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The Rise of AI-Assisted Academic Researchers: Human Capital Enhancement or Human Capital Degradation?

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ABSTRACT

The rapid integration of generative artificial intelligence into academic research practices presents a fundamental paradox for human capital development. While AI tools demonstrably enhance short-term research productivity by automating routine tasks, their long-term impact on researchers' cognitive capabilities and skill endowments remains under-theorized. This conceptual paper addressed this gap by extending human capital theory to the age of cognitive automation. The study argued that AI functions as a dual-use technology in knowledge production: it can either augment researchers' capabilities through cognitive partnership or accelerate skill atrophy through cognitive offloading. By drawing on insights from human capital theory, task-based models of labour, and cognitive psychology, the study proposed a contingency framework wherein the net effect on human capital depends on three moderating variables: usage mode, career stage, and task domain. The paper generated five testable propositions for future empirical research and discusses implications for individual researchers, higher education training programs, and development issues more broadly. The study concluded that AI is neither inherently enhancing nor degrading; rather, its developmental impact is mediated by the institutional and pedagogical contexts within which it is deployed.

INTRODUCTION

Academic research has traditionally been regarded as a profession of learning by doing. The journey of becoming a researcher, from novice undergraduate to accomplished professor, typically follows a clear path of years of apprenticeship filled with struggle, failure, and gradual mastery. Higher education students often learn to write through trial and error, improve their analysis skills by wrestling with uncooperative code, and develop critical thinking by engaging deeply with challenging arguments. This process of cognitive apprenticeship is not just a side effect of building human capital; it is essential to it. The core of learning is the struggle itself.

Over the past years, rapid technological revolutions in geopolitical, socio-economic, and environmental domains across the world have accelerated the development of artificial intelligence (Intizar & Siddique, 2026). However, the rise of generative artificial intelligence is fundamentally transforming this development process. The increasing use of generative AI for drafting, providing feedback, and presentation support has improved learning efficiency (Alipasa, 2026), and various AI research assistants now enable scholars to instantly summarize literature, produce initial drafts, debug code, and even generate hypotheses. For experienced researchers, these tools can free them from routine tasks, allowing more focus on complex synthesis. But for early-career researchers, the implications are less clear. If a higher education student can delegate the task of summarizing 100 papers to an AI, have they truly read those papers? If they can produce a literature review from a simple prompt, do they genuinely understand the field? If they never face the challenge of formulating an argument on their own, can they develop that skill independently?

This paper addresses a question of urgent significance for development economics and higher education policy: Does the integration of AI into academic research practices enhance researchers' human capital, or does it degrade it?

The question is not just theoretical. Human capital, the total of knowledge, skills, and abilities in individuals, serves as the fundamental resource in knowledge economies. Human capital is essential for individuals to thrive and represents the most valuable asset of any society (Alaka *et al.*, 2026). If AI tools are consistently diminishing the very abilities they claim to enhance, the long-term effects on research quality, independence, and institutional capacity in developing countries could be significant. Conversely, if AI provides a way to bypass traditional barriers to skill development, it could democratize research ability in resource-limited settings.

The current debate on AI in academia is divided between technological optimism and cultural pessimism. Optimists highlight productivity gains, noting that researchers can now complete tasks that once took weeks in much less time. Pessimists warn of intellectual decline, imagining researchers who cannot write without prompts or think without algorithms. However, neither side has offered a well-founded economic framework to understand AI's impact on human capital. This is what this study aims to

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The study's contribution is threefold. First, the study expand human capital theory to include cognitive automation, viewing AI not just as a tool but as a factor in the human capital development process of researchers. Second, the study combine insights from task-based labor models and cognitive psychology to develop a contingency framework that outlines the conditions under which AI improves or harms researchers' abilities. Third, the study propose a set of testable hypotheses to guide future empirical research and to provide a roadmap for further study.

The paper is organized as follows. Section 2 reviews relevant literature, integrating human capital theory with emerging research on AI and knowledge work. Section 3 describes our conceptual framework, distinguishing between augmentation and substitution, and developing our contingency model. Section 4 lays out five hypotheses for empirical testing and implications for academic training and research assessment. Section 5 offers concluding remarks.

LITERATURE REVIEW

Human Capital Theory and the Production of Researchers

The concept of human capital, systematized by Schultz (1961) and Becker (1964), fundamentally transformed how economists understand the connection between education, skills, and economic productivity. Human capital refers to the knowledge, skills, and health that individuals invest in through education, training, and experience, yielding returns over their lifetime. In Becker's framework, individuals allocate time and resources to skill development when the expected future benefits outweigh the current costs (Ubi-Abai & George-Anokwuru, 2018). Applying this idea to academic researchers shows a unique human capital production process. Researchers gain human capital through formal education (courses, degrees), apprenticeships (supervision, collaboration), and experiential learning (conducting research, writing, reviewing). Importantly, much of this learning happens through what Polanyi (1997) called "tacit knowledge", one that cannot be fully written down and must be learned through practice and immersion. A researcher learns to ask good questions not by reading instructions but by trying, failing, getting feedback, and trying again.

Task-Based Approaches to Technology and Labour

The task-based framework developed by Autor, Levy, and Murnane (2003), extended by Acemoglu and Autor (2011), offers a valuable perspective for analyzing technology's effect on work. This framework shifts focus from occupations to the individual tasks that make them up, asking which tasks are vulnerable to automation, which can be augmented, and which resist technological replacement. Acemoglu and Restrepo (2019) differentiated between the displacement effect (machines replacing labor in specific tasks) and the productivity effect (technology increasing demand for labor in non-automated tasks).

Applied to academic research, this suggests that AI might displace researchers from certain tasks (such as literature summarization, basic coding, and drafting) while increasing the value of tasks that AI cannot perform (such as creative hypothesis development, interdisciplinary synthesis, and ethical judgment). However, the task-based framework has mainly been used to analyze routine manual and cognitive tasks in industrial and clerical environments. Its application to the highly creative, non-routine work involved in academic research remains limited. Furthermore, the framework has primarily focused on how technology impacts employment and wages, rather than how it influences the skill set of workers themselves. This paper aims to fill that gap by exploring whether performing tasks with AI alters the fundamental capabilities researchers retain when AI is not present.

Cognitive Offloading and the Fluency Illusion

Cognitive psychology offers concepts essential for understanding potential degradation pathways. "Cognitive offloading" (Risko & Gilbert, 2016) refers to the use of physical action and environmental cues to reduce cognitive demands. Writing a reminder reduces memory load; using a calculator reduces arithmetic demands. AI represents an extreme form of cognitive offloading, potentially reducing demands across multiple cognitive domains simultaneously.

The concern is that such offloading may have unintended consequences for skill retention. Research on the "Google effect" (Sparrow, Liu & Wegner, 2011) found that individuals primed to expect future access to information encoded that information less deeply into memory. Similarly, the "fluency illusion" (Bjork, 1994) describes how conditions that make processing easy in the moment—such as having information provided rather than retrieved—can create overconfidence while undermining long-term learning.

These findings suggest a degradation pathway: when AI makes cognitive tasks effortless, researchers may experience a subjective sense of mastery while failing to encode the underlying knowledge or develop the neural circuitry required for independent performance. The danger is not that researchers become lazy, but that the very ease of AI-assisted work circumvents the desirable difficulties through which deep expertise is built.

Emerging Literature on AI and Knowledge Work

A nascent literature directly addresses AI's impact on knowledge workers. Dell'Acqua *et al.* (2023), in a study of consultant performance at Boston Consulting Group, found that AI assistance improved task quality and speed within AI's capabilities but also increased the likelihood of errors when tasks required judgment beyond those capabilities. Noy and Zhang (2023) found that ChatGPT significantly improved writing productivity for mid-

level professionals, though effects on learning and skill development were not examined.

Within academia specifically, studies have examined AI's role in literature review (Wagner *et al.*, 2015), peer review (Liang *et al.*, 2024), and scientific discovery (Wang *et al.*, 2023). However, these studies focus primarily on productivity and quality outcomes rather than on the developmental trajectory of researchers themselves. The question of whether AI-assisted research produces better research is distinct from whether it produces better researchers. This paper addresses the latter question, which remains theoretically underexplored.

MATERIALS AND METHODS

The study adopts a conceptual approach to synthesize existing theoretical and empirical literature to create a new framework for understanding the human capital implications of AI-assisted academic research. A conceptual design is justified for four reasons. First, the phenomenon of AI-assisted academic research is still emerging and rapidly evolving. Empirical data collected today may become outdated as technologies develop and practices change. A conceptual framework provides a durable analytical structure that remains relevant beyond any specific technological moment. Second, current discussions about AI in academia lack a solid theoretical foundation. Existing debates are polarized between technological optimism and cultural pessimism, with neither side offering a rigorous framework for understanding AI's impact on researcher development. The field requires conceptual grounding before substantial empirical research can advance. Third, the scope of inquiry is inherently global. AI assistance influences researchers across all geographical and institutional settings. Empirical work naturally narrows focus to particular contexts; a conceptual approach captures the full scope of the phenomenon. Fourth, this approach aligns with the journal's clear invitation for conceptual pieces that engage deeply with theoretical debates and present significantly new arguments.

The process of developing the framework happened in four stages. In the first stage, the literature review covered multiple disciplines. This included human capital theory (Becker, 1964; Schultz, 1961), labor economics through task-based frameworks for understanding technology's impact on work (Autor, Levy & Murnane, 2003; Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2019), and recent empirical studies on AI and knowledge worker productivity (Dell'Acqua *et al.*, 2023; Noy & Zhang, 2023), as well as AI's role in academic research (Liang *et al.*, 2024; Wagner *et al.*, 2015; Wang *et al.*, 2023).

In stage two, instead of simply summarizing existing literature, the study critically engaged with each body of work by identifying points of tension and debate within and across literatures, examining assumptions when applied to AI-assisted research, pinpointing gaps where existing frameworks fail to capture the unique features of AI mediation, and connecting disparate literatures to foster productive dialogue. This critical engagement showed that, while each body of literature offers valuable insights, none alone provides a comprehensive framework for understanding AI's impact on researcher human capital.

Stage three focused on building theory and developing a framework. Using insights from these literatures, the study constructed a contingency framework that outlines the conditions under which AI assistance either enhances or harms researchers' human capital. Developing the framework involved identifying the key difference between augmentation and substitution as the main variable in AI's impact; drawing on doctoral education scholarship to identify career stage as a crucial moderator, from cognitive psychology to determine usage modes, and on task-based models to define task domains. It also involved explaining how these three moderators interact to influence whether AI use tends to improve or diminish researchers' human capital. Finally, the framework was presented mathematically through an extended human capital production function for clarity.

Stage four produces propositions. From the framework, the study identifies five testable propositions to guide future empirical research. Each proposition logically derives from the framework, suggests a relationship that can be tested empirically, is framed as a question relevant to higher education research, and has clear implications for practice and policy.

The conceptual approach has some limitations. While the framework is theoretically sound, it requires empirical testing and validation. The propositions, although logically derived, need empirical investigation. Although the analysis is critically engaged, it remains tentative as AI technologies and research practices continue to evolve. Despite these limitations, using a conceptual approach is essential at this stage. The field needs a theoretical foundation before meaningful empirical work can begin. This paper provides that foundation, offering a framework that future research can test, refine, and expand upon.

RESULTS AND DISCUSSION

AI as Dual-Use Technology in Knowledge Production

The study conceptualizes AI not as a monolithic tool with uniform effects but as a dual-use technology whose impact on human capital depends on how it is deployed. Drawing on the task-based framework, we distinguish between two modes of AI integration:

Augmentation Mode: AI serves as a cognitive partner that enhances researchers' capabilities without substituting for the developmental experiences through which expertise is built. In augmentation mode, the researcher remains the primary cognitive agent, using AI to extend reach, verify outputs, and explore alternatives. The researcher interrogates AI suggestions, rejects inappropriate outputs, and synthesizes AI-generated materials into their own knowledge structures. The cognitive effort required for this interrogation and synthesis preserves, and may even

enhance, the developmental value of the task.

Substitution Mode: AI serves as a cognitive substitute that replaces researcher effort in tasks that would otherwise provide developmental value. In substitution mode, the researcher outsources core cognitive operations to AI, accepting outputs at face value without the interrogation, verification, or synthesis that builds understanding. The researcher receives the product of the task without performing the process; as a result, the neural pathways that would have developed remain unformed.

This distinction builds on the concept of "desirable difficulties." Tasks performed in substitution mode eliminate difficulties, potentially maximising short-term efficiency at the cost of long-term development. Tasks performed in augmentation mode may preserve or even optimize difficulties—AI can handle routine aspects while the researcher engages with the challenging core, or AI can generate alternatives that increase the cognitive demands on the researcher to evaluate and synthesize.

A Contingency Framework for Human Capital Outcomes

The distinction between augmentation and substitution provides a starting point, but it raises a further question: what determines whether AI use in a given context tends toward augmentation or substitution? We propose that three moderating variables shape this outcome: usage mode itself (as a behavioural variable), career stage, and task domain.

Usage Mode

At the micro-level, academic researchers' behaviour determines whether AI functions as a partner or crutch. Key behavioural indicators include the verification effort, the prompt iteration, and the integration work. The verification effort questions whether academic researchers independently verify AI outputs against primary sources, or if AI claims are accepted uncritically. The prompt iteration questions whether academic researchers engage in iterative refinement of prompts, treating AI interaction as a dialogue, or if initial outputs are accepted as final. The integration work questions if the academic researchers actively integrate AI outputs into their own knowledge structures through annotation, critique, and synthesis, or if AI outputs are simply compiled. These behavioural differences may be influenced by individual dispositions (curiosity, intellectual humility), incentives (time pressure, publication pressure), and training (explicit instruction in effective AI use).

Career Stage

The developmental impact of AI use likely varies dramatically across career stages. For mid-career and senior researchers with well-established knowledge structures, AI use may predominantly enhance human capital. Existing expertise provides the foundation for effective prompting, the schema for evaluating outputs, and the confidence to reject inappropriate suggestions. For these researchers, AI functions as a genuine augmentation, extending capabilities that are already robust.

For early-career researchers, including PhD students and postdoctoral fellows, the calculus is more complex. These researchers are still building the knowledge structures that senior researchers already possess. When they use AI to bypass foundational tasks such as summarising literature they have not read, generating arguments they have not formulated, and debugging code they have not written, they may deprive themselves of the very experiences through which those structures are built. AI use in this context risks substituting for development rather than augmenting existing capability. This is not to argue that early-career researchers should avoid AI entirely. Rather, it suggests that the developmental impact of AI use at this stage depends critically on how it is used, whether it preserves the desirable difficulties essential to learning or eliminates them in the service of short-term output.

Task Domain

Not all academic tasks are equal in their developmental significance. The study distinguishes between three task categories: the low-stakes, high-frequency tasks, intermediate tasks, and core competency tasks. The low-stakes, high-frequency tasks comprise formatting citations, drafting routine correspondence, and basic literature searches. These tasks offer limited developmental value; automating them may free cognitive resources for more significant work without meaningful developmental cost. The intermediate tasks comprise literature summarisation, basic data analysis, and first-draft writing. These tasks offer moderate developmental value but also consume substantial time. AI use here may enhance or degrade depending on the usage mode. Notably, using AI to generate a first draft that the researcher then substantially revises may preserve developmental value. Unfortunately, accepting the AI draft as final likely eliminates it. The core competency tasks comprise theory-building, critical analysis, argument construction, and research question formulation. These tasks are central to researcher development. AI use here is developmentally risky. Definitely, outsourcing these functions may directly erode the capabilities that define a researcher. This task-domain analysis suggests that the net human capital impact of AI depends not only on whether it is used, but on which tasks it is used for and how it is used in each domain.

The Human Capital Production Function with AI

The study formalizes these insights by extending the standard human capital production function. Let H represent the researcher's human capital at time t. In the traditional model, the human capital is specified in

$$H_t = f(L_t, H_{t-1}) \quad .. \quad .. (1)$$

equation 1.

Equation 1 states that H is produced through time allocation to various learning activities (education,

apprenticeship, practice) and prior human capital. Specifically, Lt represents learning activities L requiring cognitive effort at time t, and H(t-1) is human capital H of the previous time, t-1. With AI integration, the traditional human capital production function of equation

$$H_t = f(\alpha(L_t), S(A_t), H_{t-1}) \quad .. \qquad ..(2)$$

1 transforms to equation 2. Where $\alpha(L_t)$ represents augmented learning activities (tasks performed with AI that preserve or enhance developmental value); $S(A_t)$ represents substituted activities (tasks where AI replaces researcher effort, eliminating developmental value); the function f depends on career stage and task domain, as specified in our contingency framework.

Equation 2 states that the human capital H is a function of augmented learning activities using AI to perform tasks that enhance developmental value $\alpha(L_t)$, the substituted activities using AI to replace the researcher's effort that eliminate developmental value, $S(A_t)$. This formulation captures the central trade-off that AI can increase short-term research output while simultaneously reducing the learning activities through which human capital is built. The net effect over time depends on the balance between augmentation and substitution and on how that balance shifts with career development.

Propositions for Empirical Research

Conceptual papers gain power by generating testable propositions that guide future empirical work. This study offers five propositions derived from our framework.

Proposition 1: Career Stage Moderation

The relationship between AI use and human capital outcomes is moderated by career stage. For early-career researchers, intensive AI use for core competency tasks will be associated with lower performance on unassessed measures of those competencies. For senior researchers, the same use pattern will be associated with maintained or enhanced performance.

This proposition follows from the contingency framework that senior academic researchers possess the knowledge structures that enable augmentation; early-career academic researchers are still building those structures and risk substituting AI for development.

Proposition 2: The Inverted-U Hypothesis

The relationship between AI use intensity and human capital follows an inverted-U shape, that is, moderate use enhances human capital by automating routine tasks and freeing resources for higher-order learning; beyond a threshold, further use substitutes for developmental experiences and leads to skill atrophy.

This proposition captures the intuition that AI is not uniformly beneficial or harmful but exhibits diminishing and eventually negative returns at the margin.

Proposition 3: Usage Mode Effects

Researchers who use AI in augmentation mode, such as verifying outputs, iterating prompts, and actively integrating AI-generated materials into their knowledge structures, will demonstrate enhanced human capital outcomes relative to both non-users and substitution-mode users. Substitution-mode users will demonstrate degraded outcomes on tasks requiring independent performance.

This proposition directly tests the behavioural distinction at the heart of the framework of the study.

Proposition 4: Task Domain Specificity

AI use for low-stakes, high-frequency tasks will have neutral or positive effects on human capital regardless of usage mode. AI use for core competency tasks in substitution mode will have negative effects on the specific competencies that those tasks were intended to develop.

This proposition tests the task-domain analysis, predicting that developmental harm is concentrated in tasks central to researcher formation.

Proposition 5: The Fluency Illusion

Substitution-mode AI users will overestimate their own capabilities on tasks they have routinely outsourced to AI, demonstrating a fluency illusion. When required to perform those tasks without AI assistance, their performance will fall below both their self-assessments and the performance of non-users.

This proposition connects our economic framework to cognitive psychology, predicting a specific degradation mechanism: the experience of ease with AI creates overconfidence that masks underlying skill deficits.

Implications for Academic Training and Research Assessment

Our framework suggests implications for how academic programs should respond to AI integration. A prohibitive approach, banning AI use entirely, is likely impractical and may deprive students of opportunities to develop AI literacy that will be essential in their future careers. A laissez-faire approach, leaving AI use to individual discretion, risks the degradation of outcomes our framework predicts. A developmental approach would involve explicit training in effective AI use, emphasising augmentation over substitution; structured opportunities to practice core competencies without AI assistance, ensuring foundational skills are developed; assessment designs that evaluate both AI-assisted and unassisted performance, revealing the fluency illusion; supervisory attention to how students are using AI, with feedback that encourages augmentation and discourages substitution.

Current research assessment systems focus almost exclusively on outputs such as publications, citations, and grants. They do not assess the human capital of researchers themselves. If AI enables higher output volumes while eroding the underlying capabilities that produce them, assessment systems may miss a critical dimension of research system health. This suggests

a need for new indicators that capture researchers' capabilities rather than simply research products. Possible approaches include longitudinal tracking of researcher skills, assessment of unassisted performance at career milestones, and attention to the diversity and novelty of research contributions as proxies for intellectual independence.

CONCLUSIONS

The study addressed a question of crucial importance for the future of academic research: Does integrating AI into research practices improve the human capital of researchers, or does it cause its decline? The study argued that this question cannot be answered with a simple yes or no. AI is a dual-use technology whose developmental impact depends on how it is used.

The contingency framework specifies three key variables that influence human capital outcomes. Usage mode determines whether AI acts as a cognitive partner or a reliance. Career stage affects whether researchers have the necessary knowledge structures for augmentation. Task domain decides whether AI works on tasks that preserve developmental value or tasks that outsourcing directly diminishes core capabilities.

The framework presents five testable propositions meant to guide empirical research. If supported, these propositions would have significant implications for how researchers are trained, how research systems are evaluated, and how countries incorporate AI into their efforts to build research capacity.

The study concludes by reflecting on the normative importance of this question. Whether AI enhances or undermines a researcher's human capital is not just a technical issue. It concerns fundamental questions about what it means to be a researcher, what kinds of minds should produce knowledge, and what we are willing to exchange for efficiency. The answer will not be determined by technology alone. It will be shaped by the choices researchers, educators, and institutions make regarding how AI is integrated into the developmental paths of those who produce knowledge. The framework offered by the study aims to help these choices be made with greater awareness of what is at stake.

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