 Conceptual Framework

A sociotechnical perspective treats AI tools as components of a wider system of researchers, disciplines, data, incentives, publishers, funders, and institutional policies. Their productivity effects depend on task–technology fit, human oversight, researcher capability, secure infrastructure, and the consequences of error. The framework therefore links AI affordances to efficiency, throughput, quality, reproducibility, collaboration, and impact, while recognizing integrity, bias, privacy, deskilling, and inequality as boundary conditions. Figure 1 presents this framework.

2. Methods

2.1 Review Design and Scope

This study used a systematic literature review design, following Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 reporting principles (Page et al., 2021). Systematic review methods supported transparent searching, screening, appraisal, and synthesis of a fragmented interdisciplinary field (Snyder, 2019; Tranfield et al., 2003). Because the included evidence comprised reviews, surveys, experiments, policy analyses, and qualitative studies, synthesis was qualitative and thematic rather than meta-analytic.

The review covered January 2017–December 2025 and used Scopus to identify research across computer science, social sciences, and business, management, and accounting.

2.2 Database and Search Strategy

The search combined four concepts: AI, research activity, productivity, and higher education. The Scopus query used title, abstract, and keyword terms for artificial intelligence, generative AI, ChatGPT, large language models, machine learning, and natural language processing; research productivity, efficiency, workflows, writing, knowledge production, and research processes; and universities, academics, researchers, faculty, and doctoral students. Publication years were restricted to 2017–2025. Appendix A provides the complete reproducible search string.

2.3 Identification and Database Filtering

The search identified 212 records. Database filters reduced the corpus to 91 articles or reviews, 85 English-language records, 81 final publications, and 65 records in the selected subject areas. The export contained no missing records or duplicates; all 65 records entered title and abstract screening.

2.4 Eligibility Criteria

Eligible studies were English-language final journal articles or reviews published in 2017–2025 that addressed AI in higher education or academic research and reported an application, productivity outcome, adoption condition, governance issue, or ethical implication. Studies limited to schools,

technical model performance without a university context, student learning without research relevance, non-analytical commentary, or duplicate findings were excluded.

2.5 Screening and Full-Text Assessment

Title and abstract screening excluded 25 records. Forty full texts were assessed and 22 were excluded: 10 lacked substantive attention to research productivity or workflows, 6 addressed teaching or student performance only, 4 provided insufficient analytical evidence, and 2 lacked a higher-education context. Eighteen studies were included. No automation tool made eligibility decisions; Fig. 2 presents the selection flow.

2.6 Data Extraction

A structured matrix recorded citation details, geographical scope, population, purpose, design, data source, AI application, research stage, productivity dimension, findings, risks, recommendations, and limitations for each included study.

2.7 Quality Appraisal

Methodological quality was appraised across question clarity, design appropriateness, data adequacy and transparency, analytical coherence, and evidential support for conclusions. Each criterion was rated strong, adequate, or weak; appraisal informed interpretive weight rather than automatic exclusion.

2.8 Evidence Synthesis

Descriptive mapping summarized publication timing, design, geography, and research stage. Iterative thematic analysis (Braun & Clarke, 2021) consolidated codes into six application clusters and cross-cutting conditions, while a second analytical layer separated task efficiency from broader productivity outcomes.

2.9 Reliability and Transparency

Trustworthiness was strengthened through documented counts, prespecified eligibility criteria, standardized extraction, comparison across study types, and retention of contradictory evidence. However, a second reviewer did not independently replicate the Scopus export or all screening decisions; the reported sequence and exclusions should be checked against the author’s final screening log before submission.

Table 1 summarizes the search and eligibility protocol.

Table 1
Search and eligibility protocol

Component	Specification	Result
Database and period	Scopus; January 2017–December 2025	Initial records: 212
Document type	Journal articles and reviews	91
Language	English	85
Publication stage	Final	81
Subject areas	Computer Science; Social Sciences; Business, Management and Accounting	65
Pre-screening data check	Missing records and duplicates	0 missing; 0 duplicates
Title/abstract screening	Relevance to AI, higher education, research process, or productivity	40 full texts retained
Full-text eligibility	Direct contribution to research productivity, workflow, adoption, governance, or integrity	18 studies included

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3. Results

The 18 studies indicate rapid growth after 2022, with a shift from broad mapping of conventional AI in higher education toward generative AI, academic writing, adoption, and institutional policy. Evidence remained methodologically and geographically uneven, with limited longitudinal measurement and limited empirical representation of the Global South. Stakeholder research also reported continuing integrity and governance concerns (Yusuf et al., 2024).

3.1 Evidence Profile and Analytical Categories

Studies were categorized by research-cycle stage and productivity outcome. Six clusters emerged: literature discovery and synthesis; idea generation and research design; data management and analysis; academic writing and language support; collaboration and workflow automation; and dissemination, peer review, and research administration.

3.2 Literature Discovery, Screening, and Synthesis

AI-supported discovery can generate search terms, recommend literature, summarize abstracts, extract concepts, and organize evidence (Khalifa & Albadawy, 2024; Madanchian & Taherdoost, 2025). These functions can reduce information-handling time, but general-purpose chatbots cannot independently conduct a reliable systematic review. Sources, screening rules, and eligibility decisions must remain transparent, auditable, and manually verified.

3.3 Idea Generation and Research Design

Generative AI can support brainstorming, research-question development, theoretical connections, instrument drafting, and comparison of analytical strategies (Dwivedi et al., 2023; Ray, 2023). Its value is greatest during divergent exploration, but fluent suggestions may reproduce common assumptions or imply novelty without evidence. AI-generated ideas should therefore be treated as hypotheses requiring literature verification, feasibility assessment, and disciplinary judgment.

3.4 Data Management, Coding, and Analysis

AI supports data cleaning, transcription, classification, coding, code generation, statistical explanation, visualization, and pattern detection (Andersen et al., 2025; Madanchian & Taherdoost, 2025). These uses may expand feasible analyses, but automatically generated code and qualitative categories can contain subtle errors or lose context. Researchers must document and test each transformation, and sensitive or confidential data must be processed only in approved environments.

3.5 Academic Writing, Editing, and Multilingual Support

Academic writing is the most visible application. AI can support outlining, revision, translation, editing, and audience adaptation (Khalifa & Albadawy, 2024), while iterative human–AI collaboration appears more productive than uncritical delegation (Nguyen et al., 2024). Benefits for multilingual authors coexist with risks of homogenized voice, fabricated citations, and unreliable detection (Gao et al., 2023; Liang et al., 2023). Authors remain responsible for verifying facts, sources, and interpretations and for disclosing material use.

3.6 Collaboration, Workflow Automation, and Research Administration

AI can also coordinate schedules, summarize meetings, draft routine communication, support grant documentation, and assist distributed teams. Adoption depends on expected performance, researcher capability, facilitating conditions, and practical training (Mah & Groß, 2024; Patterson et al., 2024). Institutional policies are most useful when they specify approved tools, data restrictions, disclosure expectations, verification duties, and available support (Wang et al., 2024).

3.7 Dissemination, Peer Review, and Scholarly Communication

AI can prepare policy summaries, translations, presentation drafts, and responses to reviewers, shortening the path from analysis to communication. In peer review and editorial work, however, confidential manuscripts must not be uploaded to unauthorized systems and evaluative judgment cannot be delegated. AI systems do not meet authorship requirements because they cannot accept accountability, approve a final version, or disclose conflicts (Flanagin et al., 2023; Thorp, 2023).

3.8 Measurement of Research Productivity

The central finding is a measurement gap. Most studies infer productivity from perceived usefulness, faster completion, or task-level assistance. Direct evidence on publication output, grant success, citation impact, research quality, originality, reproducibility, time to degree, or societal impact is rare. The evidence therefore supports AI as a credible research-efficiency tool, but not yet as a proven driver of sustainable research productivity.

Table 2 summarizes the designs and principal productivity implications of the 18 included studies.

Table 2

Summary matrix of the 18 included studies

Study	Purpose / design	Key finding for research productivity	Recommendation / implication
Zawacki-Richter et al. (2019)	Systematic review; 146 studies in higher education	Mapped profiling/prediction, assessment, adaptive systems, and administration; limited educator-centered research.	Broaden educator involvement and investigate pedagogical and organizational effects.
Chen et al. (2020)	Narrative review of AI in education	AI supports administration, instruction, and learning through data-driven and adaptive functions.	Integrate technical development with educational goals and ethical safeguards.
Ouyang et al. (2022)	Systematic review of online higher-education studies	Conventional AI applications dominated; advanced human-centered uses remained limited.	Increase rigorous empirical research and theory-driven designs.
Crompton & Burke (2023)	PRISMA systematic review; 138 articles	Rapid growth in AI-in-higher-education publications, with diverse applications and uneven methods.	Strengthen methodological quality and educator-centered inquiry.
Ray (2023)	Comprehensive review of ChatGPT applications and risks	Identified research uses in ideation, coding, writing, and communication alongside bias and reliability risks.	Maintain human oversight, transparency, and ethical controls.
Dwivedi et al. (2023)	Multidisciplinary analytical synthesis	Generative AI offers wide research and policy opportunities but disrupts authorship, assessment, and trust.	Develop cross-sector governance and responsible-use norms.
Kasneci et al. (2023)	Multidisciplinary commentary/review	LLMs support research and writing but require AI literacy, fact-checking, and pedagogical redesign.	Build critical AI literacy and clear institutional strategies.
Gao et al. (2023)	Comparative study of AI-generated and original abstracts	AI-generated abstracts appeared credible; human and automated detection were imperfect.	Require verification and disclosure rather than relying solely on detection.
Liang et al. (2023)	Empirical evaluation of AI-text detectors	Detectors disproportionately misclassified non-native English writing.	Avoid punitive detector-only decisions and assess linguistic bias.
Patterson et al. (2024)	Quantitative study based on the Unified Theory of Acceptance and Use of Technology	Expected productivity gains, mentor views, peer use, and task breadth influenced adoption.	Improve facilitating conditions and compare adoption across academic groups.

Study	Purpose / design	Key finding for research productivity	Recommendation / implication
Nguyen et al. (2024)	Process study of 10 doctoral writers; 626 recorded activities	Iterative human–AI collaboration was associated with better writing processes than linear delegation.	Teach interaction strategies that preserve author agency and critical review.
Khalifa & Albadawy (2024)	Systematic review of 24 studies	AI supported ideation, structure, literature synthesis, analysis, editing, and communication.	Integrate AI transparently while retaining human insight and integrity.
Wang et al. (2024)	Policy analysis of top 100 U.S. universities	Most institutions adopted an open but cautious position emphasizing ethics, accuracy, privacy, and resources.	Develop discipline-specific guidance and protect sensitive information.
Yusuf et al. (2024)	Multicultural empirical study	Stakeholders recognized transformative potential but expressed integrity and governance concerns.	Reform assessment, strengthen literacy, and create inclusive policies.
Bond et al. (2024)	Meta-systematic review of AI in higher education	The review field expanded rapidly but showed overlap, variable quality, and recurring gaps.	Improve review rigor, transparency, and synthesis across subfields.
Mah & Groß (2024)	Faculty survey and profile analysis	Faculty use and self-efficacy varied, producing distinct professional-development needs.	Use differentiated rather than one-size-fits-all training.
Andersen et al. (2025)	National survey of 2,534 Danish researchers	Language editing and data analysis were viewed more positively than experiment design or peer review; use varied by field and seniority.	Create adaptable, discipline-specific research-integrity guidance.
Madanchian & Taherdoost (2025)	Review of AI and research efficiency	AI can automate discovery, analysis, design, and writing, but bias, privacy, infrastructure, and skills constrain value.	Invest in training, infrastructure, policy, and equitable implementation.

Table 3 consolidates the six application clusters, potential gains, and principal conditions or risks.

Table 3

Thematic synthesis of AI applications and productivity implications

Application cluster	Typical uses	Potential productivity gain	Principal condition or risk
Discovery and synthesis	Search-term generation, clustering, summarization, evidence extraction	Faster orientation and broader literature coverage	Fabricated sources, omitted evidence, visibility and language bias
Ideation and design	Research questions, hypotheses, frameworks, instrument drafts	More rapid iteration and interdisciplinary exploration	Generic designs, false novelty, weak contextual validity
Data and analysis	Transcription, coding, statistical code, debugging, modelling, visualization	Reduced repetitive labor and lower technical barriers	Privacy, analytical error, opaque transformations, reproducibility
Writing and language	Outlining, drafting, editing, translation, reviewer responses	Faster drafting and improved clarity or accessibility	Hallucination, authorship ambiguity, deskilling, homogenized voice
Collaboration and administration	Meeting summaries, project documents, grants, correspondence, task coordination	Lower administrative burden and improved team coordination	Confidentiality, unequal access, workload intensification
Dissemination and review	Lay summaries, presentations, formatting, review support	Faster translation of research for multiple audiences	Confidential peer-review data, over-delegation of judgment

4. Discussion

The findings show a portfolio of task-level gains rather than a single transformation of research productivity. AI consistently accelerates information retrieval, drafting, coding, and routine coordination, but verification, privacy, and governance costs determine the net benefit. This conclusion aligns with broader reviews that report rapid adoption alongside uneven evidence quality and strong needs for human oversight (Bond et al., 2024; Kasneci et al., 2023; Zawacki-Richter et al., 2019).

AI does not create productivity directly; it creates affordances that become productive through researcher capability and institutional readiness. Productivity should therefore be assessed as a multidimensional profile comprising efficiency, throughput, quality, novelty, reproducibility, collaboration, and impact. A gain in one dimension may be offset by errors, homogenization, deskilling, unequal access, or additional verification time.

4.1 Implications for Policy and Practice

Universities should embed AI within research governance, provide secure approved tools and role-based training, classify data before use, require verification and proportionate disclosure, and avoid detector-only integrity decisions (Liang et al., 2023; Wang et al., 2024). Researchers should keep a record of consequential AI use, including the tool, purpose, data entered, human checks, and substantive influence. Institutional evaluation should focus on research quality and researcher well-being as well as output volume.

4.2 Future Research Directions

Future research should prioritize longitudinal, experimental, and comparative designs; validated multidimensional productivity measures; disciplinary and institutional comparisons; representation of the Global South and non-Anglophone settings; doctoral and early-career development; and testing of concrete integrity controls. Studies should report the AI tool, version, task, data exposure, verification, and correction time, and should examine interaction patterns rather than tool access alone (Nguyen et al., 2024). Table 4 translates these gaps into a priority research agenda.

Table 4
Priority research agenda

Priority	Suggested design	Core outcomes	Contribution
Long-term productivity	Longitudinal panel studies	Time allocation, outputs, quality, grants, well-being	Tests whether task savings become sustained gains
Causal task effects	Randomized or quasi-experimental studies	Accuracy, originality, time, correction effort	Separates AI effects from user self-selection
Institutional readiness	Comparative multi-university studies	Policy, training, secure access, adoption, incidents	Identifies governance mechanisms that create value
Global equity	Cross-country and multilingual designs	Access, cost, local-language performance, publication outcomes	Tests whether AI reduces or widens research inequality
Disciplinary variation	Field-specific mixed-method studies	Task fit, acceptable use, validation burden	Avoids one-size-fits-all conclusions
Measurement development	Scale development and validation	Efficiency, throughput, quality, novelty, reproducibility, integrity	Creates a balanced research-productivity instrument
Doctoral development	Cohort and supervisor–student studies	Skill formation, dependency, time to completion	Distinguishes scaffolding from deskilling
Integrity controls	Field trials of governance measures	Error rates, disclosure, privacy incidents, compliance burden	Evaluates safeguards rather than discussing them abstractly

4.3 Limitations

This review used Scopus as the sole database, included English-language final journal articles and reviews, and covered a rapidly changing field through December 2025. It may therefore omit regional, non-English, technical, preprint, and later evidence. The diverse designs precluded meta-analysis, and screening and appraisal were not independently replicated by a second reviewer. Findings should be interpreted as a structured synthesis of an emerging evidence base rather than a definitive causal estimate.

5. Conclusion

Artificial intelligence is increasingly embedded in university research. The reviewed evidence supports meaningful task-level efficiency gains across literature discovery, ideation, analysis, writing, coordination, and dissemination, but direct evidence of sustained gains in research quantity, quality, novelty, reproducibility, and impact remains limited.

Benefits depend on researcher capability, disciplinary judgment, secure infrastructure, transparent disclosure, and systematic verification. Universities should therefore support responsible, task-specific adoption and evaluate outcomes empirically. AI can extend human capability, but it does not replace scholarly accountability.

Declarations

Conflict of interest:

The authors declare no conflict of interest.

Ethics approval:

Not applicable. The study synthesized published literature and did not involve human participants.

Consent to participate:

Not applicable.

Consent to publish:

Not applicable.

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Author Contribution

M.A.O. conceived the study, designed the review methodology, conducted the literature search, screened and analyzed the included studies, synthesized the findings, and wrote the original manuscript. M.M.A. contributed to the study design, assisted with data interpretation, critically reviewed and revised the manuscript for important intellectual content, and provided overall supervision throughout the research process. M.A.O. prepared all figures and tables. Both authors reviewed, approved the final version of the manuscript, and agree to be accountable for all aspects of the work.

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Figures

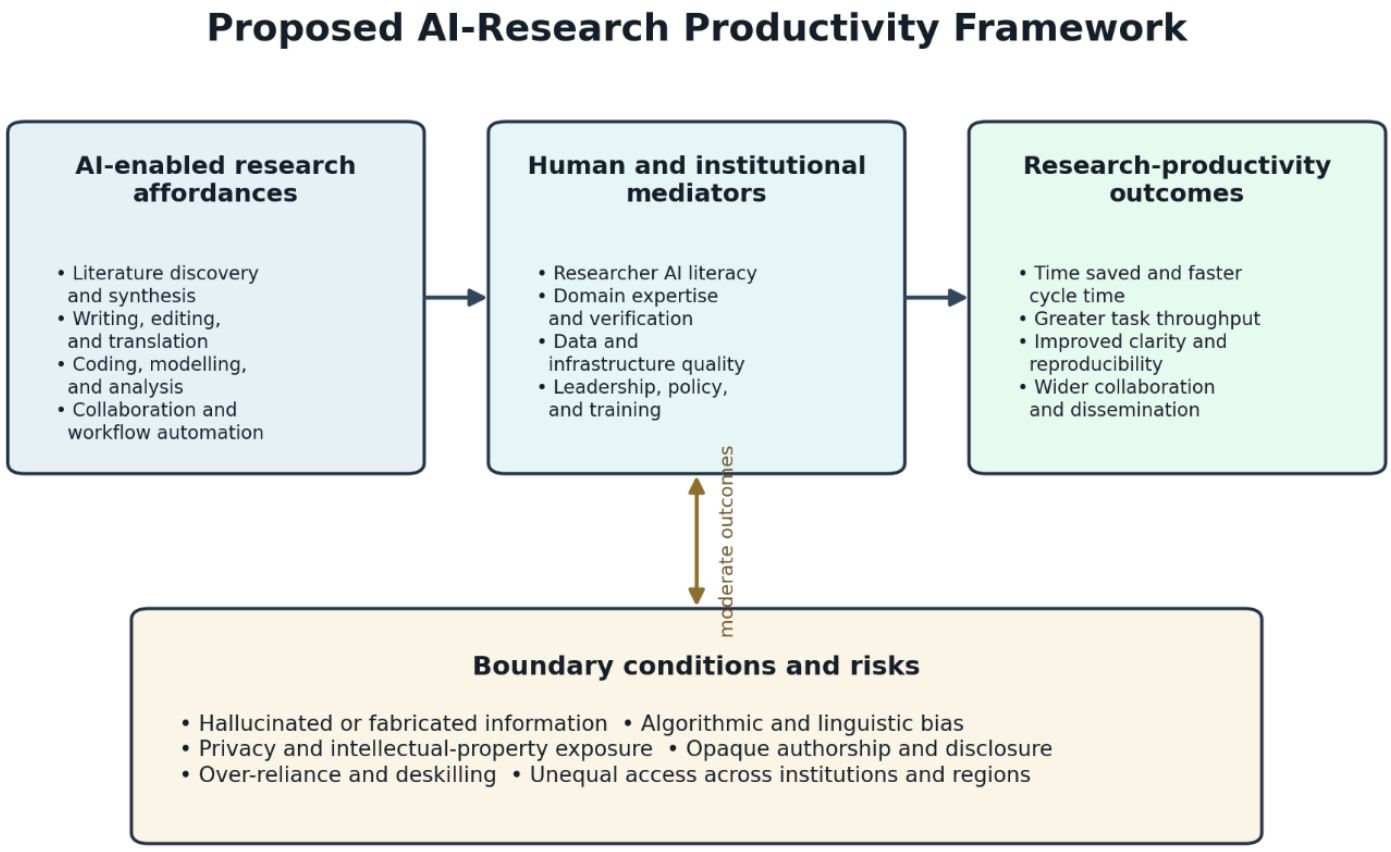


Figure 1

Proposed AI-research productivity framework

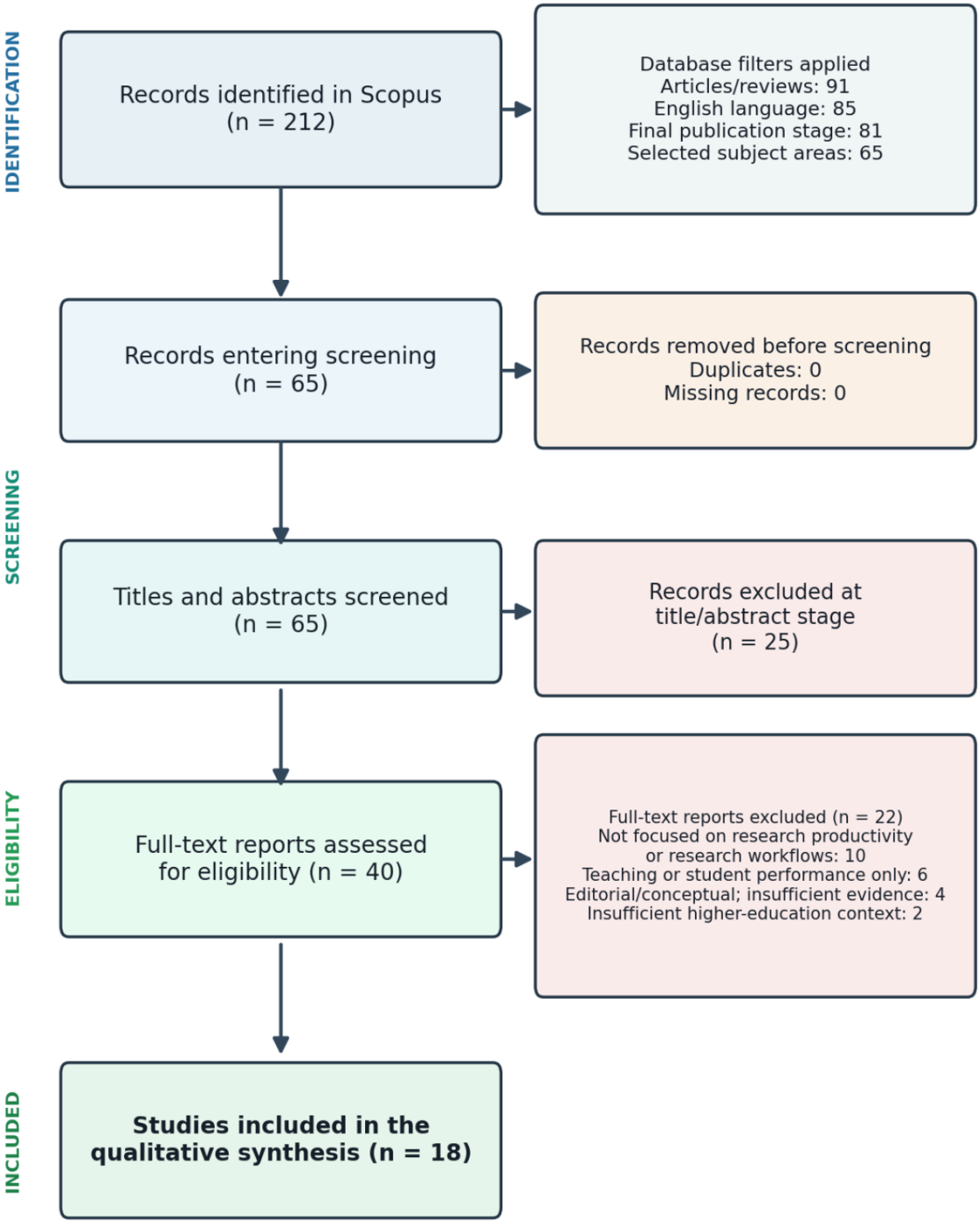


Figure 2

The Selection Flow